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The unintended effects from halting nuclear power production: Evidence from Fukushima Daiichi accident ☆

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ABSTRACT

This paper provides novel evidence of the unintended health effects stemming from the halt in nuclear power production after the Fukushima Daiichi nuclear accident. After the accident, nuclear power stations ceased operation and nuclear power was replaced by fossil fuels, causing an increase in electricity prices. We find that this increase led to a reduction in energy consumption, which caused an increase in mortality during very cold temperatures, given the protective role that climate control plays against the elements. Our results contribute to the debate surrounding the use of nuclear as a source of energy by documenting a yet unexplored health benefit from using nuclear power, and more broadly to regulatory policy approaches implemented during periods of scientific uncertainty about potential adverse effects.

Many sources of energy pose hazards to the environment and thus human health, and nuclear energy is no exception (Graff Zivin and Neidell, 2013). Yet these sources of energy also provide clear consumption benefits, some of which may offer important benefits

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to health. In this paper, we provide novel empirical evidence of the unintended health effects from the halt in nuclear power using the shutdowns resulting from the accident at Fukushima, Japan. 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. Within 14 months of the accident, nuclear power production came to a complete halt in Japan.[1]

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 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 outweighs the mortality from the accident itself.

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 price increases around 10 percent, whereas regions with higher dependence on nuclear experienced price increases up to 40 percent. The 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 across electricity regions, estimating models that include multiple fixed effects to control for many possible confounding factors. Our empirical strategy exploits several large, discrete jumps observed in the electricity price across regions at different times, and variations in price changes *within* city-by-period to estimate the effect of prices on household electricity consumption. Estimation with multiple fixed effects enables us to account for the contemporaneous, seasonal and intertemporal confounding factors such as regional and seasonal heterogeneities in energy use and policies as well as the change in the energy saving behavior after the earthquake. 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, suggesting less protection during the coldest times of the year.[2]

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. 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 covers the 21 largest cities in Japan, which represents 28 percent of the total population, the total effect for the entire nation is even larger (over 4,500 deaths from 2011-2014). As a point of comparison, the number of deaths due to the Fukushima Daiichi nuclear accident is much lower, with projections estimates of 130 cumulative deaths due to nuclear radiation exposure (Ten Hoeve and Jacobson, 2012).

In addition to providing evidence of the unintended effects from halting nuclear power production, our results contribute more broadly to regulatory policy approaches, such as the precautionary principle, which are implemented when there is scientific uncertainty about potential adverse effects.[3] While many variants exist, a generally accepted definition of the precautionary principle is that "where there is uncertainty as to the existence or extent of risks to human health, the institutions may take protective measures without having to wait until the reality and seriousness of those risks become fully apparent" (p. 23, European Commission, 2000). 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 (Sustein, 2003). Our study provides the first, to the best of our knowledge, large scale, empirical evaluation of the importance from considering the risk from the alternative option.[4]

[1] The accident also triggered opposition to nuclear production around the globe, with several nations ceasing nuclear operations shortly after the Fukushima accident.

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

[3] While there may be many specific reasons behind the decision to abandon nuclear power production, several 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] While there are case studies that evaluate this tradeoff (see, for example, those described in Adler 2000; Sunstein 2003), we are unaware of large scale, systematic evidence.

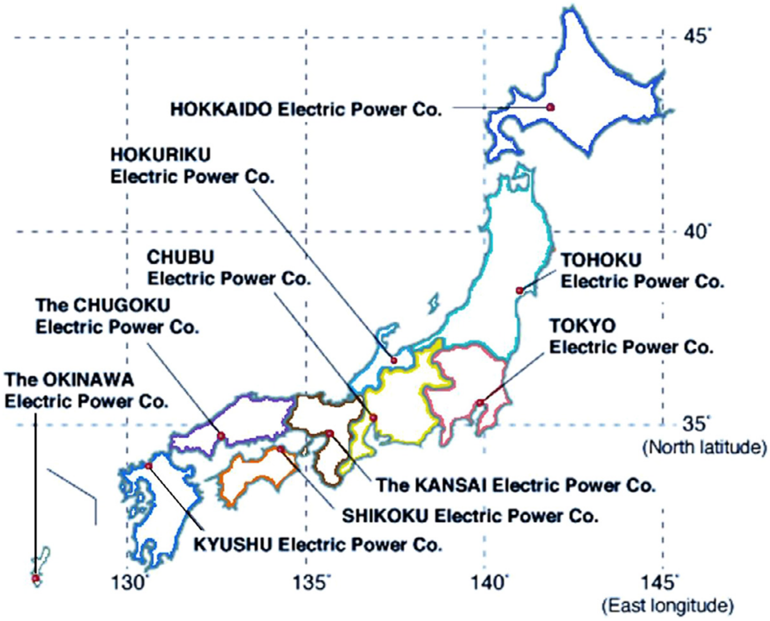

Fig. 1. The ten regions of the electricity market in Japan. Source: the Federation of Electric Power Companies of Japan.

1. Electricity markets in Japan

For the period of our analysis, 2007-2014, the electricity market in Japan was regulated.[5] The market consisted of ten regions (Fig. 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).[6] 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.[29] 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 Fig. 2, prices were relatively steady and quite comparable across 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 and 2011, each region underwent just one approved price change (in late 2008), due to the surge in world oil prices.[7]

Shortly after the Fukushima disaster, all nuclear power reactors ceased production in Japan by May 2012.[8] 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 particularly in 2012-2014. Prices rose gradually over four years after a halt of nuclear power production because power companies had to make an effort to cut costs to stabilize the electricity price before applying for permission of price change.

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 (Fig. 2).[9]

[5] The residential electricity market in Japan has been deregulated since April 2016.

[6] 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 10 amperes (10A) and the latter a minimum charge of 1-15kWh.

[29] See details in Ministry of Economy, Trade and Industry (METI) (2015).

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

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

[9] Because the electricity price was partly adjusted by the world oil price, more dependence on fossil fuels led to a more influence on the regional electricity price. The oil price peaked at more than $100/barrel in 2012 mainly 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

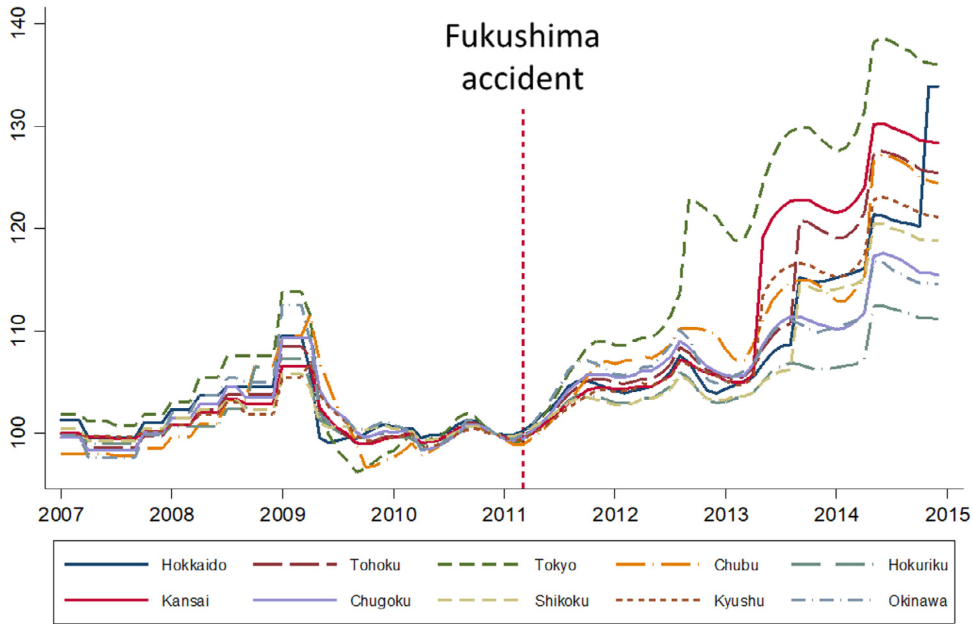

Fig. 2. Monthly average price index of residential electricity by region, 2007-2014 (January 2011 = 100). *Notes:* The figure shows the average monthly price index of residential electricity in Japan by region for the period 2007-2014. The vertical dashed line indicates March 2011 when the Tohoku earthquake and tsunami triggered the Fukushima Daiichi nuclear disaster. Data are from the retail price survey by the Ministry of Internal Affairs and Communications.

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
Kansai	44	21	5	20	-44	3	12	26
Shikoku	43	36	6	5	-43	20	13	3
Kyushu	39	27	7	19	-39	5	8	20
Hokuriku	28	44	3	0	-28	21	5	0
Tokyo	28	10	10	45	-28	7	-3	23
Tohoku	26	34	3	22	-26	6	5	12
Chubu	15	26	4	46	-15	0	-3	15
Chugoku	3	58	13	19	-3	-3	-4	6
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).[a]

[a] We thank them for kindly sharing the data with us.

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 Fig. 2, we observe several discrete jumps in the price schedule of electricity regions. These jumps coincide with the policy timing when the companies' requests of price raise were approved by the METI. Every region experienced price increases once or twice, though at different times, during 2011-14. As a result, 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 Kansai region, and 38 percent in the Tokyo region. Table 1 shows that, before

net effect of the replacement of nuclear by fossil fuels is negative. According to Ministry of Economy, Trade and Industry (METI) (2015), the average annual cost of replacement was about 3.1 trillion yen (0.65 percent of GDP) in 2011-2014.

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).[10] We exploit this regional variation in prices over time to identify the causal effects of interest.

2. Data

We collected monthly data for all the 20 “designated cities” plus the special wards of Tokyo in Japan from 2007 to 2014 on residential electricity prices, electricity expenditure, mortality rates, population, and weather (see Fig. A1 of the Appendix for a map of these 21 cities). 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.

2.1. Residential electricity price data

The monthly average price (per kWh) of residential electricity prices is obtained from the Japanese statistical office. It 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 type of contract and the fixed number of households in each group in the base year 2010 is used as weight.[11] Given the regulated nature of electricity markets, these prices are uniform for cities within the same electricity region.

2.2. 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 the Family Income and Expenditure Survey, 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).

2.3. 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.[12] 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.

2.4. 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. Fig. 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.

[10] 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.

[11] The five groups of households are those with the following types of contract: 180kWh electricity per month with a 20A contract, 270kWh (30A), 350kWh (40A), 450kWh (50A), and 700kWh (60A).

[12] City-level death counts tally up the number of death reports in a city. It is mandatory to send a death report of a citizen (by family, in general) to the municipality within seven days after the death. These data have been used also by Shigeoka (2014).

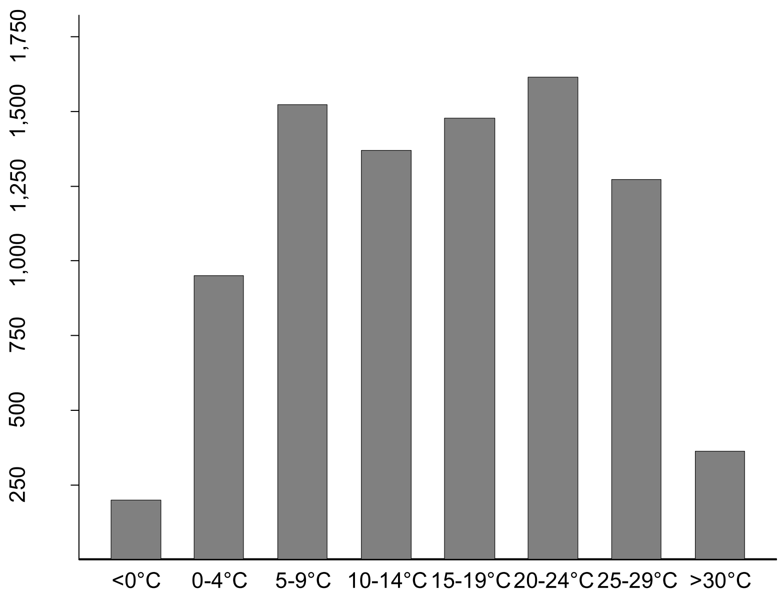

Fig. 3. Distribution of hourly temperatures, 2007-2014
Notes: The figure represents the average number of hours per year in each temperature bin (< 0, 0-4, 5-9, 10-14, 15-19, 20-24, 25-29, and ≥ 30 degrees Celsius) weighted by the total population in a city-year. The figure refers to the seven electricity 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.

Table 2
Descriptive statistics on average mortality rate and temperature extremes, 2007-2014.

	All-age mortality rate	Number of hours per year		
		< 0°C	0-4°C	≥ 30°C
Total	846.16	173 (2.0%)	882 (10.1%)	371 (4.2%)
By electricity region				
01 Hokkaido	824.73	2,011 (23.0%)	1,355 (15.5%)	27 (0.3%)
02 Tohoku	837.33	403 (4.6%)	1,650 (18.8%)	156 (1.8%)
03 Tokyo	790.79	43 (0.5%)	779 (8.9%)	357 (4.1%)
04 Chubu	905.08	68 (0.8%)	878 (10.0%)	403 (4.6%)
05 Kansai	965.33	31 (0.4%)	846 (9.7%)	495 (5.7%)
06 Chugoku	822.62	82 (0.9%)	1,006 (11.5%)	480 (5.5%)
07 Kyushu	855.07	29 (0.3%)	660 (7.5%)	438 (5%)

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 number of hours in percentages are reported in parenthesis. 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.

Other meteorological elements and air pollution are potential confounders in the relationship between temperature, price, 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.

3. Econometric models

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

3.1. Electricity prices and demand

To explore the relationship between residential electricity prices and electricity demand, we follow standard empirical models developed by Baker et al. (1989), Branch (1993), Meier and Rehdanz (2010), Krishnamurthy and Kristrom (2015), and Auffhammer and Rubin (2018). Specifically, we estimate the following equation:

$$\log\left(\mathrm{EXP}_{ct}\right) = \delta\log\left(\mathrm{P}_{ct-k}\right) + \mathrm{X}_{ct}\beta + \rho_{ct} + \varepsilon_{ct} \tag{1}$$

where EXP_{ct} is the average household expenditure of electricity in city c and month t, and $\mathrm{P}_{ct\text{-}k}$ 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.[13] 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 Eq. (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).

We exploit exogenous variation in price changes due to the shutdown of nuclear power plants to identify the parameter δ. As previously discussed, prices spread across regions after the Fukushima Daiichi accident in 2011, while they were relatively steady and quite comparable across regions before 2011. Several large, discrete jumps were observed in the electricity price across regions at different timings (see Fig. 2). This is because the extra costs spent by the electricity companies to replace nuclear power with fossil fuels after the accident differ by region. The dependence on nuclear power was predetermined prior to the accident and varied across regions, ranging from zero to 44 percent. This resulted in an exogenous and non-uniform increase in electricity prices across regions after 2011, leading to more within city-year price variation.

To control for factors that may explain energy consumption, we include several additional variables in our 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 monthly average household characteristics at the city level, 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.

In addition, this model includes several fixed effects, denoted by the term ρ_{ct}, to account for many possible confounding factors that affect supply and demand of residential electricity. We include city-by-month fixed effects to account for seasonality in electricity use by city as well as government energy assistance programs for the poor,[14] 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 city-specific 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

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[13] 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 $\frac{\partial lnq_{ct}}{\partial lnp_{ct}} = \delta - 1$ where q_{ct} is the quantity consumed, as shown in Krishnamurthy and Kristrom (2015).

[14] Both national and local governments provide monthly lump-sum energy allowances for the poor. Some cities in northern Japan (but not in our sample) also offer heating allowances during the winter. These allowance rates are fixed in our sample period and accounted for by the fixed effects.

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. Standard errors are clustered at the city level to account for 1) the fact that all residents within a city face the same electricity prices and weather shocks (Moulton, 1986, 1990; Abadie et al., 2017); and 2) potential serial correlation over time. In our analysis, we also assess sensitivity to clustering at the region level. All regressions are weighted by the number of households within a city.

To summarize, our empirical strategy exploits exogenous variations in price changes *within* city-by-period to estimate the effect of prices on household electricity consumption.

3.2. 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 at the city-month level, adhering to the specification by Barreca et al. (2016). Specifically, we estimate the following equation:

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

In this equation, M_{ct} is the monthly age-adjusted mortality rate (per 100,000) in city c and month t. As specified in Barreca et al. (2016), T_{cti} represents temperature values denoted as the number of hours in city c over the past two months (i.e., t and t-1) to account for lagged physiological effects, 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 and the 15-19 degrees Celsius bin is the excluded category. 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., demographic factors such as birth rates, age and income distributions; local economic conditions such as business climate and unemployment rates; and social welfare factors such as the number of doctors and hospital quality),[15] 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 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.

3.3. 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 Eq. (2) by adding the residential electricity price and its interaction with temperature. Specifically, we estimate the following equation:

$$\log(M_{ct}) = \Sigma_i \alpha_i' T_{cti} + \delta' \log(P_{ct-k}) + \Sigma_i \lambda_i T_{cti} \times \log(P_{ct-k}) + X_{ct}\theta' + \gamma_{ct}' + v_{ct} \tag{3}$$

where all variables are defined as in Eqs. (1) and (2), with the prime superscript separating this equation from the previous one. Our main focus is on the interaction term coefficients of the temperature bins and lagged price, λ, which indicate 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 (λ>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. We only expect the interaction term coefficients (λ) to be significant for the temperature bins that affect mortality, as uncovered from estimation of Eq. (2). During moderate temperatures, however, we expect λ=0 because, although electricity consumption may decline, moderate temperatures do not affect mortality.

The vector γ'_{ct} includes the same set of fixed effects as γ_{ct} in Eq. (2): city-by-year, year-by-month, and city-by-month fixed effects. As described in the previous subsection, these fixed effects allow us to account for several confounding factors such as local economic conditions (e.g., unemployment rates), differences in birth rates, age and income distributions across regions, time factors common to all the cities (e.g., national business cycles), and city-specific, seasonal factors (e.g., migration, seasonal employment, and epidemics). Furthermore, city-by-year fixed effects additionally account for unobserved city-specific dynamic determinants of electricity demand such as energy-saving campaigns and the energy saving behavior as delineated above in subsection A. Similarly, city-by-month fixed effects account for the effect of government energy assistance programs for the poor. Identification in this model follows from the exogeneity of temperature and price changes as described above to estimate the causal effect of electricity prices on the temperature-mortality relationship.

[15] 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).

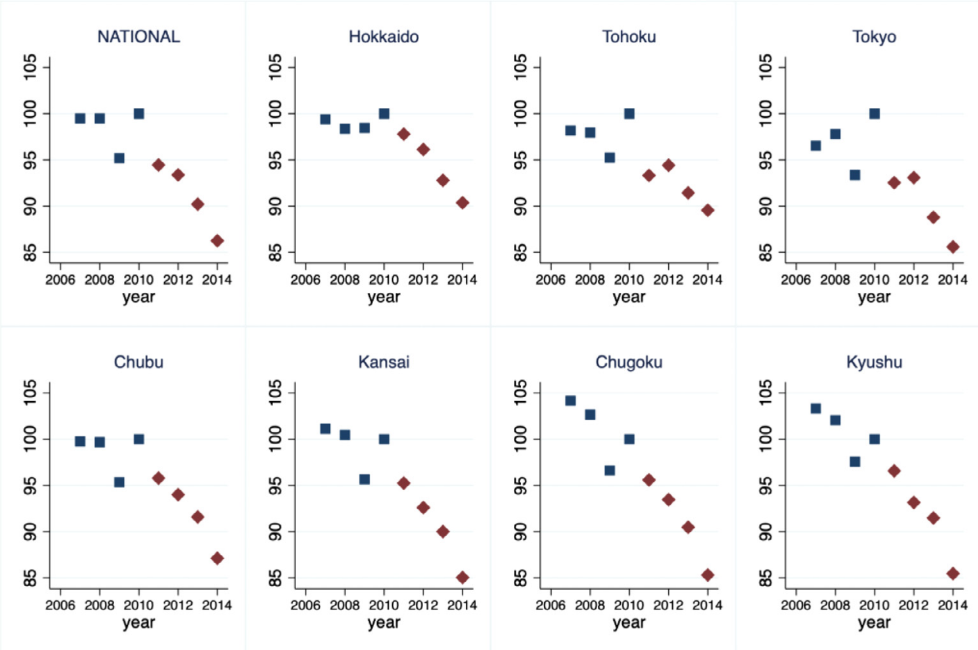

Fig. 4. Annual average residential electricity consumption per capita by region, 2007-2014 (2010 = 100)
Notes: The figure represents average residential electricity consumption per capita by region before (blue squares) and after (red diamonds) the Fukushima Daiichi Nuclear Power Station accident in 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.

4. Results

4.1. Electricity prices and demand

We first provide graphical evidence before discussing estimation results of Eq. (1). Figure 4 plots annual average residential electricity consumption per capita by region and shows a sharp decline in electricity consumption after 2011.[16] Correlation between electricity consumption and prices is about -0.9 in every region in 2007-2014. Figure A2 of the Appendix presents the association between annual average price and consumption per capita of residential electricity by region and season and shows higher correlations during the winter. These are 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 Eq. (1) with the different lagged prices to test **hypothesis 1**.[17] The estimates in columns 1-3 uses the second price lag, the first price lag, and 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 Auffhammer 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

[16] 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. Recall that the decline of electricity consumption per capita in 2008 and 2009 is driven by the surge in world oil prices as described in Figure 2.

[17] Given the slow movements in prices, and therefore high degree of collinearity across lags, we include each lag separately in these models.

Table 3
Price elasticity of residential electricity demand.

Log(price)	Second lag of price	First lag of price	Current price
	(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 Eq. (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 where the period is defined equal to one after the March 2011 earthquake and zero before then, 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)	(7)
Price elasticity	-0.303**	-0.292***	-0.338**	-0.303**	-0.303***	-0.242**	-0.277**
	(0.108)	(0.041)	(0.108)	[0.011]	[0.005]	(0.097)	(0.115)
City-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	No	No	Yes	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 Eq. (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. Columns 4 and 5 present 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 6 excludes Hokkaido and column 7 excludes Tohoku. All regressions are weighted by the number of households, and standard errors clustered at the city level are presented in parentheses except in column 5 where standard errors are clustered at the region level. Data refer to the period 2007-2014. ***, ** indicate significance at the 1% and 5% level, respectively.

from zero during the winter months (-0.249), and is more elastic than during the summer months (-0.180).[18] This suggests that people are more sensitive to electricity price during winter months and therefore potentially less protected from the elements during the coldest times of the year. One possible explanation for this difference is that inexpensive substitutes are more abundant in the cold: people can wear warmer clothes and use blankets, but there are few alternatives to the use of cooling devices for coping with heat.

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. We also apply the wild cluster bootstrap-t procedure suggested by Cameron et al. (2008) to account for the small number of city clusters (21) in column

[18] 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.

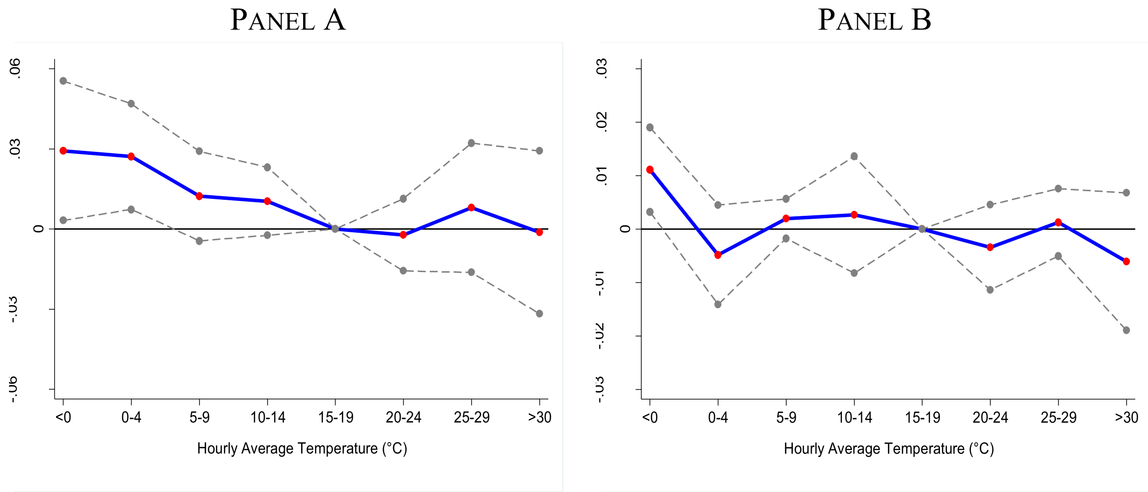

Fig. 5. The temperature-mortality relationship (Panel A) and the impact of residential electricity prices (Panel B)
Notes: Panel A shows cumulative dynamic estimates of the temperature-mortality relationship. The dependent variable is the logarithm of the age-adjusted monthly mortality rate. The figure plots the point estimates multiplied by 100 (dots in continuous line) and the 95 percent confidence intervals (dots in dashed line) of the temperature coefficients α_i obtained by fitting Eq. (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. Panel B shows the impact of a 10 percent increase in residential electricity prices on the temperature-mortality relationship. The figure plots the point estimates multiplied by 10 (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 Eq. (3) and calculated by the sum of coefficient estimates of each interaction term λ_i in the current and the previous months. In panels A and B, regressions are weighted by city population. Standard errors are clustered at the city level. Data refer to years 2007-2014.

4 and region clusters (6) in column 5. Columns 6-7 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.[19]

4.2. Temperature and mortality

Fig. 5 (panel A) displays the temperature-mortality relationship from the estimation of Eq. (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]

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, particularly in our sample of large cities, which is over 90 percent. For example, Barreca et al. (2016) find that temperatures above 90°F (32°C) affect mortality before 1990 when AC penetration rates were low, but have much smaller and statistically non-significant effects as AC rates increased after 1990, when AC penetrations rates in the US were comparable to those in Japan. In light of this, our estimates align quite closely with the previous literature.

We perform a number of robustness checks in Table 5. Column 1 presents our baseline specification, which includes the full set of fixed effects. We show that our results remain robust when we omit city-by-year fixed effects (column 2), we control for air pollution and windchill[22] (column 3), and we account for the small number of clusters (column 4).[23]

19 In addition, we control for local economic conditions by including city-specific monthly effective job openings ratio (or quarterly unemployment rate) and consumer price index. We tried different number of temperature bins, and also run unweighted regression. Our results are qualitatively the same as from our main specification.

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.

22 We use the Steadman index to measure windchill, which is a nonlinear combination of temperature and wind speed (Steadman 1984).

23 We also try several other robustness checks as described in footnote 19. Results do not change qualitatively.

Table 5
The temperature-mortality relationship: robustness checks and cause of death.

	Baseline(1)	No city-by-yearfixed effects(2)	Air pollutionand windchill(3)	Wild clusterbootstrap(4)	Cardiovasculardisease(5)	Respiratorydisease(6)	Other causes(7)
Number of hours < 0°C	0.028**	0.040**	0.030**	0.028**	0.058***	0.028	-0.020
	(0.012)	(0.018)	(0.015)	[0.015]	(0.020)	(0.016)	(0.014)
0-4°C	0.027***	0.024**	0.028**	0.027***	0.062***	0.028	-0.011
	(0.009)	(0.011)	(0.011)	[0.004]	(0.016)	(0.020)	(0.008)
25-29°C	0.008	0.013	0.006	0.008	0.003	0.010	0.015
	(0.011)	(0.010)	(0.010)	[0.428]	(0.016)	(0.025)	(0.020)
≥ 30°C	0.000	0.007	-0.003	0.000	-0.009	-0.019	0.005
	(0.014)	(0.010)	(0.012)	[1.000]	(0.030)	(0.040)	(0.017)
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	Yes
City-by-year fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	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 Eq. (2). Column 2 excludes city-by-year fixed effects. In column 3, we report estimates where in Eq. (2) 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 refers to mortality due to cardiovascular disease, column 6 due to respiratory disease, and column 7 due to other causes (neoplasm, diabetes, suicide, motor vehicle accidents, and infectious diseases). 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.

	Second lag of price (1)	First lag of price (2)	Current price (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 Eq. (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.

We also investigate the underlying cause of death in Table 5 (columns 5-7).[24] Results indicate that cardiovascular disease has a significant effect on mortality from cold temperatures. 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 U.S. On the other hand, we do not find a statistically significant effect of temperature on mortality due to respiratory disease, and the magnitude of the estimates are smaller as well.

4.3. *Electricity prices, temperature and mortality*

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 Eq. (3). Given that we only found effects on mortality from the coldest temperatures, our 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 and Fig. 5 (panel B). 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. The positive coefficient on the interaction term suggests that increased exposure to extreme cold temperatures has a larger effect on mortality when energy prices are higher. 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 Fig. 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.

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 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 city clusters or electricity region clusters by wild cluster bootstrap-t procedure as described by Cameron et al. (2008) with 1,000 replications (columns 4 and 5, 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 6-7).[25] We also investigate the underlying cause in columns 8-10 of Table 7. As before, we find a significant effect of electricity prices on

[24] 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).
[25] We perform several additional robustness checks as denoted in footnote 19. Results do not change qualitatively.

Table 7
The impact of residential electricity prices on the temperature-mortality relationship: robustness checks and cause of death.

	Baseline (1)	No city-by-year fixed effects (2)	Air pollution and windchill (3)	Wild cluster bootstrap city level (4)	Wild cluster bootstrap region level (5)	No Hokkaido (6)	No Tohoku (7)	Cardiovascular disease (8)	Respiratory disease (9)	Other Causes (10)
Number of hours < 0°C	0.108**	0.181***	0.106**	0.108***	0.108***	0.148**	0.101**	0.133*	0.039	0.066
	(0.038)	(0.028)	(0.039)	[0.002]	[0.000]	(0.072)	(0.040)	(0.077)	(0.073)	(0.055)
0-4°C	-0.049	-0.020	-0.052	-0.049	-0.049	-0.054	-0.040	-0.048	-0.01	-0.025
	(0.045)	(0.028)	(0.045)	[0.240]	[0.170]	(0.053)	(0.056)	(0.064)	(0.116)	(0.065)
25-29°C	0.011	-0.004	0.006	0.011	0.011	-0.001	0.002	0.021	-0.088	0.055
	(0.029)	(0.025)	(0.030)	[0.698]	[0.716]	(0.003)	(0.003)	(0.051)	(0.065)	(0.042)
≥ 30°C	-0.060	-0.144	-0.063	-0.060	-0.060	-0.089	-0.039	0.019	0.153	-0.062
	(0.059)	(0.073)	(0.059)	[0.250]	[0.478]	(0.059)	(0.061)	(0.112)	(0.110)	(0.074)
SPM			34.753							
			(55.899)							
Ox			72.280							
			(58.817)							
Windchill			0.147							
			(0.204)							
Fixed effects										
City-by-month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-by-year	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month	Yes	Yes	Yes	Yes	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 Eq. (3). Column 2 excludes city-by-year fixed effects. In column 3, we report estimates where in Eq. (3) we control also for air pollution (Suspended Particulate Matter, SPM; Photochemical Oxidant, Ox) and windchill. Columns 4 and 5 present 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 6 excludes Hokkaido and column 7 excludes Tohoku. Column 8 refers to mortality due to cardiovascular disease, column 9 due to respiratory disease, and column 10 due to other causes (neoplasm, diabetes, suicide, motor vehicle accidents, and infectious diseases). 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 except in column 5 where standard errors are clustered at the region level. Data refer to the period 2007-2014. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 8
Total mortality 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.

the temperature-mortality relationship for cardiovascular disease and temperature below 0°C but not for respiratory disease or other causes.

5. Total mortality impacts

We assess the impacts of temperature and residential electricity price on mortality. We use the parameter estimates of the temperature variables (α's) from Eq. (2) and the interaction terms between electricity price and temperature (λ's) from Eq. (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 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, a gap that is likely to grow with time given that the higher electricity prices have persisted since the end of our study period.[26]

6. Conclusion

In this paper, we document previously unexplored effects from the halt in nuclear power. In particular, after the Fukushima Daiichi nuclear accident, replacement of nuclear power by imported fossil fuels led to increases in electricity prices. The price increases reduced electricity consumption during the coldest times of the year. Given its protective effects from extreme weather, the reduced electricity consumption increased mortality during very cold temperatures.

Our findings relate to other studies on energy prices and health. Chirakijja et al. (2019) find that lower energy prices in the U.S. as a result of natural gas expansion decreased mortality rates due to cold weather. Similarly, Bhattacharya et al. (2003) find that cold shocks lead to decreased nutrition, particularly for low-income households. In a related paper, He and Tanaka, 2020 find that energy-savings campaigns in Japan following the closing of nuclear plants led to increased mortality.[27] This body of evidence suggests

[26] 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 Section 2).

[27] An important difference between He and Tanaka, 2020 and our study is that they find an effect from hotter temperatures, and we do not find a statistically significant effect. The most likely explanation behind this difference is their focus on energy-savings, which explains a higher fraction of energy consumption changes at high temperatures than prices.

that energy policy must account for the full welfare effects that the higher prices may cause, a particularly important topic as nations around the world seek to address climate change.

Our results also speak directly to policy around nuclear power, a controversial source of energy since its inception give the high level of risk it introduces. A meltdown, although uncommon, can be catastrophic. Although far fewer people are projected to die from radiation exposure following Fukushima when compared to the Chernobyl accident, this outcome is no guarantee. The massive evacuations surrounding Fukushima led to a high number of deaths and displacement. It also created an inhabitable area with high costs of clean up. Even in the absence of accidents, nuclear power poses a critical challenge with the storage of spent nuclear fuel.

Nuclear also creates important benefits. It has no impact on local air pollution and greenhouse gas emissions. Fossil fuels, on the other hand, emit a wide range of pollutants that deteriorate local air quality and significantly affect morbidity and mortality (Graff Zivin and Neidell 2013). Estimates from the U.S. show that closure of nuclear power plants after the Three Mile Island accident led to increased particle pollution (Severnini 2017). The same is true in Germany, which phased out nuclear after the Fukushima accident (Jarvis et al. 2019).

Our results add to the debate surrounding the use of nuclear as a source of energy by uncovering a health benefit from using nuclear. The lower costs of energy production enable households to use more energy to protect themselves from the elements. This may be particularly important for budget-constrained households (Bhattacharya et al., 2003). The implications for the future of nuclear power differ significantly depending on whether policy focuses on building new plants versus leaving existing plants in operation. The cost of building a new plant is expensive (Davis 2012), while the cost of operating an existing plant is quite low. Our results suggest that decommissioning existing plants, a growing practice in many countries, may have undesirable consequences that must be factored into the decision.[28] Furthermore, these consequences may be particularly felt by lower-income households, such that these policies may increase health inequalities.

Our findings call attention to the implementation of regulatory policy approaches like the precautionary principle when there is uncertainty about the threats of damage. While all nuclear power plants were shutdown to focus on the risk from operation, the financial and health implications from switching away from nuclear energy should be an important consideration in the decision to cease nuclear power.

Author statement

This statement indicates that we share joint responsibility for the work in this paper.

Appendix

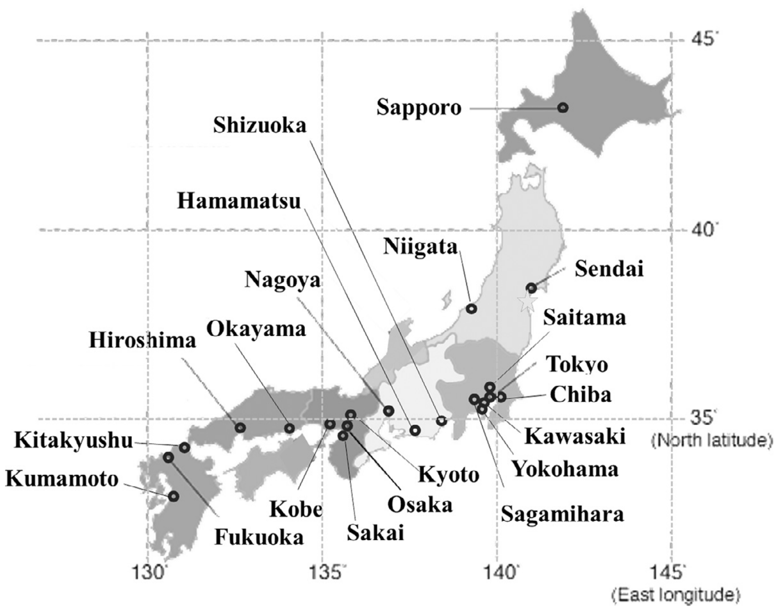

Fig. A1. Location of 21 Designated Cities
Source: Authors' drawing based on the Federation of Electric Power Companies of Japan map.

[28] For example, in the United States, 58 plants remain in full operation and 30 plants are decommissioning or already decommissioned (U.S. Energy Information Administration (U.S. EIA), 2017).

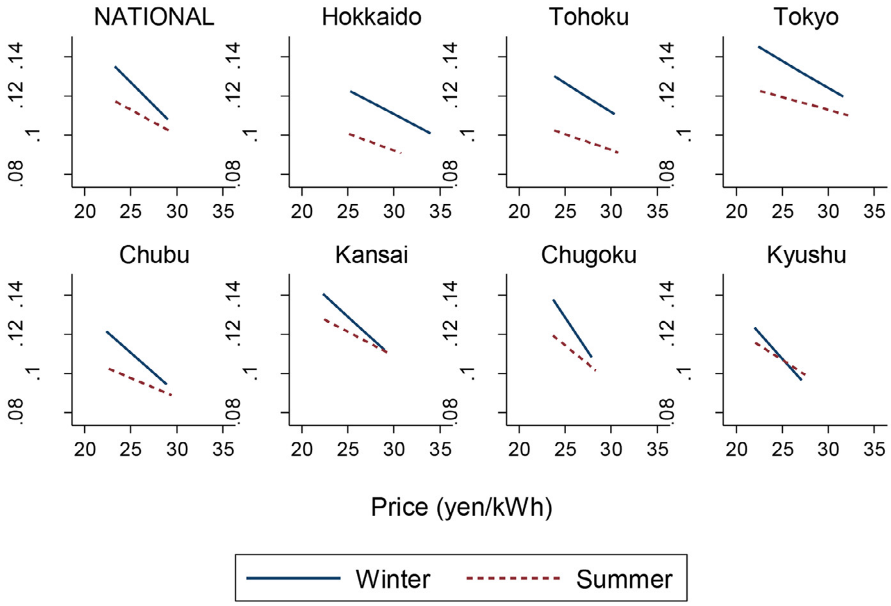

Fig. A2. Annual Average Price and Consumption per Capita of Residential Electricity by Region and Season, 2007-2014
Notes: The figure represents the association between average residential electricity price and consumption per capita by region and season in 2007-2014. The first figure refers to their association at the national level while the remaining figures refer to the seven electricity regions included in our analysis (Hokkaido, Tohoku, Tokyo, Chubu, Kansai, Chugoku, and Kyushu). Solid lines depict the association for winter months (October through March) and dotted lines for summer months (June through August). Data on price and consumption are respectively from the Japanese Statistical Office and the Electricity Statistics Information by the Federation of Electric Power Companies of Japan for years 2007-2014.

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