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Effect of global warming on willingness to pay for uninterrupted electricity supply in European nations

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Predicted changes in temperature and other weather events may damage the electricity grid and cause power outages. Understanding the costs of power outages and how these costs change over time with global warming can inform outage-mitigation-investment decisions. Here we show that across 19 EU nations the value of uninterrupted electricity supply is strongly related to local temperatures, and will increase as the climate warms. Bayesian hierarchical modelling of data from a choice experiment and respondent-specific temperature measures reveals estimates of willingness to pay (WTP) to avoid an hour of power outage between €0.32 and €1.86 per household. WTP varies on the basis of season and is heterogeneous between European nations. Winter outages currently cause larger per household welfare losses than summer outages per hour of outage. However, this dynamic will begin to shift under plausible future climates, with summer outages becoming substantially more costly and winter outages becoming slightly less costly on a per-household, per-hour basis.

Two forces are likely to have a negative impact on electricity supply security in Europe over the next decades. The first is increases in renewable generation capacity, which stresses the transmission and distribution grids with intermittent generation[1]. The second is climate change. The predicted climactic changes of increased temperatures, increased winds and storms, extreme high temperatures and ice storms can cause damage to the electricity grid and subsequent power outages[2]. However, there are numerous potential adaptations that could reduce the probability of power outages, such as rerouting transmission lines, installing external coolers to transmission components and enhancing stability standards for pylons. These adaptations will be costly and thus should be installed in regions where there is great risk of climate-related grid damage and/or regions where power outages will cause the largest costs to society. Furthermore, grid investments made today will affect supply security for years to come[3]. To ensure that the EU invests in measures to mitigate the risk of power outages to the socially optimal degree, an understanding of the costs of power outages and how these costs will change over time with global warming is necessary.

Previous studies have investigated the value of electricity supply security in the EU, estimating the value of supply security for individual EU nations[4–7]. Results from these analyses suggest that the welfare losses from blackouts vary on the basis of the duration of the outage, and the season and country in which the outage takes place, with losses being in the range of €15–25 per kWh not supplied[4,5,7,8]. A study of WTP to avoid blackouts in Cyprus found that residents have WTP of about €0.20 and €0.78 to avoid an hour of summer or winter power outage, respectively[9]. However, no past study on the topic has allowed for a comparison of the effects of power outages across a large sample of nations using consistent methodology and data. Moreover, no past research has considered the effects of temperatures on welfare losses from power outages. Temperature has been shown to be one of the most important drivers of household electricity consumption, where more extreme temperatures lead to more electricity consumed[10–12]. This is unsurprising given that nearly 65% of household energy consumption in the EU is used for space heating[13].

This paper fills these gaps in the literature by estimating the welfare losses from longer-term power outages using data that cover 19 EU nations. Furthermore, we model these welfare losses as functions of temperature. Given the observed relationship between temperature and electricity use, we posit that power outages at times of extreme temperature will cause larger welfare losses than power outages at times of mild temperature. In high-income nations, global-warming-induced temperature increases are predicted to be the dominant factor driving future changes in energy use[2]. We use climate change predictions from the Hadley CM3 to show how future increases in temperature will change the value of uninterrupted electricity, and the spatial distribution thereof. Our results confirm the hypothesis that local temperature at the time of the outage drives the welfare cost per hour of outage, with summer outages being more costly during higher temperatures, and winter outages being more costly during lower temperatures. Given the predicted temperature effects of global warming, we use our results to show that summer outages will become substantially more costly while winter outages will become slightly less costly, per affected household and hour of outage, over this century.

Temperatures drive the welfare loss from power outages

To estimate the welfare losses from power outages in our sample of EU nations, we match data obtained from a combined phone-and-postal survey, containing a choice experiment, to temperature data from the European Climate Assessment and Dataset ENSEMBLES's project 'E-OBS' gridded data set, which contains imputed daily temperatures across Europe[14]. Figure 1 shows the distribution of average January and July temperatures across the EU. The choice experiment included in each survey presented respondents with hypothetical unplanned power outage scenarios and asked whether they would pay a varying bid price to avoid each scenario. These hypothetical

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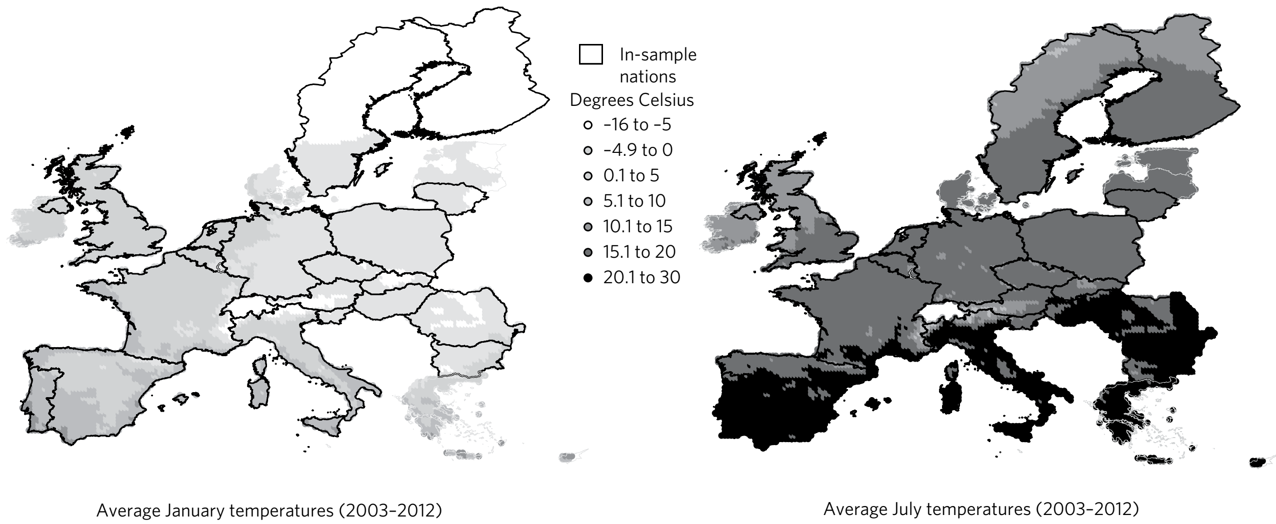

Fig. 1 | Monthly average temperatures across the EU. These monthly average temperatures are calculated from daily averages of E-OBS data. Nations in our sample of 19 are outlined; darker colours denote regions with higher average temperature.

power outages occurred in either January, the winter month, or July, the summer month. Along with the choice experiment, the survey obtained demographic and power outage history information from each respondent. The temperature measure used in the analysis is the monthly average temperature for either January or July, constructed from daily averages, averaged over the past ten years from the time the survey was taken. Other measures of temperature were tested with similar results (see Supplementary Note 1).

We posit that a causal relationship between WTP to avoid a power outage and temperature is driven, in large part, by the use of ambient heating and cooling devices. As temperatures become more extreme, more people will turn on their heaters or air conditioners and they will experience greater discomfort if these electricity-dependent systems are inoperable. However, the threshold temperature at which a person switches on their heating or air conditioning units is unlikely to be the same between regions with different climates and cultures. In some areas, air conditioner and/or heating units may not even be widely available. We account for this difference between regions by two methods. The first is by including country fixed effects in our statistical model that will account for general discrepancies between nations including the use of heating and cooling devices. The second method is to split our temperature variable into three groups using Jenks natural breaks based on the average temperatures in each nation. This will allow for temperature to have a different effect on WTP depending on the prevailing climate of the nation and thus account for cultural or technological differences in how people cope with uncomfortable temperatures. Cold nations are those in the North or Alpine regions: Austria, Belgium, the Czech Republic, Finland, Germany, UK, Sweden and the Netherlands. Mid nations are: Lithuania, Slovakia, Poland, France and Slovenia. Warm nations are those in the southern, Mediterranean region: Hungary, Bulgaria, Portugal, Romania, Italy and Spain. These groupings of nations affect only our temperature measure; other differences between the cultures and energy needs of nations are captured in nation-specific fixed effects.

We model welfare losses from power outages as the respondents' WTP to avoid outages of specified characteristics. Each respondent's WTP is a function of their own history with power outages, demographic information, country of residence, scope of the outage (whole country versus local), and the average temperature in their area in the month of the outage. These variables are summarized in Table 1. Table 2 gives a comparison of explanatory variable means across our 19 sample nations, as well as the number of respondents in each nation. This table highlights the cross-country heterogeneity in many dimensions within our sample nations. The marginal effects for the dependent variables that explain respondents' WTP are given in Table 3. The marginal effect of the 'urban' variable shows that residents of urban areas are willing to pay more to avoid power outages, probably due to concern that the outage would effect nearby desirable infrastructure, such as hospitals or traffic systems. The results from the demographic variables suggest that older residents

Table 1 | Summary statistics of explanatory variables

Variable	Description	Mean	s.d.	Min.	Max.
urban	Lives in urban area	0.27	0.45	0	1
male	Is male	0.46	0.50	0	1
age35t45	Between age 35 and 45	0.18	0.39	0	1
age46t60	Between age 46 and 60	0.36	0.48	0	1
over60	Over age 60	0.41	0.49	0	1
hhsize	Members in household	2.66	1.24	1	6
college	College degree	0.40	0.49	0	1
out1t4	Experienced 1–4 hour outage	0.32	0.47	0	1
out4t8	Experienced 4–8 hour outage	0.12	0.32	0	1
out8t24	Experienced 8–24 hour outage	0.07	0.26	0	1
over24	Experienced over 24 hour outage	0.04	0.20	0	1
numoutages	Number of outages in past year	3.14	4.42	0	25
rotation	Outage scenario ordering	0.51	0.50	0	1
wholecountry	Outage effects entire country	0.50	0.50	0	1

21,832 observations from 2,729 respondents; $\mathbf{z}_{is}$ vectors also contains country indicator variables.

Table 2 | Cross-country comparison of sample means

	Income	Male	Age	Hhsize	College	Urban	Numoutages	No. respondents
France	30,006	0.44	51.17	2.75	0.40	0.18	3.37	158
Germany	31,181	0.59	57.75	2.55	0.51	0.08	1.17	130
Italy	24,300	0.40	54.64	2.68	0.30	0.32	3.43	161
UK	26,661	0.50	53.41	2.88	0.35	0.10	2.06	146
Austria	29,235	0.56	53.86	3.03	0.31	0.13	2.62	151
Belgium	26,718	0.53	50.10	2.48	0.52	0.42	1.86	173
Finland	27,753	0.47	61.49	1.88	0.41	0.13	2.54	83
Netherlands	21,753	0.47	55.48	2.01	0.24	0.20	1.10	154
Spain	22,177	0.51	53.66	2.97	0.46	0.53	2.86	148
Sweden	26,012	0.65	58.80	1.94	0.34	0.15	1.43	99
Portugal	15,643	0.52	52.77	2.99	0.32	0.30	3.87	119
Bulgaria	4,139	0.37	52.58	2.70	0.59	0.63	5.41	132
Czech Republic	10,239	0.51	56.66	2.59	0.45	0.28	2.74	136
Hungary	5,399	0.33	57.64	2.70	0.31	0.10	5.23	172
Lithuania	5,515	0.28	55.38	2.65	0.62	0.11	2.56	151
Poland	7,141	0.47	57.33	2.77	0.42	0.41	3.62	159
Romania	3,196	0.44	55.61	2.76	0.48	0.52	7.38	140
Slovakia	7,556	0.39	55.86	2.88	0.37	0.24	3.19	156
Slovenia	14,832	0.41	57.07	2.76	0.30	0.29	2.63	161

2,729 total respondents; age mean constructed from 4 age categories by taking the middle value of each category and using 68 for those over 60; variables are defined in Table 1.

are willing to pay more while males are willing to pay less. The marginal effects of household size and college education are considered inconclusive. A respondent's history with power outages is also shown to drive their WTP, as respondents who have recently experienced a long outage of over 4 hours ('out4t8' and 'outover24') are willing to pay less to avoid future outages. This is probably due to a readiness factor, whereby these respondents have prepared for future outages by, for example, buying flashlights, candles or perhaps even a generator. The scenario specific variable 'wholecountry' shows by far the largest marginal effect on WTP, which demonstrates that outages that affect a larger geographic region have a larger negative welfare impact. Again this is probably due in part to the loss of valued infrastructure outside the home, and perhaps altruism where the respondents are concerned with the effects of the outage on friends and family.

The marginal effect of the temperature variables are highly season-dependent—being strongly negative in the winter and strongly positive in the summer. This is to be expected since increases in summer temperatures will increase the need for indoor cooling and thus the discomfort from a power outage, while increases in winter temperatures will reduce the need for heating and consequently decrease the discomfort from a winter outage. We also see that the effect of temperature on WTP is heterogeneous across our groups of nations, with lower winter temperatures having a stronger effect on WTP in colder nations, while higher summer temperatures generally have a stronger effect in warmer nations.

Global warming and the welfare loss from power outages

Using the results of the model, we calculate the average WTP to avoid one hour of summer or winter power outage for each nation in our sample. We dub this quantity 'hourly WTP'. The estimates of hourly WTP under current temperatures are given in Table 4, in the columns labelled 'current'. All WTP estimates are given in 2012 denominated Euros. We then use predictions of future temperatures from the Hadley CM3 under climate scenario A1B to predict how the hourly WTP in each country will change over time due to global warming. The imputation of WTP through time assumes that energy-related preferences remain stable and that no major changes to the structure of European society occur, such as rural–urban migration, and demographic change. Thus, our imputations should be interpreted as comparative-static cases where only temperatures change over time. The results illustrate the high level of heterogeneity in WTP to avoid power outages across our sample nations. Differences in WTP between nations are in part driven by observed variables, such as income disparities and temperature differences; however, unobserved country-level factors also strongly drive differences in WTP. These unobserved factors are accounted for in our econometric model through country-level fixed effects and may include differences in electricity infrastructure and tariffs, institutional differences and preference heterogeneity across nations. Data representing some of these factors are shown in Table 5. Also notable for our application is that mean WTP in the summer is lower than in the winter for every nation in our sample. This reflects the greater proliferation and importance of heating appliances as opposed to air conditioners in the average European household. We see that over time, as temperatures are predicted to increase, summer power outages cause greater welfare losses while winter outages cause lower welfare losses per hour of outage. Warmer nations are predicted to have relatively large increases in welfare loss from summer outages with very small decreases in welfare loss from winter outages, per person and per hour of outage. Colder nations are predicted to have the largest decreases in welfare loss from winter outages due to milder temperatures, with a nearly offsetting increase in welfare loss from summer outages, per person per hour. Mid nations are predicted to have the largest increase in welfare loss from summer outages and a nearly offsetting decrease in welfare loss due to winter outages. These differences between groups of nations are driven in the model by the differing temperature coefficients between our groups of nations, and in reality are probably driven by the different distributions of temperature between groups and the countries' use of heating or cooling technologies.

Table 3 | Marginal effects of explanatory variables on hourly WTP (2012)

	5% quantile	Mean	95% quantile	prob>0
Winter				
urban	−0.055	0.016	0.083	0.6400
male	−0.062	−0.002	0.056	0.4653
age35t45	−0.123	0.008	0.136	0.5475
age46t60	−0.074	0.052	0.18	0.7539
over60	−0.028	0.099	0.23	0.9430
hhsize	−0.022	0.004	0.031	0.5878
college	−0.051	0.006	0.064	0.5812
out1t4	−0.031	0.033	0.101	0.8008
out4t8	−0.142	−0.047	0.047	0.1931
out8t24	−0.217	−0.101	0.011	0.0638
outover24	−0.202	−0.053	0.087	0.2550
numoutages	−0.005	0.002	0.009	0.6738
wholecountry	0.448	0.732	0.935	1.0000
rotation	0.028	0.091	0.155	0.9960
Temperature—cold nations	−0.0956	−0.0516	−0.0067	0.0113
Temperature—mid nations	−0.0707	−0.0309	0.0100	0.1010
Temperature—warm nations	−0.0333	−0.0065	0.0201	0.3560
Summer				
urban	0.0080	0.1270	0.2470	0.9566
male	−0.1980	−0.1000	0.0030	0.5290
age35t45	−0.2550	−0.0260	0.1970	0.4366
age46t60	−0.0570	0.1620	0.3900	0.8763
over60	−0.0240	0.2030	0.4340	0.9172
hhsize	−0.0440	0.0000	0.0430	0.4954
college	−0.1300	−0.0300	0.0660	0.3195
out1t4	−0.1260	−0.0100	0.0990	0.4423
out4t8	−0.2080	−0.0460	0.1180	0.3198
out8t24	−0.4490	−0.2610	−0.0700	0.0137
outover24	−0.4320	−0.1910	0.0650	0.1120
numoutages	−0.0080	0.0050	0.0170	0.7277
wholecountry	0.3270	0.4070	4.7800	1.0000
rotation	−0.1250	−0.0250	0.0740	0.3307
Temperature—cold nations	−0.0017	0.0359	0.0743	0.9328
Temperature—mid nations	0.0183	0.0575	0.0969	0.9881
Temperature—warm nations	0.0044	0.0359	0.0389	0.9544

The model also includes country fixed effects. Marginal effects for each variable are calculated for one-unit increases from the sample mean, with all other variables fixed at the sample mean. The posterior distribution of each parameter is the estimation output, the 'mean' column gives the mean of this empirical distribution for each marginal effect that can be interpreted as the change in WTP to avoid one hour of power outage, which we dub 'hourly WTP', from a one-unit increase in the respective variable. The 'prob > 0' columns show the proportion of the density that falls to the right of zero, and thus provides an at-a-glance indication for whether a given marginal effect is predominantly positive, negative or indeterminate. Also shown are the 5% and 95% quantiles of the distributions of each parameter to relate the variance of the marginal effect estimates. Quantiles were calculated via the highest probability density method.

We show these results in cartographic form in Fig. 2 by imputing WTP across our 19 sample nations and through time using the predicted temperature increases from the Hadley CM3 under the A1B scenario. This illustrates how the spatial distribution of WTP will change in the future as the climate warms. Initially, winter WTP is much higher than summer WTP across our sample of Europe. However, with predicted warming, this difference narrows, especially in the southern, Mediterranean region of Europe where summer WTP is highest due to higher temperatures. Also of interest is that these southern regions are predicted to see little change in the value of supply security in the winter due to global warming.

To gain an understanding of how temperature increases will effect the value of the electricity supply on the aggregate in Europe, we calculate the total WTP to avoid an hour of power outage affecting an entire nation, by season, as shown in Table 6. This is done by multiplying the average hourly WTP to avoid a whole country outage in each NUTS 3 (Nomenclature of territorial units for statistics) region by the 2010 population estimate in that region. The results again highlight the heterogeneity between nations, both in their vulnerability to power outages, and in how this vulnerability will change over time with increased temperatures. In total across our sample of countries, the hourly welfare loss from a winter power outage that affects an entire country is predicted to decrease by about 3%, or €21.7 million, by 2055 and by about 6%, or €48.9 million, by 2089. In the summer, welfare loss from an hour of power outage that affects entire nations is predicted to increase by about 20%, or €56.4 million, by 2055 and by about 35%, or €100.1 million, by 2089. Welfare loss from summer outages is predicted to increase at a faster rate than the welfare loss from winter outages decreases. Consequently, the hourly welfare loss from power outages across our sample will increase by about 3% by 2055 and 6% by 2089, averaged over seasons.

Conclusion

Overall, the results confirm our hypothesis that the value of an uninterrupted electricity supply is strongly related to local temperatures. With respect to the value of supply security in the future, the results have two main takeaways. The first is that as global warming progresses the hourly welfare lost to summer outages will increase while the hourly welfare lost to winter outages will decrease, increasing the importance of securing the grid from summertime outage causes, such as heatwaves. Secondly, the results suggest that overall hourly WTP across our sample, averaged across seasons, will increase as the climate warms, suggesting that the importance of supply security to the average European household will increase as a result of climate change. All else equal, increases in renewable energy generation are projected to increase the likelihood of power outages. A substantial portion of the €150 billion investment in electricity infrastructure needed to reach the EU's 2030 greenhouse gas targets will also improve electricity supply security by increasing grid interconnections[15]. This research suggests that these investments should be planned to account for changes in the value of supply security that global warming will bring to the EU.

Methods

Econometric model. We specify each respondent i's indirect utility representation for two cases for each outage scenario $s \in \{1 \dots S\}$: in the event of a power outage with the characteristics stipulated by s denoted as $\tilde{v}^*_{is}$, and in the event that they pay to avoid such an outage denoted as $\tilde{v}_{is}$.

$$\begin{aligned} \tilde{v}^*_{is} &= \gamma_i m_i - d_s \mathbf{D}'_s \beta^*_{is} + d_s \tilde{\epsilon}_{is} \\ \tilde{v}_{is} &= \gamma_i (m_i - P_{is}) + d_s \tilde{\epsilon}_{i0} \end{aligned} \quad (1)$$

where m_i is the household income of respondent i, P_{is} is the bid price entered as a positive number and d_s is the outage duration measured in hours. The row vector $\mathbf{D}_s$ holds our season indicators; season refers to either winter ($\mathbf{D}_{s1} = 1$, else 0) or summer ($\mathbf{D}_{s2} = 1$, else 0), which are represented by single months, January and July.

Table 4 | Mean WTP to avoid one hour of power outage by country and season and time period (2012 €)

	Winter Current	Winter 2055	Winter 2089	Summer Current	Summer 2055	Summer 2089
France	0.52 (0.14)	0.47 (0.98)	0.43 (0.98)	0.00 (0.11)	0.02 (0.92)	0.18 (0.92)
Germany	1.29 (0.36)	1.21 (1.17)	1.10 (1.17)	0.46 (0.15)	0.56 (0.92)	0.64 (0.92)
Italy	1.84 (0.31)	1.84 (1.27)	1.83 (1.27)	0.58 (0.19)	0.73 (1)	0.83 (1)
UK	1.02 (0.25)	0.94 (0.94)	0.90 (0.94)	0.41 (0.1)	0.48 (0.83)	0.54 (0.83)
Austria	0.88 (0.42)	0.77 (1.17)	0.66 (1.17)	0.48 (0.19)	0.58 (0.95)	0.65 (0.95)
Belgium	0.95 (0.27)	0.87 (1.04)	0.80 (1.04)	0.43 (0.11)	0.54 (1.02)	0.63 (1.02)
Finland	1.59 (0.56)	1.46 (1.41)	1.32 (1.41)	0.73 (0.29)	0.82 (1.04)	0.88 (1.04)
Netherlands	0.84 (0.27)	0.78 (0.97)	0.69 (0.97)	0.31 (0.1)	0.38 (0.82)	0.43 (0.82)
Spain	1.85 (0.28)	1.85 (1.25)	1.84 (1.25)	0.69 (0.17)	0.81 (1.1)	0.89 (1.1)
Sweden	1.34 (0.38)	1.26 (1.31)	1.14 (1.31)	0.52 (0.19)	0.62 (1.1)	0.67 (1.1)
Portugal	1.28 (0.19)	1.27 (0.94)	1.27 (0.94)	0.43 (0.12)	0.55 (0.82)	0.64 (0.82)
Bulgaria	1.72 (0.33)	1.72 (1.31)	1.70 (1.31)	0.45 (0.17)	0.57 (1.05)	0.69 (1.05)
Czech Republic	0.75 (0.35)	0.67 (1.11)	0.54 (1.11)	0.30 (0.12)	0.38 (0.95)	0.45 (0.95)
Hungary	1.43 (0.35)	1.43 (1.1)	1.41 (1.1)	0.42 (0.21)	0.55 (0.94)	0.65 (0.94)
Lithuania	0.95 (0.4)	0.92 (1.1)	0.78 (1.1)	0.20 (0.15)	0.36 (0.92)	0.46 (0.92)
Poland	1.33 (0.51)	1.29 (1.17)	1.19 (1.17)	0.61 (0.27)	0.78 (1.02)	0.88 (1.02)
Romania	1.45 (0.33)	1.44 (1.24)	1.42 (1.24)	0.53 (0.18)	0.66 (1.2)	0.75 (1.2)
Slovakia	0.98 (0.4)	0.93 (1.11)	0.84 (1.11)	0.32 (0.16)	0.51 (1.01)	0.64 (1.01)
Slovenia	1.99 (0.46)	1.93 (1.35)	1.87 (1.35)	0.89 (0.23)	1.13 (1.18)	1.30 (1.18)

Standard errors given in parentheses. Negative estimates were censored at 0. The period 2046–2065 is referenced as year 2055 and the period 2080–2099 is referenced as 2089.

Table 5 | Comparison of supply security and energy statistics across our sample of 19 EU nations

	Household kwh consumed per capita	Price per mwh (Euros)	Avg. no. of outages experienced last yr	SAIFI 2012 (or most recent year)	SAIDI 2012 (or most recent year)
France	2.42	13.92	2.62	0.9	62.9
Germany	1.71	25.95	1.22	0.29	17.37
Italy	1.17	21.32	3.60	2.33	132.73
UK	1.81	16.82	1.98	0.65	68.05
Austria	2.09	19.75	2.22	0.73	38.78
Belgium	1.79	23.27	1.96	0.81	39.45
Finland	4.14	15.49	3.13	1.1	68
Netherlands	1.50	18.58	1.09	0.32	27
Spain	1.60	21.90	2.99	1.42 (2011)	58.2 (2011)
Sweden	4.10	20.27	1.71	1.33	89.01
Portugal	1.22	19.93	3.43	1.88	94.15
Bulgaria	1.48	8.46	6.47	4.65[a] (2010)	197.24[a] (2010)
Czech Republic	1.39	14.97	2.99	1.9	125.2
Hungary	1.07	15.49	4.70	1.17	76.89
Lithuania	0.88	12.60	2.77	1.82	287.73
Poland	0.73	14.18	4.33	1.4	263.19
Romania	0.60	10.50	6.59	6.5 (2009)	630[a]
Slovakia	0.88	17.16	3.40	2.15[a]	303.1[a]
Slovenia	1.54	15.42	3.32	2.99	169

Data sources in order of variables: Eurostat 2012; Eurostat 2012 'Price to Residential Consumers'; ref. [19]; ref. [26]; ref. [26]. SAIFI is defined as the avg. annual power outages per customer; SAIDI is the average number of minutes of unplanned power outage per customer. [a]These figures exclude exceptional events, while all other SAIDI/SAIFI figures include exceptional events.

The error terms capture scenario-specific factors that are unobserved yet affect utility. The slope coefficient β^*_{is} is the marginal change in repondent i's indirect utility due to an hour of power outage with characteristics s. The error terms are scaled by the duration of the outage d_s, to account for the larger variance in indirect utility associated with longer outages. Lengthy outages expose individuals to a wider variety of potential nuisances with greater extremes. For instance, a short outage may ruin a meal in the midst of being cooked, while a longer outage could ruin a series of meals that would have been cooked and spoil the entire freezer full of food. We can show the model in 'utility-space' by subtracting the above two utilities.

$$v^*_{is} = \tilde{v}_{is} - \tilde{v}^*_{is} = d_s \mathbf{D}'_s \beta^*_{is} - \gamma_i P_{is} + d_s(\tilde{\varepsilon}_{i0} - \tilde{\varepsilon}_{is}) \quad (2)$$

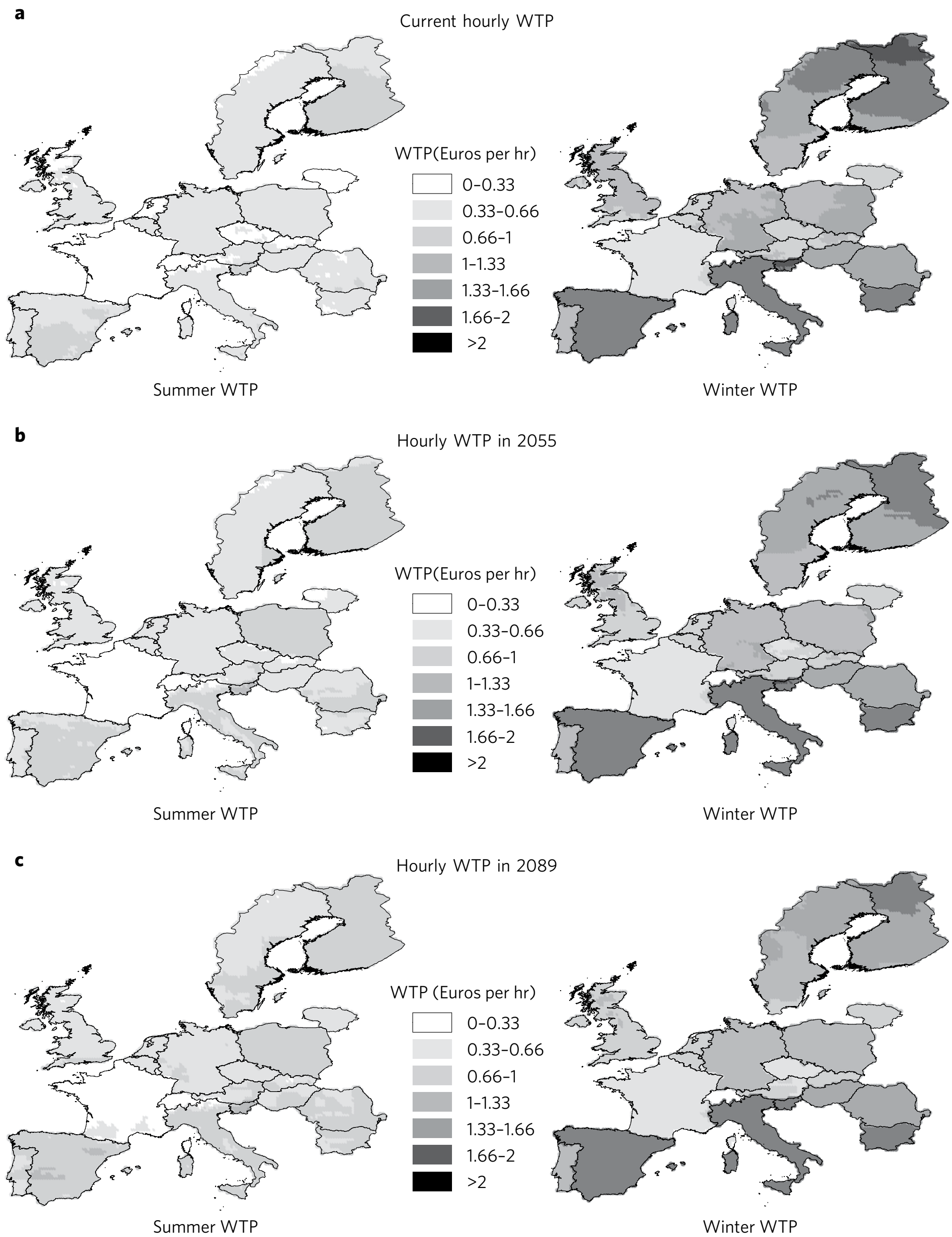

Fig. 2 | Hourly WTP across our sample of 19 European nations. a–c, Mean estimated WTP to avoid an hour of power outage imputed across space within our 19 sample nations. Imputations are based on the country mean WTP and the temperature in each area. Comparing panels **a**, **b** and **c** shows how the spatial distribution of WTP will change across our sample as temperatures warm over the century. Standard errors associated with each country's mean WTP estimate are given in Table 4. **a**, Hourly WTP in 2012; **b**, imputed hourly WTP in 2055; **c**, imputed hourly WTP in 2089.

We elect to estimate this model in 'surplus', or 'WTP space' for ease of interpretation and estimation. Thus, we divide through the previous equation by the marginal utility of income γ_i. This yields v_{is}, which can be interpreted as the difference between the full WTP to avoid the outage in menu s and the bid price to avoid the outage. We will observe a positive response to the survey question when $v_{is} > 0$, indicating that the respondent increases their utility by paying the bid price rather than experiencing the outage. Previous studies have found that estimations in WTP space perform better than those in utility space by avoiding excessively long tails on predicted WTP[16,17]. These long tails arise due to the fact that in a utility-space model, as in equation (2), marginal WTP is derived as $\frac{\beta_{is}^*}{\gamma_i}$. With a very small income parameter (γ_i), as is often the case, an inflated WTP estimate can arise. By using the WTP-space method in equation (3), we avoid this problem and estimate one parameter (β_{is}) for the marginal WTP. This WTP-space specification produces more accurate estimates for a variety of specifications[16]. However, this modelling choice comes at the expense of not being able to estimate the marginal utility of income γ_i, independent from other parameters. However, γ_i is not a construct of interest in our present analysis. Also note from equation (3) that we allow for heteroskedasticity at the respondent level (σ_i^2) through respondent-specific random effects.

$$
\begin{aligned}
v_{is} &= \frac{v_{is}^*}{\gamma_i} = d_s \mathbf{D}_s' \boldsymbol{\beta}_{is} - P_{is} + d_s \epsilon_{is} \\
\epsilon_{is} &= \frac{(\tilde{\epsilon}_{i0} - \tilde{\epsilon}_{is})}{\gamma_i} \text{ where } \epsilon_{is} \sim N(0, \sigma_i^2) \\
\boldsymbol{\beta}_{is} &= \frac{\boldsymbol{\beta}_{is}^*}{\gamma_i}
\end{aligned} \tag{3}
$$

From equation (3) our parameter of interest is vector $\boldsymbol{\beta}_{is}$, which can be interpreted as the marginal hourly WTPs per season of person i when confronted with outage scenario s. Next we add structure to $\boldsymbol{\beta}_{is}$ by introducing the matrix $\boldsymbol{\alpha}$,

Table 6 | Total WTP to avoid one hour of power outage affecting the whole country (2012 € million)

Country	Winter	Winter 2055	Winter 2089	Summer	Summer 2055	Summer 2089
France	57.2	54.2	51.7	0.9	13.5	23.7
Germany	135.0	129.0	120.0	53.5	61.2	67.1
Italy	130.0	130.0	129.0	45.5	52.8	58.2
UK	89.2	84.4	81.5	40.8	46.0	50.3
Austria	10.6	9.7	8.8	5.9	6.8	7.3
Belgium	14.8	13.9	13.2	7.2	8.4	9.3
Finland	11.2	10.5	9.8	5.1	5.5	5.9
Netherlands	20.3	19.2	17.7	8.8	9.8	10.7
Spain	102.0	102.0	102.0	39.1	43.9	48.0
Sweden	16.3	15.6	14.4	7.0	7.9	8.5
Portugal	16.8	16.7	16.7	6.4	7.7	8.6
Bulgaria	15.0	15.0	14.9	4.7	5.5	6.4
Czech Republic	11.8	10.9	9.5	5.3	6.2	6.9
Hungary	17.7	17.5	17.4	6.3	7.5	8.5
Lithuania	3.8	3.7	3.3	1.2	1.6	1.9
Poland	65.4	63.7	59.9	31.1	36.7	40.7
Romania	36.1	35.9	35.5	14.7	17.3	19.1
Slovakia	7.3	7.0	6.5	2.8	3.8	4.4
Slovenia	4.9	4.8	4.7	2.1	2.5	2.8
Total	765.4	743.7	716.5	288.2	344.6	388.3

The values were generated using data from the 19 EU countries in our sample; these nations are shown in Table 4. The period 2046–2065 is referenced as the year 2055 and the period 2080–2099 is referenced as 2089. Note that all predictions use the 2010 level of population in each NUTS 3 region; thus, these do not account for population trends.

which holds the vectors of season-specific coefficients $\boldsymbol{\alpha}_{\mathrm{D}_{s1}=1}$ and $\boldsymbol{\alpha}_{\mathrm{D}_{s2}=1}$, where we reference both subscripts as '.' where possible to avoid overlong formulae:

$$\begin{aligned}\beta_{is.} &= (1+\mathbf{z}_{is}'\boldsymbol{\alpha}.)\beta_{i.}\\ &= (1+\alpha_{1.}z_{i1}+\alpha_{2.}z_{i2}+\ldots+\alpha_{k.}z_{ik})\beta_{i.},\end{aligned}$$

where errors are considered correlated across seasons, such that

$$\boldsymbol{\beta}_i=\begin{vmatrix}\beta_{i\mathrm{D}_{s1}=1}\\ \beta_{i\mathrm{D}_{s2}=1}\end{vmatrix}=\overline{\boldsymbol{\beta}}+\boldsymbol{\delta}_i', \tag{4}$$

and with $\boldsymbol{\delta}_i \sim N(0,\boldsymbol{\Omega})$ the moments for $\boldsymbol{\beta}_{is.}$ are then defined as:

$$\begin{aligned}E(\beta_{is}) &= (1+z_{is}'\boldsymbol{\alpha})\times\overline{\beta}\\ V(\beta_{is}) &= (1+z_{is}'\boldsymbol{\alpha})'(1+z_{is}'\boldsymbol{\alpha})\Omega\end{aligned}$$

Thus, $\boldsymbol{\beta}_{is}$ is expressed as a function of observable and unobservable ($\boldsymbol{\beta}_i$) characteristics, where $\mathbf{z}_{is}$ is our vector of observed variables that explain an individual's deviation from season-specific mean marginal WTP. These observable characteristics come in two forms, those that are respondent specific, indexed by i, and one scenario-specific characteristic, indexed by s. The one scenario-specific characteristic is an indicator variable, which takes a value of one if the outage scenario s stipulated an outage that affects the entire country where the individual resides. We call this variable 'wholecountry'. Also included in $\mathbf{z}_{is}$ are country indicator variables that account for unobserved heterogeneity in WTP for supply security between nations. All variables included in $\mathbf{z}_{is}$ are centralized around their respective mean to allow interpreting $\overline{\boldsymbol{\beta}}$ as mean WTP over all respondents and all scenario characteristics, and to achieve better mixing properties of the Markov chain Monte Carlo sampler. Each $\boldsymbol{\alpha}.$ vector contains one coefficient for each of our k explanatory variables and relates these variables to deviations in marginal WTP. The average estimated hourly WTP to avoid a power outage is represented by $\overline{\boldsymbol{\beta}}$, and $\boldsymbol{\delta}_i$ captures individual-specific unobserved heterogeneity in deviations from $\overline{\boldsymbol{\beta}}$.

Let $\mathbf{y}_i$ be the vector of observed binary responses of individual i to each outage scenario s where a 1 denotes that the respondent accepted the bid price and a 0 denotes rejection of the bid price. A response of 1 will be observed when $v_{is}>0$. From the error specification in equation (3), we can write the likelihood contribution of individual i and scenario s as a standard normal cumulative distribution function conditioned on $\boldsymbol{\beta}_{is}$ and σ_i^2.

$$\begin{aligned}&prob\left(y_{is}=1 \mid d_s,\mathbf{D}_s,P_{is},\boldsymbol{\beta}_{is},\sigma_i^2\right)\\ &\quad=prob(v_{is}>0 \mid d_s,\mathbf{D}_s,P_{is},\boldsymbol{\beta}_{is},\sigma_i^2)\\ &\quad=\Phi\left(\frac{1}{\sigma_i}(d_s\mathbf{D}_s'\boldsymbol{\beta}_{is}-P_{is})\right)\end{aligned} \tag{5}$$

where Φ represents the normal cumulative distribution function. Using this likelihood, we then draw from the posterior distribution via a Gibbs sampler. For more details on the sampling procedure, see the Supplementary Methods.. The final model output is 10,000 draws of each estimable parameter. In the case of $\beta_{i\mathrm{D}_{s1}=1}$, 85.9% of these draws are positive, and for $\beta_{i\mathrm{D}_{s2}=1}$, 70.3% of these draws are positive. Using the parameter draws, we then calculate the hourly WTP to avoid a power outage ($\boldsymbol{\beta}_{is}$ in equation (3)) by country and season. This is an in-sample calculation that loops over all 10,000 usable draws of each parameter ($\boldsymbol{\alpha}.$ and $\boldsymbol{\beta}_i$) to calculate $\beta_{is.}=(1+\mathbf{z}_{is}'\boldsymbol{\alpha})\beta_{i.}$ for each of the 21,832 scenario/respondent specific observations for both summer and winter. This results in 10,000 draws from an empirical distribution of $\boldsymbol{\beta}_{is}$ for each observation. These draws are summarized by country to yield the results in Table 4.

We can then predict how increased temperatures will affect WTP by changing the temperature measures linked to each respondent (that is, changing an element of $\mathbf{z}_{is}$). We calculate the predicted change in air temperature for July and January across all of Europe using the 2020–2039 Hadley CM3 output under the Special Report on Emissions Scenarios (SRES) A1B scenario as the baseline. The A1B scenario and other comparative cases come from the Intergovernmental Panel on Climate Change SRES report[18]. The calculation yields predictions of temperature change at a resolution of 2.75° latitude and 3.75° longitude for three scenarios and two future time periods, 2046–2065 and 2080–2099. We then add these predictions to the 2012 temperatures from the E-OBS gridded data set to create predictions of future temperature at 0.25° latitude–longitude spatial resolution. This method allows for spatially specific predictions of future temperatures while allowing for the use of consistent and readily available climate predictions from a single global model. This method may also slightly underestimate the predicted temperature increase since the temperature increase between 2012 and 2020 is not added in. However, the predicted increase during this period is relatively small compared with the increases predicted by the end of the century. We use the A1B scenario as it gives a middle-of-the-road estimate of future temperatures that falls in between the more optimistic and pessimistic emissions scenarios.

We predict in-sample WTP through time according to changes in temperatures. This imputation adjusts the 10,000 draws of $\boldsymbol{\beta}_{is}$, the respondent/scenario-specific estimate of hourly WTP from equation (3), according to predicted temperature change from Hadley CM3 under scenario A1B, and the draws of the marginal effects of temperature. As we estimate a set of three marginal effects of temperature, one for each country group, the marginal effect used for each respondent is that which corresponds to their country group. These country groups are static through all imputations as the change in temperature is generally small relative to the temperature differences between groups. We multiply the predicted temperature change by the marginal effect draw and add this value to the draw of $\boldsymbol{\beta}_{is}$. Looping this procedure over the 10,000 draws of $\boldsymbol{\beta}_{is}$ and of the marginal effects allows estimation uncertainty to carry through from the initial WTP estimation and also from the projection of the effect of temperature changes on WTP. This results in the relatively large standard deviation on the future WTP estimates that are shown in the predictive columns of Table 4.

We impute current and future hourly WTP across our sample of nations to obtain the maps shown in Fig. 2. To do so, we first calculate WTP for each of the 8,173 E-OBS temperature data grid points that fall within our sample of 19 countries. The grid-point-specific WTP under current temperatures differs from the country mean WTP due to temperature differences between the country mean temperature and the temperature at that grid point, as variables are centralized around their country mean values. These observed temperature differences are multiplied by the estimated marginal effects of temperature and looped over all 10,000 draws of the marginal effects to obtain an empirical distribution of WTP at each grid point. To predict the WTP at each grid point under future temperatures, we use the predicted temperatures from the Hadley CM3 under scenario A1B, as described above, and recalculate hourly WTP at each grid point according to predicted temperatures.

It should be noted that, as with any future prediction, our hourly WTP imputations rely on the assumption that the use and importance of electricity in the European household remain static in all ways aside from increases or decreases in the usage of climate control apparatus. Societal changes such as economic development, urbanization and energy market structure can also impact household WTP to avoid a power outage. The possibility of such changes are not explicitly considered in our analysis.

Data. Data for this analysis come primarily from a survey conducted for the SESAME (Securing the European Electricity Supply Against Malicious and Accidental Threats) research project. The survey was conducted during the last two quarters of 2012 and the first quarter of 2013 in all EU-27 nations. A detailed account of survey methodology and the full English version of the survey are given in ref. [19]. The survey was given both as an Internet survey and on the phone with supplementary materials sent to phone respondents via post. This massive survey effort, encompassing over 13,000 interview hours and over 400,000 contact attempts, yielded over 8,000 completed questionnaires with around 300 survey responses per nation. Substantial effort was exerted to ensure that the final sample was representative of each nation's population in the dimensions of gender, age, working status, income and rural residents. The survey obtained demographic, energy usage and energy perception information from each individual, and included a choice experiment designed to elicit respondent's WTP to avoid blackouts with certain characteristics.

The choice experiment portion of the survey asked respondents to imagine a power outage with a specified duration, start and end time, month and area (residential street or whole country). A visual depiction of one of the eight scenarios shown to respondents is reproduced in Supplementary Fig. 1. There were two months represented in the survey, January and July. The survey used 1 hour, 4 hours, 12 hours and 24 hours as durations of the outage scenarios, generally reflecting the durations found in the literature[5,20–23]. Since the number of choice tasks is limited to eight due to length and budgetary constraints, we reveal two scenarios for each duration length to every respondent. The characteristics of all eight scenarios are shown in Supplementary Table 1.

After seeing a depiction of a power outage scenario, respondents were offered the option to pay a specified amount of money in their native currency to avoid experiencing the outage. This is referred to as the 'bid price' (P_{is}), which varies for each respondent and with a total of four possible bid prices per scenario and country. The bid price design is based on a previous, similar WTP study conducted for the nation of Austria[5]. Bid prices are designed using the D-optimality criterion with balanced utilities to set the bids[24,25]. Two of the four bids of each scenario used in the Austrian study are adopted here with a correction for the difference in income distribution between Austria and every other nation. The other two bids of each scenario are held constant between countries to enable cross-country comparison. As expected, the survey results show that a decreasing proportion of respondents are willing to pay as the bid price increases as shown in Supplementary Table 2.

The initial survey sample of 64,536 complete observations from 8,067 different respondents (8 scenarios per respondent) was reduced due to missing responses to one or more of the survey questions used in the statistical model. Respondents were not offered an opt-out response in the choice experiment questions. Thus, the full sample of usable observations is a balanced panel of 61,928 observations from 7,741 different respondents, with 8 choice observations per respondent.

For a respondent to be linked with the relevant temperature data, their location had to be approximated. The first step in this process was geocoding, or giving a cartographic point to a respondent's location. Beginning with our sample of usable survey responses, 43% of these questionnaires were completed online, leaving us with no location information for these respondents. For the respondents that used phone and postal media, we were able to obtain the first seven digits of their phone numbers (including country code) and occasionally an address fragment that contained either a postal code or city name from the survey company. For legal reasons and privacy protection of survey participants, full addresses could not be obtained. As this study is concerned with broad temperature trends, we use aggregated temperature measures in our statistical model. Therefore, precise geocoding is not necessary, since in most cases, this data aggregation will average away measurement errors from incorrectly placed respondents. On the basis of the data we obtained from respondents and the spatial data available at the European level, we attempted to match every respondent to a postal code region.

Of the 4,605 respondents who used telephone and postal media for the survey, we were able to obtain address fragments for about 1,900 of them, although these fragments were not always useful for matching the respondent to a postal code. For the remaining respondents who used telephones for the survey, we manually linked telephone area codes to postal code regions for each country. Every nation has a different system and standards in place for postal codes and telephone area codes, leading to varied levels of precision in converting area codes into postal codes. In general, area codes define larger areas than postal codes. In cases where one area code matches to multiple postal codes, an effort was made to choose the postal code with the highest population to increase the chance the postal code is correct. Thus, at worst the geocoded respondent location is in the correct area code region, and at best in the correct postal code region.

Our ability to geocode respondents on the basis of area codes dictated our final estimation sample. This sample consists of data from 19 EU nations; the number of respondents varies between nations on the basis of the exact number that used phone and post media for their survey response and our ability to geocode their locations. The number of respondents in each nation and a summary of their characteristics is shown in Table 2. Some respondents gave cellular phone numbers, which cannot be referenced geographically. There were especially high proportions of respondents using cellular phones in Sweden and Finland, which is the reason for the smaller sample sizes in these nations. Respondents located outside of continental Europe, such as those on Atlantic islands, were dropped to avoid convoluting their responses with those from the mainlands of their nations where power supply and provision may be fundamentally different.

The final sample contains complete information for 2,729 respondents with 8 observations per respondent (1 per outage scenario), leaving a total of 21,832 observations. The loss of observations is unlikely to compromise the representativeness of our sample, although the estimation sample does consist of a slightly older, less urban subset of survey respondents. The spatial distribution of our final sample of respondents is shown in Supplementary Fig. 2. We note from the figure that the level of spatial variation in our sample changes between nations, where some nations, such as Slovenia, have low intra-country variation in location and thus temperature measures, while other nations, such as Germany, have high intra-country variation in location and temperature variables.

Explanatory variables used in the statistical model ($\mathbf{z}_{is}$ vectors) are defined in Table 1. The cross-country comparison of sample means in Table 2 shows the high level of heterogeneity across the 19 EU nations in our sample in many respects, most notably average income and the average number of outages experienced in the past year. Since we use category indicator variables in our $\mathbf{z}_{is}$ vectors, one variable from each category had to be omitted to avoid perfect colinearity. The omitted category for the age groups is those younger than 35; the omitted category for the experienced outage duration is those who experienced an outage that lasted less than one hour or did not experience an outage at all; the omitted category relative to the 'urban' variable is those who live in suburban or rural settings.

The 19 EU nations represented in our estimation sample exhibit strong heterogeneity, in terms of their existing energy infrastructure and their experience with power outages. We also find that WTP to avoid power outages varies strongly between nations. For the interested reader, Table 5, collates some country-level data that reflect this heterogeneity in the electricity sector between nations. Population data at the NUTS 3 level used to impute aggregate hourly WTP in each nation are from the NUTS 2010 GISCO Eurostat (European Commission) database.

Ethics statement. The survey data were collected by Kudos Research firm, following high standards of participant data protection and voluntary participation. The data collection procedures were approved by an ethics officer of the European Commission in Brussels.

Data availability. The data that support the plots within this paper and other findings are available from the corresponding author upon reasonable request.

Furthermore, the results and imputation of this study are available upon request in shapefiles, which may be useful to policymakers and regional transmission system operators who are considering electricity infrastructure projects.

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Author contributions

J.R. and M.S. were primarily responsible for the creation and implementation of the survey instrument. J.C. was primarily responsible for the creation and management of the data set. All authors contributed to data analysis. All authors contributed to the writing of the paper with J.C. and J.R. as the primary authors.

Competing interests

The authors declare no competing financial interests.

Additional information

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