Journal of Environmental Management 394 (2025) 126937

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Climate crisis, war and pandemic: How weather and global events have shaped UK electricity demand

Charanjit Kaur [a], Jalal Siddiki [b], Prakash Singh [c,d,*]

[a] Independent Researcher, India
[b] Department of Economics, Kingston University, UK
[c] Goa Institute of Management, India
[d] Visiting Research Fellow, Department of Economics, Kingston University, UK

ARTICLE INFO

JEL classification:
C14
Q41
Q48
Q54

Keywords:
Climate change
The UK
COVID-19
Russia-Ukraine war
Non-linear electricity demand
Generalised additive models

ABSTRACT

The present study, using high-frequency hourly data from 2009 to 2023, investigates the impacts of weather conditions, carbon prices, COVID-19 pandemic, and the Russia–Ukraine war on electricity demand in the UK. Using a semi-parametric estimation technique – generalised additive models – we find that temperature, carbon prices, and snowfall have a significant non-linear impact on electricity usage. Temperature and electricity demand exhibit a non-linear, U-shaped pattern, with electricity demand decreasing during mild weather and sharply rising during extremely hot or cold weather. Carbon prices moderate the temperature effect on electricity demand, with higher prices reducing this effect. Snowfall and rain increase electricity demand due to additional heating needs. Our analyses also suggest that global events such as the COVID-19 pandemic and the Russia-Ukraine war have strongly affected the trajectory of electricity demand, reflecting broader economic disruptions driven by global and geopolitical events. The results remain consistent after controlling for electricity prices. These findings highlight the importance of adaptive energy policies, including flexible carbon pricing strategies, to effectively manage electricity demand during extreme weather events and geopolitical crises.

1. Introduction

This paper examines the non-linear impact of temperature on hourly electricity demand, along with other weather-related variables (precipitation, windspeed, and snowfall) in the UK. While doing so, we also assess the effectiveness of carbon pricing as a policy tool for electricity demand management. Furthermore, the study investigates how global events, specifically the COVID-19 pandemic and the Russia-Ukraine war, have affected electricity demand in the UK. Using high-frequency hourly data (from 2009 to 2023) and employing the generalised additive model (GAM) framework, this study intends to provide new insights into how policy instruments and external shocks interact with climate variables and influence electricity demand in the UK.

Climate change presents a major global challenge, having a profound impact on various sectors of the economy (Acevedo et al. (2020); Felbermayr et al. (2022) and Dell et al. (2014)), notably, the energy sector, which accounts for approximately 35 percent of global greenhouse gas (GHG) emissions (International Energy Agency, 2023). These GHG emissions contribute to climate change, producing heterogeneous and non-linear effects through weather shocks on the overall economy and on energy demand across different geographical locations (Dell et al. (2014)).[1]

Projections suggest that global temperature will rise by 4 °C by the end of the century, thus necessitating substantial emissions cuts to limit this temperature rise to 2 °C (Acevedo et al. (2020)). A rise in temperature of 4 °C would cumulatively cost the global economy 50.1 percent of global GDP (Kikstra et al. (2021); UCL (2021)), which is significantly higher than the total costs associated with constraining the increase to 2 °C.

The electricity sector plays a vital role, as climate change leads to temperature variations, directly affecting electricity demand/consumption (Staffell and Pfenninger (2018); Mideksa and Kallbekken (2010)). Hence, understanding the effects of temperature and carbon prices (a policy instrument for emission management) on electricity

* Corresponding author. Goa Institute of Management, India.
E-mail addresses: charan.rupal@gmail.com (C. Kaur), j.siddiki@kingston.ac.uk (J. Siddiki), prakash@gim.ac.in (P. Singh).

[1] Weather shocks affect economic outcomes by influencing agricultural and industrial output, energy demand, labour productivity, health, conflict, political stability, and economic growth. These weather effects are heterogenous, and are also often nonlinear, across geographical locations.

https://doi.org/10.1016/j.jenvman.2025.126937
Received 31 January 2025; Received in revised form 2 August 2025; Accepted 8 August 2025

consumption is necessary for a robust long-term electricity policy. Electricity demand and associated weather effects vary across hours or periods of a day, between weekdays vs. weekends and across months and seasons. Existing studies mainly rely on daily or monthly data. Consequently, weather-electricity demand relationships across hours of the day are primarily unexplored. In addition, the COVID-19 pandemic has affected electricity consumption (Torriti (2020)) and the economy (Uddin et al. (2021)).

The ongoing Russia-Ukraine war, through its effect on the global energy (fossil fuels) chain and international energy security, has increased uncertainty and electricity prices globally (Balsalobre-Lorente et al. (2023); Kumar and Mallick (2023)) and has also affected the UK electricity market (IEA (2022)).

As far as we know, no research has captured the effect of temperature on electricity demand, moderated by the carbon price, while examining the impact of the COVID-19 pandemic and the Russia-Ukraine war on the temperature – carbon price – aggregate demand relationship.

With the above background, this paper seeks to fill critical gaps in the literature by offering a comprehensive analysis of how weather variables, carbon pricing, and global disruptions interact to shape hourly electricity demand in the UK. While prior research has examined temperature-demand relationships, few studies incorporate high-frequency data to capture intraday demand dynamics. However, the interaction between climate policy instruments, such as carbon pricing, and weather extremes remains underexplored. Existing literature has also largely overlooked the influence of global events like the COVID-19 pandemic and the Russia-Ukraine war on electricity consumption patterns. By integrating these dimensions using a semi-parametric Generalised Additive Model (GAM) framework, this study provides novel insights into how electricity demand responds to complex environmental and economic shocks.

Our empirical results suggest a U-shaped relationship between temperature and electricity demand. Carbon prices mitigate the effect of temperature on electricity demand: the higher the carbon price, the lower the impact of temperature on electricity demand. Thus, the findings emphasise the importance of adapting carbon pricing as a policy strategy to respond to climate change through demand management in the UK energy market.

While it is expected that carbon pricing impacts electricity demand via its effect on electricity prices, carbon pricing can also exert a direct influence on electricity demand. Carbon pricing acts as a policy signal that influences investments in energy efficiency, consumption behaviour, and operational decisions for both firms and households. As a result, carbon pricing can potentially influence electricity demand patterns directly through regulatory, informational, and anticipatory channels, in addition to influencing demand via price adjustments (Gerarden et al., 2017; Borenstein, 2012). Recognising both direct and indirect channels is critical for assessing the overall efficacy of carbon pricing as a demand management instrument (IEA, 2021; World Bank, 2021).

This paper contains four sections. Section 1 is the Introduction. Section 2 reviews the existing literature on the weather-electricity demand relationship in the UK. The review identifies that it is an under-researched area. Furthermore, there are no empirical studies that employ hourly data, and no study examines the impact of carbon pricing, COVID-19 and the Russia-Ukraine war on aggregate electricity demand in the UK. Section 3 presents empirical analyses, which are divided into two subsections: the first one provides a detailed analysis of the descriptive statistics, while the second subsection reports and analyses the results of the modelling of electricity demand in the UK. The final section draws conclusions and outlines policy implications.

2. Review of literature

Greenhouse gas (GHG) emissions have led to global climate change, resulting in (a) rising average temperatures, (b) changes in precipitation and seasonal patterns, (c) changes in the intensity and pattern of extreme weather events, and (d) a rise in the sea level (Staffell and Pfenninger (2018); Mideksa and Kallbekken (2010)). These changes have impacted the energy sector, particularly electricity, by making supply and demand increasingly dependent on variations in weather conditions.

Existing studies suggest the presence of a non-linear U-shaped relationship between electricity demand and temperature, with both low and high temperatures creating higher electricity demand for heating and cooling, respectively (see Harish et al. (2020); Gupta (2012); Kang and Reiner (2022); Chang et al. (2016); Silva et al. (2020); Yao (2021)). As a result, electricity demand in the UK increases by 820 MW for every degree drop in temperature below 15 °C because of the increased demand for heating (drax (2016)). On the other hand, the demand for electricity in the UK rises by 350 MW for each degree increase above the upper threshold of 20 °C, driven by the higher demand for cooling (Heynes (2022)). These upper and lower thresholds of temperature are similar to those in other countries (Yao (2021)). Electricity consumption in countries with polar climates increases (decreases) in the winter (summer), while the opposite is true for countries with tropical weather.

Normal (cold) weather generally increases electricity supply and thus reduces prices since during normal weather, (a) cooling towers are more efficient, (b) power cables are more conductive, and (c) less energy is needed to prevent equipment from overheating (Government Office for Science (GOS) (2023); Cronin et al. (2018)). On the contrary, extreme weather, such as scorching heat and cold waves, can disrupt the electricity supply and its efficiency. Wind droughts, mainly caused by both extreme heat and extreme cold weather, reduce electricity supply while increasing electricity demand. Extreme weather also damages the interconnectors used to balance the demand to the UK grid, as when cables for bringing electricity from abroad can be impaired by coastal storms. Similarly, overheating and flooding adversely affect renewable energy infrastructure in the UK. The production and operation of renewables are also negatively affected by extreme weather conditions, for instance, scorching heat waves can overheat solar panels and, thus, reduce their supply capacity. With extreme weather, managing the health and safety of workers, as well as the safety and stability of the networks, is more challenging. In short, extreme weather events cause grid vulnerability, with a deficit in some areas and a surplus in other areas of Europe and the UK (GOS (2023)).

Climate patterns also affect the electricity supply from renewables, such that solar generation is abundant with the long sunny days[2] in summer and scarce during cold and rainy winters (Carabott and Beard, 2024; Cronin et al., 2018). Solar panels operate optimally at 25 °C, with efficiency being lowered by around 0.5 % for every degree above or below that figure (Heynes (2022)). In July 2022, the solar sector in the UK provided its highest share of electricity, with around 8.6 % of electricity demand, which was a jump from the previous 4 % average solar contribution. Both clouds and air quality impact solar panels' performance. Solar cells operate best in the 400–800 nm wavelength range (GOS (2023)). The performance of thermal power plants strongly depends on ambient air temperature (AAT): temperature negatively affects efficiency and production.

Climate and weather affect the supply and demand for electricity and, thus, its price. Weather can cause abrupt price fluctuations in the short term and cyclical fluctuations over the medium term (Carabott and Beard, 2024), with such fluctuations and the relationships between electricity prices and temperature varying between polar and tropical regions. In polar climates with cold weather dominating, a fall in temperature from a lower threshold can cause a corresponding rise in

[2] This causes the well-known duck curve problem (Schmalensee, 2022; John, 2017), a major challenge for the solar energy sector, when excess supply during (afternoon) hours with low levels of household consumption demand is contrasted with low supply levels in evening hours with high levels of demand.

demand and prices. For example, in the UK, every one-degree fall in temperature from 10 °C increases heating demand, raising prices by £1.10 per megawatt-hour (drax (2016)). On the other hand, a positive relationship exists between price and temperature in a tropical region or in a country dominated by hot and humid weather, since a rise in temperature pushes the demand for cooling in these countries.

There are a number of country case studies on the impact of temperature on electricity demand. Mideksa and Kallbekken (2010) identify significant research gaps in the effects of extreme weather events on demand. Harish et al. (2020) find a non-linear impact of temperature on electricity consumption, with a heterogeneous impact across states in India. Gupta (2012) finds a U-shaped demand function for temperatures. The author asserts that the adverse effects of climate change on electricity demand are asymmetric across seasons, with excess demand during hot months. Kang and Reiner (2022) find that temperature has robust and symmetric or flat effects on electricity demand across all periods, while the impact of rain and sunshine varies across hours of the day.

Data limitations constrain a detailed examination of the relationship between temperature and electricity consumption. Yao (2021) overcomes such traditional data constraints by using satellite-recorded night light and temperature data for Europe and Africa. This methodology allows for a nuanced understanding of electricity consumption patterns across different global regions, emphasising the varying effects of temperature changes in urban vs. rural and industrial vs. non-industrial areas. Using grid-level data, the author uncovers a non-linear U-shaped heterogeneous or asymmetric relationship between outside temperature and electricity consumption when the temperature is above 0 °C, while an ambiguous relation exists when it is below 0 °C. Electricity consumption reaches its minimum level for temperatures between 10 °C and 20 °C. The author also finds a critical point at 14.6 °C where the direction of the temperature-electricity demand relationship changes: it shows a negative relationship when the temperature is below 14.6 °C and a positive relationship above 14.6 °C. The author argues that the U-shaped relationship around this critical temperature most likely reflects the relative strength of cooling and heating on demand. Yao (2021) also shows that the U-shaped relationship and the critical temperature point differ across regions and across degrees of urban development, highlighting the heterogeneous impact of climate change on electricity demand.

Utilising daily Spanish data from August 1995 to August 2003, Moral-Carcedo and Vicéns-Otero (2005) find a U-shaped relationship between temperature and electricity demand. In another study, Pardo et al. (2002) employ daily Spanish data from January 1983 to April 1999 and find a significant non-linear relationship between temperature and electricity demand. The findings of these studies consider both heating and cooling needs as well as seasonal patterns in demand forecasting.

The studies mainly examine the impact of weather or climate changes on electricity consumption. However, weather also affects the real economy, which in turn a domino effect on electricity demand. The following studies assess the economic impact of weather changes. Felbermayr et al. (2022) use a new dataset that links weather data to annual average night-light emissions as a proxy for global economic activity from 1992 to 2012. The study focuses on the economic impact of extreme weather events, such as storms, excessive precipitation, and cold spells. Using spatial econometric panel techniques, the authors find that extreme weather reduces the growth of economic activity at the local level, with such adverse effects tending to be short-lived and transformed into positive growth spillovers in neighbouring areas.

Acevedo et al. (2020) use within-country and across-country year-to-year fluctuations in temperature and precipitation for more than 180 economies during 1950–2015. The study finds that temperature negatively affects output, with high temperatures adversely affecting investment, labour productivity, human health, and agricultural and industrial output. These adverse effects are heterogeneous across low, middle and high-income countries, with hot, low-income countries experiencing the highest costs compared to warm, high-income countries.

Using data from eight developing countries in South and Southeast Asia from 1990 to 2015, Sharif et al. (2020) examine the effects of renewable energy and other macroeconomic variables on the ecological footprint - the impact of human activities on the Earth's ecology. The authors find that the increased use of renewable energy has significantly reduced the environmental footprint in these regions.

Dagar et al. (2024) assess the dynamic interplay between financial integration, political stability, infrastructure, and global integration in enhancing energy security and energy equity in 50 economies from 2006 to 2018. They find that increased financial integration and political stability enhance energy supply chains and energy security. Conversely, rapid urban growth and inadequate social integration pose challenges to achieving energy equity. Eskander and Fankhauser (2023) find that climate legislation in 111 countries from 1996 to 2018 has reduced trade-related international carbon emissions. Jiang et al. (2021) examine the impacts of the COVID-19 pandemic on the energy sector in China and underscore it's substantial effect on energy demand and consumption. The study also highlights the heterogeneity of the region's energy recovery. Additionally, Balsalobre-Lorente et al. (2023) highlight the influence of the Russia-Ukraine conflict on the global energy markets and electricity consumption patterns, particularly through price volatility and supply chain disruptions.

The above literature review clearly reveals that the weather-related electricity demand in the UK is an under-researched area. Furthermore, the existing studies mainly rely on daily or monthly data. Consequently, weather-electricity demand relationships across hours of the day remain largely unexplored. While existing literature extensively covers the weather-electricity demand nexus, few studies have examined the interaction between economic instruments, such as carbon pricing, and climate variability. This gap is critical because carbon pricing can significantly alter demand patterns during extreme weather, a point that has major implications for energy policy.

The COVID-19 pandemic further reshaped electricity demand patterns globally and in the UK. Torriti (2022) highlights how changes in residential consumption have influenced electricity demand. Uddin et al. (2021) document heightened energy market volatility resulting from pandemic-driven economic disruptions. Similarly, Kumar and Mallick (2023) discuss how the Russia-Ukraine war has influenced global electricity demand through disruptions in fossil fuel supply and increased energy prices.

To the best of our knowledge, no empirical study for the UK has assessed the impact of COVID-19 and the Russia-Ukraine war on aggregate electricity demand. This paper seeks to fill this gap.

3. Data and methods

3.1. Data

The study is based on hourly data spanning from January 02, 2009 to December 21, 2023,[3] with electricity demand as the response variable.[4] The key predictor variables are temperature, carbon prices, precipitation, windspeed and snowfall. The descriptions of variables and their sources are explained in Appendix (see Table A1).

3.2. Modelling non-linear relationships in electricity demand with GAMs

Climate and economic variables have non-linear effects on electricity

[3] Selection of the data period is primarily based on the availability of consistent data for each variable.

[4] The electricity demand data are available half-hourly, while weather data are only available on an hourly basis. Thus, for consistency electricity data were aggregated to an hourly frequency.

demand (Gupta (2012); Harish et al. (2020) and Yao (2021)). Generalised additive models (GAMs) capture such non-linear relationships without specifying a particular parametric form (Wood (2017)). Understanding these non-linear relationships are crucial for informing adaptive energy pricing strategies, particularly because of frequent occurrences of extreme weather events and geopolitical shocks. Thus, we adapt GAMs in our analyses to model non-linear relationships between electricity demand and weather variables, which can be written as follows:

$$log(ed) = \beta_0 + \sum_{j=1}^{p} s_j(X_j) + \epsilon \tag{1}$$

where $log(ed)$ is the logarithm of electricity demand; β_0 is the intercept term; $s_j(.)$ represents a smooth function for the j^{th} predictor variable X_j, which captures the impact of X_j on electricity demand; p is the number of predictor variables; ϵ is the error term assumed to be independently and identically distributed.

Weather variables influence electricity consumption due to heating and cooling needs (Auffhammer et al., 2017; Staffell and Pfenninger, 2018). Specifically, below a certain threshold level, a fall in temperature increases the electricity demand for heating and again, beyond a specific temperature, an increase in temperature raises the electricity demand for cooling. Precipitation and snowfall affect heating demand, whereas windspeed influences demand (via wind chill) and supply (via renewable generation efficiency). Thus, we have included temperature (*temp*), precipitation (*precip*), windspeed (*wind*), and snowfall (*snow*) as predictor variables. Carbon price (*carbon*) is included as an economic policy variable to understand whether carbon prices affect electricity demand directly and whether it also moderates the effect of temperature on electricity demand. We also employ several factor variables to capture and control the impact of (a) COVID-19, (b) the Russia-Ukraine war and (c) seasonal variations that include spring, summer, and autumn (reference category).

COVID-19 and the Russia-Ukraine war dummy variables at the hourly level are introduced to capture the major global shocks affecting electricity demand through changes in economic activity, mobility, and energy market volatility, as discussed by Jiang et al. (2021) and Kumar and Mallick (2023). The COVID-19 and Russia-Ukraine war dummy variables are constructed as binary variable at the hourly level, where all hours prior to March 23, 2020 (the UK's first national lockdown) are coded as 0 and all subsequent hours as 1 for the COVID-19 dummy; similarly, hours before February 24, 2022 are coded as 0 and all hours after as 1 for the war dummy.

These dummy variables are designed to capture the structural change in electricity demand potentially resulting from COVID-19 and Russia-Ukraine war, while we acknowledge that the impacts of these events are dynamic and phased over time rather than instantaneous shifts. However, to maintain model parsimony and reduce risks of overfitting and multicollinearity—particularly given the partial overlap between the COVID-19 and war periods and the complexity of the semi-parametric GAM framework—we opted for dummy variable approach. Further, to address potential oversimplification of the model, we conducted detailed robustness checks including subsample analyses comparing pre- and post-event periods, which consistently reinforce the validity of the binary dummy approach for capturing the principal regime shifts in electricity demand. We also include extensive temporal controls (seasonality, day/night, trends) to mitigate confounding influences.

In the baseline model, we excluded electricity prices from the analysis due to concerns about endogeneity and methodological complexity. Electricity prices are often determined simultaneously with demand and are influenced by the same weather variables included in our model, creating potential circular causality. Additionally, incorporating electricity prices as a smooth term in the GAM framework, which already models multiple non-linear interactions, would significantly increase model complexity and risk overfitting, thereby compromising interpretability. However, given that price is an important determinant of demand, we have included electricity price as the smooth term in the model and re-estimated all the models to control the indirect effect of carbon price on electricity demand through electricity prices.

The smooth functions $s_j(.)$ were modelled using a penalised spline regression. Penalisation is applied to control the wiggliness of the smooth terms, which prevents overfitting but allows sufficient flexibility to capture non-linear patterns (Wood, 2017). Smooth function $s_j(.)$ is uniquely estimated for each corresponding predictor variable. The degree of smoothness for each term was determined by minimising the restricted maximum likelihood (REML) criterion during model estimation.

We follow a step-by-step approach to comprehensively analyse each factor's impact on electricity demand. Starting with a baseline model, each model progressively adds variables to gradually capture the complex nature of relationships between electricity and its predictors. It also allows us to isolate each factor's incremental impact and assess the relationships' dynamics. To do so, we employ six different models to progressively capture the increasingly complex nature of weather effects on electricity demand. Each of the model specifications is described below.

Model 1: the following baseline generalised additive model (GAM) includes smooth terms for temperature, precipitation, windspeed, snow, and carbon price:

$$\log(ed) = \beta_0 + s_1(temp) + s_2(precip) + s_3(wind) + s_4(snow) + s_5(carbon) + \epsilon \tag{1.1}$$

Model 2: Model 1 is extended by adding an interactive smooth term between the carbon price and temperature as follows:

$$\log(ed) = \beta_0 + s_1(temp) + s_2(precip) + s_3(wind) + s_4(snow) + s_5(carbon) + s_6(carbon * temp) + \epsilon \tag{1.2}$$

Model 3: We further extend Model 2 by incorporating a binary dummy for COVID-19:

$$\log(ed) = \beta_0 + s_1(temp) + s_2(precip) + s_3(wind) + s_4(snow) + s_5(carbon) + s_6(carbon * temp) + \gamma_1(covid) + \epsilon \tag{1.3}$$

Model 4: In Model 2, a categorical dummy for seasons is added to account for seasonal variations:

$$\log(ed) = \beta_0 + s_1(temp) + s_2(precip) + s_3(wind) + s_4(snow) + s_5(carbon) + s_6(carbon * temp) + \sum_{k=1}^{3} \gamma_k\,(season_k) + \epsilon \tag{1.4}$$

where $season_k$ represents spring, summer, and winter (autumn is used as the reference category).

Model 5: Model 2 is extended in Model 5 by including a dummy for the Russia-Ukraine war:

$$\log(ed) = \beta_0 + s_1(temp) + s_2(precip) + s_3(wind) + s_4(snow) + s_5(carbon) + s_6(carbon * temp) + \gamma_2(war) + \epsilon \tag{1.5}$$

Model 6 is derived by adding the interaction of carbon prices, temperature and the war period variables to Model 2:

$$\log(ed) = \beta_0 + s_1(temp) + s_2(precip) + s_3(wind) + s_4(snow) + s_5(carbon) + s_6(carbon * temp * war) + \epsilon \tag{1.6}$$

Table 1
Descriptive statistics.

Variables	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
ed	65,406.18	15,864.26	28,650	117,957	0.25	2.37
temp	12.05	6.03	−7.2	39.80	0.17	2.85
precip	0.07	0.63	0	36.446	17.86	471.52
wind	10.54	8.47	0	59	0.58	3.01
snow	0.00	0.02	0	5.04	145.25	25,840.35
carbon	24.21	26.22	2.7	98.01	1.53	3.93

Note: N = 93,530. ed: national electricity; temp: temperature (in °C); precip: precipitation in millimeters (mm); wind: wind speed in km/hour; snow: snowfall (mm); carbon: carbon prices in US$.

Models 1–6 are estimated using the *'mgcv'* package in R (Wood, 2017), which provides efficient algorithms for the GAM estimation method. The estimation process involves the penalised likelihood maximisation (REML), which balances the model's fit.

3.3. Patterns in electricity demand and weather effects

The empirical analyses of this paper are split into two subsections, with this section focusing on descriptive analyses and the following subsection examining empirical modelling. The descriptive statistics in Table 1 provide an overview of key variables such as electricity demand (*ed*), temperature, precipitation, windspeed, snow, and carbon prices. Electricity demand (*ed*) has a mean value of 65,406 MW and ranges from 28,650 MW to 117,957 MW, indicating substantial variation in demand. Extreme weather, economic activity, and seasonal effects are possible sources of this variation.

For the temperature variable, the average is 12.05 °C, which is consistent with the mild climate of the UK. A wide range from −7.2 °C to 39.8 °C reflects periods of extreme cold and heat, both of which influence electricity demand (for heating or cooling). The mean precipitation (0.07 mm) is a relatively low average, but the maximum of 36.44 mm shows occasional occurrence of intense precipitation events. The mean wind speed of 10.54 km/h reflects typical wind conditions in the UK. Windspeeds range from calm (0 km/h) to strong winds (59 km/h), influencing renewable energy generation (especially wind power) and potentially impacting electricity demand, with wind chill increasing heating needs. The mean carbon price is £24.21 per ton during our study period. Prices fluctuate significantly, from as low as £2.70 to £98.01, suggesting that market-based carbon pricing mechanisms and policy shifts strongly influence carbon price. The correlation heatmap visually depicts the relationships between the variables in our analyses, providing insights into how different factors influence electricity demand (see Fig. 1). In conclusion, that electricity demand in the UK is correlated with weather variables.

To grasp more in-depth insights into the relationships between electricity demand and its key determinants, we further analyse the behaviour of electricity demand, supply, and temperature in the UK (see Figure A.1 in the Appendix). We begin with the electricity demand. Its distribution appears to be slightly skewed to the right, with a long tail extending toward higher electricity demand values (Panel A in Figure A.1 in the Appendix). This demand pattern could be attributed to extreme weather conditions, seasonal variations, or economic activity.

Next, we add box plots of electricity demand across months in Panel B in Figure A.1, with horizontal lines inside each box representing the median electricity demand. The plots show a clear pattern of electricity use during winter months (December–March), mainly for heating usage. The demand starts falling in February and reaches its lowest in August before starting to pick up again. Our scatter plots of electricity demand against temperature (Panel C in Figure A.1 in the Appendix) reveal a U-shaped relationship between electricity demand and temperature: demand decreases at mild temperatures but increases both during extreme cold and hot weather. The temperature distribution exhibits normal distribution over the period (Panel D in Figure A.1 in the Appendix) with slight skewness to the right. Skewness with a longer tail extending towards higher temperatures suggests more extreme warm temperatures than extreme cold temperatures. The peak of the distribution lies around 10 °C.

Fig. 2 describes the percentage contributions of various energy sources to the overall electricity generation mix from 2010 to 2023. Nuclear, hydro and gas have consistently been the dominant energy sources throughout the period, with a collective contribution of around 50–60 percent of the total generation. Coal's contribution has declined significantly over the years, dropping from around 40 percent in 2010 to less than 20 percent in 2023. The contribution of natural gas has increased gradually, potentially replacing some of the decline in coal generation. Renewable energy sources such as wind and solar have seen substantial growth, with wind rising from a small percentage in 2010 to around 10–15 percent by 2023, and solar also gaining a notable share in the later years. Other renewable sources, such as geothermal and biomass waste, have maintained a relatively small but consistent presence in overall generation. Oil appears to have a diminishing role in electricity generation, contributing only a minimal percentage in recent years.

The widespread use of renewable energy has helped improve environmental quality in developed and developing countries (Sharma et al. (2021)). Thus, the electricity production data suggests a transition towards a more diversified and cleaner energy mix, with a reduction in the reliance on fossil fuels, namely coal and an increasing adoption of renewable energy sources such as wind and solar, potentially driven by factors such as environmental concerns, technological advancements, and policy initiatives.

3.4. Results and discussion

In this sub-section, we report and analyse the results from the generalised additive method. We employ six step-by-step models with different model specifications explained in Section 3.2 above, and the results are reported in Table 2. Each model progressively adds variables to gradually capture the complex nature of relationships between electricity and its predictors. We start with a baseline model, including weather variables and the carbon price in Model 1. We then add interaction terms - carbon prices and temperature in Model 2, COVID-19 in Model 3, seasons in Model 4, and the Russia-Ukraine war in Model 5, and end up with a complex interaction among carbon price, temperature, and the war period in Model 6. Across all models, temperature, windspeed, and carbon prices consistently show strong non-linear effects on electricity demand.[5] Including COVID-19, seasonality, and the war provides a deeper understanding of how environmental and socio-economic factors interact to shape electricity consumption patterns.

We first explain Model 1, which examines the non-linear effects on electricity demand of precipitation, temperature, windspeed, snow, and carbon prices. All predictors have significant effects, with temperature and carbon price showing particularly strong non-linear relationships. The model explains 28.3 % of the variability in electricity demand, indicating that weather and carbon prices are important factors influencing electricity consumption. This model allows us to observe how these factors individually influence demand patterns, highlighting how extreme temperatures or high carbon prices might cause significant changes in energy usage.

[5] We have also re-estimated Models 1–6 using data for 'apparent temperature (AT)' following Steadman (1994) instead of using standard temperature measures (temp). The AT, also known as the heat index or 'feels like' temperature, captures the combined effects of windspeed, air temperature, and relative humidity, which account for the joint effects perceived by humans. The results for both AT and temp are qualitatively similar and thus are not reported here to conserve space.

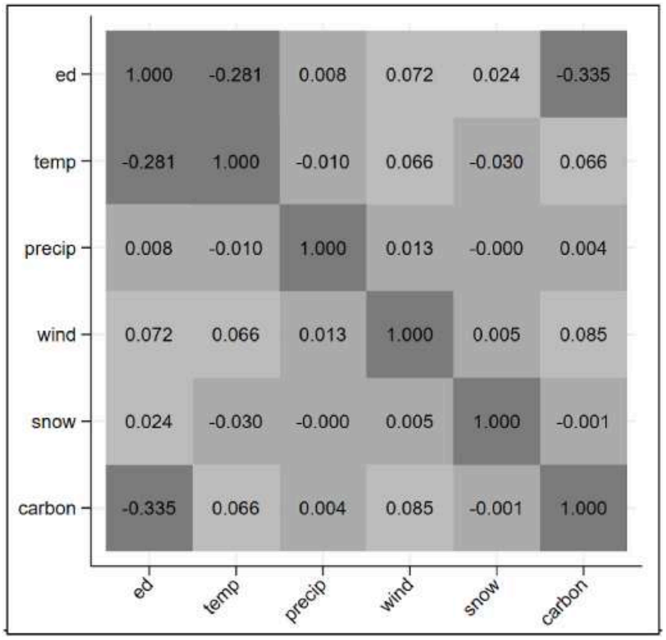

Fig. 1. Correlation heatmap.

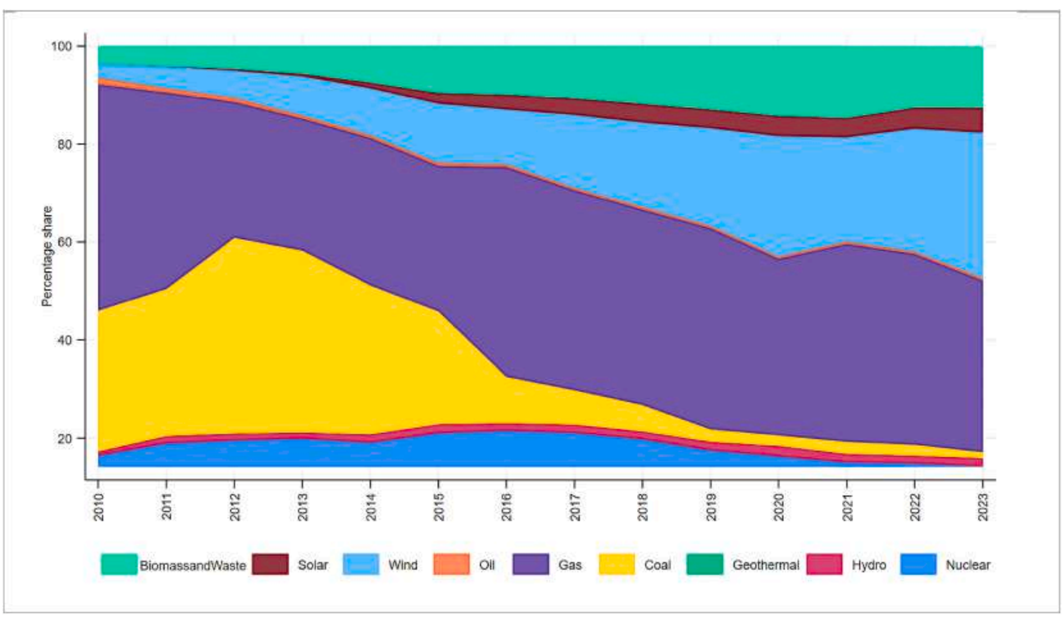

Fig. 2. Percentage share of different sources of electricity generation in the UK.

The intercept represents the expected value of electricity demand when all smoothed predictors are at their mean values. The estimated value of the intercept term is 11.06 in Model 1, which is statistically significant. Temperature has a significant non-linear effect on electricity demand with the high effective degrees of freedom for the smooth term ($edf = 8.616$). These results indicate that electricity demand increases during extremely high and low temperatures to meet cooling and heating needs. This pattern aligns with Harish et al. (2020), who also report non-linear temperature effects in Indian cities, though with more pronounced cooling-driven demand spikes. This non-linear relationship suggests that temperature plays a dual role in driving electricity demand. From a climate policy perspective, this finding underscores the importance of introducing energy efficiency measures during both hot and cool seasons. Extreme weather increases energy demand, while meeting such demand becomes unsustainable with an inefficient energy sector. Improving efficiency requires significant fixed costs,[6] highlighting a potential policy trade-off between efficiency gains and large fixed investment.

Similarly, carbon prices with edf = 18.872 suggest a significant negative, non-linear effect on electricity demand, indicating more pronounced effects as the carbon price increases. This negative relationship suggests that higher carbon prices incentivise energy conservation, particularly among industrial and commercial consumers who are more sensitive to carbon-related cost increases. Furthermore, the impact of

[6] https://blogs.adb.org/blog/energy-efficiency-why-not-enough-being-invested.

Table 2
Generalised additive models (GAM) estimate of weather, carbon price, and external shocks on UK electricity demand.

Term	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Parametric coefficients						
Intercept	11.06***	11.06***	11.09***	11.07***	11.07***	11.06***
Factor variable						
covid			−0.115***			
seasons = spring				−0.013***		
seasons = summer				−0.152***		
seasons = winter				0.119***		
Russia-Ukraine war (*war*)					−0.11***	
Smooth terms						
precipitation (precip)	3.111**	2.835**	2.780**	2.948***	3.088**	3.209***
temperature (temp)	8.616***	8.285***	8.390***	7.950***	8.147***	6.108*
windspeed (wind)	8.404***	8.383***	8.374***	8.201***	8.276***	8.237***
snowfall (snow)	1.914*	1.848*	1.865**	2.062***	1.928**	2.111**
carbon prices (carbon)	18.872***	18.753***	18.675***	18.667***	18.744***	13.833**
carbon price*temperature (carbon*temp)		25.555***	26.044***	24.846***	25.327***	
carbon price*temperature*Russia-Ukraine war (carbon*temp*war)						94.659***
Adjusted R-squared	0.283	0.293	0.299	0.358	0.295	0.304
Restricted maximum likelihood (REML) score	12,958	13,504	13,926	18,040	13,677	14,148
Scale estimates	0.044	0.044	0.043	0.040	0.044	0.043
Number of observations	93,530	93,530	93,530	93,530	93,530	93,530

Note: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$; for parametric coefficients of the factor variables, coefficient values and their significance level are reported. For the "smooth terms", effective degrees of freedom (edf) and their significance level are reported. Scale estimates indicate residual variances, with a small value indicating a good model fit in terms of prediction accuracy. Models 1–6 represent equations (1)–(6), respectively, in section 3.2.

the carbon price on electricity demand presents a non-linear and higher-order polynomial pattern. This finding highlights the effectiveness of carbon prices as a market-based instrument in reducing electricity demand, particularly when the carbon price crosses its threshold. Our results indicate that demand elasticities of electricity become more responsive with higher carbon prices and vice versa. They also suggest that a sharp rise in carbon prices could lead to disproportionate impacts on energy-intensive industries and vulnerable populations. Thus, policymakers should consider complementary measures, such as subsidies for developing energy-efficient technologies or income support for low-income households, to mitigate the adverse consequences of (high) carbon taxes.

It is observed that the estimated degrees of freedom (*edf*) of precipitation (precip) are relatively low (3.11) compared to temperature and carbon price; thus, the nonlinearity in the effect of precipitation on electricity demand is less complex. We find that windspeed with edf = 8.404 also has a non-linear impact of a higher-order polynomial on electricity demand. Such non-linear effects depend on windspeeds, which can reduce demand in warmer periods (i.e., cooling effects) while increasing demand to meet heating needs during colder months (i.e., heating effects). We further find that snowfall with edf = 1.914 has a significant but moderate non-linear impact on electricity demand. Snowfall is a key driver of electricity consumption in colder climates, with demand rising during winter and heavy snowfall episodes. Integrating weather forecasting with energy planning could ensure a more efficient energy supply during snowy seasons.

Next, Model 2 in Table 2 builds on Model 1 by adding an interaction between carbon prices and temperature, denoted by *carbon*temp*. The coefficient of this interaction term suggests that carbon prices during extreme temperatures have a stronger impact than otherwise on electricity demand. The inclusion of *carbon*temp* improves the explanatory power from 28.3 % in Model 1 to 29.3 % in Model 2. The edf for *carbon*temp* is 25.555 and is highly significant, indicating that the impact of carbon prices on electricity demand is even more non-linear compared to Model 1, which does not include the interaction term (*carbon*temp*). Carbon prices have a stronger effect during extremely high and extremely low-temperature spells. The high impact of the interaction variable highlights that carbon pricing alone may not be effective in normal weather, while it becomes crucial during extreme temperature episodes. Thus, policymakers can miss opportunities to reduce electricity demand during extreme weather events when they rely solely on carbon pricing to manage demand. Hence, an innovative, flexible carbon pricing strategy, such as introducing higher (lower) pricing during extreme (mild) weather, will help mitigate the excessive economic burden.

In the next step, Model 3 includes the COVID-19 pandemic, denoted by *covid*, along with weather variables and carbon prices in order to capture its moderating impact on electricity demand. The coefficient for *covid* is −0.115, which is statistically significant, indicating a lower electricity demand during the pandemic and the post-period compared to the pre-COVID period. The inclusion of *covid* dummy further improves the model's fit to 30 %, confirming that the pandemic altered consumption patterns. All variables remain significant. This finding aligns with the ensuing economic downturn during COVID-19. A persistently high edf of *carbon*temp* suggests that the joint impact of carbon prices and temperature on electricity demand remains non-linear with a higher order polynomial. Furthermore, the results reflect that *covid* has also affected the combined effects of carbon prices and temperature, thus indicating that consumers' responses to changes in carbon prices vary with temperatures and during COVID-19.

We further incorporate seasonal effects as the additional moderator in Model 4 in Table 2 to assess how demand changes across different seasons. Winter increases electricity demand, while spring and summer reduce it. The inclusion of seasonal effects with *carbon*temp* further improves the explanatory power of the model to 35 %, offering a more nuanced view of how weather and economic factors interact throughout the year. Our findings confirm the presence of significant seasonal effects on electricity demand, with the highest impact in winter and the lowest in summer. Electricity demand, compared to the baseline estimate of 11.073, decreases by 0.017 and 0.154 in spring and summer, respectively, and increases by 0.117 in winter. A substantial drop in *edf* of the carbon price indicates that their effects on electricity demand are non-linear, with a distinct seasonal pattern. The impact of *carbon*temp* on electricity demand remains non-linear, with a pronounced impact when temperature and carbon prices reach their highest level. The smooth terms for all other variables are statistically significant and have a similar *edf*, suggesting that their relationships with electricity demand remain consistent with the baseline model.

We re-estimate the model by incorporating the Russia-Ukraine war as a moderator, denoted by *war*, in Model 5 in Table 2. The results show

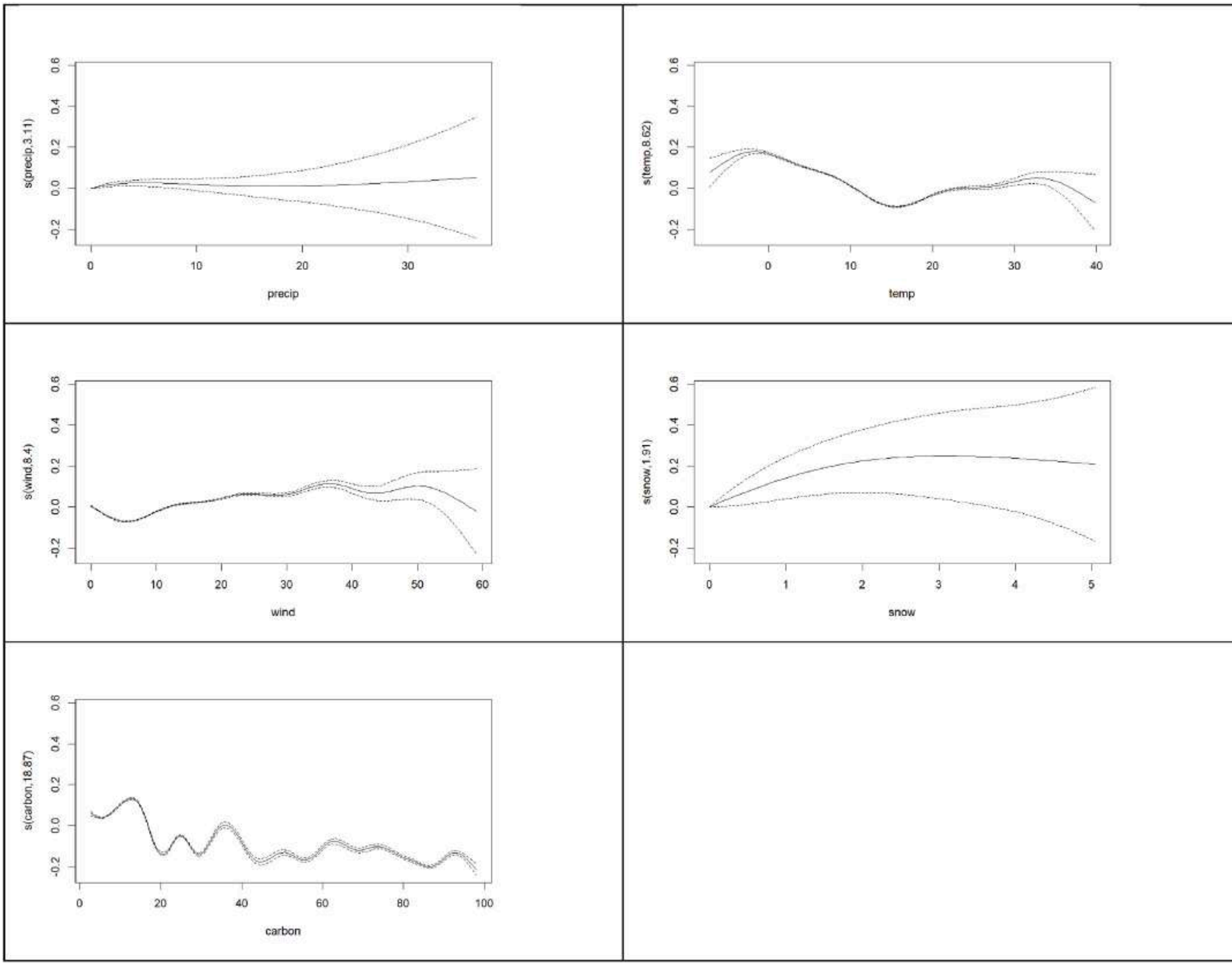

Fig. 3. Baseline Model (Model 1): Weather Effects on Electricity Demand. Note: The solid line in each figure shows the estimated effect of each predictor, while the dashed lines represent the confidence intervals.

electricity demand during the war decreased by 0.114 compared to its baseline estimate of 11.072, and the smooth terms for all variables remain significant. This reduction in electricity demand after the onset of the war may be attributed to higher global energy prices and supply chain disruptions, which constrained economic activity. This reduction reflects the adverse consequences of the war on energy consumption and the economy. Kumar and Mallick (2023) similarly note that geopolitical tensions increase input costs for electricity generation, suppressing demand. The result highlights the importance of energy security and resilient energy systems during phases of geopolitical instability. Thus, policy should focus on diversifying energy sources and decentralised power generation to mitigate such risks. Similar to Model 4, the impact of carbon prices remains significant but with reduced nonlinearity as the edf declines to 8.373, suggesting that part of the non-linear effects of carbon prices is captured in the *war* variable. The impact of *carbon***temp* on electricity demand remains non-linear with a higher order polynomial ($edf = 25.451$). These results suggest that carbon price-temperature interactions have a persistent non-linear effect on electricity demand.

In our final model (Model 6 in Table 2), we include non-linear terms for precipitation, temperature, windspeed, snow, and carbon prices, as well as a three-way interaction of carbon prices, temperature, and the war period, denoted by *carbon***temp* **war*. The coefficient for the interaction term is significant, highlighting how carbon pricing, jointly with extreme temperatures and the war, can significantly affect electricity demand in non-linear ways, with a higher-order polynomial. The effects of precipitation, temperature, windspeed, and snowfall remain significant and persistently similar to those of the baseline model. Finally, Model 6 reveals that while individual weather variables (precipitation, temperature, windspeed, and snow) influence electricity demand, the interactive *carbon***temp***war* term provides a more complex and nuanced understanding of electricity demand dynamics.

Having discussed the static non-linear relationships estimated in Models 1–6 (Table 2), we now focus on the dynamic non-linear effects on electricity demand of predictors: seasons, the pandemic, the Russia-Ukraine war, and interactions between variables. Figs. 3 and 4 capture these dynamic effects, where Fig. 3 corresponds to Model 1 and Fig. 4 corresponds to Models 2–5. We find a non-linear impact of all predictors

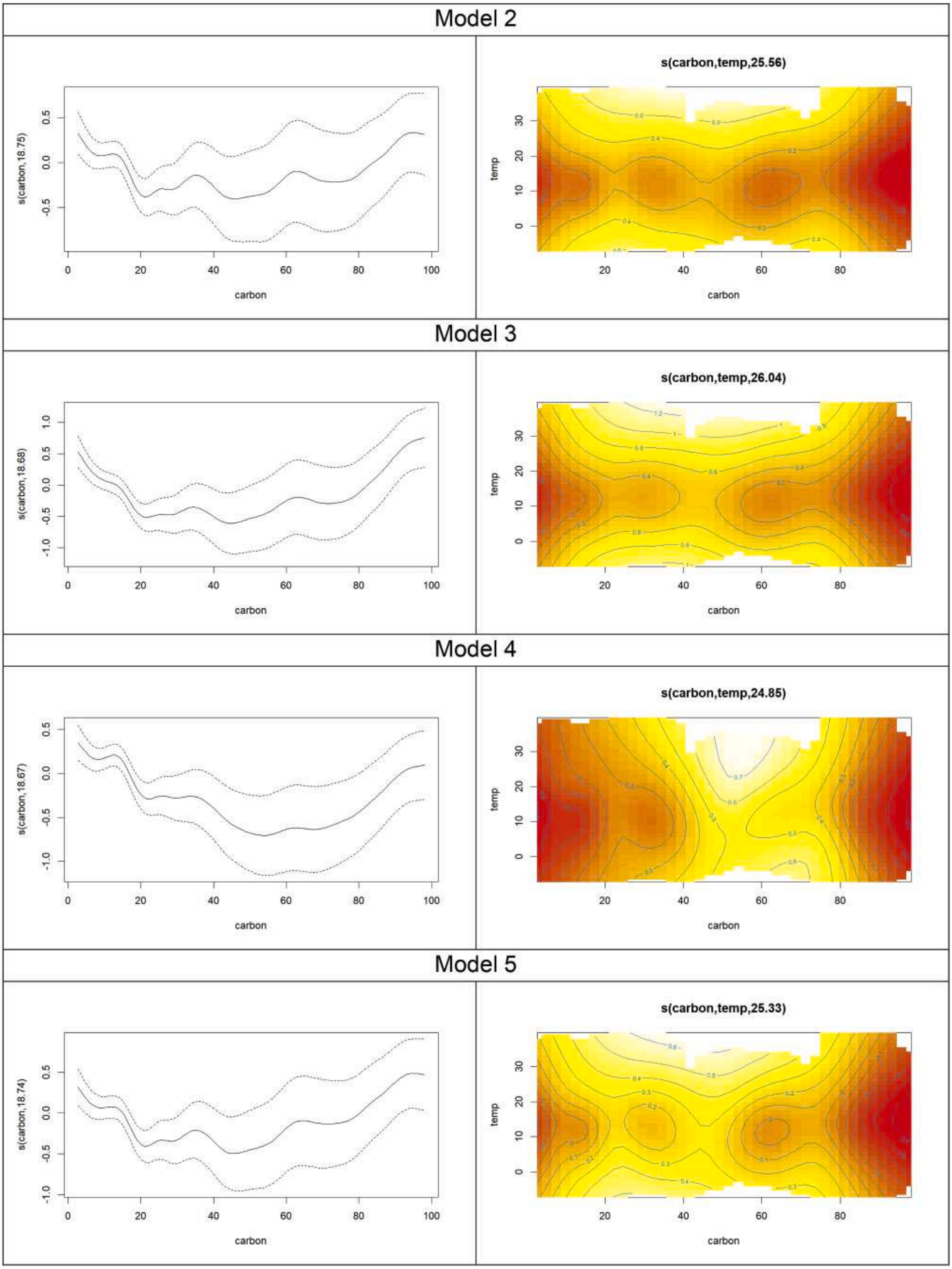

Fig. 4. Effects of carbon prices and *carbon*temp* on electricity demand Models 2–5. Note: The solid line in each figure shows the estimated effect of each predictor, while the dashed lines representing the confidence intervals.

across model specifications, although such effects vary across variables and models. Results show that the strongest non-linear effects prevail for temperature, carbon price, and snowfall, while a low or mild non-linear impact exists for other variables. We further find that the interaction terms also exert non-linear effects on electricity demand. Importantly, the inclusions of interaction terms in the model reduce the strength of the non-linear effects of individual variables.

To gain further insights into the complex polynomial nature of relationships, we choose Fig. 3 as an example to thoroughly analyse the relationship between electricity demand with its predictors. Fig. 3 reveals a U-shaped relationship between temperature and electricity demand, consistent with our findings in sub-section 3.3, with electricity demand increasing during extremely high and low temperatures to meet cooling and heating needs, respectively. This non-linear relationship demonstrates that temperature plays a dual role in driving electricity demand. We further find that electricity demand initially drops when windspeed is around 35 km/h and starts rising when windspeed reaches around 42 km/h, and falls again when windspeed is at around 50 km/h.

Concerning snowfall, we observe that electricity demand increases with snowfall, and then starts falling gradually when snowfall reaches 20 mm. From a climate policy perspective, this result underscores the importance of considering energy efficiency measures during both heating and cooling seasons. If energy efficiency improvements (such as better insulation or more efficient HVAC systems) are not implemented, the rising frequency of extreme temperatures due to climate change could lead to unsustainable increases in electricity demand. However, such investments would require significant upfront costs, which could be a barrier for lower-income households, highlighting a potential policy trade-off.

For carbon prices, we observe that electricity demand decreases with an increase in carbon prices, with the impact being more pronounced when carbon prices reach their highest level. Furthermore, the effect of carbon prices on electricity demand reveals a varying consumer response pattern across carbon price ranges. The results highlight the effectiveness of market-based instruments, such as carbon pricing, in reducing electricity demand, particularly when prices reach higher levels. From an economic standpoint, our findings support the view that elasticities of electricity demand become more responsive at higher carbon price levels. If carbon prices remain low, they may not induce significant changes in consumer behaviour.

The movements of the carbon price variable across Models 2–5 reveal that carbon prices at higher levels become less effective in curbing electricity demand (see Fig. 4). This ineffectiveness is possibly due to the limited alternative electricity supply during periods of peak electricity demand. The interaction effect of carbon prices and temperature indicates that their combined effects on electricity demand are more pronounced when both carbon prices and temperature are at their highest or lowest levels. The magnitudes of such effects are influenced by seasons, COVID-19 and the Russia-Ukraine war. Thus, the findings of our analysis suggest the need for a flexible and adaptive carbon pricing strategy that accounts for factors influencing the carbon price-electricity demand sensitivity. Pursuing this strategy will promote stabilising the demand for electricity under extreme weather conditions and simultaneously aid in achieving environmental goals.

We introduced electricity price (*log_dap*) as a smooth term in all six models to isolate its effect and avoid confounding it with the carbon price. Without explicitly including electricity price, the carbon price term might have inadvertently captured both the policy effect and market-based price fluctuations. Additionally, the precipitation variable is respecified as precip1 by subtracting snowfall from total precipitation to better reflect actual precipitation effects without overlapping with snow-specific effects.[7]

The revised estimated model results are presented in Table 4A. The estimated effective degrees of freedom (*edf*) for the smooth term s (*log_dap*) remain high and statistically significant across all models, indicating a strong non-linear relationship between price and electricity demand. Importantly, the effective degrees of freedom (*edf*) for the smooth term (*carbon*) remain consistently high and significant, suggesting that even after including both carbon prices and electricity prices in the model, the carbon price continues to exhibit a strong and significant effect on electricity demand. This persistent effect suggests that carbon pricing influences demand via direct channels in addition to the price channel. Our findings, therefore, highlight that carbon pricing serves not only as a price-based instrument but also as a broader policy instrument for managing demand.

In contrast, s(*precip*1) is statistically insignificant with *edf*~1.00 in all the models except Model 4, suggesting a near linear and limited influence of precipitation on demand. Snow appears to have a significant effect only in Models 1, 4, and 6. Meanwhile, windspeed is consistently significant across all models and exhibits strong non-linear relationships with electricity demand. The smooth term of temperature remains significant and strong in all models, thus suggesting a non-linear influence on electricity demand.

Overall, the results are robust and broadly consistent with those from the baseline results. The inclusion of electricity price strengthens the findings by removing potential endogeneity between price and policy variables. Except for the reduced significance of the precipitation variable, the main conclusions remain unchanged, confirming the non-linear impact of temperature, wind, and carbon price on electricity demand.

3.4.1. Subsample analysis

In this section, we assess whether the impact of weather and carbon price on electricity demand is affected by COVID-19 and the Russia-Ukraine war. Thus, we split our sample between pre- and post-COVID-19 and the pre- and post-Russia-Ukraine war and re-execute the GAM model. Here, it is essential to note that given the data limitation, we have analysed only the selected models (Models 1, 2, 3, 4 and 5) out of Models 1 to 6.[8] Results from the sub-sample analyses are reported in Tables 2A and 2B and Figures A.2 and A.3 in the Appendix.

Our findings from sub-sample periods indicate a marginal reduction in UK electricity demand during the post-COVID-19, as indicated by a drop in the intercept from 11.11 during the pre-COVID to 10.89–10.94 during the post-COVID. Temperature remained a significant factor. However, its non-linearity declined during the post-COVID period (Table 2A and Figure A.2). The impact of carbon prices diminished while the joint non-linear effect of carbon price and temperature persisted but differed between the pre- and post-sub-sample period, as indicated by a slight decline in demand during the post-war period (Table 2A and Figure A.2 in the Appendix). The non-linear effects of temperature and carbon prices diminished at higher values (Table 2B and Figure A.3). However, the combined effect of temperature and carbon price remains highly non-linear with differing effects for the pre- and post-subsample periods (Table 2B and Figure A.3). These findings from sub-sample analyses highlight how systemic shocks such as COVID-19 and the Russia-Ukraine war have influenced the UK electricity demand trajectory.

Consistent with the full sample analysis, we included the electricity price (*log_dap*) as the smooth term across all the sub-sample models to separate the effect of electricity price from that of the carbon price. We also replaced the precipitation variable with *precip*1 (precipitation minus snow) to isolate its influence. Tables 4B and 4C show results aligned with the earlier findings. The COVID-19 and Russia-Ukraine war

[7] We are grateful to one of the reviewers for pointing out the potential issue of double counting and overlap in the definition of precipitation, which we have now addressed.

[8] For the pre-Covid sub-sample we have analysed model 1, 2 and 4 whereas for the post-Covid sub-sample we have estimated model 1, 2, 4 and 5. Similarly, for the pre-war we have estimated model 1, 2, 3 and 4 and for the post-war sub-sample we have analysed model 1, 2 and 4.

sub-sample models confirm the robust non-linear effect of carbon price, temperature, and windspeed on electricity demand. Electricity price shows a consistently strong non-linear effect across all sub-samples. Notably, the impact of temperature appears to weaken in the post-war periods, potentially reflecting changing consumer behaviour or shifting the industrial response. The *precip*1 variable has remained statistically insignificant across the sub-samples, while wind continues to have a consistent non-linear impact on demand.

3.4.2. Quantile on quantile analysis results

To assess the robustness of our GAM model results, we performed quantile-on-quantile regression analyses, and results are reported in Tables 3A and 3B and Figure A.4 in the Appendix. For brevity, we have only presented the results for the electricity demand-temperature and electricity demand-carbon price pairs. Results suggest that the impact of temperature on electricity demand increases with demand and becomes more pronounced when temperature is in the bottom 0.1–0.3 quantiles. These results confirm our earlier findings on the presence of non-linear relationships between temperature and electricity demand. The impact of carbon prices on electricity demand presents a nuanced picture – at the lower level of demand, the effects of carbon prices are negative and on an increasing trend, but this negative impact lessens at the 0.7–0.9 quantile. Such diminishing effects at the upper quantiles of demand reflect the limitations of using carbon pricing as an instrument when demand is already at its upper quantiles.

4. Conclusions

This paper examines the nuanced relationship between electricity demand and temperature in the UK, framed within the broader context of carbon pricing, climate change and geopolitical events such as the COVID-19 pandemic and the Russia-Ukraine war. In particular, the study tests the possibility of non-linear or U-shaped influences of temperature on electricity demand and how carbon prices as policy instruments moderate the effect of temperature on electricity demand. Furthermore, the study analyses the influence of recent events such as COVID-19 and the Russia-Ukraine war on the UK's electricity demand.

Our findings—drawn from both descriptive and generalised additive models (GAMs)—confirm a non-linear (U-shaped) relationship between temperature and electricity demand. Demand decreases at moderate temperatures and increases during extreme temperatures, particularly due to heightened heating needs in colder months. This U-shaped demand pattern is attributed to the UK's climate and built environment, which are more oriented towards heating requirements. Electricity demand also exhibits seasonal variation, with electricity peaking during winter due to increased economic activity and heating requirements.

Furthermore, our results show that carbon pricing plays a crucial role in reducing electricity demand, particularly during periods of extreme temperature. The interaction between carbon pricing and temperature reveals that policymakers must consider adaptive pricing mechanisms to avoid inequitable access to energy services during extreme weather. We also introduced electricity prices as a smooth term to distinguish policy-driven effects from market responses. The results suggest that even after controlling for electricity prices, carbon pricing continues to exhibit a strong, non-linear influence on electricity demand. This indicates the robustness of carbon price effects and the potential of adaptive carbon pricing schemes to regulate demand without distorting market signals. The analysis also reveals the significant impacts of the COVID-19 pandemic and the ongoing Russia-Ukraine war on electricity demand patterns, reflecting broader economic and social disruptions. We also find the influence of weather-related variables such as snow and precipitation on increasing demand to meet heating requirements. Furthermore, substituting precipitation with a refined measure (precip1, excluding snow) did not change the overall results.

We find a varying electricity demand across months, with colder months showing augmented electricity demand due to increased heating requirements and a rise in economic activity around the Christmas period. A gradual downward trend in demand over the years is primarily due to gains or improvements in energy efficiency from a wide range of government energy-saving schemes (ONS (2023); Safarzadeh et al. (2020); Bertoldi and Mosconi (2020)). We further find that the UK is reducing its reliance on fossil fuels by introducing a more diversified and cleaner renewable energy mix.

Sub-sample analysis (pre- and post-COVID, pre- and post-Russia-Ukraine war) confirms the robustness of our results. While the effects of electricity and carbon prices remain strong and non-linear, we observed a decline in temperature sensitivity in the post-war period, possibly due to changes in consumer behaviour, industrial adjustments, or broader energy efficiency gains.

The results of the GAM model provide crucial insights for designing climate adaptation policies. The non-linear interactions between temperature, carbon pricing, and electricity demand highlight the need for adaptive pricing schemes that respond to extreme weather conditions. Additionally, the counter-intuitive findings—such as the amplified effect of carbon pricing during periods of extreme temperatures and the reduction in demand during wartime and pandemics—emphasise the importance of designing resilient energy systems. Based on our findings, we recommend implementing adaptive carbon pricing schemes that adjust rates during temperature extremes to control electricity demand more effectively. Improving the efficiency of heating and cooling systems should be a priority to reduce large swings in electricity demand during extreme weather. To mitigate the geopolitical risks posed by the COVID-19 pandemic and the Russia-Ukraine war, energy policy should prioritise supply diversification, decentralised energy systems, and targeted support for vulnerable households facing price volatility.

In conclusion, this comprehensive analysis contributes to our understanding of the electricity demand-temperature nexus in the UK. It highlights the broader implications of climate change and geopolitical events on energy systems. Future research on the temperature–electricity demand relationship using disaggregated data will be beneficial for improving the management of electricity supply from different sources and its demand for various uses, given the recurring extreme weather shocks in recent times.

CRediT authorship contribution statement

Charanjit Kaur: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Jalal Siddiki:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Prakash Singh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We are grateful to the two anonymous reviewers, the journal editor, and Paul Auerbach for their constructive comments on an earlier draft of this paper, which significantly improved its quality. We also thank the participants of the EFS-2024 conference (14–16 May 2024, University of Leeds) for their valuable feedback.

Appendix

Table A1
Variable Descriptions and Data Sources

Variable names	Variable description	Data sources
temp	Mean temperature	Visual Crossing Weather (2009–2023); https://www.visualcrossing.com/
humidity	Relative humidity	
precip	Precipitation	
precip1	Precipitation- Snowfall	
wind	Windspeed	
snow	Snowfall	
ed	Electricity demand	Ofgem: https://data.nationalgrideso.com/data-groups/demand
log_dap	Dap price	Nordpool
carbon	UK carbon price	https://uk.investing.com/commodities/carbon-emissions-historical-data
year	Dummy for years	
month	Dummy for months	
weekend	Dummy variable (weekend = 1 and weekdays = = 0)	
covid	Dummy to capture Pre and Post COVID-19 lockdown of March 23, 2020	
war	Dummy to capture start of Russia-Ukraine war on February 24, 2022	

Note: Sample period of the study is January 02, 2009-December 21, 2023.

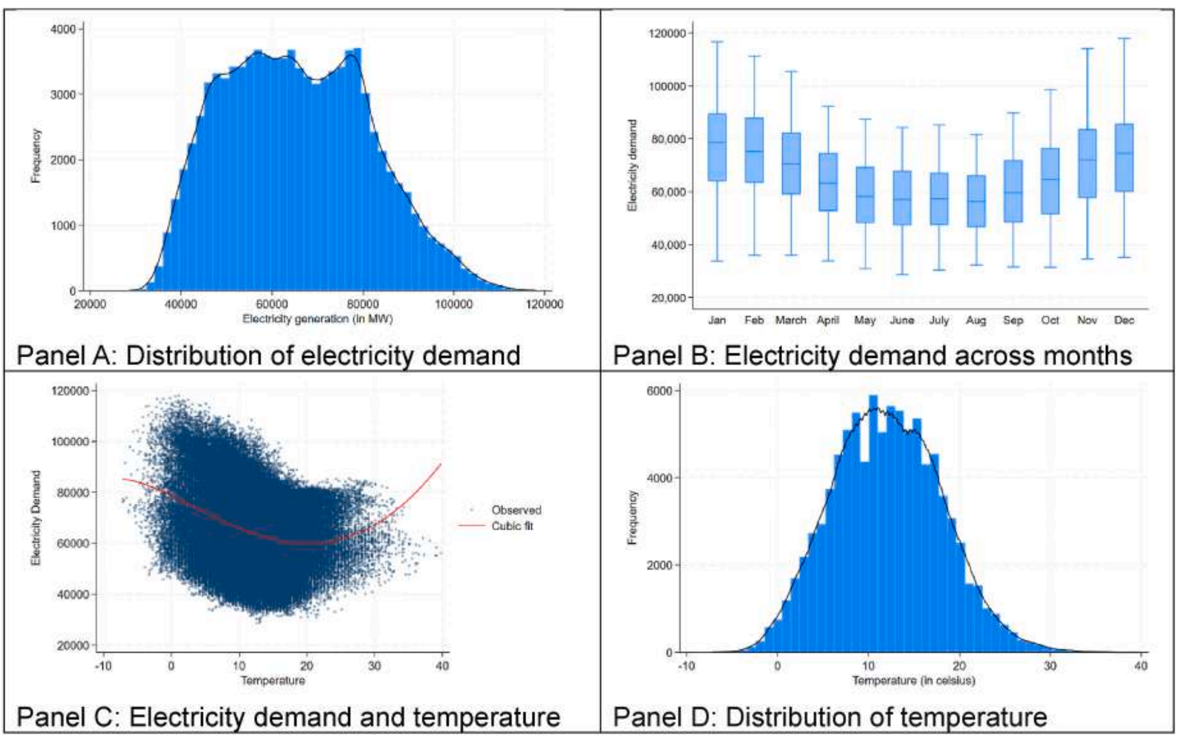

Fig. A.1. Electricity Demand and Temperature Characteristics

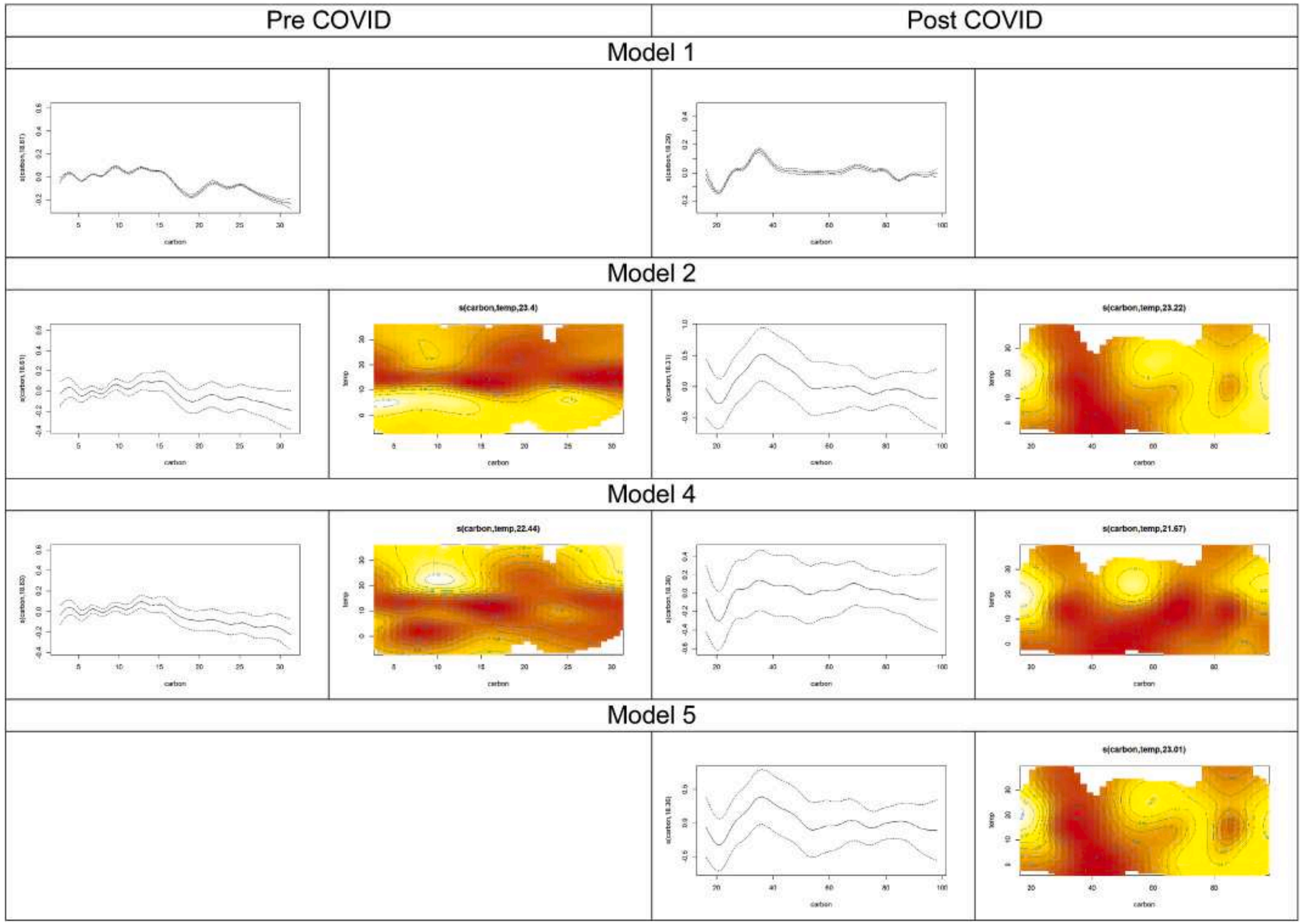

Fig. A.2. Effects of carbon prices and *carbon*temp* on electricity demand pre- and post-Covid

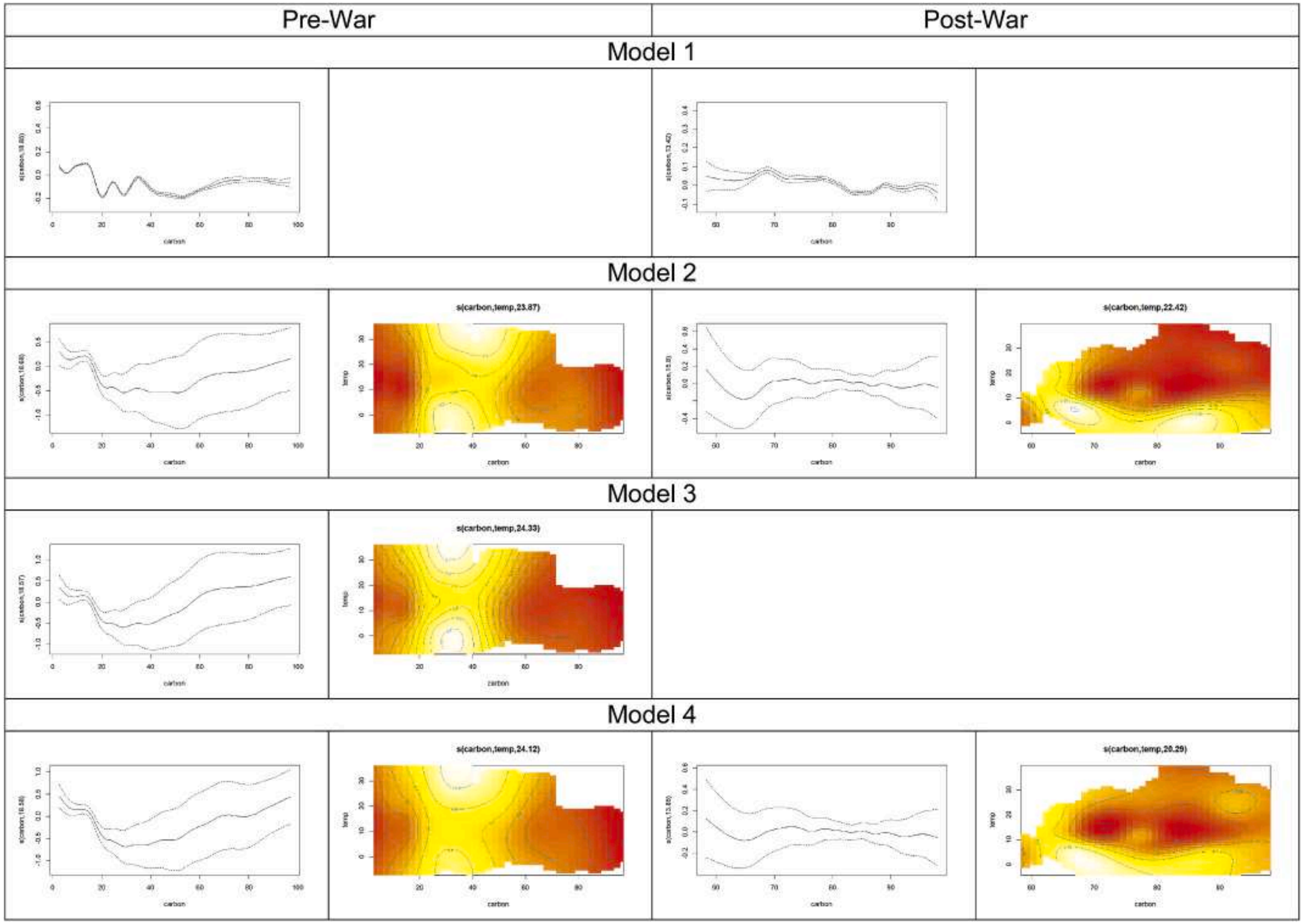

Fig. A.3. Effects of carbon prices and *carbon*temp* on electricity demand pre and post Russia-Ukraine War

Table 2A
Generalised additive models (GAM) estimate of weather, carbon price, and external shocks on UK electricity demand (Covid sub-sample)

Term	Pre COVID			Post COVID			
	Model 1	Model 2	Model 4	Model 1	Model 2	Model 4	Model 5
Parametric coefficients							
Intercept	11.11***	11.11***	11.12***	10.89***	10.89***	10.91***	10.94***
Factor variable							
seasons = spring			−0.006**			0.002	
seasons = summer			−0.158***			−0.134***	
seasons = winter			0.116***			0.116***	
Russia-Ukraine war (*war*)							−0.086***
Smooth terms							
Precipitation (*precip*)	2.843**	2.883**	2.639***	1.959	1.905	2.573	2.172
Temperature (*temp*)	8.473***	7.111***	6.532***	7.819***	6.743***	5.776	6.236**
windspeed (*wind*)	8.043***	8.023***	7.875***	8.564***	8.525***	8.313***	8.274***
snowfall (*snow*)	1.900*	2.157**	1.996**	1.001	1.000	1.006*	1.001
carbon prices (*carbon*)	18.609***	18.609***	18.630***	18.292***	18.308***	18.378***	18.365***
carbon price*temperature (*carbon*temp*)		23.404***	22.441***		23.223***	21.673***	23.007***
Adjusted R-squared	0.186	0.194	0.27	0.216	0.247	0.297	0.251
Restricted maximum likelihood (REML) score	9448.2	9733	13,232	4885.1	5299.6	6108.3	5361
Scale estimates	0.045	0.044	0.040	0.038	0.037	0.034	0.036
Number of observations	70,297	70,297	70,297	23,233	23,233	23,233	23,233

Note: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$; for parametric coefficients of the factor variables, coefficient values and their level of significance are reported. For the "smooth terms", effective degrees of freedom (edf) and their level of significance are reported.

Table 2B
Generalised additive models (GAM) estimate of weather, carbon price, and external shocks on UK electricity demand (Russia-Ukraine war sub-sample)

Term	Pre-War				Post-War		
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 4
Parametric coefficients							
Intercept	11.084***	11.08***	11.101***	11.09***	10.86***	10.86***	10.87***
Factor variable							
covid			−0.117***				
seasons = spring				−0.019***			0.025***
seasons = summer				−0.157***			−0.111***
seasons = winter				0.112***			0.128***
Smooth terms							
Precipitation (*precip*)	2.955**	2.864**	2.815**	2.574***	1.004*	1.003*	3.438*
Temperature (*temp*)	8.654***	8.346***	8.366***	7.590***	7.789***	4.302	5.646
windspeed (*wind*)	8.159***	8.189***	8.172***	8.025***	7.847***	7.618***	7.494***
snowfall (*snow*)	1.965*	1.897*	1.906*	1.868*	1.422	1.000	1.000*
carbon prices (*carbon*)	18.850***	18.676***	18.572***	18.579***	13.417***	15.795***	13.853***
carbon price*temperature (*carbon*temp*)		23.872***	24.329***	24.120***		22.418***	20.286***
Adjusted R-squared	0.235	0.243	0.251	0.311	0.198	0.223	0.275
Restricted maximum likelihood (REML) score	10,992	11,392	11,817	15,263	2601.9	2739	3130.3
Scale estimates	0.045	0.044	0.044	0.040	0.036	0.035	0.033
Number of Observations	82,249	82,249	82,249	82,249	11,281	11,281	11,281

Note: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$; for parametric coefficients of the factor variables, coefficient values and their significance level are reported. For the "smooth terms", effective degrees of freedom (edf) and their significance level are reported.

Table 3A
Quantile-on-quantile regression results for electricity demand and temperature

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	−6.570 (0.000)	−7.195 (0.000)	−7.642 (0.000)	−8.124 (0.000)	−8.701 (0.000)	−9.136 (0.000)	−9.679 (0.000)	−10.203 (0.000)	−10.238 (0.000)
0.2	−6.487 (0.000)	−7.353 (0.000)	−8.073 (0.000)	−8.784 (0.000)	−9.613 (0.000)	−10.509 (0.000)	−11.523 (0.000)	−12.551 (0.000)	−12.697 (0.000)
0.3	−6.597 (0.000)	−7.901 (0.000)	−8.949 (0.000)	−9.945 (0.000)	−11.276 (0.000)	−12.882 (0.000)	−14.514 (0.000)	−16.083 (0.000)	−17.156 (0.000)
0.4	−7.937 (0.000)	−8.737 (0.000)	−9.111 (0.000)	−9.327 (0.000)	−9.645 (0.000)	−10.500 (0.000)	−12.178 (0.000)	−14.408 (0.000)	−16.367 (0.000)
0.5	−8.015 (0.000)	−8.161 (0.000)	−7.954 (0.000)	−7.846 (0.000)	−7.765 (0.000)	−7.366 (0.000)	−6.787 (0.000)	−6.008 (0.000)	−4.338 (0.000)
0.6	−8.030 (0.000)	−8.290 (0.000)	−8.058 (0.000)	−7.906 (0.000)	−7.725 (0.000)	−7.347 (0.000)	−6.612 (0.000)	−5.682 (0.000)	−3.486 (0.000)
0.7	−9.144 (0.000)	−8.485 (0.000)	−7.573 (0.000)	−6.696 (0.000)	−5.723 (0.000)	−4.148 (0.000)	−1.709 (0.000)	0.881 (0.000)	3.502 (0.000)
0.8	−7.922 (0.000)	−6.562 (0.000)	−5.334 (0.000)	−4.574 (0.000)	−3.698 (0.000)	−2.345 (0.000)	−0.535 (0.000)	1.344 (0.000)	3.393 (0.000)
0.9	−7.271 (0.000)	−6.477 (0.000)	−5.702 (0.000)	−5.323 (0.000)	−4.661 (0.000)	−3.574 (0.000)	−1.906 (0.000)	0.000 (1.000)	1.883 (0.000)

Note: Parentheses reports the p-value.

Table 3B
Quantile-on-quantile regression results for electricity demand and carbon prices

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	−0.817 (0.000)	−1.299 (0.000)	−1.984 (0.000)	−9.275 (0.000)	−16.097 (0.000)	−22.415 (0.000)	−34.552 (0.000)	−70.674 (0.000)	−98.347 (0.000)
0.2	−0.750 (0.000)	−1.027 (0.000)	−1.752 (0.000)	−6.888 (0.000)	−14.887 (0.000)	−21.408 (0.000)	−32.088 (0.000)	−65.005 (0.000)	−100.331 (0.000)
0.3	−0.746 (0.000)	−0.956 (0.000)	−1.656 (0.000)	−5.203 (0.000)	−14.604 (0.000)	−20.528 (0.000)	−30.907 (0.000)	−58.605 (0.000)	−102.310 (0.000)
0.4	−0.919 (0.000)	−1.480 (0.000)	−2.236 (0.000)	−9.737 (0.000)	−17.681 (0.000)	−21.577 (0.000)	−35.716 (0.000)	−62.577 (0.000)	−84.984 (0.000)
0.5	−1.038 (0.000)	−2.382 (0.000)	−5.056 (0.000)	−14.079 (0.000)	−20.018 (0.000)	−23.323 (0.000)	−49.332 (0.000)	−71.535 (0.000)	−81.185 (0.000)
0.6	−1.076 (0.000)	−2.513 (0.000)	−7.605 (0.000)	−15.047 (0.000)	−20.781 (0.000)	−25.217 (0.000)	−54.717 (0.000)	−74.272 (0.000)	−83.060 (0.000)
0.7	−1.347 (0.000)	−3.339 (0.000)	−8.941 (0.000)	−17.722 (0.000)	−22.366 (0.000)	−27.121 (0.000)	−57.298 (0.000)	−73.730 (0.000)	−30.629 (0.000)
0.8	−1.259 (0.000)	−3.309 (0.000)	−8.884 (0.000)	−18.702 (0.000)	−24.283 (0.000)	−30.197 (0.000)	−64.107 (0.000)	−85.139 (0.000)	−31.970 (0.000)
0.9	−1.176 (0.000)	−3.016 (0.000)	−6.119 (0.000)	−16.616 (0.000)	−22.644 (0.000)	−28.442 (0.000)	−58.609 (0.000)	−82.666 (0.000)	−51.010 (0.000)

Note: Parentheses reports the p-value.

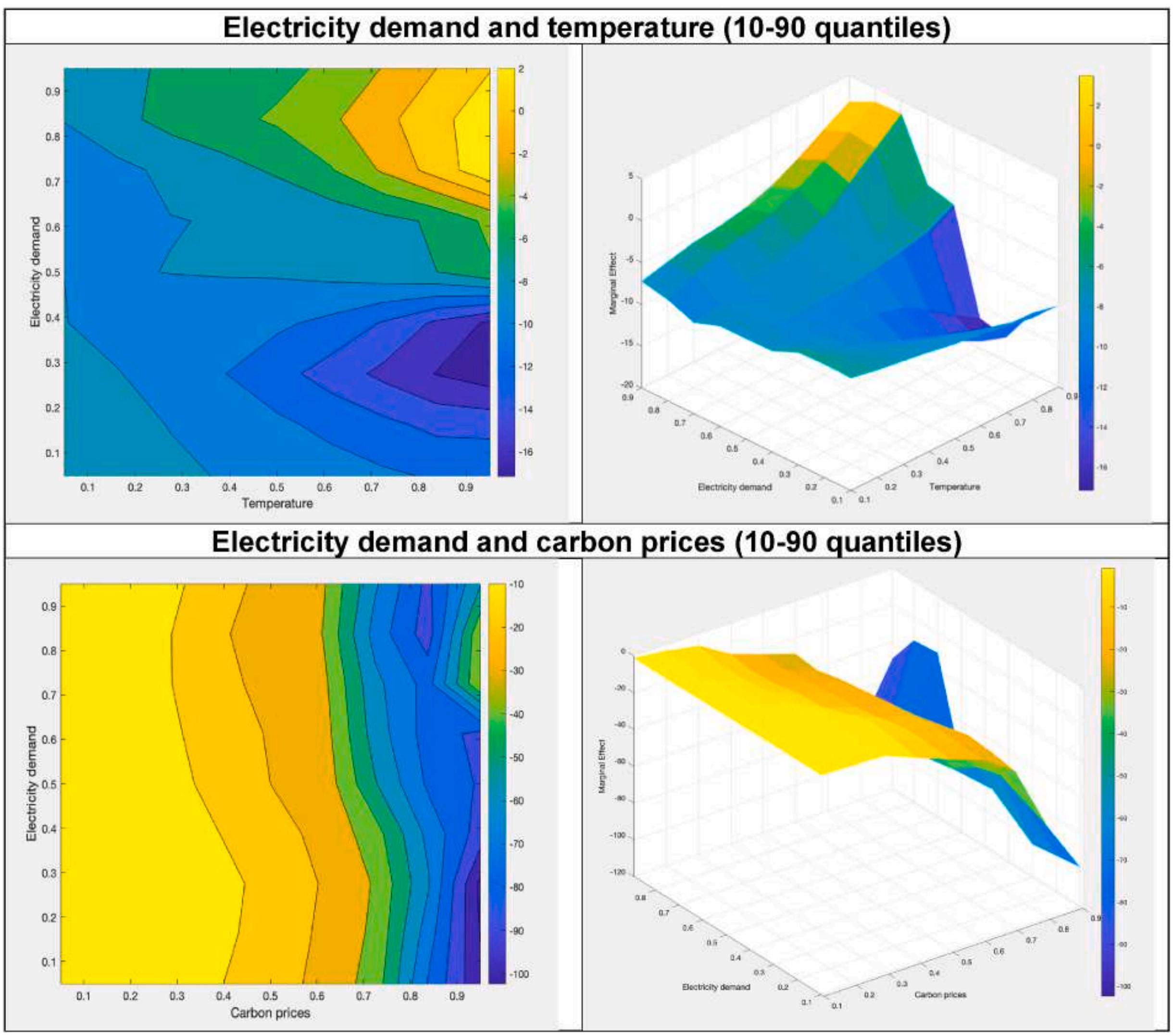

Fig. A.4. Quantile-on-quantile regression results for electricity demand, temperature and carbon prices

Table 4A
Generalised additive models (GAM) estimate of weather, carbon price, and external shocks on UK electricity demand (after controlling for Electricity Price)

Term	Model1	Model2	Model3	Model4	Model5	Model6
Parametric coefficients						
Intercept	11.048***	11.048***	11.037***	11.043***	11.057***	11.048***
Factor variable						
covid			0.042***			
seasons = spring				0.016***		
seasons = summer				−0.1***		
seasons = winter				0.113***		
Russia-Ukraine war (war)					−0.07***	
Smooth terms						
electricity price (log_dap)	8.951***	8.948***	8.948***	8.939***	8.948***	8.946***
precipitation1 (precip1)	1.002	1.001	1.002	1.002*	1.004	1.002
temperature (temp)	8.337***	8.481***	8.472***	6.904***	8.366***	4.245
windspeed (wind)	8.473***	8.478***	8.48***	8.334***	8.399***	8.35***
snowfall (snow)	1.754*	1.556	1.651	3.417*	2.018	4.759**
carbon prices (*carbon*)	18.921***	18.836***	18.848***	18.835***	18.836***	16.905***
carbon price*temperature (*carbon*temp*)		26.302***	26.293***	25.669***	26.242***	
carbon price*temperature*Russia-Ukraine war (carbon*temp*war)						96.358***
Adjusted R-squared	0.556	0.562	0.563	0.602	0.563	0.572
REML score	−33510.333	−34033.673	−34117.082	−38149.828	−34138.481	−34870.602
Scale estimate	0.027	0.027	0.027	0.024	0.027	0.026
Observations	86,797	86,797	86,797	86,797	86,797	86,797

Note: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$; for parametric coefficients of the factor variables, coefficient values and their level of significance is reported. For the "smooth terms", effective degrees of freedom (edf) and their level of significance are reported.

Table 4B
Generalised additive models (GAM) estimate of weather, carbon price, and external shocks on UK electricity demand (after controlling for Electricity Price) for Covid sub-sample

Term	Pre-COVID			Post-COVID			
	Model1	Model2	Model4	Model1	Model2	Model4	Model5
Parametric coefficients							
(Intercept)	11.102***	11.102***	11.095***	10.899***	10.899***	10.92***	10.936***
Factor variable							
seasons = spring			0.018***			−0.024***	
seasons = summer			−0.099***			−0.128***	
seasons = winter			0.109***			0.100***	
Russia-Ukraine war (*war*)							−0.076***
Smooth terms							
s(log_dap)	8.817***	8.808***	8.791***	8.808***	8.836***	8.805***	8.836***
s(precip1)	1.004	1.005	1.005	1.001	1.002	1.003	1.002
s(temp)	8.129***	8.738***	8.522***	7.447***	7.744***	7.518***	7.244***
s(wind)	7.977***	7.91***	7.752***	8.451***	8.376***	8.056***	8.073***
s(snow)	1.382	4.065*	1.709	1.001*	1.001	1.611*	1.002*
s(carbon)	18.909***	18.907***	18.925***	17.31***	17.903***	17.349***	17.957***
s(carbon, temp)		25.853***	25.302***		24.442***	23.316***	24.076***
Adjusted R-squared	0.525	0.534	0.577	0.453	0.478	0.521	0.481
REML score	−25867.26	−26391.146	−29482.2	−9138.397	−9606.914	−10596.547	−9677.002
Scale estimate	0.026	0.025	0.023	0.026	0.025	0.023	0.025
Observations	63,646	63,646	63,646	23,151	23,151	23,151	23,151

Note: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$; for parametric coefficients of the factor variables, coefficient values and their level of significance is reported. For the "smooth terms", effective degrees of freedom (edf) and their level of significance are reported.

Table 4C
Generalised additive models (GAM) estimate of weather, carbon price, and external shocks on UK electricity demand (after controlling for Electricity Price) for Russia-Ukraine war sub-sample

Term	Pre-War				Post-War		
	Model1	Model2	Model3	Model4	Model1	Model2	Model4
Parametric coefficients							
(Intercept)	11.074***	11.074***	11.067***	11.062***	10.87***	10.87***	10.912***
Factor variable							
covid			0.045***				
seasons = spring				0.025***			−0.033***
seasons = summer				−0.086***			−0.17***
seasons = winter				0.112***			0.09***
Smooth terms							
s(log_dap)	8.946***	8.95***	8.949***	8.941***	8.604***	8.571***	8.491***
s(precip1)	1.001	1.004	1.004	1.002	1.002	1.001	1

(*continued on next page*)

Table 4C (*continued*)

Term	Pre-War				Post-War		
	Model1	Model2	Model3	Model4	Model1	Model2	Model4
s(temp)	8.383***	6.871**	6.995**	7.121***	6.991***	4.572	5.469
s(wind)	8.229***	8.244***	8.249***	8.098***	7.306***	6.837***	7.054***
s(snow)	4.334*	4.337*	4.339*	3.669	1.005	1	1.001*
s(carbon)	18.908***	18.768***	18.785***	18.753***	16.504***	16.792***	15.928***
s(carbon, temp)		23.874***	23.864***	24.705***		23.537***	22.179***
Adjusted R-squared	0.552	0.558	0.559	0.594	0.374	0.401	0.469
REML score	−30724.616	−31173.72	−31268.948	−34346.717	−4006.93	−4208.42	−4878.74
Scale estimate	0.026	0.026	0.025	0.023	0.028	0.027	0.024
Observations	75,561	75,561	75,561	75,561	11,236	11,236	11,236

Note: *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$; for parametric coefficients of the factor variables, coefficient values and their level of significance is reported. For the "smooth terms", effective degrees of freedom (edf) and their level of significance are reported.

Data availability

Data will be made available on request.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., Topalova, P., 2020. The effects of weather shocks on economic activity: what are the channels of impact? J. Macroecon. 65, 103207. https://doi.org/10.1016/j.jmacro.2020.103207.

Auffhammer, M., Baylis, P., Hausman, C.H., 2017. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. Proc. Natl. Acad. Sci. 114 (8), 1886–1891. https://doi.org/10.1073/pnas.1613193114.

Balsalobre-Lorente, D., Sinha, A., Murshed, M., 2023. Russia-Ukraine conflict sentiments and energy market returns in G7 countries: discovering the unexplored dynamics. Energy Econ. 125, 106847. https://doi.org/10.1016/j.eneco.2023.106847.

Bertoldi, P., Mosconi, R., 2020. Do energy efficiency policies save energy? A new approach based on energy policy indicators (in the EU Member States). Energy Policy 139, 111320. https://doi.org/10.1016/j.enpol.2020.111320.

Borenstein, S., 2012. The private and public economics of renewable electricity generation. J. Econ. Perspect. 26 (1), 67–92. https://doi.org/10.1257/jep.26.1.67.

Carabott, M., Beard, E., 2024. How the climate and weather affect electricity prices. Leading Edge Energy. https://www.leadingedgeenergy.com.au/news/how-the-climate-and-weather-affect-electricity-prices/.

Chang, Y., Kim, C.S., Miller, J.I., Park, J.Y., Park, S., 2016. A new approach to modeling the effects of temperature fluctuations on monthly electricity demand. Energy Econ. 60, 206–216. https://doi.org/10.1016/j.eneco.2016.09.016.

Cronin, J., Anandarajah, G., Dessens, O., 2018. Climate change impacts on the energy system: a review of trends and gaps. Clim. Change 151, 79–93. https://doi.org/10.1007/s10584-018-2265-4.

Dagar, V., Rao, A., Dagher, L., Doytch, N., 2024. Climate change dynamics for global energy security and equity: evidence from policy stringency drivers. J. Environ. Manag. 370, 122484. https://doi.org/10.1016/j.jenvman.2024.122484.

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798. https://www.jstor.org/stable/24434109?seq=51.

drax, 2016. Some like it hot: how temperature affects electricity prices. https://www.drax.com/electrification/some-like-it-hot-how-temperature-affects-electricity-prices/. (Accessed 21 March 2024).

Eskander, S.M.S.U., Fankhauser, S., 2023. The impact of climate legislation on trade-related carbon emissions 1996–2018. Environ. Resour. Econ. 85, 167–194. https://doi.org/10.1007/s10640-023-00762-w.

Felbermayr, G., Gröschl, J., Sanders, M., Schippers, V., Steinwachs, T., 2022. The economic impact of weather anomalies. World Dev. 151, 105745. https://doi.org/10.1016/j.worlddev.2021.105745.

Gerarden, Todd D., Newell, Richard G., Stavins, Robert N., 2017. Assessing the energy-efficiency gap. J. Econ. Lit. 55 (4), 1486–1525. https://doi.org/10.1257/jel.20161360.

Government Office for Science (GOS), 2023. How well do we understand the impacts of weather conditions on the UK's renewable wind and solar energy supplies? bit.ly/4c4ZqdM. (Accessed 21 March 2024).

Gupta, E., 2012. Global warming and electricity demand in the rapidly growing city of Delhi: a semi-parametric variable coefficient approach. Energy Econ. 34 (5), 1407–1421. https://doi.org/10.1016/j.eneco.2012.04.014.

Harish, S., Singh, N., Tongia, R., 2020. Impact of temperature on electricity demand: evidence from Delhi and Indian states. Energy Policy 140, 111445. https://doi.org/10.1016/j.enpol.2020.111445.

Heynes, George, 2022. How do heat waves hit the UK's energy system? https://bit.ly/3P5pZ8A. (Accessed 21 March 2024).

International Energy Agency (IEA), 2022. The electricity market report. www.iea.org.

International Energy Agency (IEA), 2021. Net zero by 2050: a roadmap for the global energy sector. https://www.iea.org/reports/net-zero-by-2050.

International Energy Agency (IEA), 2023. Greenhouse gas emissions from energy data explorer. https://www.iea.org/data-and-statistics/data-tools/greenhouse-gas-emissions-from-energy-data-explorer (Accessed 21 March 2024).

Jiang, P., Fan, Y.V., Klemeš, J.J., 2021. Impacts of COVID-19 on energy demand and consumption: challenges, lessons and emerging opportunities. Appl. Energy 285, 116441. https://doi.org/10.1016/j.apenergy.2021.116441.

John, J., 2017. Eia Data Reveals California's Real and Growing Duck Curve, vol. 25. Greentech Media.

Kang, J., Reiner, D.M., 2022. What is the effect of weather on household electricity consumption? Empirical evidence from Ireland. Energy Econ. 111, 106023. https://doi.org/10.1016/j.eneco.2022.106023.

Kikstra, J.S., Waidelich, P., Rising, J., Yumashev, D., Hope, C., Brierley, C.M., 2021. The social cost of carbon dioxide under climate-economy feedbacks and temperature variability. Environ. Res. Lett. 16 (9), 094037. https://doi.org/10.1088/1748-9326/ac1d0b.

Kumar, A., Mallick, S., 2023. Oil price dynamics in times of uncertainty: revisiting the role of demand and supply shocks. Energy Econ. 129, 107152. https://doi.org/10.1016/j.eneco.2023.107152.

Mideksa, T.K., Kallbekken, S., 2010. The impact of climate change on the electricity market: a review. Energy Policy 38 (7), 3579–3585. https://doi.org/10.1016/j.enpol.2010.02.035.

Moral-Carcedo, J., Vicéns-Otero, J., 2005. Modelling the non-linear response of Spanish electricity demand to temperature variations. Energy Econ. 27 (3), 477–494. https://doi.org/10.1016/j.eneco.2005.01.003.

Office for National Statistics (ONS), 2023. ONS website, article, energy efficiency of housing in England and Wales: 2023. https://bit.ly/3PBth3A.

Pardo, Angel, Meneu, Vicente, Valor, Enric, 2002. Temperature and seasonality influences on Spanish electricity load. Energy Econ. 24 (1), 55–70. https://doi.org/10.1016/S0140-9883(01)00082-2.

Safarzadeh, S., Rasti-Barzoki, M., Hejazi, S.R., 2020. A review of optimal energy policy instruments on industrial energy efficiency programs, rebound effects, and government policies. Energy Policy 139, 111342. https://doi.org/10.1016/j.enpol.2020.111342.

Schmalensee, R., 2022. Competitive energy storage and the duck curve. Energy J. 43 (2), 1–16. https://doi.org/10.5547/01956574.43.2.rsch.

Sharif, A., Baris-Tuzemen, O., Uzuner, G., Ozturk, I., Sinha, A., 2020. Revisiting the role of renewable and non-renewable energy consumption on Turkey's ecological footprint: evidence from Quantile ARDL approach. Sustain. Cities Soc. 57, 102138. https://doi.org/10.1016/j.scs.2020.102138.

Sharma, R., Sinha, A., Kautish, P., 2021. Does renewable energy consumption reduce ecological footprint? Evidence from eight developing countries of Asia. J. Clean. Prod. 285, 124867. https://doi.org/10.1016/j.jclepro.2020.124867.

Silva, Susana, Soares, Isabel, Pinho, Carlos, 2020. Climate change impacts on electricity demand: the case of a southern European country. Util. Policy 67, 101115. https://doi.org/10.1016/j.jup.2020.101115.

Staffell, I., Pfenninger, S., 2018. The increasing impact of weather on electricity supply and demand. Energy 145, 65–78. https://doi.org/10.1016/j.energy.2017.12.051.

Steadman, R.G., 1994. Norms of apparent temperature in Australia. Aust. Meteorol. Mag. 43, 1–16.

Torriti, J., 2022. Household electricity demand, the intrinsic flexibility index and UK wholesale electricity market prices. Environ. Econ. Pol. Stud. 24, 7–27. https://doi.org/10.1007/s10018-020-00296-1.

UCL, 2021. Economic cost of climate change could be six times higher than previously thought. https://www.ucl.ac.uk/news/2021/sep/economic-cost-climate-change-could-be-six-times-higher-previously-thought. (Accessed 21 March 2024).

Uddin, M., Chowdhury, A., Anderson, K., Chaudhuri, K., 2021. The effect of COVID–19 pandemic on global stock market volatility: can economic strength help to manage the uncertainty? J. Bus. Res. 128, 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061.

Wood, S.N., 2017. Generalised Additive Models: an Introduction with R, second ed. (second ed. Chapman and Hall/CRC. https://doi.org/10.1201/9781315370279.

World Bank, 2021. State and trends of carbon pricing 2021. https://openknowledge.worldbank.org/handle/10986/35620.

Yao, Jiaxiong, 2021. Electricity consumption and temperature: evidence from satellite data. IMF Work. Pap. 21/22.