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We empirically derive the determinants of British public preferences for different low-carbon energy sources using machine learning algorithm-based variable selection methods (ridge, lasso, and elastic net regression models). We seek to understand the drivers of support for solar, wind, biomass, and nuclear energy, which are the largest low-carbon energy sources and together account for the majority of UK power generation. Explanatory variables examined include those related to demographics, knowledge, perceptions of climate change, and government policy. We carry out a comparative study by synthesising the results of our independent analyses for each energy source and find that the preferred energy sources vary with respondents' views on anticipated climate change impacts. Those who believe that potential effects of climate change will be catastrophic tend to prefer renewable energy sources whereas those less concerned about climate change tend to prefer nuclear power. The public also prefer energy sources about which they are more familiar or knowledgeable.

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Contact Juyong Lee: jylee@changwon.ac.kr
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Juyong Lee[a, b] and David M Reiner[a*]

[a] Energy Policy Research Group, Cambridge Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG, UK

[b] Department of Industrial and Systems Engineering, Changwon National University, Changwon, Republic of Korea

Juyong Lee, Ph.D.
Assistant Professor
Department of Industrial and Systems Engineering, Changwon National University, Changwon, Republic of Korea
Tel: +82-55-213-3726
E-mail: jylee@changwon.ac.kr

David Reiner, Ph.D. (*Corresponding author)
Professor of Technology Policy
Energy Policy Research Group, Cambridge Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG, UK
Tel: +44 (0) 1223 339616
E-mail: d.reiner@jbs.cam.ac.uk

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We empirically derive the determinants of British public preferences for different low-carbon energy sources using machine learning algorithm-based variable selection methods (ridge, lasso, and elastic net regression models). We seek to understand the drivers of support for solar, wind, biomass, and nuclear energy, which are the largest low-carbon energy sources and together account for the majority of UK power generation. Explanatory variables examined include those related to demographics, knowledge, perceptions of climate change, and government policy. We carry out a comparative study by synthesising the results of our independent analyses for each energy source and find that the preferred energy sources vary with respondents' views on anticipated climate change impacts. Those who believe that potential effects of climate change will be catastrophic tend to prefer renewable energy sources whereas those less concerned about climate change tend to prefer nuclear power. The public also prefer energy sources about which they are more familiar or knowledgeable.



*Keywords:* low carbon energy; nuclear power; renewable energy; variable selection models; energy mix; public trust; climate change perceptions.

## 1. Introduction

Decarbonising the electric power sector is a necessary first step to achieve the goals of the 2015 Paris Agreement [1,2] and this will depend, in turn, on public support for decarbonisation both in terms of local deployment and the wider backing for government schemes to accelerate deployment.

The UK was the first major economy to formally declare a goal of phasing out coal and imposed a carbon price floor that created a price differential with gas-fired generation [3]. As a result, the proportion of coal power generation has recently decreased to single-digit percentages, strengthening the UK's status as a leading country in its response to climate change and greenhouse gas reduction policies [4]. Although Brexit has enabled the UK to adopt different policies from the EU, on climate change, it has sought to be as ambitious or even more ambitious than the EU. In 2021, the UK set a 2030 target of 68% and a 2035 target of 78% [5]. To achieve these long-term targets, the UK has shifted towards an energy mix centered on low-carbon energy sources and steadily reduced the proportion of coal power generation.

In December 2020, the UK government published its 'Energy White Paper 2020' [6]. The White Paper presents British ambitions through 2030 for ten key low-carbon energy priorities, including solar, biomass, nuclear, and offshore wind energy. The urgency of supporting new large-scale nuclear power plant construction was driven in part by existing nuclear power plants reaching their end of life within the next ten years. Up to £385 million of investment in next-generation nuclear reactors is expected by creating the Advanced Nuclear Fund including £215 million for small-scale reactors (SMR). In the case of biomass energy, which can replace fossil fuel-based products and activities, the Government published a Biomass Policy Statement in 2021 although a more extensive new Biomass Strategy including greater clarity on the pathway for biomass energy with carbon capture storage (BECCS) was delayed.

Whereas past national energy policies often emphasised energy security, both in terms of geopolitical supply considerations and in terms of availability and resource adequacy, environmental considerations, notably climate change, has risen dramatically in the global energy discourse amd in the UK in particular. As the main source of greenhouse gas emissions, the need for an energy transition away from fossil fuels and towards low-carbon energy sources have been actively debated in most countries [7]. A study in four European countries found about 90 per cent of respondents supported reducing the proportion of fossil fuels, expanding renewable energy, and increasing investment in response to climate change [8]. Renewable energy accounted for about 75 per cent of investment in new power generation in OECD countries and grid parity, i.e., the generation cost of renewable energy becomes equal to or less than that of fossil fuels, is expected to be achieved in a few years [9]. The International Energy Agency has predicted that the trend of expansion of low carbon energy sources would continue reinforced by efforts to reduce greenhouse gases and reflecting the public preferences for eco-friendly and low-cost energy sources [10,11]. In this situation, identifying factors influencing public perceptions and preferences for low carbon energy sources can be helpful when alleviating conflicts and confrontations surrounding the energy transition and enhancing the effectiveness of related government policies.

The purpose of this study is twofold: (1) to explore the determinants of public preferences for low carbon energy sources; and (2) to identify similarities and differences through comparative analysis of determinants across energy sources. In our study we focus on solar, wind, nuclear, and biomass energy, the leading sources of low-carbon generation, which account for a large and growing share of the UK energy mix (55%-60% in 2021 and 2022). The analysis was performed on data from a survey of over 2000 UK households carried out in May 2021. Similar to Steg et al (2015) who identify knowledge, motivations and contextual factors as primary drivers in understanding the human element in the energy transition, explanatory variables were divided into (i) demographics, (ii) perceptions of climate change, (iii) preferences over government energy and climate policy, and (iv) knowledge about energy [12].

To identify the specific determinants to be considered in our analysis, we employ lasso, adaptive lasso, ridge, and elastic net regressions, which are widely-used feature selection models. All four models are similar insofar as they optimise the regression model by penalising coefficients of the less relevant variables and are commonly used to identify the model that best explains the behaviour of the dependent variable through comparative analysis [13,14].

The rest of the study is organised as follows: Section 2 presents the literature review, Section

3 describes the methodology and data, Section 4 presents the results of the analysis and discussion; finally, we conclude in Section 5 and discuss the limitations of this study and possible future directions.

## 2. Literature Review

In order to determine the factors that influence public preferences for low-carbon energy sources, we need to consider a range of variables from demographic factors such as age, region, and gender to cognitive and social variables such as individual political ideology, awareness of climate change issues, and familiarity with low carbon energy sources [15,16]. In this section, we review previous studies of the drivers of public preferences for low-carbon energy sources.

As the first step, we consider demographic factors. Sardianou and Genoudi analysed Greek preferences for the introduction of renewable energy and found that middle-aged respondents and those with higher education and income levels were more supportive [17]. In a study in Finland, Kosenius and Ollikainen, found that men and younger people were more positive about introducing new and renewable energy [18]. In Australia, Hobman and Ashworth found that men, older people, those with higher education levels and higher levels of knowledge about climate change and energy sources had a positive perception of renewable energy [19]. Li et al. found that across the OECD, higher income and educational level have a significant positive impact on preferences for renewable energy [20]. In a study in Malta by Briguglio and Formosa, younger, higher-income respondents and those who owned their own homes were more supportive of a policy to install solar power panels [21]. Unlike renewables, for nuclear power, demographics has consistently been a strong determinant, notably men are much more supportive than women. Arikawa et al. analysed Japanese perceptions of nuclear energy after the Fukushima nuclear accident [22] and found that men with higher education levels supported nuclear energy more. Similarly, Sundstrom and McCright, found preferences for nuclear energy was consistently more negative among women compared to men's over a 25-year period (1986 to 2011) [23].

In contrast to the somewhat inconsistent findings regarding renewables for the other demographic variables, political ideology was found to have a relatively consistent influence. The study by Costa-font et al. of British citizens found that left-wingers were less favourable toward nuclear energy [24]. Ansolabehere and Konisky found that in the United States Democrats tended to oppose coal and natural gas power generation [25], while Choma et al. found that Conservatives in Britain tend to perceive benefits more than risks of fossil fuel-related technologies [26]. Clulow et al. also demonstrated that, based on surveys in the UK and Australia, left-wingers prefer renewable energy sources while right-wingers prefer non-renewables [27]. Thus, previous studies have found that a wide range of demographic factors such as gender, age, educational level, and political ideology influence preferences for low-carbon energy sources.

Framing a technology as contributing to addressing climate change can influence preferences. Bickerstaff et al. analysed changes in the British perception of nuclear energy [28]. When they re-framed nuclear power to emphasise its usefulness as a means of responding to climate change, they found that the acceptability of new nuclear power plant construction increased. A study by Bolsen and Cook also showed that the more Americans perceived nuclear energy as a stable electricity supply and a solution to national energy security, the more positive their view of nuclear energy [29].

However, recognising nuclear energy as a low-carbon energy source does not necessarily result in consistent support. Pidgeon et al. found that although a majority of British people agreed that nuclear energy contributes to climate change mitigation, it is not preferred nearly as highly compared to renewable energy [30]. Culley et al. showed that Americans' negative perceptions of nuclear energy and fossil fuels was consistent with those who held more 'eco-centric' views [31]. Overall, many of these studies of nuclear provide evidence of a 'reluctant acceptance', which reflects a balancing of nuclear energy's ability to provide stable, low-carbon power supply against concerns over the environmental risks associated with nuclear energy [32].

Ansolabehere and Konisky found that environmental risk perception significantly affected the preference for energy sources [25]. Further, Corner et al. [33] and Vainio et al. [34] showed that various factors such as concerns about climate change and the environment, energy security, and personal environmental values had complex effects on preferences for nuclear energy. In addition to nuclear energy, several studies have shown that concerns about ecosystem destruction caused by the construction of renewable energy-based power generation facilities such as tidal power generation and photovoltaic panels have a negative effect on the preference for the low-carbon energy source in question [35,36]. To summarise these studies – the level of awareness of the risks of climate change, the perceived environmental performance of low-carbon energy sources and individual perceptions of the environment all affect preferences for different energy sources.

In general, the acceptability of science and technology, including energy sources, is proportional to the level of related knowledge, and as the level of knowledge increases, there is a tendency to perceive the level of technology-related risks as low [37]. Several studies analysed the impacts of knowledge and information on technology preferences. Ertor-Akyazi et al. found that knowledge of climate policies, such as the Kyoto Protocol and greenhouse gas reduction plans, positively affected preferences for low-carbon energy sources, including both nuclear and renewable energy [38]. Whitmarsh et al. showed that providing information on economic and environmental benefits to people who do not have a strong preference for shale gas significantly increased their preference [39]. On the other hand, they also found that the greater the level of information and knowledge about the costs and risks of each energy source, the more negative the view of each source. Sutterlin and Siegrist showed that preferences for solar energy decreased after providing specific and detailed pricing policies and information on photovoltaic power generation [40]. According to a study by Costa et al., the more people knew about the negative aspects of an energy source, the higher their level of risk perception for the energy source, which in turn negatively affected preferences [41]. Therefore, in addition to overall level of education, knowledge about specific low-carbon energy sources has a significant effect on the preference for the energy source, which may be positive or negative depending on the contents of the information and policies acquired by the individual.

Previous studies on the preferences for and acceptance of low carbon energy sources have confirmed the influence of factors such as the level of knowledge and information regarding the energy industry, the level of subjective perception of climate change risks, views of government or energy policy institutions, and demographic factors such as gender, age, education level, and political ideology. However, most studies have focused on the acceptance and preference of a single energy source. Moreover, interest and concern about climate change accelerated with governments establishing legally-binding net-zero targets so it is essential that studies continue to update our understanding of the evolving view of the public across a range of low-carbon energy technologies.

## 3. Methodology

We first applied well-known variable selection techniques for multiple regression models to identify the key variables affecting public preferences for low-carbon energy sources and compare predictive powers between the models. Variable selection methods seek to optimise the combination of variables and the number of dimensions to be used in the model by selecting significant variables and eliminating unnecessary variables from the given model. The simplest approach, carrying out an exhaustive search (also known as a brute-force search) is not practical for datasets with a large number of variables because it requires high computational complexity as the dimensionality of the dataset increases. Therefore, in this study, the optimal regression model is derived by employing ridge [42], Lasso (Least Absolute Shrinkage and Selection Operator) [43], and elastic net (a convex combination of ridge and lasso) approaches [13], which are most widely used as variable selection methods for high-dimensional regression models that need to address multicollinearity [44–46]. As correlation among variables grows, the ordinary least squares (OLS) estimator becomes increasingly unstable, which can cause a severe overfitting problem. Thus, we do not consider forward or backward stepwise regression. The following subsections briefly describe each model.

### *3.1. Ridge regression*

For high-dimensional data, where multicollinearity problems may often occur, the error is large because the prediction results are unstable, and the variance is high. To solve the multicollinearity problem, Hoerl and Kennard proposed ridge regression to improve prediction precision by reducing the size of the linear regression coefficient [42]. The objective function of the ridge regression can be expressed as Equation (1), and it can be presented as the case where alpha[1] is zero in figure 1:

$$\hat{\beta}^{ridge} = argmin_{\beta}|Y - X\beta|^2 + \lambda_1 \|\beta\|_2 \tag{1}$$

where $\beta$ is the regression coefficient and $\lambda$ is the tuning parameter. The ridge regression has L2-norm ($\|\beta\|_2$) constraint (the square root of the sum of the square of each dimension) in the objective

[1] Alpha is the regularization parameter for each regression model and can be calculated from the formula in figure 1. When alpha is 0, the regression produces the same coefficients as a linear regression. The higher the alpha, the most feature coefficients are 0.

function of the multivariate linear regression analysis, and it aims to reduce the prediction error due to multicollinearity by reducing the size of the linear coefficient value of the regression model. The magnitude of the linear coefficient value can be infinitely small but cannot be zero.

### *3.2. Lasso regression*

Tibshirani first proposed lasso regression as an alternative to ridge regression to overcome ridge's limitation of not being able to directly eliminate variables by setting their coefficients exactly to zero [43]. The objective function is presented as Equation (2), and it can be expressed as a case where alpha is 1 in figure 1:

$$\hat{\beta}^{lasso} = argmin_{\beta}|Y - X\beta|^2 + \lambda_2\|\beta\|_1. \tag{2}$$

Lasso regression has L1-norm ($\|\beta\|_1$) constraint (adding up the absolute value of every dimension) in the objective function. Lasso regression is a type of linear regression that utilises the technique of shrinkage to mitigate complexity by implementing a penalty term on the coefficients. The magnitude of the penalty is controlled through a hyperparameter, leading to some coefficients reaching zero and being removed from the model. By reducing the number of features used in the model, lasso regression can help prevent overfitting and improve the interpretability of the model.

Figure 1 presents the distribution of constraint equations for the ridge, lasso, and elastic net regressions and the regression coefficient estimates. The L2-norm regularisation of ridge regression is spherical, so it always represents the same constraint from the origin. Thus, the point of contact between the ridge regression and the distribution of the regression coefficients is a point on the sphere, not on an axis. By contrast, since the L1-norm regularisation of lasso regression has a multidimensional diamond shape, the point of contact with the distribution of the regression coefficients is on the axis. Hence, it is highly likely that the coefficients are set equal to zero, which enables lasso regression to perform variable selection.

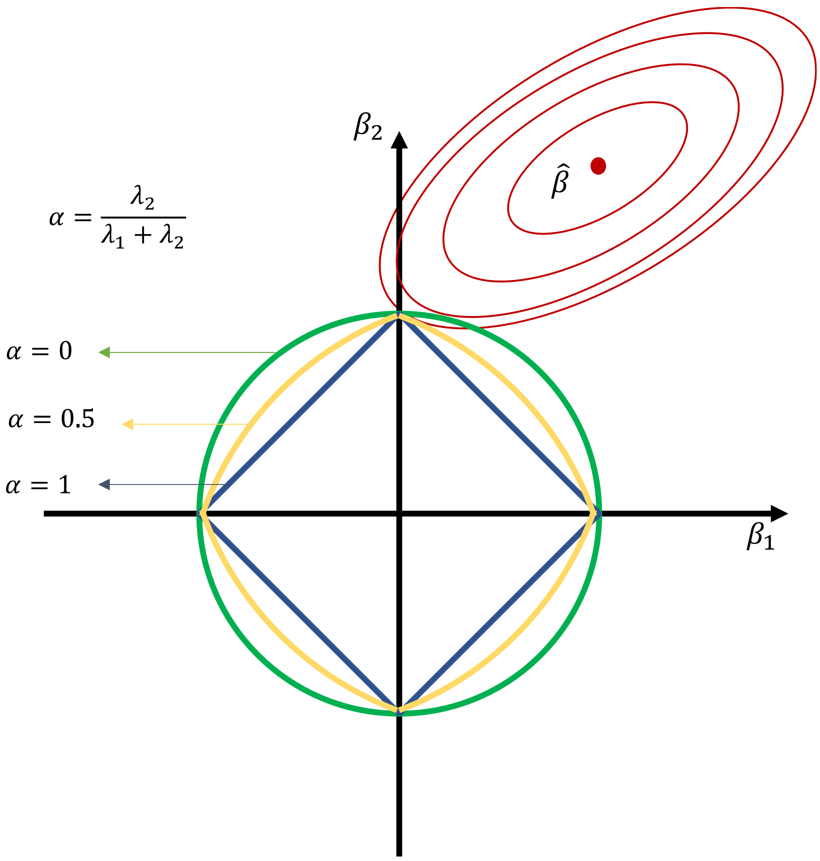


**Fig 1.** Contours of the error and constraint functions of shrinkage methods

*3.3. Elastic net regression*

Elastic net is a regression model that is penalised by both the L1-norm and the L2-norm [13]. It has the effect of simultaneously shrinking coefficients (as in ridge regression) and setting some coefficients to zero (as in lasso regression). The objective function of the elastic net is described by Equation (3), and it can be expressed as the case where alpha is between 0 and 1 in figure 1[2]:

$$\hat{\beta}^{elastic\ net} = argmin_{\beta}|Y - X\beta|^2 + \lambda_1\|\beta\|_2 + \lambda_2\|\beta\|_1 \quad (3)$$

subject to a constraint that is the sum of the L1-norm and L2-norm. It is easy to interpret by selecting only significant variables among many variables. It also has a grouping effect so that the highly correlated but significant variables can be selected. For example, a variable that affects the dependent variable is $X_1$, and if there is a variable $X_2$ that has a high correlation with $X_1$, there may be a case in

[2] In this study, a grid search was performed to select the alpha value with the highest R-squared value, where the grid was 0.1 to 0.9 at intervals of 0.1.

which it can be statistically judged as if $X_2$ also affects the dependent variable. In this case, $X_1$ can be eliminated while $X_2$ is selected when using lasso regression, or the coefficients of both $X_1$ and $X_2$ are shrunk so that both cannot be selected when using ridge regression. The elastic net regression has been used to solve these problems. However, selecting all highly correlated variables may not always be the best variable selection method – it is necessary to derive the combination of variables that best explains the dependent variable by comparing across various methods. Therefore, we analyse each low-carbon energy source using all the previously introduced approaches – ridge, lasso, and elastic net – and the results presented and associated discussions are based on the model with the highest goodness-of-fit.

### *3.5. Data and variables*

The dataset employed in this study is obtained through an online survey of environmental attitudes of 2,016 participants in the UK, conducted from June 14 to 17, 2021 and carried out by YouGov plc. (a global market research firm based in the UK). The survey respondents were selected by applying stratified sampling to obtain a representative sample of the UK. The basic demographic characteristics of the survey participants are presented in Table A1 in the Appendix.

For all questions, responses were recorded as either Yes/No or on a Likert scale, and data cleaning was performed by removing "prefer not to say", "don't know", and non-response data. The candidate variables are categorised as being either *demographic*, *knowledge*, *perception,* or *policy*. The *knowledge* variables capture respondents' background knowledge about energy sources, such as how knowledgeable they are about how energy is produced, delivered, and used (Likert scale) and whether they have read or are familiar with solar, wind, biomass, nuclear energy, and other low-carbon technologies such as carbon capture and storage and negative emissions (yes or no). The *perception* variables reflect the priority placed on climate change (Likert scale) and whether the respondents consider climate change as the most important environmental problem (yes or no[3]). The *policy* variables include whether respondents are optimistic about the UK government's environmental and energy policies (Likert scale) and whether they think that low-carbon energy sources should be the top priority

3 For example, we collected data from respondents who selected climate change among several environmental problems facing the UK, such as climate change, ecosystems destruction, water pollution, ozone depletion and smog.

in future energy policy directions (yes or no). Future policy direction was based on the government having 5 billion GBP to spend and respondents were given a list of options to choose from. The variables for each category are presented in Table 1.

**Table 1.** Variables for each category.

| Category | Variables | Scale |
|---|---|---|
| *Knowledge* | Knowledgeable about how energy is produced, delivered, and used | 1 to 5 |
| | Have read about solar energy in the past year | Y/N |
| | Have read about wind energy in the past year | Y/N |
| | Have read about nuclear energy in the past year | Y/N |
| | Have read about bioenergy/biomass in the past year | Y/N |
| *Perception* | The potential impact of climate change would be catastrophic | 1 to 11 |
| | Day-to-day life has been impacted by climate change | 1 to 4 |
| | Government can do a great deal in addressing climate change | 1 to 5 |
| | Companies can do a great deal in addressing climate change | 1 to 5 |
| | Climate change is the most important environmental problem facing the UK today | Y/N |
| *Policy* | Government responses to climate change to date effectively | 1 to 5 |
| | Climate change should have a higher priority than economic growth | 1 to 11 |
| | New renewable energy sources should be the top priority when spending £5 billion | Y/N |
| | Nuclear power should be the top priority when spending £5 billion | Y/N |

*Notes: Y/N means yes or no questions, and 1 to 4, 5, and 11 refer to Likert scale questions; The number of answers that responded "Yes" to the question on low-carbon technologies (negative emission, zero emission target, CO2 utilisation, carbon capture storage, etc.) was counted.*

Each of the four main energy sources considered (solar, wind, biomass, and nuclear) was treated as the dependent variable for each variable selection model (lasso, ridge, and elastic net) to conduct a comparative analysis. To analyse the characteristics of respondents who prefer to use low-carbon energy sources, the Likert scale scores of respondents who reported positive attitudes (i.e, those who chose "definitely use" or "probably use") toward each energy source were employed as dependent variable data.[4] To guarantee a fair comparison of the 12 independent datasets (4 energy sources by 3 models) with others, three procedures were set up. First, we generated two subsamples by randomly splitting the original data in half. Then we fit each model on the first subsample by using 10-fold cross-validation (90% of the total set used for the fit and the remaining 10% used for validation). After that, out-of-sample prediction was conducted with the testing set, which is the remaining half of the data. The testing set was used as evaluation criteria, and the models with the highest R-squared and the lowest MSE (mean squared error) were selected for each energy source. The MSE is a qualitative measure of the accuracy of statistical estimation, and the smaller the value, the more accurate the estimation. It gives information about the size of the error but does not give information about the size of the actual data value. That is, if the value of MSE is the same but the size of the data value is different, the performance will need to be evaluated differently. In this case, only R-squared is utilised. When calculating R-squared, the size of the error (usually MSE) is divided by the size of the data (mainly the variance of the data). Thus, the closer the value of R-squared is to 1, the better the performance. R-squared is widely used to determine the goodness-of-fit of regression models and is a value related to the ratio between the variance of the actual data and the regression error rather than the size of the error itself. In other words, it is a relative value that focuses on the degree of occurrence of error compared to the amount of change. The evaluation criteria of each model are shown in Table 2.

[4] The analysis reflecting the full Likert scale of responses are included in the appendix as Table A2 for completeness (this is the equivalent of Table 3 in the main text).

**Table 2.** Evaluation criteria of each model for the training and the testing samples.

| | | Training Sample | | | Testing Sample | | |
|---|---|---|---|---|---|---|---|
| | | MSE | $R^2$ | Obs | MSE | $R^2$ | Obs |
| Solar | Ridge | 0.5243 | 0.2511 | 840 | 0.4891 | 0.2732 | 851 |
| | Lasso | 0.5253 | 0.2497 | 840 | 0.4902 | 0.2717 | 851 |
| | **Elastic net** | 0.5240 | 0.2515 | 840 | **0.4888** | **0.2737** | 851 |
| Wind | **Ridge** | 0.6876 | 0.2326 | 926 | **0.6676** | **0.2497** | 931 |
| | Lasso | 0.6894 | 0.2307 | 926 | 0.6688 | 0.2483 | 931 |
| | Elastic net | 0.6896 | 0.2304 | 926 | 0.6684 | 0.2488 | 931 |
| Biomass | Ridge | 1.2460 | 0.2684 | 855 | 1.2971 | 0.2735 | 853 |
| | Lasso | 1.2763 | 0.3051 | 924 | 1.2961 | 0.2704 | 924 |
| | **Elastic net** | 1.2818 | 0.3108 | 924 | **1.2904** | **0.2748** | 924 |
| Nuclear | Ridge | 0.6214 | 0.3268 | 870 | 0.7267 | 0.3625 | 875 |
| | Lasso | 0.6194 | 0.3898 | 792 | 0.7143 | 0.3962 | 800 |
| | **Elastic net** | 0.6187 | 0.3918 | 792 | **0.7128** | **0.3994** | 800 |

*Notes: Bold numbers indicate the smallest MSE and largest R-squared for each energy source; Obs = the number of observations.*

We can see that the cross-validation process was appropriately performed since the performance of the training sample and the testing sample is similar. The numbers of observations for the training and testing sets were slightly different for some of the models. This is because each model contains different sets of selected variables, so the number of missing values is also different. By comparing results of the variable selection models, the ridge model was selected for wind energy, and the elastic net models were selected for the other energy sources.

The MSE and R-squared values indicate the goodness of fit for the models for each energy source. The MSE measures the magnitude of the error in the model's predictions, while R-squared measures the proportion of variation in the target variable that is explained by the model. The lower the MSE, the better the model fits the data, with 0 being a perfect fit. A higher R-squared value means a better fit, with 1 being a perfect fit. Based on the MSE values, it can be concluded that the solar energy model has the best fit, followed by the nuclear energy model. The biomass energy model has the highest MSE, suggesting that the model's goodness of fit is the lowest among the energy sources. On the other hand, based on the R-squared values, the nuclear energy model has the best fit while other models have similar R-squared values. Overall, these results imply that it is difficult to determine which has the best or worst goodness of fit among the energy sources.

## 4. Empirical analysis

Of the total candidate variables, 7 determinants were selected for the model of preferences for solar energy, 8 for wind and biomass, and 6 for nuclear energy. Table 3 presents the regression coefficients of the determinants for each energy source. For convenience, codes are assigned to each variable and utilised as references in the ensuing discussion.

**Table 3.** Results for each energy source.

| Code | Responses | Solar | Wind | Biomass | Nuclear |
|---|---|---|---|---|---|
| De-1 | Gender | -0.1648 (0.000) | -0.1724 (0.000) | 0.1637 (0.003) | -0.4543 (0.000) |
| De-2 | Education | 0.0079 (0.039) | | | |
| De-3 | Political ideology (Left - Right) | | | 0.0455 (0.029) | 0.1214 (0.000) |
| Kn-1 | Knowledgeable about how energy is produced, delivered, and used | | | | 0.0899 (0.005) |
| Kn-2 | Have read about solar energy | 0.1856 (0.000) | | | |
| Kn-3 | Have read about wind energy | 0.1272 (0.017) | 0.2053 (0.000) | | |
| Kn-4 | Have read about nuclear energy | | | | 0.3450 (0.000) |
| Pe-1 | Day-to-day life has been impacted by climate change | | | -0.1038 (0.017) | -0.1270 (0.005) |
| Pe-2 | Potential impact of climate change is catastrophic if left unchecked | 0.0633 (0.000) | 0.0438 (0.000) | 0.0562 (0.000) | |
| Pe-3 | Climate change is the most important environmental problem facing the UK today | | 0.1126 (0.027) | 0.1187 (0.046) | |
| Pe-4 | Government can do a great deal in addressing climate change | | | 0.0684 (0.014) | |
| Pe-5 | Companies can do a great deal in addressing climate change | 0.1197 (0.000) | 0.1533 (0.000) | | |
| Po-1 | Government responses well to climate change to date | | | 0.0920 (0.004) | |
| Po-2 | Climate change should place a higher priority to economic growth | | 0.0984 (0.006) | | |
| Po-3 | New energy sources should be the top priority if government has £5 billion to spend | 0.2701 (0.000) | 0.4340 (0.000) | 0.3164 (0.000) | |
| Po-4 | Nuclear power should be the top priority if government has £5 billion to spend | | -0.1298 (0.031) | | 1.2065 (0.000) |
| Constant | | 3.1202 (0.000) | 2.7711 (0.000) | 2.4924 (0.000) | 2.6582 (0.000) |

*Note: Values in parenthesis are p-values.*

Men prefer solar, wind, and nuclear energy while women prefer biomass energy although, as expected, the gender effect is strongest for nuclear power. In addition, those with a higher level of scientific education are more likely to prefer to use solar energy. Respondents with a more right-wing political orientation tend to prefer biomass and especially nuclear energy but there is no relationship found between ideology and wind or solar. This result is similar to previous studies that right-wingers prefer non-renewable sources [47,27]. However, age and UK region do not significantly affect preferences for any energy source. We summarise below the major characteristics of people with a clear preference for each energy source.

*Solar energy*: Perhaps unsurprisingly, those with a greater preference for solar tend to be more knowledgeable about renewables such as solar and wind energy, but knowledge of other low-carbon energy options has no significant effect. They are more likely to perceive the potential impacts of climate change to be risky, and believe that companies, rather than the government or individuals, should play a greater role in addressing it. In addition, they place renewables at the top of the government's investment priorities for addressing climate change.

*Wind energy*: Supporters were found to have a relatively high level of knowledge about wind energy, perceived climate change as one of the most critical issues currently facing the UK and recognised the potential impacts of climate change as dangerous. Like those who favour solar energy, they tend to believe that the companies can play a bigger role than the government and individuals in addressing climate change. They also believe that the government should prioritise solving climate change issues over economic growth and that investment in renewable energy sources should be given the highest priority to address climate change. On the other hand, they are more negatively inclined towards government investment in nuclear energy.

*Biomass energy*: Those with a greater preference for biomass energy tend to believe that the government can do a great deal to address climate change problems and that renewable energy sources should be the top priority for government investment. They also believe their day-to-day lives have not been impacted by climate change, but that the potential impact could be catastrophic. In addition, they judge the government's current response to address the climate change problems is appropriate. In summary, those who prefer biomass energy are highly aware of the potential risks of climate change and the need to solve them but tend to be optimistic about the current government's strategy.

*Nuclear energy*: Supporters are more likely to be knowledgeable about nuclear energy and energy in general and think that government investment in nuclear energy should be the top priority to solve climate change. They believe that their daily lives are not significantly affected by climate change. Interestingly, for those who prefer nuclear energy, variables such as the potential risks of climate change and the importance of solving the climate change issues are not found to be significant determinants of support.

Several meaningful implications can be derived from the empirical analysis of preferences for each low carbon energy source, and we draw out three key points in particular. First, the higher the professed knowledge about a specific low-carbon energy source, the more positive the view of that energy source. Knowledge-related determinants were only ever positively associated with greater preferences for low-carbon energy sources. In other words, raising levels of awareness and understanding via a government-led education campaign or other means of raising understanding whether through schools or social media or would seem likely to increase public acceptance. Of course, more work must be done to identify which are more trusted sources of information.

On the other hand, respondents' educational level (De-2) is not a significant determinant of preferences for low-carbon energy sources except solar energy. The level of knowledge about other low-carbon energy technologies, such as carbon capture and storage and negative emissions, also did not significantly affect preferences for low-carbon energy sources. Therefore, when drawing a social consensus on a specific low-carbon energy source, it is more important to transmit information or disseminate knowledge focused on the energy source rather than enhancing the public's educational level (De-2) or general understanding of the energy system (Kn-1).

Secondly, public concerns over climate change produce a marked difference in preferences for nuclear versus renewable energy sources (solar, wind, and biomass). Those who consider the potential impact of climate change to be catastrophic tend to favour renewable sources (Pe-2). In addition, they believe that the government should give priority to investing in renewable sources to solve climate change issues (Po-3). On the other hand, people who prefer nuclear energy are relatively optimistic about climate change and, unsurprisingly, think that government's investment in nuclear energy should be the top priority. Thus, it can be easier to implement renewable-centred policies than other policies regarding low carbon energy sources if the public perceives the climate change crisis as serious. Existing studies have pointed out high power generation costs and low knowledge about renewable energy as reasons for the low public preference for renewable energy sources compared to coal or nuclear energy [48,49]. However, this study suggests that, in addition to these causes, it is necessary to investigate whether the public is not aware of the seriousness of climate change and reflect on it as a variable.

The third is about public trust in the government's climate change policies, i.e., the belief that government is responding appropriately to climate change. Several studies have shown that public trust in government policy is a significant determinant of increasing public acceptance of low-carbon energy sources [50–52]. In this study, variables related to the public trust include the public's satisfaction with the government's current climate change policies (Po-1) and the public's expectations for future policies (Pe-4). We found that only support for biomass energy increases as the public trust in the government's response to climate change increases. On the other hand, respondents who prefer solar and wind energy tend to view companies rather than government as playing a more significant role in addressing climate change (Po-4, Po-5). Thus, public trust in the government's climate change response policies was not a significant determinant of preferences for any low-carbon energy sources apart from biomass energy. Taken together with these findings, we find public perceptions of potential risks of climate change but not trust in government policy has a significant effect on preferences for solar and wind energy. Preference for nuclear energy is not significantly affected by climate change-related variables. These findings indicate that although the four sources investigated here are all nominally low-carbon energy sources, the strategies, and policies that the government should take to enhance public acceptance are different for each source. In addition, our findings indicate that the energy source preferred by the public may vary depending on how the government responds or is perceived to be responding to climate change issues.

## 5. Conclusion

To better understand which climate change policies would garner greatest public support, our study empirically derives the determinants of public preferences for different low-carbon energy sources. Furthermore, since both social acceptance and cost need to be considered when expanding low-carbon energy [53,54], we conduct a comprehensive analysis by categorising the determinants of support for different option based on individuals' environmental perceptions, views of government's climate change policies, and knowledge of energy technologies, as well as demographic characteristics. We use ridge, lasso, and elastic net regression models in our analysis because it is more appropriate to use machine learning algorithm-based variable selection methods than traditional multivariate regression analysis when there are a number of explanatory variables that can cause overfitting problems. This study is novel since unlike previous studies that derived the determinants based on demographic and knowledge variables, this study also examines public perception about current and potential impacts of climate change and government's climate change policies as possible drivers.

Our study demonstrates the need for new approaches and strategies to increase the acceptance of low carbon energy sources as part of any future energy transition. Given that the government's low-carbon energy policies and public perceptions of climate change were found to have a significant effect on preferences for low-carbon energy sources, policies for the energy transition need to be adjusted to better reflect what drives public acceptance. Apart from incentives for low-carbon electricity, it is also necessary to identify ways to secure policy support considering the characteristics of each energy source and expand public awareness of climate change and individual technologies. On the other hand, demographic variables such as political ideology or region, which have been shown to be significant determinants in several existing studies, and public trust in the government policy were not found to have a significant effect on preferences for most energy sources considered in this study. This result is due to the shrinkage algorithm, in which variables of relatively small importance are excluded from the variable selection models used in the analysis.

Despite these contributions, this study has some notable limitations. First, since the survey data was restricted to British citizens, the results may have limited applicability to other countries. In this study, solar, wind, biomass, and nuclear energy, which make up a large share of low-carbon energy in the UK, were selected as dependent variables. However, the energy mix varies by country, and countries such as Poland, Czech Republic, and South Korea where the proportion of coal power is still dominant [55,56] are in a quite different situation from the UK. In our study, the most notable differences were between nuclear and non-nuclear energy sources rather than differences among renewables. However, in countries such as Australia or Norway, where no nuclear power is present, differences between renewable energy sources will be more salient. In addition, for a more holistic analysis of low-carbon energy sources in the UK in the future, it would be helpful to include more energy sources such as hydropower, or CCS technologies or new vectors such as hydrogen as dependent variables in comparative analysis. Given the longstanding debate over onshore wind in the UK, it would also be helpful to distinguish between onshore and offshore wind energy. As renewable penetration grows, more effort should be put into exploring the role of energy storage given its growing significance in the energy system.

Second, after data cleaning, we considered the responses of all survey participants as part of the analysis. However, further consideration could be given to focus only on those respondents with a particularly strong preference (whether high or low) for specific energy sources (i.e., strong advocates or opponents). We did perform a preliminary analysis as part of this study, but results were not significant because the number of observations was considerably reduced. Therefore, either a much larger sample size would be needed, or a scoping question could be included at the start to identify those with strong preferences, and then a more detailed survey could be administered to them.

Third, a paradigm shift in the energy industry, such as social ownership of energy infrastructure, decentralisation of the energy system, and greater liberalisation of energy trade, is being actively considered or even pursued in many countries, including the UK [57,58]. Although the share of energy prosumers, who produce and consume electricity, is currently small, active electricity production and trading activities among energy prosumers will increasingly occur under a more decentralized, small-scale grid. In this situation, the facility size or technology level of the energy source may be one of the important determinants for energy prosumers to select an energy source and the level of awareness and understanding of more households will increase. However, as a representative survey, the percentage of prosumers among respondents who participated in this survey is expected to be small considering current UK level of penetration, and the vast majority will have been using electricity supplied by one of the main energy suppliers. As the number of prosumer households rise, it will be possible to carry out surveys that divide respondents into prosumers and non-prosumers and identify how their views might differ. In addition, it would be helpful to include facility size, investment and management cost, and technology level to potential determinant variables.

Lastly, we explored the variable selection methods most commonly used in previous studies and did not consider more novel methods. For example, there have been various ridge-extensions such as Choquet integral ridge [59] and partial robust ridge [60]; and lasso extensions such as prior lasso [61], spike-and-slab lasso [62], and Pythagorean fuzzy lasso [63]. Although the elastic net regression that we used is an extension of the ridge and lasso approaches, the elastic net regressions did not always prove to be the best variable selection method. Therefore, future studies might be able to improve model performance by comprehensively exploring both original variable selection methods as well as more complex extended models.

## Appendix

**Table A1.** Demographic characteristics of survey participants.

| Characteristic | Group | Number of respondents | Ratio (%) |
|---|---|---|---|
| Gender | Male | 835 | 41.42 |
| | Female | 1181 | 58.58 |
| Age | Below 30 | 294 | 14.59 |
| | 30-39 | 343 | 17.01 |
| | 40-49 | 323 | 16.02 |
| | 50-59 | 334 | 16.57 |
| | 60-69 | 396 | 19.64 |
| | 70 or above | 326 | 16.17 |
| Region | Northeast | 86 | 4.27 |
| | Northwest | 203 | 10.07 |
| | Yorkshire and the Humber | 177 | 8.78 |
| | East Midlands | 153 | 7.59 |
| | West Midlands | 157 | 7.79 |
| | East of England | 187 | 9.28 |
| | London | 194 | 9.62 |
| | Southeast | 284 | 14.09 |
| | Southwest | 197 | 9.77 |
| | Wales | 103 | 5.11 |
| | Scotland | 185 | 9.18 |
| | Northern Ireland | 90 | 4.46 |
| Education (science or engineering) | Below GCSE | 420 | 20.83 |
| | To GCSE | 719 | 35.66 |
| | To AS/A | 278 | 13.79 |
| | To undergraduate | 243 | 12.05 |
| | Postgraduate or above | 118 | 5.85 |
| Political ideology (left-right) | 1 (left) | 59 | 1.04 |
| | 2 | 250 | 8.79 |
| | 3 | 316 | 16.67 |
| | 4 | 386 | 27.15 |
| | 5 | 283 | 24.88 |
| | 6 | 165 | 17.41 |
| | 7 (right) | 33 | 4.06 |

**Table A2.** Analysis results for each energy source (full Likert scale for dependent variables).

| Category | Responses | Solar | Wind | Biomass | Nuclear |
|---|---|---|---|---|---|
| Demographic | Gender (Men – Women) | -0.1561 (0.000) | -0.1914 (0.000) | -0.2447 (0.000) | -0.4722 (0.000) |
| | Age | 0.0026 (0.0022) | | | |
| | Education | 00096 (0.013) | 0.0100 (0.026) | 0.0127 (0.003) | |
| | Political ideology (Left - Right) | | | | 0.0947 (0.000) |
| Knowledge | Knowledgeable about how energy is produced, delivered, and used | | | | 0.0918 (0.005) |
| | Have read about solar energy | 0.1753 (0.001) | | | |
| | Have read about wind energy | 0.1173 (0.023) | 0.1836 (0.000) | | |
| | Have read about biomass energy | | | 0.1357 (0.020) | |
| | Have read about nuclear energy | | | | 0.3177 (0.000) |
| Perception | Potential impact of climate change is catastrophic if left unchecked | 0.0656 (0.000) | 0.0317 (0.016) | 0.0828 (0.000) | |
| | Climate change is the most important environmental problem facing the UK today | | 0.1081 (0.041) | | 0.1447 (0.034) |
| | Government can do a great deal in addressing climate change | | 0.0738 (0.043) | | |
| | Companies can do a great deal in addressing climate change | 0.1201 (0.000) | 0.1045 (0.003) | | |
| Policy | Government responses well to climate change to date | | | 0.1671 (0.000) | 0.0837 (0.021) |
| | Climate change should place a higher priority to economic growth | | 0.0990 (0.010) | | -0.0391 (0.002) |
| | New energy sources should be top priority if government has £5 billion to spend | 0.2679 (0.000) | 0.4353 (0.000) | | |
| | Nuclear power should be top priority if government has £5 billion to spend | | -0.1388 (0.036) | | 1.1862 (0.000) |
| Constant | | 2.9504 (0.000) | 2.6623 (0.000) | 2.0717 (0.000) | 2.4961 (0.000) |

*Notes: Values in parentheses are p-values.*

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