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Understanding Public Acceptability of Climate Policies in Europe

**Shouyu Zhang, Department of Agricultural & Applied Economic, University of Georgia,
sz36066@uga.edu**

**Susana Ferreira, Department of Agricultural & Applied Economic, University of Georgia,
sferreir@uga.edu**

**Berna Karali, Department of Agricultural & Applied Economic, University of Georgia,
bkarali@uga.edu**

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Understanding Public Acceptability of Climate Policies in Europe

Abstract

Public acceptability of climate policies is widely discussed by economists and politicians. While much research focuses on individual-level characteristics and country-level variation of public attitudes, few discusses their regional variation. To address it, we combine individual survey data derived from European Social Survey Round 8 with regional indicators to conduct the analysis of the drivers of public support to three different climate policies, including carbon tax, renewable energy subsidies, energy efficiency laws. Our results indicate the vital role of living environment in predicting individual's attitude towards climate policies. Residents who are living in rural area are more likely to be opposed to carbon taxation policy, while people living in polluted area with high exposure to PM_{2.5} are more likely to vote for renewable energy subsidy policy or energy efficiency law. A high perceived national unemployment rate will increase public aversion of all climate policies, especially for carbon tax. However, living in a well-developed region with high GDP per capita, local residents are more willing to vote for carbon tax.

1. Introduction

To limit global warming below 2 degrees Celsius, urgent action is needed to mitigate greenhouse gas emissions. Policy makers have a wide array of policy instruments at their disposal ranging from conventional regulation policy (command-and-control) to market-based instrument including taxes and subsidies as well as tradable permits (Fisher 2015). The market-based approach, which puts a price on carbon, is widely supported by economists as a cost-effective tool for emissions reductions (Boyce 2018). However, only 45 national jurisdictions have implemented carbon pricing initiatives and only 27 tax carbon (World Bank 2021). Why so few? Mainly because carbon taxes are very unpopular. For example, in France, the “Yellow Vests” protests erupted in 2018 after the French government proposed to increase fossil fuel taxes, responding to what were perceived as uneven tax policies and privileges for the upper class (Chamorel 2019). Australia also repealed a carbon tax proposal due to public opposition (Wente 2014), and in the United States, a carbon tax in the state of Washington was declined twice in 2016 and 2018 referendums with less than 50% support (Karciski et al. 2020; Reed et al. 2019). These cases provide evidence that the public acceptability of a policy is crucial for its implementation. However, this factor is often neglected by economists, who mainly focus on efficiency considerations (and to a lesser extent on equity), when designing environmental policies (Klenert et al. 2018).

A common explanation for the rejection of climate policies by the public has been the outright denial of climate change (Ding et al. 2011) and that climate change is perceived as a future event competing with more pressing demands (Brügger 2020). However, while a small

minority of people remain skeptical about the scientific basis of anthropogenic climate change (Leiserowitz et al. 2021), the reasons for the opposition to climate change policy, and carbon pricing in particular, are much more nuanced. Hornsey et al. (2016) demonstrated that climate change beliefs only have limited effect on how people take action to reduce carbon emissions. Learned helplessness was found to moderate the link of using climate change concerns to predict people's pro-environmental behaviors (Landry et al. 2018).

Carattini et al. (2017) review existing studies and summarize five reasons to explain the public rejection of carbon taxation, including perceptions of high personal cost, perceived low efficiency in discouraging high-carbon behavior, potential regressivity, fear of negative effects on the economy, and lack of trust in government. People might overestimate the negative impact of a tax on their purchasing power and hold a biased belief about the environmental effectiveness of carbon taxes (Douenne & Fabre 2020). This is despite an increasing number of studies demonstrating that they are an effective tool for reducing greenhouse gas emissions (see e.g., Hájek et al. 2019; Tan & Lin 2020; Metcalf and Stock 2020; Chen et al. 2021). Other studies posit personal responsibility, revenue salience, and policy stability as additional determinants of public perceptions towards carbon taxation and argue that an appropriate allocation of the generated revenue (e.g., distributing it as a “dividend” to the public) and making it salient can raise public support (Klenert et al. 2018; Levi 2021). These findings connect with an older literature on public support for environmental taxation. For example, Dresner et al. (2006) identify that, historically, the main reasons of the unpopularity of environmental taxes in the U.K. have been conceptual problems in policy design, distrust about

the distribution of revenue, lack of understanding the purposes of increasing environmental tax and lowering labor tax, as well as a perceived “penalty” of bad behaviors. On the last point, De Groot & Schuitema (2012) illustrated that providing correct and transparent social norm for environmental policies increases their popularity.

The public perception of carbon taxes is more negative than for other climate policies (Davidovic & Harring 2020), but few papers compare how the specific drivers of public acceptance, including those discussed above, differ among alternative policy instruments (Davidovic & Harring 2020; Kulin & Johansson Sevä 2021). In fact, the literature exploring the acceptability of policy instruments other than taxes is scant.

In this paper we fill in this gap and compare the drivers of public support for three alternative policies to combat climate change: carbon taxation, renewable energy subsidies, and energy efficiency laws. We combine survey data from the 8th round of European Social Survey (ESS8 hereafter) with regional socio-economic and environmental indicators to provide a comprehensive, comparative analysis of the drivers of public perceptions of those three climate policies.

Our study contributes to the existing literature by modeling the regional variation of public perception for climate policies. In contrast, previous studies only consider individual characteristics and country-level variation. We do so by incorporating regional factors in the analysis and by using a three-level (as opposed to a two-level) model based on the hierarchical structure of the nested data. Related to the contextual determinants of climate policy acceptance, a second contribution of our study is to examine whether the air quality respondents experience

in their region is associated with their support for different climate policies. Thus, we explore a different, additional reasoning that relies on the complementarity and correlation between carbon emissions, a global pollutant, with other pollutants responsible for local environmental quality. Everything else equal, support for climate policies may arise out of an immediate concern to improve the quality of local environment. Climate change and local air pollution are two major environmental challenges that are intertwined. A carbon tax designed to reduce greenhouse gas emissions would reduce PM2.5 by reducing fossil fuel combusting and other local air pollutants (Rafaj et al. 2013; Takeshita 2012). To the best of our knowledge, ours is the first study investigating the existence and strength of this link in the public's attitudes towards different climate change policies. A third contribution of our work is to examine whether a concern for unemployment would be a severe barrier to support the implementation of climate policies, especially carbon taxation. Researchers and practitioners alike put a large weight on labor market outcomes when they analyze policy performances. Former President Trump portrayed a negative attitude towards climate policies by repeatedly arguing that climate actions are “job-killing” and “economy-destroying” policies, which led to a largely adverse effect of environmental policy in the United States and worldwide (Bomberg 2021).

Our results suggest that our focus on regional economic and environmental factors of public support to climate policies is well placed. People suffering more exposure to PM2.5 are more willing to support renewable energy subsidies and energy efficiency law, rather than a carbon tax. The perceived unemployment rate plays a vital role in predicting people's attitudes towards climate policies. With a higher perceived country-level unemployment rate, people are

more opposed to any climate policy, and especially to carbon taxation. A larger level of regional economic activity, measured by regional GDP, however, is associated with a larger acceptance of carbon taxation but not of the other two policies. This is in addition to individual income.

The comparative study of a comprehensive list of potential drivers provides a detailed report of people's preferences towards alternative climate policies. Our findings confirm the importance of individuals' political trust and climate change concern reported in previous studies (Drews & van den Bergh 2016; Klenert et al. 2018; Fairbrother et al. 2019; Davidovic & Harring 2020). In addition, we provide new insights on the climate policy preferences of politically important population sub-groups: the elder people and rural people. In the literature, older people are found to more likely to participate in voting in a survey in the Netherlands (Zaslove et al. 2021), and rural people are found to be more willing to vote than people living in urban areas, which might influence voter turnout (Wolfinger & Rosenstone 1980). In our study, we find older people accept energy efficiency mandates more compared to young people but refuse the other two policies. Rural people, on the other hand, strongly reject a carbon tax but their level of support for the other two policies is no different from their urban counterparts. Regarding the acceptability of a carbon tax, our results suggest that attitudes towards carbon tax is more likely to be a sign of political stand, rather than a rational choice derived from considering costs and benefits.

2 Data and Methodology

2.1 Individual Survey Data

We employ data from the ESS8 which was designed specifically to study attitudes, perceptions,

and policy preferences towards climate change across 23 European countries. We keep 24402 observations after dropping all missing values. Similar to the regression model of Fairbrother et al. (2019), we keep most variables from the survey and extend more related factors to understand how public perception of carbon tax changed by different factors.

One of the dependent variables we use to measure people's support for carbon tax policy is the answer to the question "To what extent are you in favor or against increasing taxes on fossil fuels, such as oil, gas and coal to reduce climate change?" This answer captures the level of support or opposition for increasing carbon tax and is coded into a five-point scale from 0 (strongly against) to 4 (strongly favor). We also capture the public perception of renewable energy subsidy policy by the answers to the question "To what extent are you in favor or against using public money to subsidize renewable energy such as wind and solar power?" Finally, we utilize the answer to the question "To what extent are you in favor or against a law banning the sale of the least energy efficient household appliances?" to measure the public perception of energy efficiency policy of banning the least energy efficiency household appliance.

Two significant factors influencing public support for climate policies discussed in the existing literature are individuals' self-concerns on climate change and political trust to government. Kitt et al. (2021) proved the significant role of political trust to government in determining the citizen's support for environmental policies including carbon tax based on the representative survey of Canadian citizens. Davidovic & Harring (2020) compared the effects of quality of government and people's political trust on different climate policies including carbon tax. Kousser & Tranter (2018) put forward the idea that the opinion of political leader

would change public attitudes about environmental policies according to the results of an experiment in Australia. Hence, we have a strong belief that political factors and preferences would influence individual's own evaluation of the acceptability of carbon taxation. In our paper, political trust is measured by three dimensions based on the answers to "How much do you personally trust parliament?" "How much do you personally trust politicians?" and "How much do you personally trust political parties?" with the scale from 0 (No trust at all) to 10 (Complete trust). We use factor analysis to code these three answers into an index by principal-component factor method. The factor analysis ignores the survey sampling weights and shows that all three factor loadings are large (0.88, 0.95, 0.93). People's beliefs towards climate change are calculated based on trend, attribution, and impact skepticisms. The answer to the question "Do you think the world's climate is changing?" ranging from 1 (definitely changing) to 4 (definitely not changing) measures skepticism of climate changing, that is coded into 0 to 3. Higher values refer to a stronger belief of climate change. The answer to "Do you think that climate change is caused by natural processes, human activity, or both?" ranging from 1 (entirely by natural processes) to 5 (entirely by human activity) measures attribution skepticism. The answer to "How good or bad do you think the impact of climate change will be on people across the world?" ranges from 0 (extremely bad) to 10 (extremely good). We reverse this eleven-point scale from 0 to 10. A higher value means a more negative view of the impact of climate change. The factor score of climate change belief is calculated as political trust index with factors loadings (0.71, 0.73, 0.71).

Following Douenne & Fabre (2020) and Fairbrother et al. (2019)'s findings on the

determinants of attitudes toward climate policies, the explanatory variables in our paper also include demographic information, such as age, income, sex, education level, egalitarianism attitudes, and left-and-right political preference. Rotaris and Danielis (2019) used an Italian case study to suggest that women, high-income people, well-educated group, and younger people were more willing to pay more for carbon tax, while living in rural would negatively affected people's willingness-to-pay for fossil fuel tax. Gupta (2016) used Indian cities survey and concluded that people's willingness to pay for carbon taxes was highly dependent with their environmental interests and related activities, education, income, and age factors. Rhodes, Axsen, and Jaccard (2017) emphasized the average highest level of citizen opposition to carbon tax compared with other environmentally policy and indicated that citizens living in rural and with low political trust to government are more likely to against carbon tax policy.

To best examine the control variables used in the previous papers, all variables mentioned above are included in the predictors. Left-and-right scale is the answer to the question "where would you place yourself on this scale, where 0 means left and 10 means right". High value of this variable refers to a right preference for political ideology. The egalitarian attitudes summarize the extent of acceptability for the statements "Large differences in people's incomes are acceptable to properly reward differences in talents and efforts." and "For a society to be fair, differences in people's standard of living should be small". The two statements showed reverse attitudes about income equity. We coded one statement reversely and then summarized the egalitarian attitudes from 0 to 8. Higher value refers to a preference as "an egalitarian". Other demographic information including age, education level, household

income dummy variables of living in rural area (country village, farm or home in countryside), and gender dummy variable (1 as female) are also controlled in our study. The income level was categorized into 10 country deciles (higher value refers to a higher ranking of income in their own country). We code the 10 categories of income level into the average value for each range of income decile.

2.2 Regional Environmental and Socio-economic Predictors

Previous studies emphasized how individual political and economic factors influence people's votes for carbon tax policy, but few studies talked about personal experience of local air pollution change people's attitudes as well as policy choices.

In some papers, researchers believed some external conditions would change people's beliefs about climate change (Rüttenauer 2021), while there lacks consistent answer whether these factors would increase their willingness to pay or the probability of changing behavior to improve the environment. Rüttenauer (2021) revealed that people's beliefs in climate change could be related with their experience of extreme weather, while their past behaviors were hardly changed by the extreme weathers. Shum (2012) found no significant effect from variation in the annual temperature to the people's concerns with climate change. These findings against the hypothesis that extreme weather experience would gain people's support for carbon tax implementation.

However, Zanoocco et al. (2019) proved limited positive relationship between self-reported harm from extreme weather events according to the survey of ten communities in the United States. Tvinnereim et al. (2017) showed that people would likely to link the causes of

climate change to air pollution and they valued the co-benefit of mitigate climate change such like global warming and reduction of air pollution, although they could distinguish their physical manifestations. Whitmarsh (2008) argued that flood victims would not show a different climate change attitudes with other people who suffer less from severe weather events or disasters, but air pollution victims are more likely to regard climate change as a serious risk and take efficient actions to against the trend. The difference might because of different characteristics of extreme weather events and air pollution. Local air pollution would influence people persistently in a fixed area, but extreme weathers only work for a limited period. Bazrbachi et al. (2017) found out the significant relationship between respondents' previous health issues related with air pollution and their current willingness to change their behaviors to reduce private vehicle use and then improve air quality which might support our hypothesis that air quality nearby is supposed to change individual's answer to their support to climate policies discussed in this paper. Hart & Feldman (2018) provided a new statement that linking air pollution exposure to climate change would not effectively increase people's willingness to take action to reduce pollution but emphasize other non-climate change risks could help. Our present paper would contribute to the limited existing paper by providing evidence of relationship between air quality conditions and public perception of carbon tax policy. Thus, air pollution variables can be a good indicator to describe the clean level of people's residential area that could therefore influence people's choice in environmentally policy. Since people can ignore the possible harm in the future but cannot escape from the current harm by the environmental pollution.

To better understand how environmental conditions influence residents' choices to support carbon taxes or be against, we combine individual survey data with spatial distribution of weather conditions and air quality collected from the European Environmental Agency based on Nomenclature of Territorial Units for Statistics (NUTS) classification, which is an instrument to classify subdivisions in the main part of Europe. This hierarchical system is used to represent regions for each country in the EU with agreement. In ESS8, all respondents correspond to their NUTS regional code. We employ NUTS code to match regional variables with ESS8 data.

Respondents living in United Kingdom and Germany are assigned to their region based on NUTS 1 level classification. In the United Kingdom, there are 1378 observations from 12 NUTS 1 regions in our analysis. The range of GDP per capita is from €30129 to €68132. London region has the highest level of GDP per capita. In the German, there are 2385 observations from 16 NUTS 1 regions included in our analysis. GDP per capita is from €25018 to €60924, the NUTS 1 region with highest GDP per capita is Hamburg.

Respondents living in Austria, Belgium, Switzerland, Spain, France, Italy, Netherland, Norway, Poland, and Portugal are assigned to their region based on NUTS 2 level classification. There are 10,876 observations from 118 NUTS 2 regions. GDP per capita is from €7703 (Pomeranian Voivodeship in Poland) to €74919 (Oslo og Akershus in Norway).

Finally, respondents living in the remaining countries are assigned with NUTS 3 regions. There are 9,796 observations from 108 NUTS 3 regions. GDP per capita is from €5075 (Nógrád in Hungary) to €73254 (Dublin in Ireland).

As stated by Perera (2017), the burning of fossil fuels will produce toxic air emission including PM_{2.5}, NO₂, PM₁₀. Although CO₂ is the main pollutants by fossil fuels, it generally cannot be detected by residents and wouldn't cause direct health damage to residents in a given density (Fearmongering et al. 2017). Other local air pollutants including PM_{2.5}, NO₂, PM₁₀ which are regarded as biproducts of fossil fuels combustion would be detectable in people's lives and lead to direct health risk to residents living in the environment with high-density of them. Feng et al. (2016) stated that PM_{2.5} invoked huge concerns with high risk to induce cardiopulmonary disorders, impairments, and other adverse health effects even in a low-level of environmental exposure. Pui et al. (2014) also mentioned the fossil fuels combustion to be a main source of PM_{2.5} and the strong correlation between atmospheric visibility and PM_{2.5} concentration. Therefore, we selected PM_{2.5} as a typical indicator representing the damage to local population because of its visibility and rising concerns of health risk.

There are several methods to calculate the air pollutant concentration given spot concentration level monitored by stations. Denby et al. (2009) emphasized the necessary of data interpolation in air quality access model. Researchers need a more accurate model to access the exposure of air pollutants to population since monitoring stations are only able to provide point data of air pollutants with XY coordinates (Ferreira et al. 2013). Kumar et al. (2016) introduced interpolation technique was a necessary tool for the spatial analysis of air quality without collecting meteorological or emission data. Inverse distance weighting (IDW) interpolation is a common method to describe the spatial pattern Ajaj et al. (2018). However, Andersson and Mitchell argued that involving population in the raster map can generate the map that reflecting

population rather than area. To measure the total exposure and its effect of air pollutants, the Integrated Population-Weighted Exposure (IPWE) method was widely applied in air quality models (Abdul Shakor et al. 2020; Aunan et al. 2018; Hystad et al. 2011; Singh et al. 2020).

We obtain inverse distance weighted interpolation data of air pollution distribution across the Europe from European Environment Agency air quality database from 2014-2015, in which we select the grid cell size of interpolation as 1km to make a more precise estimation of population-weighted exposure to air pollutants PM2.5. The 1km² grid population data in 2011 was collected from Eurostat to match the requirement of calculating spatial distribution of air pollution.

Using ArcGIS software, we got the regional exposure to specific air pollutants by taking their population weights as show below.

$$PWEL_n = \frac{\sum(P_i \times C_i)}{\sum P_i}$$

where i represents each 1km cell size grid, $PWEL_n$ represents the population-weighted average exposure of PM2.5 in the defined NUTS 3 region n . C_i is the PM2.5 concentration level in grid i , $\sum P_i$ is the number of populations in the same grid i , P_i calculated the total number of populations in region n . The spatial distributions are shown in Figure2, Figure3. We calculated percentage change from 2014 to 2015, mean level in 2014-2015 and annual level in 2015 (the most recent year before the survey) of PM2.5 exposure to represent air quality dynamic change and recent mean level separately.

In the Appendix B Figure, residents living in the four northern European countries including Sweden, Norway, Finland have little exposure to PM2.5 in 2014-2015. People living

in the eastern part of Europe, especially in Poland expose heavily to the air pollutant PM2.5 in 2014-2015. Poland is a typical country relied on fossil fuel energy. The fossil fuel energy takes 90.3% in the total energy consumption in 2015, which can be regarded as an explanation of high PM2.5 concentration and residents' exposure in Poland.

Regional economic factor can also be considered as a main source of public perception of climate policies. Otto & Gugushvili (2020) emphasized the important roles of people's socioeconomic and ideological characteristics and the context of people's living country to predict public perception of climate change policy. Hafstead & Williams (2018) applied a new general-equilibrium two-sectors search model to investigate how unemployment rate changed by environmental policy which had been a severe concern of carbon tax as previous studies suggested. Metcalf and Stock (2020) found a zero to modest positive impact of carbon tax in Europe on GDP and employment growth rates and no evidence of the negative influence of carbon tax on employment or GDP growth. Tollefson (2017) reported Trump's announcement to get the United States out of Paris Agreement, insisting that being compliance with Paris Agreement would kill 2.7 million jobs in the United States in 2025. However, Vona (2019) emphasized that affected workers' support for climate policies would be highly discouraged due to the 'job-killing' arguments, although the economic losses caused by climate policies was less than the benefits. Regional GDP per capita has been used to predict people's perception of climate changing (Weckroth & Ala-Mantila 2022). Therefore, we consider social-economic characteristics including NUTS2-level unemployment rate and NUTS3-level GDP per capita which provided general economic status of regions in 2015.

The spatial distributions of GDP per capita and unemployment rate are represented in the Appendix C. The northern European countries have a higher level of GDP per capita in general, compared with all other countries mapped in the graph. In Scandinavia, the average GDP per capita is from €40000 - €60000 in 2015, the unemployment rate is also lower than 10%. The United Kingdom shows a relatively high GDP per capita and low level of unemployment rate. However, the southern part of Europe represents a lower level of GDP per capita which is approximately below €40000 in 2015, and a quite high level of unemployment rate. In the southern part of Spain, there are several regions with about 30% unemployment rate in 2015.

2.3 Multilevel Mixed-Effects Linear Regression Model

Since our survey sample is measured at three levels, drawn from 254 regions in 19 European countries, we use a multilevel mixed-effects linear maximum likelihood regression model (Olson-Hazboun et al. 2018) to reflect the hierarchical structure of our data in estimating the public support for three climate policies. In the mixed-effects linear model, the data is nested into groups, such like country, state, or county. The sample observations are clustered within groups which violate the OLS assumption, leading to potential correlated error terms and biased estimated coefficients. By mixed-effects linear regression, we assume that there are group characteristics in our dataset and the spatial autocorrelation of the public perception of climate policies, showing the regional characteristics' effects on local attitudes for carbon tax, renewable energy subsidy and energy efficiency law. Although we include 4 region-level variables and 1 country-level variable to capture spatial variation of public attitudes, multilevel

regression can help to capture the variation caused by potential omitted variables in region or country level. Therefore, we apply three-level mixed-effects liner regression model to explain the determinants of public perceptions of climate policies. We define individual as the first level, region as the second level, and country as the third level.

The multilevel random intercept regression model is given by following:

$$Y_{ikj,n} = \beta_0 + \beta_1'X_{ikj} + \beta_2'Z_{kj} + \beta_3'P_j + u_k + u_j + \varepsilon_{ijk},$$

where individuals i are nested in region $k = 1, \dots, 254$ and country $j = 1, \dots, 19$. $Y_{ikj,n}$ represents the extent of individual i 's support for a specific climate policy $n = 1, 2, 3$, which represents carbon tax, renewable energy subsidy, or energy efficiency law separately. X_{ikj} is a vector of individual variables including demographic information and personal attitude. Z_{kj} is a vector of regional variables, representing the socio-economic and environmental indicators including GDP per capita (current euros), unemployment rate, annual employment rate changes for different sectors, average annual exposure to PM2.5 air pollutant. P_j only includes the national electricity price at the country-level. u_k and u_j are the random effects, which are independently normally distributed, representing random region intercepts for region $k = 1, \dots, 254$ and random country intercepts for country $j = 1, \dots, 19$ respectively.

The dependent variable $Y_{ijk,n}$ is an ordinal categorical variable, the multilevel ordinal probit model is also considered to be applied in our paper. For easier interpretation, we use multilevel linear model in the main part. The multilevel ordinal probit model results are shown in the Appendix J, leading to the equivalent marginal effects with multilevel linear model regression results.

3 Empirical Results

In the first part, we begin with the analysis of country level climate change beliefs and public carbon taxes acceptability with raw data provided by ESS8, then describe the full data by matching regional data with survey data and dropping observations with missing values. We will discuss the multilevel regression results by mixed-effects linear model in the second part.

3.1 Descriptive results

Figure 1 demonstrates the mean levels of national public support the country level to increase taxes on fossil fuels / use public money to subsidize renewable energy / a law banning the sale of the least energy efficient household appliances. In general, carbon tax has the least support in all listed countries, implying public is strongly against the “tax.” The subsidy for renewable energy has the highest support with a large gap with carbon tax in all listed countries. Hungary and Slovenia have the highest level of national support for carbon subsidy, which might be due to their own political system. Poland has the lowest level of national carbon tax support. As we stated before, the energy industry is highly dependent on fossil fuel consumption. Sweden and Finland show the highest national support for carbon tax and relatively small gaps between the three policies, which is not surprising that countries with high welfare in the Scandinavian Peninsula are the pioneers in fighting climate change.

We combine the individual survey data with regional climatic and socio-economic data. In the matching process, we first transform NUTS classification in the 2016 standard as defined by Eurostat. To match data from different NUTS level, we assign smaller regions in the survey data to their corresponding upper-level regions and take the average value of all smaller regions

included in the upper-level NUTS region in survey data. After merging individual survey data with regional environmental data and dropping all missing values, our full dataset contains 24,402 observations. The descriptive statistics of our variables are shown in Table 1.

3.2 Regression results

Table 2 presents multilevel mixed-effects linear regression results that examine determinants of public attitudes towards three different climate policies. We set the group variables as country and region to represent the variation towards public attitudes in 254 regions nested in 19 countries.

The first column in Table 2 shows that climate change concern and political trust are still two main significant drivers to predict public attitudes for carbon taxation policy as Fairbrother et al. (2019) stated . As we described before, the climate change concern and political trust are two indices transformed by factor analysis. A one unit increase in climate change concern would increase public support for carbon taxation by 0.170 points and in political trust by 0.212 points. A citizen who trusts more on the country's parliament, politicians, and political parties or with more concern about climate changing issues are more likely to have a relatively high level of advocacy of carbon taxation policy. One unit increase of egalitarian attitude would also increase people's support to carbon taxation by 0.025, which indicates a higher willingness to vote for carbon tax of an egalitarianism compared with people who don't care social equity. In general, younger females with higher education and income levels, and left political preferences would be more likely to vote for carbon taxation. The coefficient of the rural dummy variable is statistically significant, suggesting that residents

residing in rural areas have less support to carbon taxation compared with urban residents. The mean value of the difference between two residential groups is 0.093. Rural people might consume more fossil fuel for transportation and agricultural equipment use, leading high dependency on traditional energy. By increasing the fossil fuel tax, people living in rural areas would face a higher energy bill than before, explaining the strong opposition to carbon taxation policy. People's personal perception of their country's unemployment ($b=-0.026$) could also be a barrier when people vote for carbon taxation. When people believe that there are over half people unemployed in their country, their support to carbon taxation would be 0.26 lower than people who think all working-age people employed in their country, no matter how the truth of unemployment is. As for the regional factors, we find that none of the air quality index or weather conditions are statistically significant, indicating that the living environment does not alter the extent of residents' support for carbon taxation. The alternative explanation could be that people are more concerned about other factors besides policy effectiveness of reducing carbon emission or health co-benefit, such as economic inequity, inflation, or harm to the employment. From regional economic aspect, people living in high-GDP-per-capita areas are more willing to vote for carbon taxation, while unemployment rate is not a concern for people to consider carbon taxation policy. The national electricity price doesn't play an important role in predicting public perception of carbon taxation. The robustness regressions for PM2.5 and unemployment rate for carbon taxation are attached in Appendix D and E¹.

The second column in Table 2 represents the multilevel regression results for renewable

¹ In Appendix D-I, Model 1 is the null model, controlling only for the group variables (country and region). We calculate the intraclass correlation coefficients (>0.05) to prove the necessary of using multilevel model.

energy subsidy policy. One unit increase in climate change concern would increase public support to renewable energy subsidy by 0.203 points, which is highest compared with other two policies. One unit increase in political trust would increase support to renewable energy subsidy by 0.071 points. One unit increase of egalitarian attitude would also increase people's support to carbon taxation by 0.035. Female people with higher education level, higher income level, left political preference, as well as less age would be more likely to vote for renewable energy subsidy. Residents residing in rural areas and urban areas cannot be differentiated in the support to renewable energy subsidy. People's personal perceptions of their country's unemployment ($b=-0.007$) would be negatively correlated with support for renewable energy subsidy. When people believe that there are over half people unemployed in their country, their support to renewable energy subsidy would be 0.07 lower than people who think all working-age people employed in their country, which is also based on their perceptions rather than real data. As for the regional factors, we find that both the mean level of annual population-weighted PM2.5 in 2014-2015. One unit increase of population-weighted exposure of PM2.5 would increase residents' support to renewable energy subsidy by 0.13. From regional economic aspect, neither of employment nor GDP per capita is the driver for residents to change their mind of renewable energy subsidy policy. The national electricity price doesn't play important role in predicting public perception. The robustness regressions for PM2.5 and unemployment rate for renewable energy subsidy are attached in Appendix F and G.

The third column in Table 2 represents the multilevel regression results for energy efficiency policy, which is a law of banning the least energy efficiency household appliance.

One unit increase in climate change concern would increase public support to energy efficiency policy by 0.195 points, in political trust by 0.057 points. One unit increase of egalitarian attitude would also increase people's support to energy efficiency policy by 0.031 points. Overall, older female people with higher education level, higher income level, left political preference would be more likely to vote for energy efficiency policy. Similar to the renewable energy subsidy policy, people's personal perceptions of their country's unemployment would decrease their support for renewable energy subsidy ($b=-0.009$). Looking at the air pollutants influence, residents living in regions with higher exposure of constant level of PM_{2.5} are more supportive to the energy efficiency law ($b=0.019$). Unlike regional air pollutant, the economic factors including local GDP and unemployment rate don't have any impact on public mind of energy efficiency policy. However, the country-level electricity price made a vital effect on the extent of support. One percentage increase in the national electricity price would increase public support to energy efficiency policy by 0.516. The robustness regressions for PM_{2.5} and unemployment rate for energy efficiency law are attached in Appendix H and I.

To better understand various effects of all predictors on public perception of three climate policies, we compare the signs and magnitudes of estimated parameters in Table 2. The estimated coefficients with 95% confidence intervals are plotted in Figure 2-4.² It's worth noting that political trust is the most important predictor in determining carbon taxation support ($b=0.212$) but has less importance in predicting support for the other two policies ($b=0.071$, 0.057). Considering other variables included in the regression, we believe that carbon taxation

² The estimated coefficients of country-level national electricity price are not included in Figure 2-4, since the magnitudes are too large to be comparable with other estimates.

is a special policy that mainly depends on the political system, regime and public attitudes towards government and country. Therefore, we can understand the disconnection of regional pollutant and local demand of implementing carbon taxation to combat pollution. Carbon taxation policy is more and more regarded as a political issue rather than the tool of reducing carbon emissions. When we are looking at the pollution and economic development in a specific region, carbon taxation would not be the primary choice to solve the problem, since it is more closely related to political stand, national interests, or even international negotiation.

In contrast to previous studies, regional unemployment rate seems not to be the barrier for the implementation of carbon taxation, but regional GDP does. Regional GDP level would be a concern of implementation of carbon taxation. A region with higher GDP per capita yields stronger average support of carbon taxation. The real region unemployment rate would not affect people's support for any climate policy. Significantly, the comparison of personal perception of unemployment and real regional unemployment provides new insights to understand the impact of unemployment on people's policy choice. As we discussed before, personal perception of country's unemployment plays the most vital role in carbon taxation compared to the other policies, which corresponds to the characteristics of carbon taxation. The regional unemployment rate seems to have no contribution in explaining people's attitudes for climate policy.³ People are more likely to decide their policy choice by believes rather than data or fact report. This finding is embodied obviously in the carbon taxation policy analysis. The magnitude of perceived unemployment coefficient ($b=-0.026$) is much higher than in other two

³ We run the same regression by removing regional unemployment rate, proving the results that real unemployment rate doesn't make any contribution in predicting people's attitudes towards three climate policies.

policies ($b=-0.007, -0.009$). When people are considering carbon tax policy and its effects, they do value the unemployment, but based on the national level and from the perceived views. Therefore, we believe carbon taxation is more related to the country's interests and personal beliefs, rather than real benefits for local people.

Among all the demographic characteristics of respondents, we pay special attention to age and living rural areas. The opposite signs of age coefficients for three policies are worthy to discuss. Older people are more against carbon tax and renewable energy subsidy, but in favor of energy efficiency law. It seems like they are more willing to improve the environment by doing something in real life by themselves, rather than look at the financial report about building or developing “giant” equipment or take money out of their pockets. The differentiated attitudes towards carbon taxation between urban and rural areas are also notable. It is not surprising that rural people are more against increasing taxes on fossil fuel based on their large consumption and demand (Muratory 2014). Although people would choose carbon taxation as a sign of own political stand or beliefs, a large amount of expenditure increase in daily energy use could be a big reason for people to reject carbon tax.

Unlike the consanguineous relations between carbon tax policy and political system of the country, renewable energy subsidy policy can be regarded as a policy targeting the development of renewable energy industries and would work on consumer's daily energy consumption. High local pollutants provide incentives for residents to develop renewable energy to replace the high-polluted local facilities.

For the energy efficiency policy, it is more specifically related to households' daily life

based on the description in ESS8. The finding echoes the positive significant coefficient of national electricity price in regression for energy efficiency policy. With high national electricity price, citizens hold more willingness to deduct energy bill by replacing the current appliance with energy-saving household appliances, leading advocacy of energy efficiency policy. Besides, older people are more against carbon taxation as well as renewable energy subsidy but more supportive to energy efficiency policy.

4 Conclusions

As global climate and environment rapidly deteriorate, carbon pricing has been much discussed by economists and policy makers. This study extends Fairbrother et al. (2019)'s work of analyzing the relationship between climate change beliefs and support for fossil fuel tax to a broader range of environmental factors' impacts on three climate policies, including carbon tax, renewable energy subsidy, and energy efficiency law.

Although carbon tax is widely believed as the most effective policy tool to reduce carbon emissions and climate change (Hájek et al. 2019; Tan & Lin 2020; Chen et al. 2021), its effectiveness does not play a dominant role in public preferences towards climate policies. Based on our empirical results, we interpret public perception of carbon tax to be linked with political trust, personal perception for country-level unemployment, regional GDP level, and whether living in rural area which might be related to the energy use habits. Promoting carbon tax cannot rely on its effectiveness, but on changing people's perception and believes. Our findings support previous argument that building a green image of government and political system and increasing people's confidence in government would be the most efficient way to

lay the foundation for carbon tax (Davidovic & Harring 2020).

Our most important contribution is to combine individual and contextual level predictors in analyzing people's support to climate policies. A citizen's living area or place of residence might play a vital role in predicting his political action in voting for climate policies. We argued that an individual's political preferences between climate policies would not only be the consequences of personal characteristics and experience, but also be driven by both social and natural environment.

As such, this paper contributes to several implications in designing climate policies. The increasing trend of local pollutant persuades people to vote in favor of climate policies except carbon taxation. Making a link between local pollution and effectiveness of carbon pricing might be the passway to win the support for carbon tax. They can interact with each other and lead to both global improvement and local health benefit. Furthermore, we find a weak evidence of negative correlation between real regional unemployment and policy support. However, there is a strong association between personal perception of unemployment and support for climate policies. People are more conservative with their negative perception of unemployment, rather than the real data of local labor market. Therefore, we argue that convincing people to accept carbon pricing and other climate policies requires policymakers to correct citizens' biases in both current situation of unemployment and expected consequences of climate policies on future unemployment. Our study implies a multi-angle strategy as above to reduce possible concerns of citizens against climate policies, and to design policies that are more acceptable by the public.

While our study provides the first evidence of regional variation of public attitudes towards three climate policies and the power of using regional air quality to predict residents' supports to climate policies, there are some limitations due to the ESS8 data. In that survey, the region codes of respondents are not consistent in the NUTS level, which leads to less accuracy in the process of matching regional factors with individual survey responses. This issue can be resolved by conducting survey by asking region code by NUTS 3 level. In this way, the regional variation of public perceptions could be captured with more details when we introduce NUTS level in multilevel model. Our study could also be expanded to examine whether regional natural disaster or other environmental indicators have a direct impact on people's support for climate policies.

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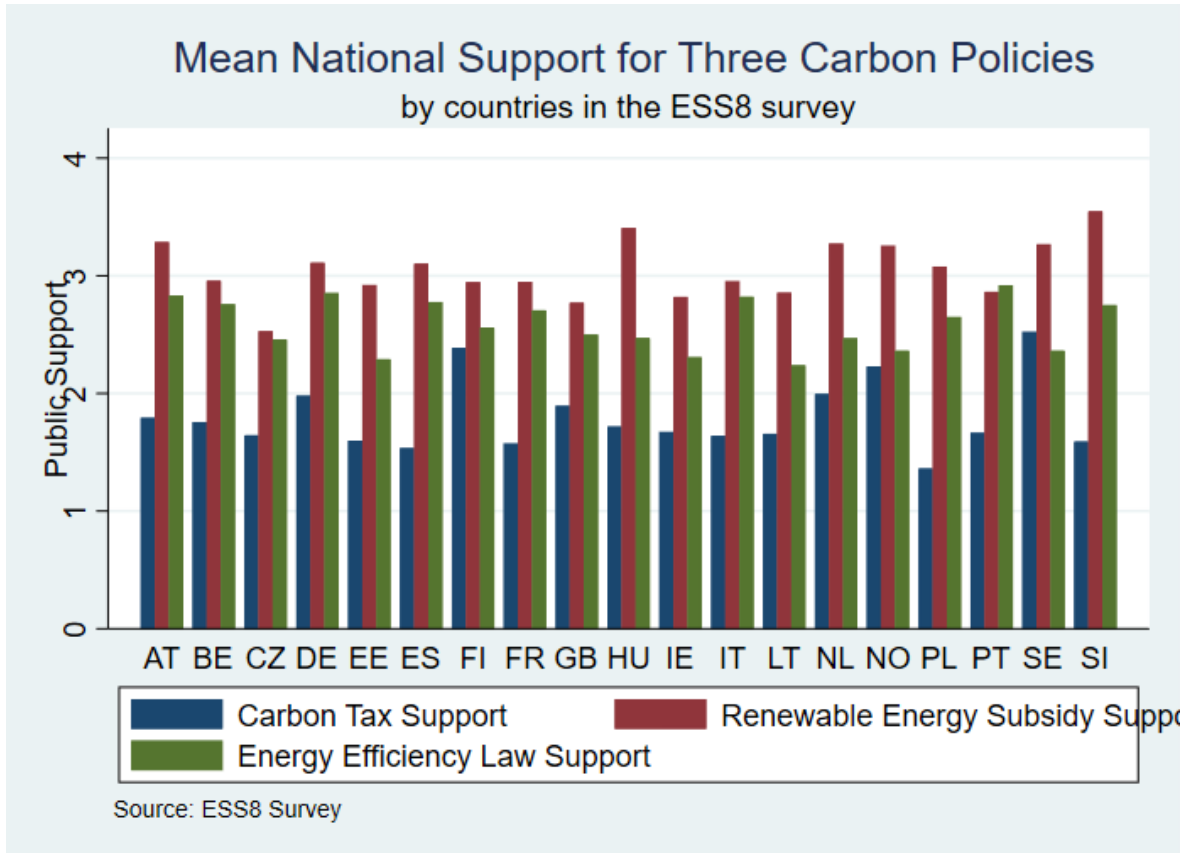


Figure 1: Mean national support for three carbon policies. The abbreviations of the countries are AT Austria, BE Belgium, CZ Czech Republic, EE Estonia, ES Spain, FI Finland, FR France, GB United Kingdom, DE Germany, HU Hungary, IE Ireland, SI Slovenia, IT Italy, LT Lithuania, NL Netherlands, NO Norway, PL Poland, PT Portugal, SE Sweden, SI Slovenia.

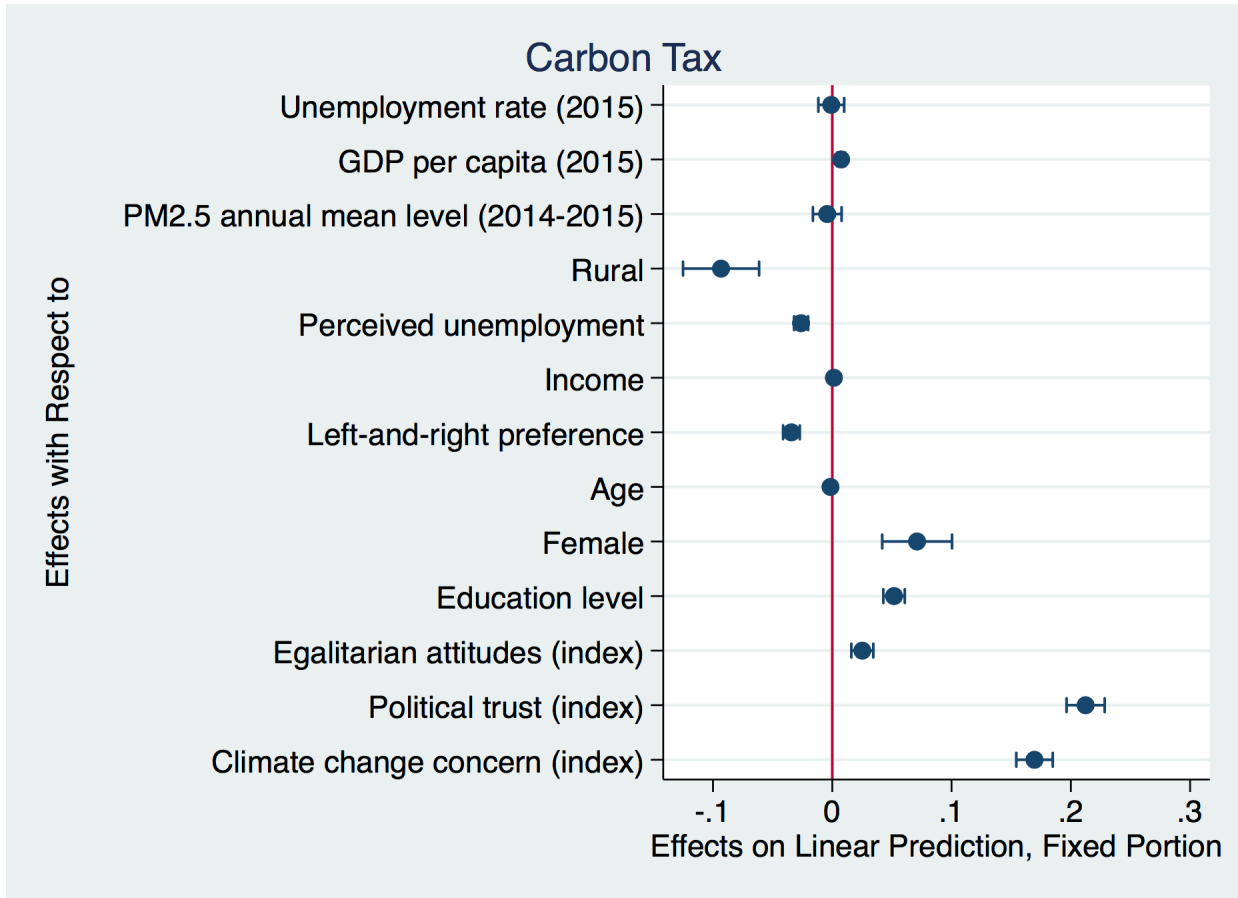


Figure 2: Individual-Level and Regional-Level Fixed Effects with 95% Confidence Interval (Carbon Tax)

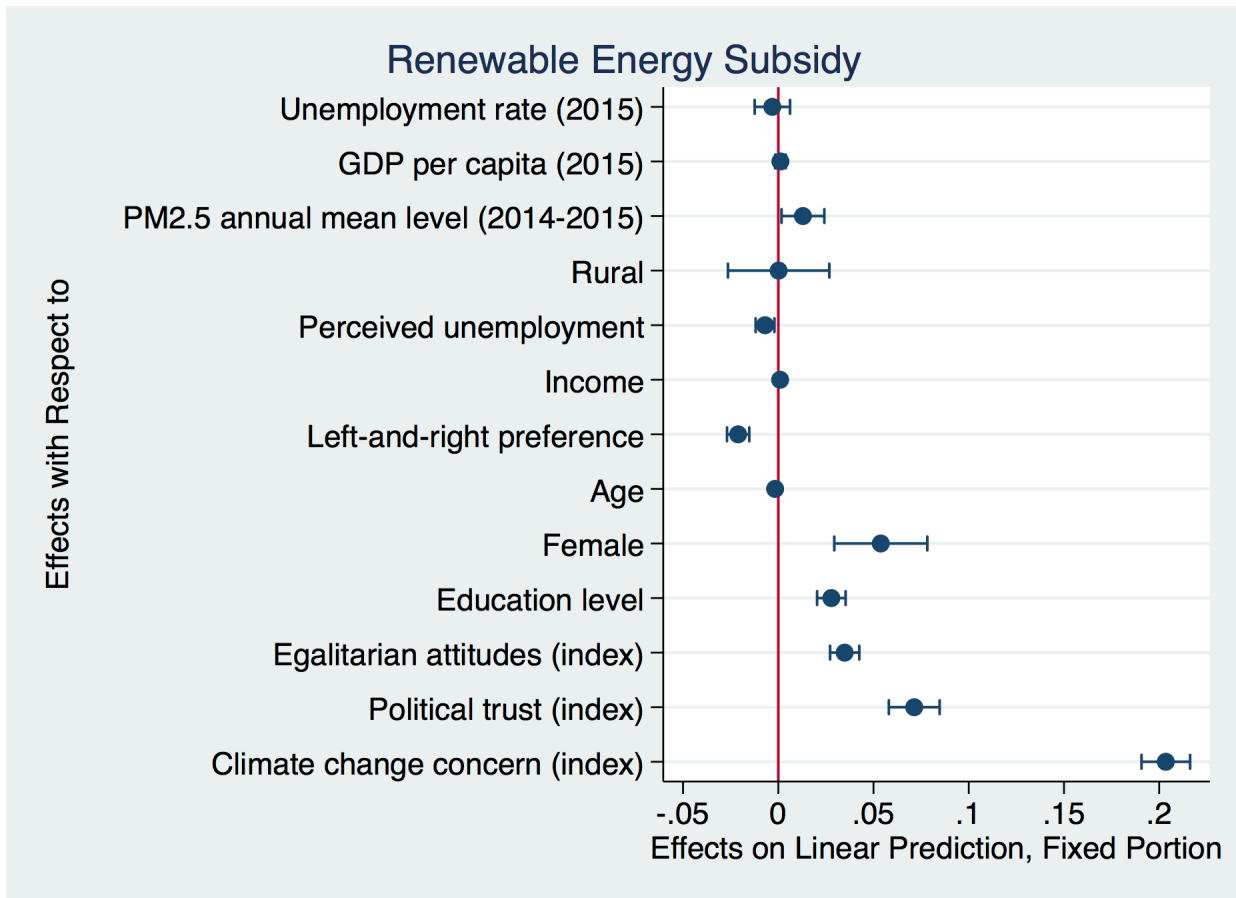


Figure 3: Individual-Level and Regional-Level Fixed Effects with 95% Confidence Interval (Renewable Energy Subsidy)

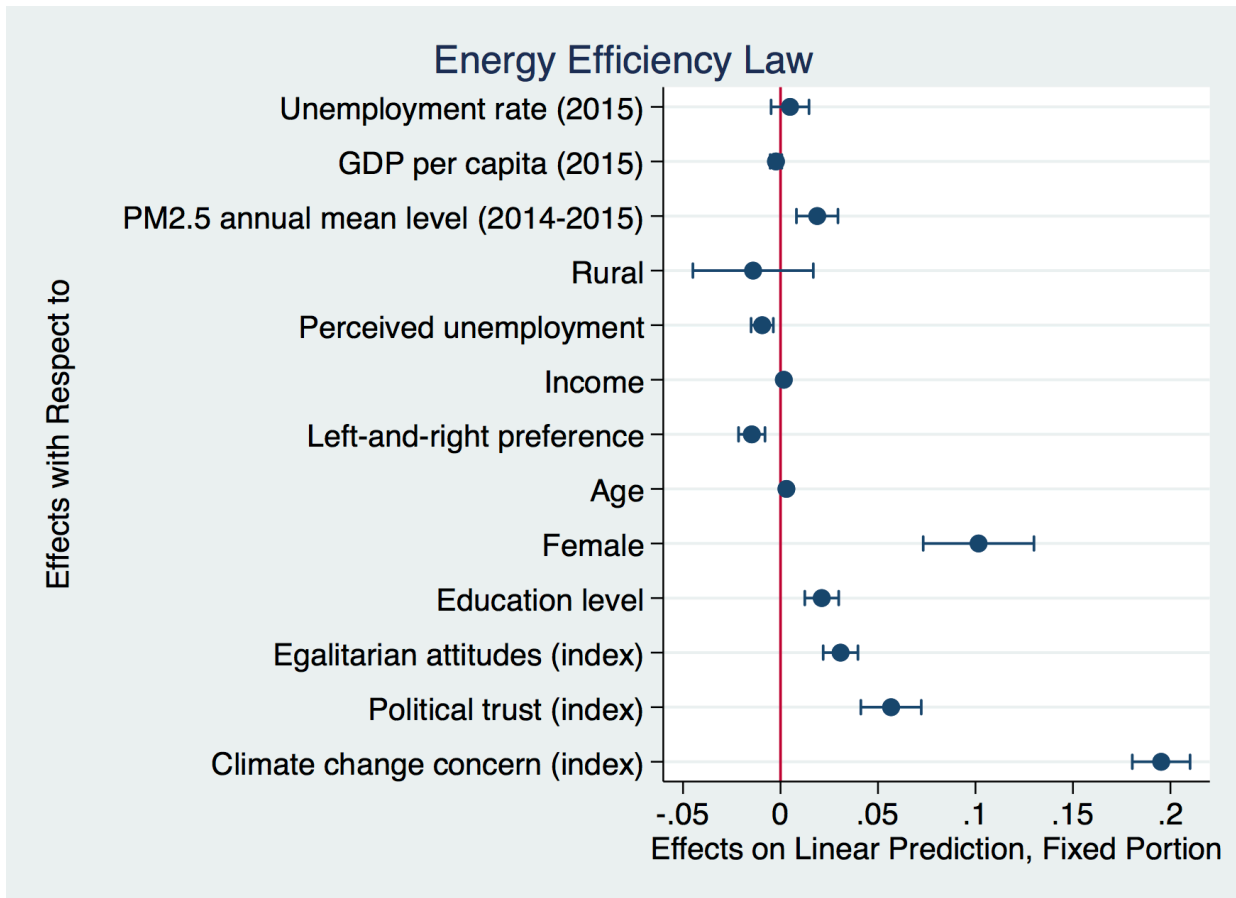


Figure 4: Individual-Level and Regional-Level Fixed Effects with 95% Confidence Interval (Energy Efficiency Law)

Table 1: Descriptive statistics

Panel A: Individual Factors	Mean	Standard Deviation	Min	Max
Carbon Tax Support (0-4)	1.85	1.24	0.00	4.00
Renewable Energy Subsidy Support (0-4)	3.03	1.02	0.00	4.00
Energy Efficiency Law Support (0-4)	2.59	1.16	0.00	4.00
Political Trust (Index)	0.00	1.00	-1.91	2.71
Climate Change Concern (Index)	0.00	1.00	-4.20	2.01
Egalitarian Attitudes (Index)	4.54	1703	0.00	8.00
Highest level of education, ES - ISCED	4.14	1.84	1.00	7.00
Female	0.51	0.50	0.00	1.00
Age	49.68	17.67	15.00	100.00
Left-and-Right Preference	5.06	2.17	0.00	10.00
Income	49.94	27.15	5.00	95.00
Rural	0.37	0.48	0.00	1.00
Unemployment in 100 working age	4.90	2.85	1.00	11.00
Panel B: Socioeconomic Factors	Mean	Standard Deviation	Min	Max
GDP per capita (2015 1000EUR)	31.57	15.76	5.08	7.49
Unemployment rate (% 2015)	8.23	4.47	2.80	31.50
Log of national electricity price (country-level)	-1.68	0.26	-2.18	-1.22
Panel C: Environmental Factors	Mean	Standard Deviation	Min	Max
PM2.5 annual mean level (2014-2015)	11.71	4.45	3.77	28.50
Flood region (2015)	0.08	0.28	0.00	1.00
Observations	24402			

Table 2: Multilevel Linear Regression

Panel A Individual Characteristics	(1) Carbon Tax	(2) Renewable Energy Subsidy	(3) Energy Efficiency Law
Level 1			
Climate change concern (index)	0.170*** (0.008)	0.203*** (0.007)	0.195*** (0.008)
Political trust (index)	0.212*** (0.008)	0.071*** (0.007)	0.057*** (0.008)
Egalitarian attitudes (index)	0.025*** (0.005)	0.035*** (0.004)	0.031*** (0.005)
Education level	0.052*** (0.005)	0.028*** (0.004)	0.021*** (0.004)
Female	0.071*** (0.015)	0.054*** (0.012)	0.102*** (0.014)
Age	-0.001*** (0.000)	-0.002*** (0.000)	0.003*** (0.000)
Left-and-right preference	-0.034*** (0.004)	-0.021*** (0.003)	-0.015*** (0.003)
Income	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
Perceived unemployment	-0.026*** (0.003)	-0.007** (0.003)	-0.009** (0.003)
Rural	-0.093*** (0.016)	0.000 (0.014)	-0.014 (0.016)

Panel B Spatial Characteristics	(1) Carbon Tax	(2) Renewable Energy Subsidy	(3) Energy Efficiency Law
Level 2			
PM2.5 annual mean level (2014-2015)	-0.004 (0.006)	0.013* (0.006)	0.019*** (0.005)
GDP per capita (2015)	0.007*** (0.002)	0.001 (0.001)	-0.002 (0.002)
Unemployment rate (2015)	-0.001 (0.006)	-0.003 (0.005)	0.005 (0.005)
Level 3			
Log National electricity price (2015 Euro)	-0.089 (0.162)	-0.089 (0.205)	0.516*** (0.138)
Constant	1.482*** (0.318)	2.609*** (0.374)	2.885*** (0.275)
Variance (country)	0.023	0.045	0.016
Variance (region)	0.034	0.020	0.027
Observations	24402	24402	24402
<i>AIC</i>	75767.538	66940.502	74283.526
<i>BIC</i>	75913.381	67086.346	74429.369

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix A. Variables Description

Variables	Source	Description
Individual Variables	8 th ESS	
Carbon Tax Support		Favour increasing taxes on fossil fuels to reduce climate change: 0 (Strongly against) - 4 (Strongly in favor)
Renewable Energy Subsidy Support		Favour using public money to subsidise renewable energy such as wind and solar power: 0 (Strongly against) - 4 (Strongly in favor)
Energy Efficiency Law Support		Favour a law banning the sale of the least energy efficient household appliances: 0 (Strongly against) - 4 (Strongly in favor)
Climate Change Concern (Index)		Factor score of “Do you think the world’s climate is changing”, “Do you think that climate change is caused by natural processes, human activity, or both?” and “How good or bad do you think the impact of climate change will be on people across the world?”
Political Trust (Index)		Factor score of “how much do you personally trust parliament?”, “how much do you personally trust politicians?” and “how much do you personally trust political parties?”
Egalitarian Attitudes (Index)		Sum index of “Large differences in people’s incomes are acceptable to properly reward differences in talents and efforts” (reverse-coded) and “For a society to be fair, differences in people’s standard of living should be small”
Household Income		Households’ total net income (deciles of income level in their country), We take mean level for each decile.
Education Level		Highest education level based on ES-ISCED Levels (1-7)
Left-and-Right Preference		Self-placement of political ideology 0(Left)-10(Right)
Female (Dummy Variable)		1: Female 0: Male
Age		Respondent’ age in years
Rural (Country village, farm or home in countryside)		1: Living in the rural area 0: Not living in the rural area

Perceived Unemployment		Of every 100 working age in your country how many would you say are unemployed and looking for work? (1-11) 1: 0-4 2: 5-9 3: 10-14 4: 15-19 5: 20-24 6: 25-29 7: 30-34 8: 35-39 9: 40-44 10: 45-49 11: 50 or more
Regional Environmental Variables		
PM2.5 Interpolation data ($\mu g/m^3$)	EEA	1km grid
Regional Socio-economic Variables		
GDP per capita (Thousand Euro)	Eurostat	GDP at NUTS3 level in 2015
Unemployment rate (%)	Eurostat	Unemployment rate at NUTS2 level in 2015
National electricity price (Euro)	Eurostat	Country-level electricity price in 2015

Appendix B. Spatial Distribution of Mean Level of PM2.5 Population-Weighted Exposure (NUTS level)

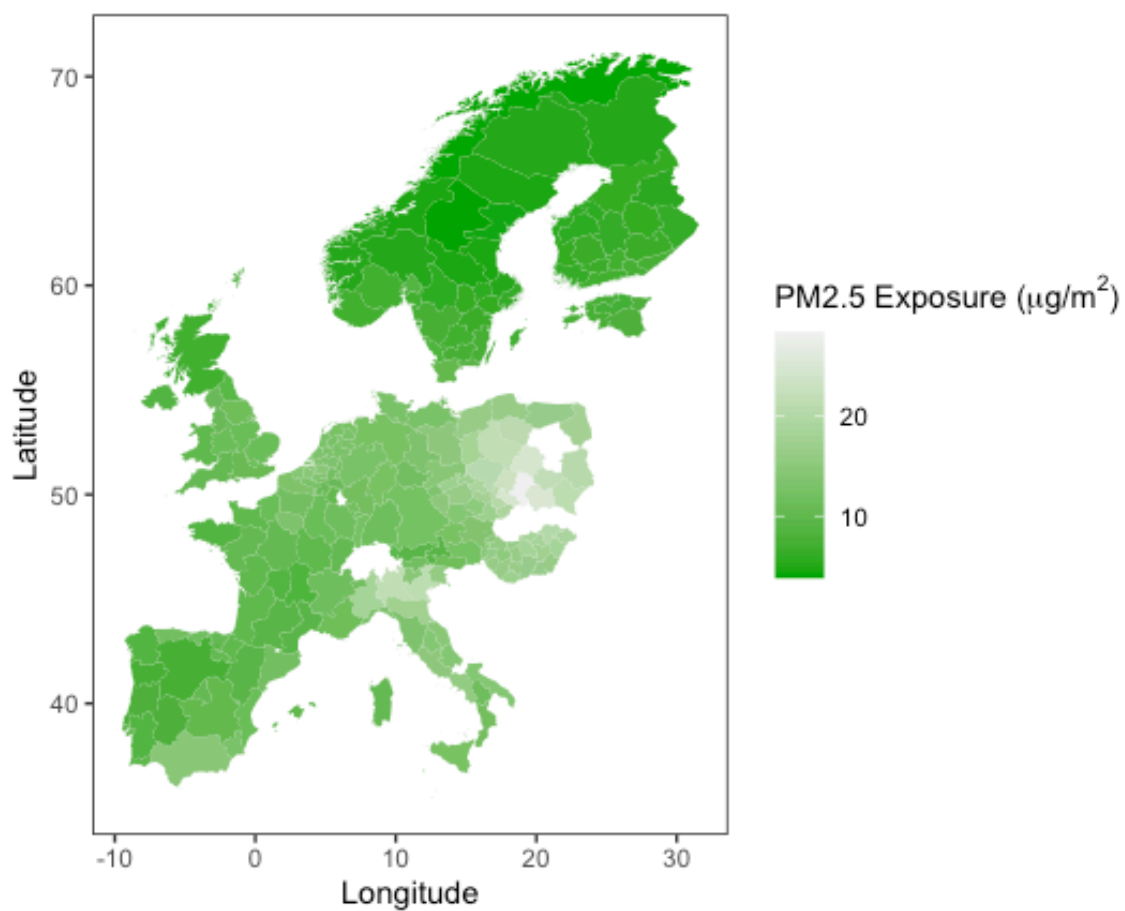


Figure: Mean Level of Exposure to Air Pollutant (PM2.5) in 2014-2015

Appendix C. GDP per capita and unemployment distribution (NUTS level)

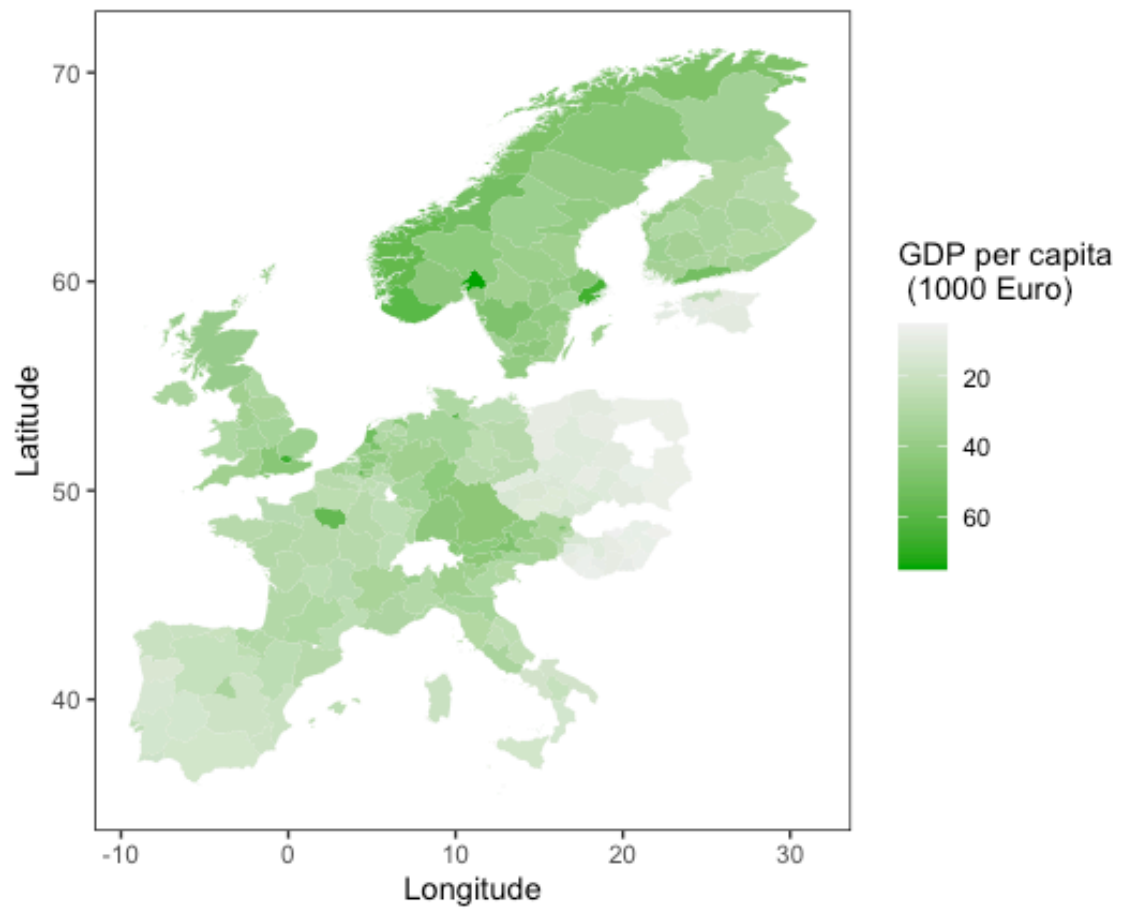


Figure (a): Spatial Distribution of GDP Per Capita in 2015

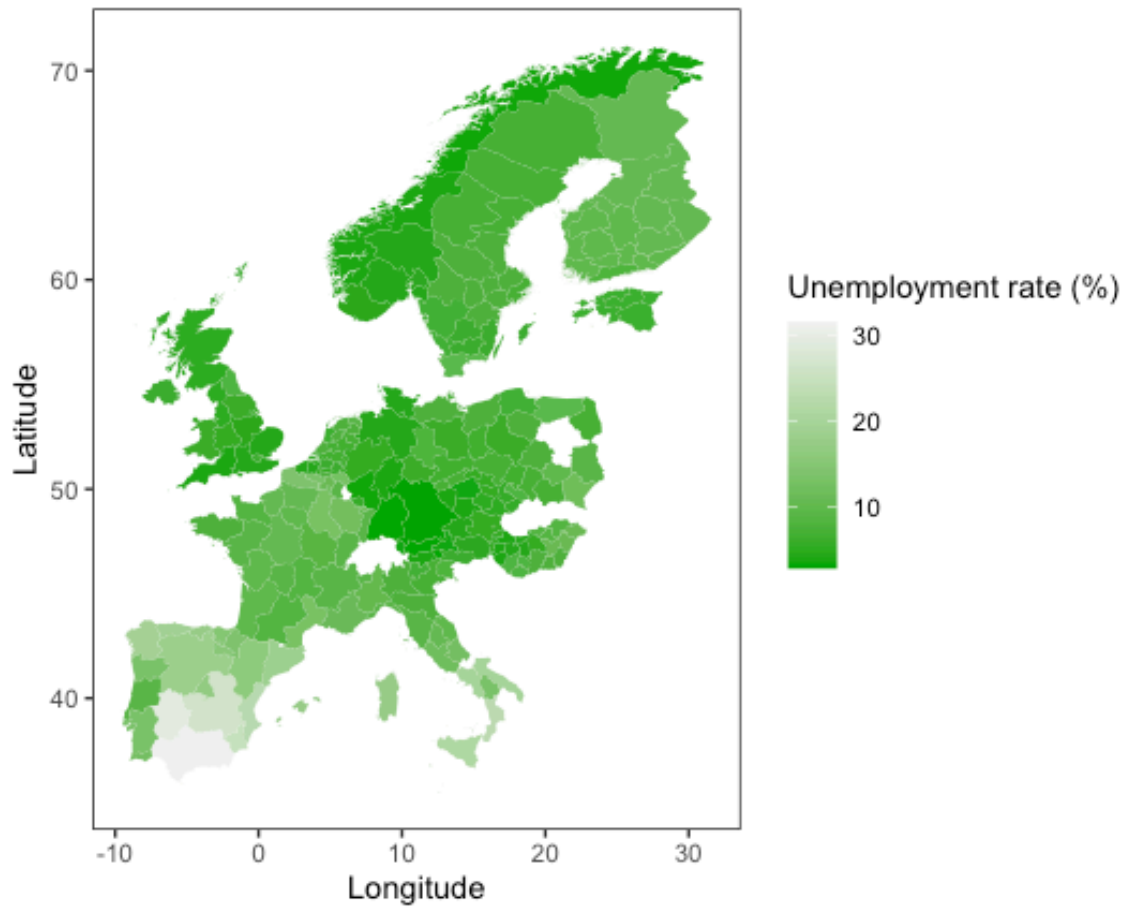


Figure (b): Spatial Distribution of Unemployment Rate in 2015

Appendix D: Multilevel Linear Regression for Carbon Tax

Panel A	(1)	(2)	(3)	(4)	(5)
Individual	Model 1	Model 2	Model 3	Model 4	Model 5
Characteristics					
Level 1					
Climate change concern (index)		0.170*** (0.008)		0.170*** (0.008)	0.170*** (0.008)
Political trust (index)		0.213*** (0.008)		0.213*** (0.008)	0.212*** (0.008)
Egalitarian attitudes (index)		0.025*** (0.005)		0.025*** (0.005)	0.025*** (0.005)
Education level		0.052*** (0.005)		0.052*** (0.005)	0.052*** (0.005)
Female		0.072*** (0.015)		0.072*** (0.015)	0.071*** (0.015)
Age		-0.001*** (0.000)		-0.001*** (0.000)	-0.001*** (0.000)
Left-and-right preference		-0.034*** (0.004)		-0.034*** (0.004)	-0.034*** (0.004)
Income		0.001*** (0.000)		0.001*** (0.000)	0.001*** (0.000)
Perceived unemployment		-0.026*** (0.003)		-0.026*** (0.003)	-0.026*** (0.003)
Rural		-0.098*** (0.016)		-0.098*** (0.016)	-0.093*** (0.016)

Panel B Spatial Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 2					
PM2.5 annual mean level (2014- 2015)			0.005 (0.008)	-0.004 (0.007)	-0.004 (0.006)
GDP per capita (2015)					0.007*** (0.002)
Unemployment rate (2015)					-0.001 (0.006)
Level 3					
Log National electricity price (2015 Euro)					-0.089 (0.162)
Constant	1.780*** (0.067)	1.785*** (0.069)	1.716*** (0.121)	1.831*** (0.105)	1.482*** (0.318)
Variance (country)	0.079	0.040	0.087	0.037	0.023
Variance (region)	0.052	0.038	0.051	0.038	0.034
Observations	24402	24402	24402	24402	24402
<i>AIC</i>	77869.203	75779.120	77870.870	75780.857	75767.538
<i>BIC</i>	77901.612	75892.554	77911.382	75902.393	75913.381

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix E: Multilevel Linear Regression for Carbon Tax (Robustness Check for Unemployment)

Panel A Individual Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 1					
Climate change concern (index)		0.172*** (0.008)	0.170*** (0.008)	0.170*** (0.008)	0.170*** (0.008)
Political trust (index)		0.221*** (0.008)	0.213*** (0.008)	0.213*** (0.008)	0.212*** (0.008)
Egalitarian attitudes (index)		0.024*** (0.005)	0.025*** (0.005)	0.025*** (0.005)	0.025*** (0.005)
Education level		0.059*** (0.005)	0.052*** (0.005)	0.052*** (0.005)	0.052*** (0.005)
Female		0.050*** (0.015)	0.072*** (0.015)	0.071*** (0.015)	0.071*** (0.015)
Age		-0.001** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Left-and-right preference		-0.035*** (0.004)	-0.034*** (0.004)	-0.034*** (0.004)	-0.034*** (0.004)
Income		0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Rural		-0.093*** (0.016)	-0.098*** (0.016)	-0.098*** (0.016)	-0.093*** (0.016)
Perceived unemployment			-0.026*** (0.003)	-0.026*** (0.003)	-0.026*** (0.003)

Panel B Spatial Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 2					
Unemployment rate (2015)				-0.006 (0.006)	-0.001 (0.006)
PM2.5 annual mean level (2014- 2015)					-0.004 (0.006)
GDP per capita (2015)					0.007*** (0.002)
Level 3					
Log National electricity price (2015 Euro)					-0.089 (0.162)
Constant	1.780*** (0.067)	1.607*** (0.067)	1.785*** (0.069)	1.837*** (0.084)	1.482*** (0.318)
Variance (country)	0.079	0.042	0.040	0.039	0.024
Variance (region)	0.052	0.040	0.038	0.038	0.034
Observations	24402	24402	24402	24402	24402
<i>AIC</i>	77869.203	75854.814	75779.120	75780.022	75767.538
<i>BIC</i>	77901.612	75960.145	75892.554	75901.558	75913.381

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix F: Multilevel Linear Regression for Renewable Energy Subsidy (Robustness Check for PM2.5)

Panel A Individual Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 1					
Climate change concern (index)		0.204*** (0.007)		0.203*** (0.007)	0.203*** (0.007)
Political trust (index)		0.071*** (0.007)		0.072*** (0.007)	0.071*** (0.007)
Egalitarian attitudes (index)		0.035*** (0.004)		0.035*** (0.004)	0.035*** (0.004)
Education level		0.028*** (0.004)		0.028*** (0.004)	0.028*** (0.004)
Female		0.054*** (0.012)		0.054*** (0.012)	0.054*** (0.012)
Age		-0.002*** (0.000)		-0.002*** (0.000)	-0.002*** (0.000)
Left-and-right preference		-0.021*** (0.003)		-0.021*** (0.003)	-0.021*** (0.003)
Income		0.001*** (0.000)		0.001*** (0.000)	0.001*** (0.000)
Perceived unemployment		-0.007** (0.002)		-0.007** (0.002)	-0.007** (0.003)
Rural		-0.002 (0.014)		-0.001 (0.014)	0.000 (0.014)

Panel B Spatial Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 2					
PM2.5 annual mean level (2014- 2015)			0.017** (0.006)	0.013* (0.006)	0.013* (0.006)
GDP per capita (2015)					0.001 (0.001)
Unemployment rate (2015)					-0.003 (0.005)
Level 3					
Log National electricity price (2015 Euro)					-0.089 (0.205)
Constant	3.040*** (0.056)	2.922*** (0.066)	2.842*** (0.095)	2.760*** (0.095)	2.609*** (0.374)
Variance (country)	0.056	0.049	0.059	0.048	0.046
Variance (region)	0.028	0.021	0.026	0.020	0.020
Observations	24402	24402	24402	24402	24402
<i>AIC</i>	68633.731	66939.458	68628.965	66935.986	66940.502
<i>BIC</i>	68666.141	67052.892	68669.477	67057.522	67086.346

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix G: Multilevel Linear Regression for Renewable Energy Subsidy (Robustness Check for Unemployment)

Panel A Individual Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 1					
Climate change concern (index)		0.204*** (0.007)	0.204*** (0.007)	0.204*** (0.007)	0.203*** (0.007)
Political trust (index)		0.074*** (0.007)	0.071*** (0.007)	0.071*** (0.007)	0.071*** (0.007)
Egalitarian attitudes (index)		0.035*** (0.004)	0.035*** (0.004)	0.035*** (0.004)	0.035*** (0.004)
Education level		0.030*** (0.004)	0.028*** (0.004)	0.028*** (0.004)	0.028*** (0.004)
Female		0.049*** (0.012)	0.054*** (0.012)	0.054*** (0.012)	0.054*** (0.012)
Age		-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Left-and-right preference		-0.021*** (0.003)	-0.021*** (0.003)	-0.021*** (0.003)	-0.021*** (0.003)
Income		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Rural		-0.001 (0.014)	-0.002 (0.014)	-0.002 (0.014)	0.000 (0.014)
Perceived unemployment			-0.007** (0.002)	-0.007** (0.003)	-0.007** (0.003)

Panel B Spatial Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 2					
Unemployment rate (2015)				-0.004 (0.005)	-0.003 (0.005)
PM2.5 annual mean level (2014- 2015)					0.013* (0.006)
GDP per capita (2015)					0.001 (0.001)
Level 3					
Log National electricity price (2015 Euro)					-0.089 (0.205)
Constant	3.040*** (0.056)	2.874*** (0.064)	2.922*** (0.066)	2.955*** (0.077)	2.609*** (0.374)
Variance (country)	0.056	0.050	0.049	0.049	0.045
Variance (region)	0.028	0.022	0.021	0.021	0.020
Observations	24402	24402	24402	24402	24402
<i>AIC</i>	68633.731	66945.658	66939.458	66940.780	66940.502
<i>BIC</i>	68666.141	67050.989	67052.892	67062.317	67086.346

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix H: Multilevel Linear Regression for Energy Efficiency Law (Robustness Check for PM2.5)

Panel A Individual Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 1					
Climate change concern (index)		0.196*** (0.008)		0.196*** (0.008)	0.195*** (0.008)
Political trust (index)		0.056*** (0.008)		0.057*** (0.008)	0.057*** (0.008)
Egalitarian attitudes (index)		0.031*** (0.005)		0.031*** (0.005)	0.031*** (0.005)
Education level		0.021*** (0.004)		0.021*** (0.004)	0.021*** (0.004)
Female		0.101*** (0.014)		0.101*** (0.014)	0.102*** (0.014)
Age		0.003*** (0.000)		0.003*** (0.000)	0.003*** (0.000)
Left-and-right preference		-0.015*** (0.003)		-0.015*** (0.003)	-0.015*** (0.003)
Income		0.002*** (0.000)		0.002*** (0.000)	0.002*** (0.000)
Perceived unemployment		-0.009** (0.003)		-0.009** (0.003)	-0.009** (0.003)
Rural		-0.014 (0.016)		-0.013 (0.016)	-0.014 (0.016)
Panel B	(1)	(2)	(3)	(4)	(5)

Spatial Characteristics	Model 1	Model 2	Model 3	Model 4	Model 5
Level 2					
PM2.5 annual mean level (2014-2015)			0.017** (0.006)	0.015* (0.006)	0.019*** (0.005)
GDP per capita (2015)					-0.002 (0.002)
Unemployment rate (2015)					0.005 (0.005)
Level 3					
Log National electricity price (2015 Euro)					0.516*** (0.138)
Constant	2.586*** (0.050)	2.205*** (0.068)	2.385*** (0.090)	2.023*** (0.098)	2.885*** (0.275)
Variance (country)	0.043	0.040	0.039	0.033	0.016
Variance (region)	0.030	0.028	0.029	0.027	0.027
Observations	24402	24402	24402	24402	24402
<i>AIC</i>	75380.855	74295.286	75376.033	74291.440	74283.526
<i>BIC</i>	75413.264	74408.719	75416.545	74412.977	74429.369

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix I: Multilevel Linear Regression for Energy Efficiency Law (Robustness Check for Unemployment)

Panel A Individual Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 1					
Climate change concern (index)		0.196*** (0.008)	0.196*** (0.008)	0.195*** (0.008)	0.195*** (0.008)
Political trust (index)		0.059*** (0.008)	0.056*** (0.008)	0.057*** (0.008)	0.057*** (0.008)
Egalitarian attitudes (index)		0.030*** (0.005)	0.031*** (0.005)	0.031*** (0.005)	0.031*** (0.005)
Education level		0.024*** (0.004)	0.021*** (0.004)	0.021*** (0.004)	0.021*** (0.004)
Female		0.094*** (0.014)	0.101*** (0.014)	0.102*** (0.014)	0.102*** (0.014)
Age		0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Left-and-right preference		-0.015*** (0.003)	-0.015*** (0.003)	-0.015*** (0.003)	-0.015*** (0.003)
Income		0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Rural		-0.013 (0.016)	-0.014 (0.016)	-0.014 (0.016)	-0.014 (0.016)
Perceived unemployment			-0.009** (0.003)	-0.009** (0.003)	-0.009** (0.003)

Panel B Spatial Characteristics	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Level 2					
Unemployment rate (2015)				0.008 (0.005)	0.005 (0.005)
PM2.5 annual mean level (2014- 2015)					0.019*** (0.005)
GDP per capita (2015)					-0.002 (0.002)
Level 3					
Log National electricity price (2015 Euro)					0.516*** (0.138)
Constant	2.586*** (0.050)	2.145*** (0.064)	2.205*** (0.068)	2.132*** (0.080)	2.885*** (0.275)
Variance (country)	0.043	0.039	0.040	0.038	0.016
Variance (region)	0.030	0.028	0.028	0.028	0.027
Observations	24402	24402	24402	24402	24402
<i>AIC</i>	75380.855	74302.863	74295.286	74294.628	74283.526
<i>BIC</i>	75413.264	74408.194	74408.719	74416.165	74429.369

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix J: Multilevel Ordinal Probit Regression

Panel A Individual Characteristics	(1) Carbon Tax	(2) Renewable Energy Subsidy	(3) Energy Efficiency Law
Level 1			
Climate change concern (index)	0.163*** (0.007)	0.255*** (0.008)	0.196*** (0.007)
Political trust (index)	0.197*** (0.008)	0.072*** (0.008)	0.049*** (0.008)
Egalitarian attitudes (index)	0.025*** (0.004)	0.047*** (0.005)	0.031*** (0.004)
Education level	0.048*** (0.004)	0.039*** (0.004)	0.021*** (0.004)
Female	0.061*** (0.014)	0.043** (0.015)	0.090*** (0.014)
Age	-0.001*** (0.000)	-0.002*** (0.000)	0.003*** (0.000)
Left-and-right preference	-0.034*** (0.003)	-0.028*** (0.004)	-0.014*** (0.003)
Income	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
Perceived unemployment	-0.025*** (0.003)	-0.008** (0.003)	-0.007** (0.003)
Rural	-0.085*** (0.015)	-0.001 (0.016)	-0.016 (0.015)

Panel B Individual Characteristics	(1) Carbon Tax	(2) Renewable Energy Subsidy	(3) Energy Efficiency Law
Level 2			
PM2.5 annual mean level (2014-2015)	-0.004 (0.006)	0.016* (0.007)	0.019*** (0.005)
GDP per capita (2015)	0.007*** (0.002)	0.001 (0.002)	-0.002 (0.001)
Unemployment rate (2015)	-0.001 (0.005)	-0.003 (0.006)	0.004 (0.005)
Level 3			
Log National electricity price (2015 Euro)	-0.083 (0.149)	-0.145 (0.260)	0.511*** (0.130)
Cut points			
cut1	-0.709* (0.292)	-1.396** (0.472)	-1.915*** (0.262)
cut2	0.134 (0.292)	-0.814 (0.472)	-1.185*** (0.261)
cut3	0.737* (0.292)	-0.327 (0.472)	-0.572* (0.261)
cut4	1.853*** (0.292)	0.974* (0.472)	0.497 (0.261)
Variance (country)	0.019	0.075	0.014
Variance (country region)	0.030	0.030	0.025
Observations	24402	24402	24402
AIC	71589.275	57869.671	69330.398
BIC	71751.324	58031.719	69492.446

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$