**Analysis**

The following section illustrates the different steps undertaken to obtain a prediction model for pro-environmental action. In particular, the first step consists of Exploratory Data Analysis, to investigate climate change attitudes. Then, the best fitting models tested to predict the final price are presented.

**Exploratory Data Analysis**

Climate change attitudes do not vary only between countries but also between citizens in the same country (Xie et al., 2019). As you can see in figure 1, the percentage of those who believe that climate change is the single most serious problem varies significantly according to country. For example, Bulgaria and Croatia obtain a smaller percentage, that is 11% of citizens who think climate change is the single most serious problem. On the contrary, about 1 out 2 of Sweden’s citizens indicated climate change.



Figure 1: Single Most Serious Problem

Another interesting example is the difference in the climate change risk perception. As you can see in figure 2, about half of the citizens of Malta and Luxemburg declared that they are extremely worried about the phenomenon studied.



Figure 2: Climate Change Risk Perception



Attitudes among countries could so vary since they are influenced by different contextual factors (Echavarren et al., 2019; Krajhanzl, 2010). According to Echavarren and colleagues (2019), opinion, perception, and behavior could change due to different natural hazards and political contexts. For example water deficit or temperature growth regarding natural hazards and the “level of environmentalism in the political arena of a given country” (Echavarren et al., 2019, p. 815) for political variables. These macro-variables should be significant mediators in explaining risk perception or pro-environmental behavior. Some indexes are considered with the sole purpose of remembering that they could affect and moderate the phenomenon studied. Then, they are not inserted in the final models since only the multilevel method could be adopted. Besides, the aim of the research is not to evidence national or cultural differences, but on the contrary, it is to find patterns at individual levels, regardless of the place of origin. However, these differences at the macro levels are presented.

For the natural hazards the 2020 Environmental Performance Index (EPI) is used (the 2019 EPI is not available to use the same data of year of the survey) (Yale Center for Environmental Law & Policy, 2020). EPI quantifies numerically environmental health and ecosystem vitality around the world. Some indicators that composed the index are air pollution, drinking water quality, species protection. These phenomena could positively affect climate change concerns and opinions (Echavarren et al., 2019). Citizens should perceive biodiversity loss or temperature increases, leading to greater apprehension. Figure 3 shows the score across European Union (EU). The best score is obtained from Denmark, while the worst from Bulgaria.

Figure 3: The 2020 EPI

For the political context, the 2019 Climate Change Policy Performance is selected, which is a measurement of national and international climate policies (Burck, 2018) developed by organization Germanwatch. It is one of the indicators that belong to the Climate Change Performance Index (CCPI). The indicator constitutes the measurements taken by governments to reduce the current level of GHG emissions per capita or the use of renewable energy. Briefly, it is defined as a measure of countries’ progress and their capacity for climate protection (Burck, 2018). In the Climate Change Policy, the record goes to Portugal and Bulgaria gets the lowest score in all European Union, as figure 4 shows.

According to scholars (Echavarren et al., 2019; van der Linden, 2015) socio-cultural context influces individual attitudes towards climate change concerns. Therefore, the notable diferencess in attitudes across coutries should be also due to these indicators. In fact, “sociological research suggests that contextual factors and processes can be powerful forces shaping how individuals and communities engage with the issue” (Lee et al., 2015, p. 1014). There are different ecological tax reforms or cultural habits that affect and shape individual climate change attitudes and behavior.

Figure 4:The 2019 Climate Change Policy

In this way, It is important to remember that these macro-factors should affect also individual preferences.

**Analysis: Data Exploratory**

**3.1 Correlation Class Analysis**



Figure 5: CCA

The first step is to perform CCA, a method for partitioning the dataset into classes to apprehend unobserved heterogeneity (Rossoni et al., 2021). For our dataset, the CCA algorithm produces five groups. Figure 5 illustrates the individual modules or classes created as a network. Each node corresponds to one item, while the edges show the statistically significant correlation between variables (Rossoni et al., 2021). The more line is thicker, the more significant is the correlation. [[1]](#footnote-1) In group 1 the correlations between all pairs of variables are set to 1. Group 2 obtains a high positive correlation (0.8) mainly between qb4\_3 and qb4\_5. Group 3 has a slight correlation among all variables, except for qb4\_5. In group 4 we find a strong positive correlation among qb7, qb8, and qb9 and separately between qb4\_3 and qb4\_5. Lastly, group 5 has a strong correlation between the following pair of variables: qb4\_5 and qb7; qb4\_5 and qb8; qb4\_5 and qb9. In this case, qb4\_3 is completely isolated.

Figure 6: CCA and Country

In the second place, it is interesting to analyse how CCA’s groups are distributed according to country, as shown in figure 6. The aim is to understand whether there are some shared meanings among citizens of the same country. We analyse the percentage of individuals belonging to the CCA’s groups for each country. Group 2, 4, and 5 are composed of a similar proportion of citizens from each country. Instead, if we look at the composition for each country, we find that over 30% of citizens from Cyprus, Ireland, Malta, Portugal, Slovakia, Spain, and United Kingdom belong to group 1. Additionally, over 30% of citizens from Austria, Bulgaria, Czech Republic, Estonia, Finland, France, Germany, Greece Italy, Latvia, Luxemburg, and Sweden belong to group 3. In both cases, we can not find some specific patterns, such as belonging to the same part of Europe. It is interesting to find similar shared meanings schemas among subjects in nations extremely different and opposite such as Italy and Estonia.

**3.2 Partitioning Around Medoids Clustering**

PAM clustering is an unsupervised method that looks for patterns without any knowledge of the classification purpose. The aim is to partition citizens into classes (clusters) according to similar *green-identity*. Clustering groups the similar observations within each group, while the observations in different groups are different from other clusters. Grouping the attitudes of citizens in clusters means dividing them according to similar opinions about the governance of climate change. We remember that also in this case the questions about climate change (qb4\_3, qb4\_5, qb7, qb8, qb9) are fitted in that algorithm.

PAM requires, as a parameter, the number of clusters. “One of the most commonly applied methods for assessing cluster validity is silhouette width which encompasses two clustering criteria: separation (i.e., the average distance to the closest other clusters) and compactness (i.e., average within‐cluster distance)” (Lengyel & Botta‐Dukát, 2019, pag. 13232). Silhouette width indicates how well each cluster divides observations, as shown in figure 7. The best choice is 2.

Figure 7: Clustering silhouette

Observations are then divided into two clusters with PAM. The summary results of PAM clustering are shown in Figure 8. The distribution is balanced: 11171 individuals belong to cluster 1, and 10807 belong to cluster 2. Although overall the level of agreement or importance of these questions is elevated (the mode of qb4\_3, qb4\_5 is 2, while the mode of qb7, qb8, qb9 is 1), we can see that 2 clusters resemble two different types of green-identity, which we call “moderate green identity”, “extreme green-identity”.

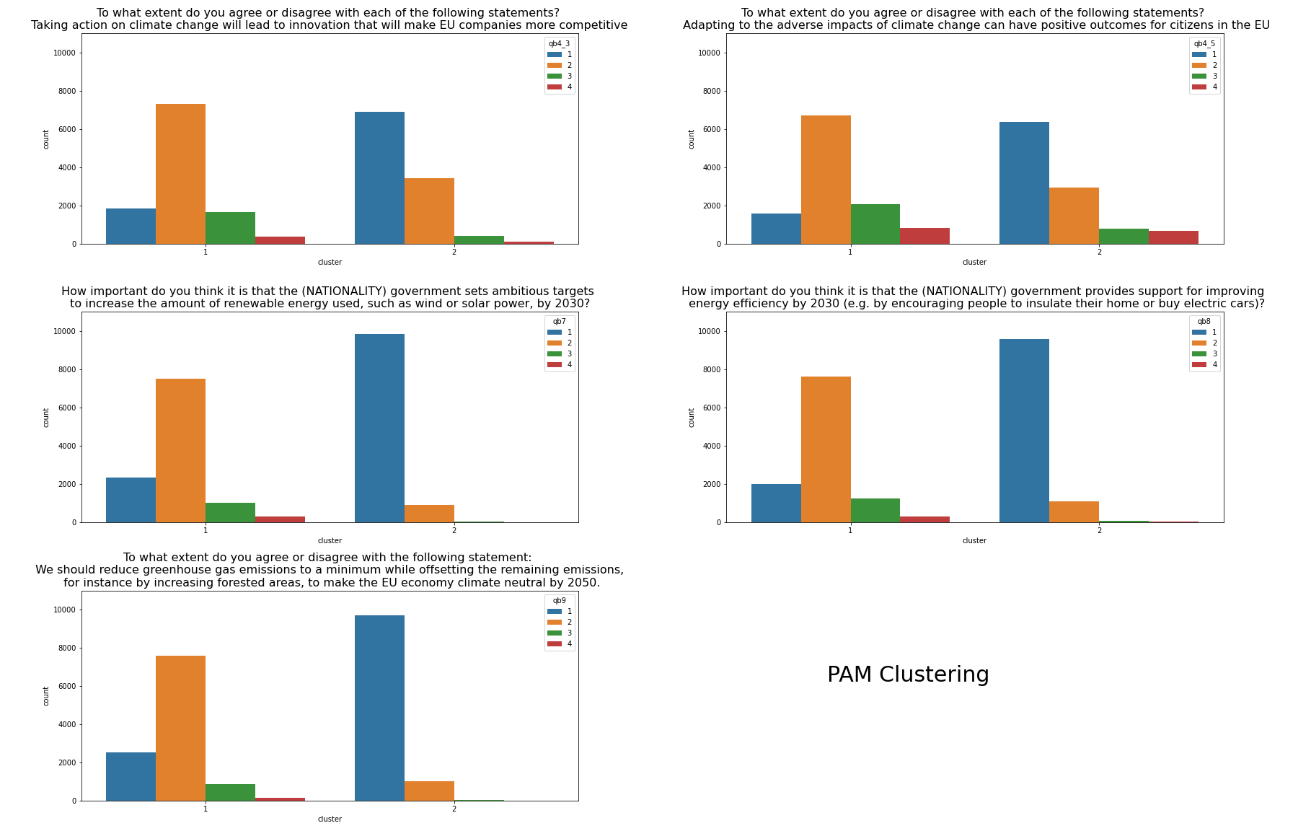


Figure 8: Summary of PAM Clustering

**Cluster 1: Moderate green identity**

* More than 75% answered questions (qb3\_4,qb4\_5, qb7, qb8, qb9 ) with moderate answers (option 2 or 3);
* There is no difference among genders;
* 70% of citizens belong to centre, centre-left or centre-right;
* 57% stopped studying at the latest at 19, 35% stopped studying after 20, 6% are still studying;
* More than 65% of the citizens of Czech Republic, Estonia, Finland, Latvia, Poland belong to this cluster;
* the average age is 51 years old;
* the average climate change risk perception is 7.2;
* 56% take place a pro-environmental behaviour.

**Cluster 2: Extreme green-identity**

* More than 60% answered qb3\_4 and qb4\_5 questions with the maximum answer (1), and about 90% answered qb7, qb8, qb9 questions with the maximum answer (1).
* There is no relevant difference among genders;
* 66% of citizens belong to centre, centre-left or centre-right
* 49% stopped studying at the latest at 19, 41% stopped studying after 20, 7% are still studying;
* More than 65% of the citizens of Cyprus, Denmark, Spain, United Kingdom belong to this cluster;
* The average age is 50 years old:
* The average climate change risk perception is8.6;
* 75% take place a pro-environmental behaviour.

To sum up, cluster 1 is composed of citizens that are more moderate in the answers to climate change items than the citizens of the opposite cluster. Additionally, cluster 2 is composed of slightly younger, more educated, more worried, and more active citizens.

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**APPENDIX D. Correlation matrix for each CCA’s group.**

Group 1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | 1 | 1 | 1 | 1 |
| **qb4\_5** | 1 | 1 | 1 | 1 | 1 |
| **qb7** | 1 | 1 | 1 | 1 | 1 |
| **qb8** | 1 | 1 | 1 | 1 | 1 |
| **qb9** | 1 | 1 | 1 | 1 | 1 |

Group2

|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| --- | --- | --- | --- | --- | --- |
| **qb4\_3** | 1 | 0.8209258 | 0.34825902 | 0.1660830 | 0.22869773 |
| **qb4\_5** | 0.8209258 | 1 | 0.48758501 | 0.3021902 | 0.13889897 |
| **qb7** | 0.34825902 | 0.48758501 | 1 | 0.3923910 | -0.01232148 |
| **qb8** | 0.1660830 | 0.3021902 | 0.3923910 | 1 | -0.14657797 |
| **qb9** | 0.22869773 | 0.13889897 | -0.01232148 | -0.14657797 | 1 |

Group 3

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | 0.07469395 | 0.4400537 | 0.5437509 | 0.5195602 |
| **qb4\_5** | 0.07469395 | 1 | -0.1859863 | -0.1112473 | -0.1150310 |
| **qb7** | 0.44005368 | -0.18598635 | 1 | 0.4965637 | 0.4023176 |
| **qb8** | 0.54375089 | -0.11124727 | 0.4965637 | 1 | 0.5111735 |
| **qb9** | 0.51956019 | -0.11503102 | 0.4023176 | 0.5111735 | 1 |

Group 4

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | 0.9001736 | -0.2393692 | -0.2281035 | -0.2411191 |
| **qb4\_5** | 0.9001736 | 1 | -0.1607610 | -0.1477551 | -0.1715444 |
| **qb7** | -0.2393692 | -0.1607610 | 1 | 0.8869407 | 0.8548438 |
| **qb8** | -0.2281035 | -0.1477551 | 0.8869407 | 1 | 0.8476377 |
| **qb9** | -0.2411191 | -0.1715444 | 0.8548438 | 0.8476377 | 1 |

Group 5

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | -0.1514635 | -0.05905457 | -0.03462609 | -0.1298436 |
| **qb4\_5** | -0.15146353 | 1 | 0.75879238 | 0.73159084 | 0.8669082 |
| **qb7** | -0.05905457 | 0.7587924 | 1 | 0.54913637 | 0.6663558 |
| **qb8** | -0.03462609 | 0.7315908 | 0.54913637 | 1 | 0.6540521 |
| **qb9** | -0.12984356 | 0.8669082 | 0.66635581 | 0.65405206 | 1 |

1. See appendix D for the correlation of each class separately. [↑](#footnote-ref-1)