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DIPARTIMENTO DI ECONOMIA, METODI QUANTITATIVI E STRATEGIA DI IMPRESA

Climate change awareness: Empirical evidence for the European Union*

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Abstract

In this paper, we assess public attitudes on climate change in Europe over the last decade. Using aggregate figures from the Special Eurobarometer surveys on Climate Change, we find that environmental concern is directly related to per capita income, social trust, secondary education, the physical distress associated with hot weather, media coverage, the share of young people in the total population, and monetary losses caused by extreme weather episodes. It is also inversely related to greenhouse gas emissions, relative power position of right-wing parties in government and tertiary education. Moreover, we find a significant, opposite impact for two dummies for years 2017 and 2019, which we respectively associate with the effects of Donald Trump's denial campaigns and the U.S. Paris Agreement withdrawal announcement, and Greta Thunberg's environmental activism.

Keywords: climate change, environmental attitudes/concern, mitigation policy, EU

JEL classification: Q50, Q54, Q58

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1 Introduction

What are public perceptions of climate change? Initially at low levels in the early 1980s, when the issue started to be widely acknowledged in most industrialized countries, public concern for climate change appears to have converged to consensus levels over the next two decades, as a consequence of growing scientific evidence and higher mass media coverage and political debate (Nisbet and Myers, 2007; Boykoff and Yulsman, 2013). International consensus on the urgency of climate change mitigation also appears to have been achieved by mid-2000s. Yet awareness of the contribution of various human activities to the phenomenon, such as energy use, animal farming, food miles and waste, does not appear to have risen much over time (Laiserowitz, 2008; Attari et al., 2010; Brechin, 2010; Whitmarsh et al., 2011; Bailey et al., 2014).

The 2015 "Paris Agreement" represents the highest level of worldwide consensus ever achieved since the Rio Earth Summit in 1992, in relation to the existence of climate change, its human-made origin, and the urgent need to implement mitigation and adaptation policies. Under the agreement, 196 countries committed to the goal of keeping the increase in global average temperature well below 2°C above pre-industrial levels and, in particular, to limit this increase to 1.5°C, in order to reduce the risks and impacts of climate change.

The Paris Agreement was even more remarkable as it followed a period of widespread skepticism. This had started in the late 2000s and intensified during Donald Trump's campaign for the U.S. Presidency, his election in 2016 and his announcement of U.S. withdrawal from the agreement in June 2017 (Laiserowitz et al., 2014; 2017). Donald Trump, who defined climate change as a "hoax", during his U.S. presidency consistently acted against the objectives of the Paris Agreement and dismantled many environmental protection measures in the U.S.[1]

Recent evidence shows that, at current levels of greenhouse gas emissions, the carbon budget for meeting the Paris Agreement target of 2°C will be exhausted in less than three decades, while less than a decade is left to limit the increase in global temperature to 1.5°C.[2] Yet these scenarios might even be optimistic, since greenhouse gas emissions are still increasing globally and there might in fact be no time left to avoid large-scale discontinuities in the climate system. It could be that there is no time left to avoid tipping points and that the only remaining possibility is to limit damage as tipping points are reached: "The stability and resilience of our planet is in peril. International action -not just words- must reflect this" (Lenton et al., 2019).

In the light of this evidence, understanding the drivers of climate change attitudes is an important and urgent task, since in democratic systems the legitimacy of political decisions on climate change mitigation actions relies on the support of public opinion. This will be in favour only where there is sufficient concern for the economic, human and social implications of climate change. In this paper we focus on the evolution in climate change concern in Europe over the last decade. The period investigated is interesting, as it allows us to assess how European climate change attitudes have been affected by the "Paris Agreement", the election of Donald Trump as U.S. President, his denial campaigns and the environmentalists' response led by Greta Thunberg and the "*Fridays for future*" movement. To the authors' knowledge, there are no studies in the literature focusing on data more recent than 2014. Moreover, our assessment is based on the Special Eurobarometer surveys on Climate Change, which are in-depth thematic

[1] See the running list maintained by The National Geographic: https://www.nationalgeographic.com/news/2017/03/how-trump-is-changing-science-environment/.

[2] According to IPCC (2018), the atmosphere can absorb, calculated from end-2017, no more than 420 (1,170) gigatonnes (Gt) of CO2 if it is to stay below the 1.5°C (2°C) threshold. Since around 42 Gt of CO2 is emitted globally every year, i.e. 1,332 tonnes per second, this carbon budget is expected to be used up in about nine (twenty six) years.

studies integrated into Standard Eurobarometer's polling waves and published every two years since 2009. Although the Special Eurobarometer surveys provide an accurate view of climate change attitudes, they have been neglected in the literature so far. Finally, unlike previous studies, our analysis focuses on aggregate survey results over different countries. This paper thus fills some important gaps in the literature.

We find that, over the last decade, climate change concern in Europe has increased with the level of per capita income. We name this relationship "*climate change/environmental awareness curve*" (CCA curve). This curve is theoretically motivated by the public good nature of environmental quality, for which demand increases with the level of income, and is well described by a logistic function. This curve is also related to the "environmental Kuznets curve", which describes an inverse-U shaped relationship between greenhouse gas emissions and the level of per capita income. Intuitively, once threshold income level is crossed, economic development becomes sustainable, i.e. higher income levels are associated with lower emissions, and, in our framework, also with higher climate change concern. Significant effects are also found for social trust, greenhouse gas emissions, education, the physical distress associated with hot weather, the share of young people in the total population, relative power position of right-wing parties in government, media coverage and economic losses caused by extreme weather episodes. All these variables act as shift factors for the climate change awareness curve (in its awareness-income space), in some cases also impacting on its slope.

Moreover, we also find a significant impact for two temporal dummies for year 2017 and 2019, accounting for a sizable drop and a sizable increase in environmental concern, respectively, ceteris paribus. While our study cannot establish causal linkages, consistent with our theoretical framework and the available empirical evidence on political leader-follower linkages, in relation to climate change attitudes, we are inclined to associate these changes with Donald Trump's denial campaigns and politicization of climate change and Greta Thunberg's environmental activism, respectively. By keeping in mind the above mentioned caveat on causality, in the light of the estimated effects, the positive *Thunberg effect* appears to have prevailed over the negative *Trump effect.* Climate change concern in the EU would have then risen as a consequence of public controversy brought to the fore by the election of Donald Trump as U.S. President.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on climate change attitudes in Europe. Section 3 provides some stylized facts about climate change attitudes for the EU member countries. Section 4 presents the environmental awareness/concern dissemination model and its econometric specification. Section 5 describes the data, Section 6 presents the empirical results and Section 7 concludes.

2 Literature review

Psychology has traditionally identified three components of mind: cognition, affect, and conation. Cognition is the process of rationally understanding a phenomenon, through the acquisition and processing of information. Affect refers to the emotional response to the acquisition of this knowledge. Conation refers to the personal, intentional action, i.e. the proactive behavioral response caused by the cognitive and affective experiences (Tallon, 1997). The literature on environmental attitudes has explored all three of the above components, i.e. the understanding of the climate change phenomenon, the emotions associated with this knowledge and the actions taken to mitigate its impact and adapt to its effects. Comprehensive surveys by Lorenzoni and Pidgeon (2006), Upham et al. (2009) and Whitmarsh and Capstick (2018) provide a broad overview of the field.

Concerning recent European evidence, Wicker and Beckern (2013) analyze Eurobarometer 75.4 survey data, collected in June 2011 from a sample of 26,840 respondents. Survey questions concern the perceived severity of climate change, relative to concerns about energy availability and the economic situation, and any personal action taken by respondents to fight climate change during the six months before the interview. For instance, questions cover the purchase of new low fuel consumption cars or new low-energy homes, the consumption of locally produced and seasonal food, and transport habits in relation to alternatives to the use of private cars (walking, bike, public transport, car-sharing). By means of linear regression analysis, they find a positive impact of education, wealth and life satisfaction, as well as of concerns about economic, energy availability and climatic conditions, on respondents' proactive behavior. Socio-demographic factors also matter, since women and young people appear to be more active in environmental protection than men and old people. The above findings are confirmed by Meyer (2015), using data from Eurobarometer 68.2 (November 2007-January 2008) and 75.2 (April-May 2011) and regression discontinuity analysis.

D'Amato et al. (2019) focus on determinants of environmentally-friendly behavior, in relation to waste reduction, waste recycling, water saving and energy saving activities. The data investigated are from three Special Eurobarometer surveys on attitudes of European citizens towards the environment, collected in 2008, 2011 and 2014. By means of a system of simultaneous linear regressions, they find a positive influence of the level of information, especially through internet sources, the level of trust on organization and scientists, the level of GDP, and, in some cases, the level of mean temperature, environmental expenditure and energy taxation, on environmentally-friendly behavior. However, a negative impact is found for tertiary education. Drews et al. (2018), using the same survey data, also find that respondents tend to view economic growth and environmental protection as compatible objectives, even prioritizing the environment in a trade-off situation.

Poortinga et al. (2018) investigate data collected in Round 8 of the European Social Survey. The sample consists of 44,387 respondents in 23 European countries. The survey covers climate change beliefs and concerns and environmental policy preferences. The evidence shows that about 90% of respondents believe that the climate is changing, partly as a consequence of human activities. Moreover, although 70% of respondents, on average, expect climate change effects to be bad or very bad, only 25% state that they are very worried. Consistently with this, the majority of respondents say that it is less than likely that they will undertake mitigation activities in the near future, for instance in relation to their energy use.

A larger international sample of European and non European countries is considered in Franzen and Vogl (2013) and Smith and Mayer (2018), who use data for 33 countries from the International Social Survey Programme (ISSP) on environmental protection, for the years 1993, 2000, and 2010, and data for 35 countries from the Life in Transition II Study (LITS II) conducted by the World Bank and the European Bank for Reconstruction and Development in 2010, respectively. ISSP data are also employed by Lo and Chow (2015). In particular, Franzen and Vogl (2013) construct an index of environmental concern, accounting for both the cognitive and conative components of climate change attitudes, Smith and Mayer (2018) focus on the determinants of the willingness to act to fight climate change, and Lo and Chow (2015) consider the *ranking* of climate change in terms of its importance relative to other problems and the *danger* associated with it in terms of sense of insecurity and risk. By means of panel regression techniques, Franzen and Vogl (2013) and Smith and Mayer (2018) find a positive impact of education, social and institutional trust, GDP or per capita GDP on environmental attitudes. Moreover, by means of a multilevel logistic regression and using EU27 data, Harring (2014) finds that in relatively more corrupt and economically unequal (Southern European) countries, economic pro-environmental policy instruments (EIs) are considered less effective than in relatively less corrupt and economically unequal (Northern European) countries. This is consistent with the fact that corrupt public institutions tend to waste economic resources and to have lower levels of trust in public policy. These results are important, as public support for climate mitigation action is high when the perceived policy effectiveness is also high. Smith and

Mayer (2018) also find a positive effect for the perceived gravity of climate change, while Franzen and Vogl (2013) also point to significant impacts of gender, age and political factors. On the other hand, Lo and Chow (2015) document a positive impact of per capita GDP on the *relative* ranking of climate change across challenges, but negative effects of per capita GDP, energy use and the Global Adaptation Notre-Dame Index (ND-GAIN) on its (*absolute*) perceived gravity. See also the earlier studies of Diekkman and Franzen (1999), Sandvik (2008) and Freymeyer and Johnson (2010), based on various international survey data on European and non European consumers' environmental attitudes.

Interesting results are also reported in Frondel et al. (2017) and Andor et al. (2018), based on survey data collected by the German institute *forsa Gesellschaft für Sozialforschung und statistische Analysen*. The survey counts more than 6,000 respondents, representative of the population of German speaking households aged 14 and above. The survey is updated regularly and available for various years and increasing sample size, i.e. 2012 (6,404 respondents), 2013 (6,522 respondents), 2014 (6,602 respondents) and 2015 (7,077 respondents). In particular, Frondel et al. (2017) focus on the association of public perception of climate change with heat waves, storms and floods, and their financial and physical costs. Andor et al. (2018) consider the perceived importance of taking action against climate change. By means of ordered logit regression estimation, they find that personal experience with adverse natural events, particularly personal losses, lead to higher environmental concern, and that older people are not likely to personally engage in fighting climate change or supporting policy measures aiming at climate change mitigation. Survey data, based on about 1,000 respondents in Germany only, are also used in Schwirplies (2018). In particular, perceptions of climate change are assessed in relation to global warming, climate change mitigation policies, i.e. the development of renewable energy sources and energy-efficient technologies, and climate change adaptation policies, i.e. the construction of infrastructures to protect against future natural disruptions. By means of bivariate ordered probit regressions, she finds that support for mitigation and adaptation actions positively correlates with the recognition of the anthropogenic origin of climate change (responsibility factor), the view that these actions can still be effective and political support for the green party. On the other hand, a negative linkage is found for the level of income and mixed effects for education.

3 Stylized facts about climate change concern in the European Union

Our proxy variables for climate change concern are based on *aggregate* country figures, retrieved from the *Special Eurobarometer surveys on Climate Change*, collected every two years, over the period 2009-2019. In particular, we consider results contained in Volume C (Country/socio-demographics). The issues investigated are no. 322 (2009), 372 (2011), 409 (2013), 435 (2015), 459 (2017) and 490 (2019).[3] The sample includes the 27 current EU member countries plus the UK.[4] Hence, we provide an up to date assessment of climate change attitudes in Europe, based on specialized surveys.

More specifically, our analysis focusses on the following questions: "Which of the following do you consider to be the single most serious problem facing the world as a whole?", "Which others do you consider to be serious problems?", "And how serious a problem do you think climate change is at this moment?". These questions cover the cognitive component of climate

[3] See, for instance, https://data.europa.eu/euodp/en/data/dataset/S2212_91_3_490_ENG.

[4] Current EU Member States are Austria, Belgium, Bulgaria, Cyprus, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Sweden, Slovakia, Slovenia and Spain.

change attitudes and, to some extent, its emotional component, assuming that a negative feeling is associated with environmental concern, and the intensity of the feeling is proportional to the degree of perceived gravity of the environmental problem.

In the first two cases, we use the percentage of respondents that identify climate change as *the single most serious global challenge* in each country ($QB1a$) or that rank climate change *the second to fourth most serious global challenge* ($QB1b$).[5] For the third question, we select those respondents who consider climate change as a *serious problem* ($QB2s$) and as a *very serious problem* ($QB2vs$), by assigning scores within ranges 5-6 and 7-10, respectively (in a scale from 1 to 10, with "1" meaning it is "not at all a serious problem" and "10" meaning it is "an extremely serious problem").

Moreover, we also aggregate the above figures and obtain three additional proxy variables. The aggregation of $QB1a$ and $QB1b$ yields the percentage of respondents who rank climate change as *one of the four most important global challenges* ($QB1$). The aggregation of $QB2s$ and $QB2vs$ yields the percentage of respondents who consider climate change *at least a serious problem* ($QB2$), giving a score within the range 5-10. The interaction (product) of $QB1$ and $QB2$ yields an *estimate* of the percentage of respondents who rank climate change as *one of the four most important challenges and at least of serious gravity* ($QB1QB2$).[6] All these series are used in our study as alternative proxy variables for environmental concern, i.e. $y_t = QB1a$, $QB1b$, $QB2s$, $QB2vs$, $QB1$, $QB2$, $QB1QB2$.

3.1 The empirical evidence

As shown in Table 1, (on average) 58% of the interviewed EU citizens in 2019 view climate change as one of the four major global challenges (Panel C), and 22% of them rank it as the biggest challenge (Panel A). As regards gravity, 16% of respondents view it as a serious problem (Panel D) and 77% of them as a very serious problem (Panel E).

The comparison with earlier Eurobarometer results shows that EU environmental attitudes have not evolved linearly over time. For instance, (on average) climate change is ranked within the first four most important challenges by 50% of the respondents already in 2009 (Panel C). This figure does not alter sizably until 2019 (+6% (12%) relatively to 2009 (2017)), apart from the most sizable contraction occurred in 2017 (-7% relatively to 2009). Similarly, 18% of the respondents already rank climate change as the most important threat in 2009 (Panel A). This figure then sizably raises in 2019 (+4% (9%) relative to 2009 (2017)). The *perceived gravity* of the phenomenon shows a steadier pattern, since 63% of the respondents consider climate change at least a serious problem already in 2009 (Panel F). This figure then increases to about 67% over the three following survey periods, to 72% in 2017 and, eventually, to 77% in 2019. Similar information is provided by our overall climate change concern measure $QB1QB2$ (Panel G). In fact, according to interacted figures, (on average) in 2009 already 45% of respondents regard

[5] As well as climate change, the other possible responses are: international terrorism, poverty, hunger and lack of drinking water, spread of infectious diseases, the economic situation, proliferation of nuclear weapons, armed conflicts, increasing global population and other items.

[6] As we can access aggregated figures only, we cannot compute *exactly* the percentage of respondents who simultaneously rank climate change as one of the four most important challenges (A) and assigned a score between 5 and 10 to its perceived gravity (B). In terms of probabilities, we have $P(A \cap B) = P(A) \times P(B|A)$, which we estimate as $P(A) \times P(B)$. Yet 1) it is very likely that a respondent ranking climate change as one of the four most important challenges will also consider it a threat of at least serious gravity, i.e say $P(B|A) > 0.9$; 2) in our sample $P(B)$ (across countries and time) ranges between a minimum of 0.7 and a maximum of 0.99, taking a median value equal to 0.91. Then, we can conclude that using $P(B)$ in the place of $P(B|A)$ in our case might yield a satisfactory estimate of the unobserved quantity of interest. With this caveat in mind, in what follows we then simply refer to $QB1QB2$ as if it were the actual measure, rather than the estimated measure, of the percentage of respondents who rank climate change as one of the four most important challenges and at least of serious gravity.

climate change as one of the four most important challenges and at least of serious gravity. A sizable drop can then be noted in 2017 and an even more sizable increase in 2019 (+9% (14%) relative to 2009 (2017)).

In Figure 1 we compare cross-sectional distribution patterns in years 2009 and 2019. Density estimation is performed through (Gaussian) kernel smoothing, under optimal bandwidth selection (Silverman, 1986). As shown in Figure 1, distributional dynamics provide additional insights on raising climate change concern in the EU over the last decade. For instance, evidence of emerging polarization or bi-modality can be seen in the distribution of $QB1a$, consistent with the formation of a group of (leading) countries for which climate change might have become the most important challenge. The shrinking dispersion in the distribution of $QB1b$ sends a similar message. Over time, the perception that climate change is one of the four main important challenges has become more homogeneous across countries. Consistently with this, the distribution of $QB1$ (sum of $QB1a$ and $QB1b$) shows a clear-cut rightward shift in 2019 relative to 2009.

Moreover, just as the distribution of respondents seeing climate change as a *very serious* problem shows a rightward shift ($QB2vs$), the distribution of respondents seeing climate change as an *at least serious* problem also shows a similar pattern. This indicates an overall increase in the number of Europeans concerned about the gravity of climate change. The distribution of the interacted variable $QB1QB2$ also shows a rightward shift, which still appears to be bimodal in 2019, yet of shrinking dispersion relative to 2009 figures.

However, as shown by the heat maps reported in Figure 2 for $QB1QB2$ and in Figure A1 (in the Online Appendix) for the other proxy variables, geographical dispersion in attitudes is still sizable even in 2019. In particular, environmental concern appears to be highest for Northern European countries and lowest for Eastern European countries. For instance, Northern European countries show the highest percentages of respondents who rank climate change as the most important challenge (Figure A1, Panel A); Western and Southern European countries show the highest percentages of respondents who rank climate change between the second and fourth most important challenges (Figure A1, Panel B); Northern and Southern European countries show the highest proportion of interviewed that rank climate change as a very serious threat (Figure A1, Panel D). Coherently, the shares of respondents who rank climate change as one of the four most important challenges (Figure A1, Panel E), a threat of at least serious gravity (Figure A1, Panel F), and one of the four most important challenges, of at least serious gravity (Figure 2), are higher for Northern, Western and Southern European countries than Eastern European countries.

The overall conclusion from the above results is that concern for climate change in the EU has risen over time, but neither in a linear nor a homogeneous manner. Most interesting are the sizable drop in 2017 and the even more sizable raise in 2019. In the light of recent events and the potential effect of leadership cues on public polarization on environmental issues (Lewis-Beck et al., 2011), we are inclined to associate these changes with Donald Trump's denial campaigns and Greta Thunberg's environmental activism, which have impacted on climate change attitudes worldwide over the last three years. In fact, the drop in concern in 2017 might possibly reflect Donald Trump's denial speeches and the U.S. Paris Agreement withdrawal announcement in June 2017. Withdrawal was not effective before November 2020, but the announcement already impacted on the prospects of compliance by raising the cost of emission cuts for compliant countries and aggravating the leadership deficit in addressing climate change. Politicization of climate change by the Trump administration to some extent also jeopardized the authority of scientific evidence on climate change. On the other hand, the sizable upward shift in EU environmental attitudes in 2019 possibly reflects public response to Greta Thunberg's environmental activism and the "*Fridays for future movement*". Greta Thunberg's "*solo*" protest, which started in September 2018, rapidly became a worldwide phenomenon, and involved about 4 million people across 169 countries by September 2019. Over the last year, Greta Thunberg has attended various high-profile events across Europe and the U.S., including U.N. climate meetings. In March 2019 she was nominated for the Nobel Prize, in May 2019 was named one of the world's most influential people by the Time magazine and in December 2019 its Person of the Year.

This interpretation appears to be consistent with the very robust evidence on the political leader-follower linkage, in relation to climate change perceptions, already available for the U.S. For instance, Dunlap (2014) argues that conservative political leaders in the U.S. contribute to distrust in scientific evidence on climate change and to climate change skepticism among lay conservatives. Brulle et al. (2012) and Carmichael and Brulle (2016) also find that Congressional attention on climate change, which in turn influences media coverage, is the single most important determinant of public concern in the U.S. In this respect, the impact of elite opinion on mass opinion would be indeed mediated through media coverage. Similar conclusions are also drawn in Egan and Mullin (2017); see also Björnberg et al. (2017).

4 The climate change awareness curve

Nonlinearity and the potential role played by opinion leaders, noted in the above descriptive analysis, are reminiscent of the "S-shaped" information dissemination model, recently reproposed by Shiller (2017). This model predicts that an "innovation", when the decision to adopt is voluntary, will spread among the members of a social system in an S-shaped curve (sigmoid curve), in a manner similar to infection diseases. In our context, the S-shape, which describes the evolution of climate change attitudes, is modelled through the following logistic function

$$y = \frac{1}{1 + \exp\left(-\mathbf{x}'\boldsymbol{\gamma}\right)}, \tag{1}$$

where y is a given proxy for climate change concern, $\mathbf{x}$ is a vector of socio-demographic, economic, political and climatological control variables and $\boldsymbol{\gamma}$ the associated vector of parameters.

Standard theory posits that the S-shape arises from the engagement of *opinion leaders*, who actively diffuse the innovation and introduce it to other potential adopters, the *characteristics* (complexity) of the innovation and the *capability of adoption* of the social system, which depends on socio-demographic, economic and political characteristics. This dissemination process is also consistent with leader-follower relations grounded on elite cues, whereby leaders influence their respective group identifiers by providing 'cues' that help their followers to shape their beliefs on specific issues (Lewis-Beck et al., 2011).

Adoption then proceeds through a multi-stage process of assessment, acceptance and assimilation. It takes time for new ideas and concepts to become widely accepted. The S-curve posits a very slow rate of dissemination for a new idea at its inception. But if the spread of the new concept persists over time, what is initially accepted by only a few, and possibly ridiculed or even opposed by many, subsequently enters the mainstream and is accepted as *self-evident* and *given* by the majority. This pattern is traditionally grounded in the Kermack-McKendrick model of epidemics of disease, but the progressive saturation process is also reminiscent of the earlier, more general view expressed by the German philosopher Arthur Schopenauer (1788-1860), in his important book, *The World as Will and Representation*: "*The truth is always destined to have only one brief victory parade between two long time spans in which it is first being condemned as paradoxical and then belittled as trivial.*"[7] This quotation fits the basis of our theory of climate change attitudes, which can be specified mathematically by a function describing logistic dissemination, conditional to a set of determining variables.

[7] Der Wahrheit ist allezeit nur ein kurzes Siegesfest beschieden zwischen den beiden langen Zeiträumen, wo sie als paradox und als trivial gering geschätzt wird. [The World as Will and Representation, Preface to the First Edition, p. xxv; German: Die Welt als Wille und Vorstellung].

Within the set of determining factors already highlighted in the literature, we expect per capita income to play a key role in the determination of climate change attitudes. The direct link between climate change concerns and the level of per capita income can be theoretically motivated by the public good nature of environmental quality, for which demand increases with the level of income (Inglehart, 1995; Diekkman and Franzen, 1999; Franzen and Meyer, 2010). We name this relationship the "*climate change/environmental awareness curve*" (CCA curve). This curve is naturally related to the "environmental Kuznets curve" (EK), which describes an inverse-U shaped relationship between greenhouse gas emissions and the level of per capita income. Intuitively, once threshold income level is crossed, economic development becomes sustainable, i.e. higher income levels are associated with lower emissions, and, in our framework, also with higher climate change concern. This is because, as citizens enjoy a higher standard of living, they value more postmaterialistic values and public goods, such as the quality of life in general and of the environment too. Hence, income increases above threshold level are also associated with an increase in the demand for environmental protection, i.e. with an improvement in environmental attitudes.

In Figure 3, we report some descriptive evidence in support of the existence of such a linkage. In particular, in Panel A we report a cross-plot of climate change concern, as measured by the most comprehensive proxy $QB1QB2$, and real per capita GDP; in Panel B we report a cross plot of relative greenhouse gases emissions and real per capita GDP. In both cases temporal averages over the 2009-2019 period are employed As shown in the plot, a S-shaped pattern is noticeable in the climate change awareness curve, holding over the downward sloping portion of the environmental Kuznets curve.

Apart from real per capita GDP, consistent with the existing literature, we expect other variables, related to the socio-demographic, economic and political context, and to the acquisition and processing of information on climate change, to contribute to climate change attitudes. These additional variables might then account for shifts and changes in the slope in the CCA curve (in its awareness-per capita income space). In particular, we posit and asses the role of opinion leaders, the relative power position of right-wing parties in government, demographic effects, education, media coverage, social trust, financial damages inflicted by extreme weather episodes, physical distress associated with raising temperatures.

4.1 The econometric specification

The econometric specification of the climate change attitudes dissemination function is

$$y_t = \frac{1}{1 + \exp\left(\mathbf{x}'_{t-1}\boldsymbol{\beta} + \varepsilon_t\right)}, \tag{2}$$

where y is a given proxy for climate change concern, $\mathbf{x}$ is a vector of control variables, $\boldsymbol{\beta}$ its associated vector of parameters and ε_t is a zero mean $i.i.d.$ stochastic disturbance term. The model can be easily linearized, yielding the OLS estimable function

$$ln(\frac{1}{y_{i,t}} - 1) = \mathbf{x}'_{t-1}\boldsymbol{\beta} + \varepsilon_t, \tag{3}$$

which, for our panel of 28 countries, becomes

$$y^*_{i,t} = \mathbf{x}'_{i,t-1}\boldsymbol{\beta} + \varepsilon_{i,t}, \tag{4}$$

where $y^*_{i,t} = ln(y^{-1}_{i,t} - 1)$, $i = 1, ..., N$ is the country index, which refers to the 28 European countries in the sample (EU27 member countries plus the UK) and t is the temporal index, which refers to years 2009 through 2019, apart from Croatia, for which we have data only since 2013. Hence, the panel counts 166 observations in total, since our proxy variables for climate change concern are available at a biannual frequency. Moreover, $\varepsilon_{i,t} \sim i.i.d.\left(0, \sigma_{\varepsilon}^2\right)$. Then, comparison between (1) and (2) yields $\hat{\boldsymbol{\gamma}} = -\hat{\boldsymbol{\beta}}$.

The lead-lag model is a natural setting for the investigation of the data at hand, since survey results are collected in March/April and therefore much earlier than the contemporaneous control variables. Accordingly, all the regressors sampled at an annual frequency enter the specification with a one year lag. When 2018 figures are missing, as in a few cases, they are replaced with their 2017 values.

Since the conditioning regressors are predetermined, under poolability conditions, the OLS estimator is expected to provide consistent and asymptotically normal estimates.

Still within the above *pooled* specification, the panel data nature of our data can be taken into account by the inclusion of some conditioning variables that are either time-invariant (allowing to control for stochastic country-effects) or country-invariant (allowing to control for stochastic time-effects).

Given the large set of potential regressors available, we implement a *general to specific* specification strategy, which, through a sequential reduction procedure based on statistical testing, yields a final parsimonious econometric model describing the phenomenon of interest.

The specification in (4) can however be augmented to account also for unknown sources of cross-sectional *random effects* (in addition to those already controlled for by the inclusion of time-invariant regressors), yielding

$$y_{i,t}^{*} = \delta_i + \mathbf{x}_{i,t-1}' \boldsymbol{\beta} + \varepsilon_{i,t}, \tag{5}$$

where $\varepsilon_{i,t} \sim i.i.d.\left(0, \sigma_{\varepsilon}^2\right)$, $\delta_i \sim i.i.d.\left(0, \sigma_{\delta}^2\right)$, and $\varepsilon_{i,t}$ and δ_i are mutually independent. Moreover, the regressors are still predetermined, and therefore not contemporaneously correlated with $\varepsilon_{i,t}$ and δ_i. Under these conditions the OLS estimator of $\boldsymbol{\beta}$ is consistent, but delivers distorted standard errors. Consistent and more accurate estimation can then the performed by means of the Estimable Generalized Least Squares Estimator (EGLS).

Since some of the potentially relevant regressors are time-invariant, the alternative *fixed effects* approach cannot be implemented using the standard *within* transformation. Fixed effects can however be accounted for, also when time-invariant regressors are included in the model, by following a general to specific procedure, implemented through an autometrics/saturation algorithm (Hendry et al., 2008; Johansen and Nielsen, 2009; Doornik, 2009).[8]

The specification in (4) can then be augmented to account for deterministic country and time effects, as well as for influential observations, yielding

$$y_{i,t}^{*} = \mathbf{x}_{i,t-1}^{*\prime} \boldsymbol{\beta} + \sum_{j=1}^{N} d_{i,t}^{j} \delta_i + \sum_{s=1}^{T} \tau_t^{s} \eta_s + \sum_{\substack{j=1 \\ s=1}}^{\substack{T \\ N}} i_{i,t}^{j,s} \theta_{is} + \varepsilon_{i,t}, \tag{6}$$

where $d_{i,t} = 1$ if $i = j$ and 0 else (*step country-i* effect), $\tau_{s,t} = 1$ if $s = t$ and 0 else (*year-s* effect), $i_{i,t}^{j,s} = 1$ if $i = j$, $s = t$ and 0 else (*impulse country-i* at *year-s* effect), δ_i, η_s, θ_{is} are parameters, and $\varepsilon_{i,t} \sim i.i.d.\left(0, \sigma_{\varepsilon}^2\right)$. Since the regressors are predetermined, OLS yields consistent and asymptotically normal estimation.

Deterministic time and country effects are then selected, as for the other conditioning variables, through an automated general to specific reduction strategy. Hence, relative to standard panel data modelling, our approach is also likely to yield efficiency improvements, due to the parsimony ensured by the general to specific estimation strategy. Moreover, in the light of the results of the descriptive analysis, the saturated regression analysis makes it possible to assess

[8]The econometric analysis and GETS specification analysis has been performed by means of the OxMetrics 8 package by D.F. Hendry and J.Doornik. The package is available at https://www.timberlake.co.uk/software/oxmetrics.html#products.

the robustness of our findings to potential sources of model misspecification, such as outliers and structural change. These can be attributed to events gone unaccounted in the model and to shifting distributions, for instance in terms of sudden location shifts and changes in the trend rate of growth, respectively.

Since the selected deterministic country effects are potentially large in our context, efficiency and estimation accuracy might be increased by combining the retained deterministic effects in a single variable, as delivered by their linear combination, with weights appropriately selected. This constrained version of model (4) is the *restricted* or *constrained* saturated model

$$y^*_{i,t} = \mathbf{x}^{*\prime}_{i,t-1}\boldsymbol{\beta} + \alpha FCE_{i,t} + \sum_{s=1}^{T} \tau^s_t \eta_s + \varepsilon_{i,t}, \tag{7}$$

where

$$FCE_{i,t} = \sum_{j=1}^{N} d^j_{i,t} w(\delta_i) + \sum_{\substack{j=1\\s=1}}^{\substack{T\\N}} i^{j,s}_{i,t} w(\theta_{is}),$$

and $w(\delta_i)$, $w(\theta_{is})$ are the weights employed in the linear combination of fixed country effects $FCE_{i,t}$. Upon testing the restrictions implicit in the construction of $FCE_{i,t}$, the constrained model in (7) can be consistently estimated by OLS. The constrained model grants the same fit, specification and robustness properties of its unconstrained version, yet a higher efficiency and accuracy, due to the larger number of degrees of freedom available.

Finally, notice that the transformed dependent variable $y^*_{i,t}$, by construction, takes values in the $[-\infty, +\infty]$ interval, making our linearized specification in principle compatible with an additional assumption of conditional Gaussianity for the error term; this would grant to the OLS estimator the usual interpretation in terms of ML estimator, therefore ensuring consistent, asymptotically normal and asymptotically efficient estimation.

Also, in the empirical implementation, in order to improve numerical accuracy, the non-negative explanatory variables are transformed according to the function

$$x^*_{ij,t} = \frac{x_{ij,t} - \min(\mathbf{x}_j)}{\max(\mathbf{x}_j) - \min(\mathbf{x}_j)},$$

where $x^*_{ij,t}$ is the country i, time period t panel observation for the generic regressor j; $\max(\mathbf{x}_j)$ and $\min(\mathbf{x}_j)$ are the maximum and minimum values for the generic regressor j over the panel sample, respectively. Thus, by construction, the transformed regressors take values in the $[0, 1]$ interval.

5 The data

The proxy variables for climate change attitudes are denoted by the variable $y_t = QB1a$, $QB1b$, $QB2s$, $QB2vs$, $QB1$, $QB2$, $QB1QB2$. All these series are already described in Section 2. On the other hand, various control variables for the underlying socio-demographic, economic, and political environment and (academic and non-academic) information sources are included in the set of regressors $\mathbf{x}_t$ in (4).

Firstly, consistent with the direct linkage between environmental attitudes and standard of living described by climate change/environmental awareness curve, we include real per capita GDP (GDP). The series employed in the study is the chain linked volumes (2010) Euro per capita gross domestic product at market prices, available from Eurostat for each of the countries in the sample.

Secondly, we posit a role for two *opinion leaders*, i.e. U.S. President Donald Trump ("brown" leader) and Greta Thunberg ("green" leader), whose activities might be best associated with events occurring in 2017 and 2019, respectively. Hence, two dummy variables are included, i.e., an impulse time dummy for year 2017 (DT), to control for the potential impact of *Donald Trump* denial campaigns, dismantling of environmental protection in the U.S. and announcement of the U.S. withdrawal from the Paris Agreement in 2017; an impulse time dummy for year 2019 (GT), to control for the potential impact of *Greta Thunberg's* environmental activism and the "*Fridays for Future*" movement, which, started in 2018, became a worldwide phenomenon in early 2019.

Moreover, a lower environmental concern might be expected in countries ruled by right-wing/conservative parties, which generally represent the interests of business and industries in Western countries (Franzen and Vogl, 2013; McCright et al., 2016).[9] As a measure of *Government political composition,* we then include an index of relative power position of right-wing parties in government, based on their share of seats in parliament, measured as a percentage of the total parliamentary seat share of all governing parties, weighted by the number of days in office in a given year (GRP). This index is available annually for each of the countries in the sample. The source is the Comparative Political Data Set 1960-2017, compiled by the Institute of Political Science of the University of Berne (https://www.cpds-data.org/).

The dissemination process might also be expected to proceed at a quicker pace in countries with a relatively higher proportion of *young* people in the total population, as they are the generation most exposed to the impact of climate change, which will manifest in full only in the years to come. To control for demographic effects, we thus include the ratio of *young people* in the total population (YTH), as measured by the ratio of population from 15 to 29 years old in total population. The series is available annually for each of the countries in the sample from Eurostat.

Another potentially relevant variable is the degree of *trust* that the country's citizen have in their institutions. This might follow from the nature of environmental protection as a public good. Greater trust in others might thus indicate greater concern for public goods, as well as the belief that others will cooperate to provide and maintain them (Franzen and Vogl, 2013; Harring, 2014; Smith and Mayer, 2018). It can however also follow from "social trap" argument, whereby higher trust amplifies the effect of risk perceptions on climate policy support or climate behaviors (Rothstein, 2014). We thus also include an overall social *trust* index in institutions (TRT), computed by averaging the rating (0-10) of trust in police, the legal system, the political system and in others, by all citizens aged 16 years or over. The four component series of the index are available from Eurostat for each of the countries in the sample for year 2013 only. Since this variable is time-invariant, it also controls for *stochastic country effects.*

There is also an interesting mechanism of taking *responsibility* for the human-made origin of climate change and, therefore, of a country's contribution to the phenomenon. This might explain the direct linkage existing between emissions and environmental concern (Schwirplies, 2018). Yet, consistent with the linkage between the CCA and EK curves, the expected linkage might also be negative, as beyond per capita income threshold level economic development becomes sustainable, and therefore associated with lower GHG emissions. We thus include per capita *greenhouse gas emissions* (GHG) in order to control for a *responsibility assumption* effect, as well as coherent with our theoretical framework. The series comprise the total (all NACE activities) greenhouse gases Kilogram per capita emissions (CO2, N2O in CO2 equivalent, CH4 in CO2 equivalent).

The acquisition and processing of information might be expected to play a key role in developing the cognitive dimension of climate change attitudes (Franzen and Vogl, 2013; Smith and Mayer, 2018). Academic and non-academic sources of information are probably important.

[9]Right-wing/conservative' skepticism toward environmental sciences might also originate from a conflict between specific ideological values and the proposed environmental solutions (Campbell and Kay, 2014).

Information acquired during primary, secondary and tertiary education comes from academic sources. In general, education can make individuals more concerned with overall social welfare, including the external benefits of their actions. But the findings on the effects of tertiary education are conflicting (Wicker and Beckern, 2013; D'Amato et al., 2019), and a negative linkage might well originate from cultural polarization and conflict of interest (Kahan et al., 2011; Kahan et al., 2012), in addition to cognitive bias and self-denial. Therefore, we consider, as factors which might contribute to the accumulation of *theoretical knowledge* about climate change, the levels of secondary and a tertiary education. These are measured by the percentages of total population (aged from 15 to 64 years) with a secondary (SEC) and a tertiary (TER) education level, respectively. Both series are available annually for the various countries in the sample from Eurostat.

Printed and online media, such as blogs, magazines and newspapers, are non-academic sources of information. We then also consider a volume index for *climate change media coverage* in our analysis. The index is computed from the average monthly volume of media articles in which the words "climate change" are cited more than 3 times over the three months preceding the survey, i.e. January, February and March. The index is available for years 2015, 2017 and 2019, for 25 out of the 28 European countries in the sample (data are missing from Germany, Romania, Latvia). The source is the Centre for Advanced Studies of the European Commission, Joint Research Centre (unofficial database produced under the Big Data and Forecasting of Economic Developments (bigNOMICS) project). Given the time mismatch, this information is included through three separate variables, one for each of the available years, i.e. $MC15$, $MC17$, $MC19$.

In addition to "theoretical" knowledge, direct "*experience*" of climate change should also be considered. This is associated with the appreciation of the human, monetary and physical impact of climate change, i.e. the damages and fatalities caused by extreme weather episodes, as well as direct experience of heatwaves, heavy rainfalls or floods, droughts, sandstorms, windstorms, or avalanches (Andor et al., 2018; Bergquist and Warshaw, 2019; Konisky et al., 2016; Zaval et al, 2014; D'Amato et al., 2019; Kaufmann et al., 2017). Hence, concerning the factors which might contribute to the accumulation of *practical knowledge* about climate change, we include two proxy variables for the *monetary* impact of climate change. These data are available annually in million Euro for the EU economy as a whole ($EULOSS$) and as per capita euro cumulative figures (1980-2017) for each of the countries in the sample ($LOSS$) from the European Environment Agency (EEA) and Eurostat, respectively. The annual overall EU series is deflated by means of the EU average harmonized consumer price index, which is also available from Eurostat. Notice that $EULOSS$, by being country-invariant, also control for *stochastic time effects*. Moreover, by being time-invariant, $LOSS$ controls for *stochastic country effects*.

Moreover, we include two indicators of perceived climatological change, in relation to its physical impact, i.e. the number of *cooling degree days* ($COOL$), which yields a measure of the intensity of the use of cooling facilities, and the negative component of the Southern Oscillation Index ($SOI\_$), which corresponds to El Niño episodes. In Europe, El Niño episodes are associated with hotter summers and wetter and warmer autumns and early winters (King et al., 2018). While the El Niño-Souther Oscillation (ENSO) cycle is a natural phenomenon, global warming can be expected to enhance its intensity (see Morana and Sbrana (2019) and references therein). Hence, we also include $SOI\_$ as a source of additional information on climate change, in relation to perceived temperature increases over summers, autumns and early winters. In this respect, the more negative the realization in $SOI\_$ and the more intense the El Niño phase, the warmer summer to early winter weather will be. Cooling degree days data are available annually for each of the countries in the sample from the European Environment Agency (EEA) and Eurostat. The Southern Oscillation Index is also available annually; since it is country-invariant, it allows to account for *stochastic time effects*.[10]

In terms of $\boldsymbol{\gamma}$ parameters in (4), (5), (6), and (7), we thus expect a positive linkage between climate change concern and percapita (GDP), environmental activism (GT), the share of young people in the total population (YTH), social trust (TRT), the level of secondary education (SEC), media coverage (MC), financial losses associated with extreme weather episodes ($LOSS$, $EULOSS$), physical distress associated with raising temperatures ($COOL$), and a negative linkage for denial campaigns (DT), the relative power position of right-wing parties in government (GRP), and the negative component of the Southern Oscillation Index (SOI_{-}). On the other hand, we have no a priori assumptions concerning the level of tertiary education (TER) and greenhouse gases emissions (GHG). Full details on the variable employed in the study can be found in the Online Appendix.

6 Estimation results

As already mentioned in the methodological Section, given the large set of potential regressors available, we implement a *general to specific* specification strategy, using a 5% target significance level. Through a sequential reduction procedure based on statistical testing, this approach yields a final parsimonious econometric model, describing the determination of climate change concern. Still within this framework, we also carry out an impulse saturation analysis (Hendry et al., 2008; Johansen and Nielsen, 2009; Doornik, 2009). The saturated regression analysis makes it possible to assess the robustness of our findings to potential sources of model misspecification, such as outliers and structural change. This is also the framework where we can handle deterministic country effects, given the inclusion of some time-invariant regressors in the model, which would prevent the implementation of standard approaches, such as least squares dummy variable estimation (LSDV). We double check the validity of the reduction process by carrying out variable-by-variable omission tests in both the standard and saturated estimation settings.

The (final) econometric models are shown in Tables 2-4 and Table A3 in the Online Appendix, while the results of the omission tests in Tables A1, A2, A4, A5 in the Online Appendix. In all cases, results are reported for each of the proxy variables for climate change concern used in the study, i.e. $QB1a$, $QB1b$, $QB2s$, $QB2vs$, $QB1$, $QB2$, $QB1QB2$. The tables also report the estimated $\boldsymbol{\gamma}$ parameters, as delivered by the transformation $\hat{\boldsymbol{\gamma}} = -\hat{\boldsymbol{\beta}}$.

6.1 Results for the benchmark proxy variable

We initially focus our discussion on our preferred proxy variable for climate change attitudes $QB1QB2$, which measures the percentage of respondents who rank climate change as one of the four most serious global threats ($QB1$) and view this challenge as at least of serious gravity ($QB2$). As shown in Table 2, the explanatory power of the pooled model (4), as measured by both the adjusted (64%) and unadjusted (67%) coefficients of determination, is highly satisfactory.

Our results indicate that, over the last decade, concern for climate change has increased with the level of per capita income (GDP), yet at a decreasing rate, as shown by the negative impact of its squared value ($GDP2$). This finding provides additional support to the descriptive evidence on the CCA curve already presented, which is then robust to the inclusion of alternative/complementary determinants of climate change attitudes. Hence, since European countries over the time span assessed belong to the downward sloping portion of the EK curve (Figure 3), we can then expect that further improvements in standard of living be associated with lower relative GHG/GDP emissions and higher environmental attitudes.

[10] SOI data are available at https://www.ncdc.noaa.gov/teleconnections/enso/indicators/soi/.

Significant effects are also found for social trust and greenhouse gas emissions, which enter the regression function interacted with per capita income ($TRUSTGDP$ and $GHGGDP$). These variables affect the slope of the CCA curve, respectively amplifying and dampening the effects of income. The first result is consistent with the nature of environmental protection as a public good, as the higher social trust and concern for public goods, the greater the belief that others (citizens and institutions) will cooperate to provide and maintain public goods (Franzen and Vogl, 2013; Smith and Mayer, 2018). Moreover, the negative impact of greenhouse gas emissions is consistent with the posited linkage between the CCA and EK curves, and the downward slope of the EK curve prevailing over the assessed sample (Figure 3). Moreover, we also find a significant impact for the time dummies for years 2017 and 2019, accounting for a sizable drop and a sizable increase in environmental concern, respectively, ceteris paribus. While our study cannot establish causal linkages, consistent with the expected role of opinion leaders in our theoretical framework, and the already available empirical evidence for the U.S. (Dunlap, 2014; Brulle et al., 2012; Carmichael and Brulle, 2016), we are inclined to associate these changes with Donald Trump's denial campaigns and Greta Thunberg's environmental activism, respectively. While keeping in mind the above mentioned caveat on causality, in light of the estimated impacts, the positive *Thunberg effect* appears to have prevailed over the negative *Trump effect*. Consequently, concern for climate change in the EU would have risen thanks to the environmentalist response to Trump's denial campaigns. The net effect is thus an upward shift in the environmental awareness curve in the income-awareness space.

Moreover, consistent with previous findings, we also find a significant impact of education on the formation of environmental attitudes. We find a positive link between secondary education (SEC) and climate change concern (Franzen and Vogl, 2013; Smith and Mayer, 2018). However, a negative, dampening effect is found for tertiary education (TER) (see also D'Amato et al., 2019). This implies that, *ceteris paribus*, the higher the percentage of citizens with tertiary education, the higher the country level of skepticism on climate change. This finding is fully consistent with previous evidence in the literature (Kahan et al., 2011; Kahan et al., 2012), pointing to various explanations, ranging from cognitive bias and self-denial to elitist cultural worldviews and conflict of interest.

Finally, we also detect a contribution to the change in attitudes of experience of climate change effects, in relation to the physical distress associated with hot weather and damages caused by extreme weather episodes. In particular, concerning the experience of raising temperatures (global warming), our analysis points to cooling degree days ($COOL$), i.e. the intensity of usage of cooling devices, as an important explanatory variable. This is consistent with other results in the literature (Kaufmann et al., 2017; D'Amato et al., 2019), which show that the understanding of global warming might help to deepen perception of climate change. Similar considerations hold for the effects of extreme weather episodes (Andor et al., 2018), in terms of the financial loss caused ($LOSS$). Financial loss enters the econometric model also interacted with GDP ($LOSSGDP$) and provides a dampening mechanism for the effects of income, by flattening the slope of the CCA curve in the awareness-income space. This is consistent with the fact that a country's ability to face climate change is proportional to its level of income. The same amount of loss would contribute differently to climate change attitudes in countries with different levels of income, i.e. the higher the income, the lower the impact of the same amount of loss on environmental concern. However, as for the understanding of global warming and for education, loss also enters the specification non interacted with income, thus acting as a shift factor too.

6.1.1 Results for the random effects model

While the pooled specification shows a desirable fit and no evidence of misspecification in terms of the Pesaran residual cross-section test, it appears to fail the Honda test for omitted random cross-country effects. This means that the included time-invariant regressor, i.e. cumulative financial losses from extreme weather ($LOSS$), might not be sufficient to account for cross-country random variability.

In the light of this finding, in Table 3 we show results for EGLS estimation of a random-effects model (5). When comparing the pooled and the random-effects models, two main differences might be noted, i.e. the omission of the interacted $LOSSGDP$ regressor and the inclusion of the climate change media coverage index for year 2019 $MC19$. The latter enters the regression with a positive coefficients, confirming the view that focusing public attention on climate change improves environmental attitudes. Apart from the above mentioned changes, all the other findings obtained from the pooled model are confirmed, i.e. the positive and nonlinear impact of living standard, the positive (negative) impact of secondary (tertiary) education, the negative impact of GHG emissions and the positive impact of social trust (both interacted with GDP), the positive impact of distress associated with higher temperatures (cooling degree days), as well as of financial losses caused by extreme weather. Also the Trump vs. Thunberg effect is fully confirmed for the cross-sectional random effects model. As shown by the coefficient of determination computed for the unweighted data, the random effects model has a similar explanatory power to the pooled model and largely passes the Pesaran residual cross-sectional dependence test, supporting the specification of the final econometric model delivered by the general to specific reduction procedure.

6.1.2 Results for the fixed effects model

In order to assess the robustness of the above findings, in Tables A3 in the Online Appendix and Table 4 we report the results of OLS estimation of the fixed time and country effects models (6) and (7), implemented through the autometrics/saturation procedure. The autometrics procedure allows for accurate selection of potentially omitted deterministic country effects, also in the form of influential observations, as well as of potentially omitted deterministic time effects. In particular, in Table A3 in the Online Appendix we report the results for the *unconstrained* specification (6), where the retained deterministic components are shown in Panel A, the retained conditioning regressors are shown in Panel C, the linear combinations ($FCE_{i,t}$) of the various retained fixed country effects are shown in Panel B, as well as the restrictions implicit in their construction and the p-value of their Wald test. Finally, in Table 4 we report the estimation results for the *constrained* saturated model (7), obtained by imposing the restrictions holding for the retained fixed country effects, validated by the Wald test.

As shown in Table A3, Panel A, 16 deterministic country effects are retained in the specification for $QB1QB2$. Of these, ten are step dummy country effects, pointing to higher than average environmental concern for Belgium, Germany, Greece, Spain, France, Hungary, Malta, Sweden and Slovenia, and lower than average concern for Poland. The remaining impulse country effects, point to higher than average environmental concern for Belgium, Cyprus, Greece and Slovenia for year 2009; the Netherlands for year 2017; Latvia for year 2011. As shown in Table A3, Panel C, the retained conditioning variables are the same as those selected for the pooled model, also pointing to quantitatively similar results. In this respect, all the findings obtained from the pooled model are fully confirmed, i.e. the positive and nonlinear effect of living standard, the positive (negative) effect of secondary (tertiary) education, the negative effect of GHG emissions and the positive effect of social trust (both interacted with GDP), the positive effect of distress associated with higher temperatures (cooling degree days), as well as of financial losses caused by extreme weather. Moreover, also the Trump vs. Thunberg effect is fully confirmed. Relatively, to the random effects model, the media coverage variable for year 2019 is not any longer included in the specification. While the variable appears to be statistically significant, positively impacting on climate change attitudes, its exclusion is required by the Schwarz-Bayes (SC) information criterion. Notice also that diagnostics and fit are sizably better in the saturated specifications. In particular, the coefficient of determination shows an increase of about 20% compared to the non-saturated models. Moreover, the Pesaran residuals cross-dependence test is largely passed and no evidence of unaccounted random effects is detected by the Honda LM test.

In Table A3, Panel B, we then report the proposed linear combination of the retained fixed country effects, the implicit null hypothesis supporting its construction, and the p-value of the associated Wald test. In the light of the non rejection of the restrictions, the constrained saturated regression model is estimated by OLS. As reported in Table 4, the constrained saturated regression model shows, relatively to its unconstrained form, the same fit, specification and robustness properties than its unconstrained form. The constrained model however benefit from higher efficiency and accuracy, due to the larger number of degrees of freedom available (153 rather than 138, as for its unconstrained version).

6.1.3 Robustness results

In order to double check the validity of the reduction procedure used in the paper, t-ratio tests for the omission of a relevant variable were also run. The tests were run variable-by-variable, for each of the regressors that were eventually omitted from the final econometric model. The results for the constrained saturated regression model are reported in Table A4 in the Online Appendix.[11]

As shown in Table A4, the validity of the reduction analysis is fully confirmed, as none of the omitted variables turns out to yield any improvement to the fit of the model in terms of the SC information criterion, even when turning statistically significant, as for the media coverage index for year 2019 ($MC19$), or the step country dummy variables for Bulgaria and Denmark.

Finally, in Table A5 in the Online Appendix we also report the test for omission of additional potentially relevant variables, useful to characterize the underlying socio-economic and political context, such as the level of internet access (IA), the Notre-Dame Gain Index (NDG), the total environmental taxes to GDP ratio (ET), an index of vegetarian/health attitudes (VH), an index of passengers cars efficiency ($CO2$), an index of energy productivity (ENE), the Environmental Performance Index (EPI), an alternative political index measuring Government political composition, in relation to preferences for right-wing parties (GRC), the Global Gender Gap Index (GGG) and its Political Empowerment Subindex (PEG). Additional climatological variables, such as the European temperature anomaly ($TEMP$), heating degree days ($HEAT$), the number of fatalities caused by extreme weather and climate related events (FAT), the Accumulated Cyclone Energy Index (ACE) are also considered. Full details about the construction of these variables can be found in the extended data section reported in the Online Appendix. As shown in the Table, none of these regressors is found to significantly contribute to climate change attitudes over the sample considered.

6.2 Results for the other proxy variables

As shown in Tables 2-4 and A3 in the Online Appendix, most of the above findings are fully robust to the climate change concern proxy and the estimation strategy employed. In this respect, the positive linkage between climate change concern and standard of living (GDP) is fully confirmed across specifications and estimation methods; however, quadratic effects turn out to be significant only for $QB1b$ (the percentage of respondents who rank climate change the second to fourth most important challenge), and $QB1$ (the percentage of respondents who rank climate change as one of the four most important challenges).

[11] Selected results for the pooled and random effects models are available in Table A1 and A2 in Online Appendix.

Also fully confirmed is the dampening impact on the slope of the CCA curve of green house gas emissions ($GHGGDP$), apart from $QB1b$, and the negative impact of tertiary education (TER). On the other hand, secondary education (SEC) appears to have a fully robust positive impact only for $QB1b$, and is retained in the model for $QB1$ only (pooled and random effects models).

Moreover, fully robust is the impact of the Thunberg effect (GT); on the other hand, concerning the Trump effect (DT), a negative impact can only be found on the relative ranking of climate change among the various challenges, but not on the appreciation of its gravity. In fact, DT enters with a negative coefficient in the specification for $QB1a$ (the percentage of respondents who rank climate change as the first most important challenge), as well as $QB1b$ and $QB1$. These results indicate that Trump's denial campaigns might have then lowered the ranking of climate change relative to the other potential major challenges. Yet DT enters with a positive coefficient in the specifications for $QB2vs$ (the percentage of respondents who rank climate change as a very serious threat) and for $QB2$ (the percentage of respondents who rank climate change as at least a serious threat). This indicates that Trump's denial campaigns might have not undermined, but enhanced the perceived seriousness of the climate change threat in Europe.

Also confirmed is the positive impact of physical distress in relation to raising temperatures, as measured by the use of cooling facilities ($COOL$), and of financial losses caused by extreme weather episodes ($LOSS$). Both variables cause an upward shift of the CCA curve for all the specifications, apart from $QB1a$, which is positively affected by the other measure of monetary damages caused by extreme weather, i.e. the aggregate EU figure $EULOSS$. In addition to $Q1a$, $EULOSS$ exercises a positive impact also for $QB2s$ (the percentage of respondents who rank climate change as a serious threat), $QB2vs$, and $QB2$. Interestingly, in the light of the positive impact of $EULOSS$ on $Q1a$, its negative (and less sizable) impact on $Q1b$ (in the pooled and random effects specifications) suggests that the appreciation of monetary damages inflicted by extreme weather episodes has upward shifted climate change in the ranking of the most important challenges, i.e. from the second to fourth most important challenge to the most important one. Moreover, the appreciation of changing climate, as portrayed by the intensity of El Niño episodes, also seems to have had a positive impact on climate change concern for $QB2$ ($SOI\_$ shows a negative coefficient).

Less clear-cut is the evidence for the impact of social trust ($TRUSTGDP$) and financial losses associated with extreme weather episodes ($LOSSGDP$) on the slope of the CCA curve. For instance, a robust amplifying impact of social trust is found for $QB1$ and $QB1a$; a dampening effect of financial losses associated with extreme weather episodes is found for $QB1$, $QB2$ and $QB2vs$, yet robust across estimation methods only for $QB2vs$.

Also not fully clear-cut is the impact of media coverage on climate change attitudes. While the pooled specifications do not retain any of the media coverage variables, positive significant impacts are found for $MC19$ for $QB1$, $QB1a$ and $QB2vs$ in the random effects and fixed effect (saturated) regressions. $MC19$ also enters significantly in the random effect specification for $QB2s$. Similarly for the saturated regression, albeit the media variable is there not retained, due to its impact on the SC information criterion (see Table A4 in the Online Appendix). Finally, a positive impact is also found for $MC17$ in the saturated regression for $QB2vs$ only.

Interestingly, two additional regressors seem to have mattered concerning the ranking of climate change as the most important challenge ($QB1a$), i.e. the share of young people to total population (YTH), which exercises a robust, positive impact; the relative power position of right-wing parties in government (GRP), which exercises a negative impact in the fixed effects (saturated) regression. These results are consistent with expectations, as well as with previous evidence for the U.S.. In fact, the positive impact of YTH is consistent with the fact that young people show a greater ability to adapt to changes, and are also the generation most exposed to the impact of climate change (Franzen and Vogl, 2013). Moreover, the negative impact of GRP is consistent with previous evidence pointing to a lower environmental concern in countries ruled by right-wing/conservative parties (Franzen and Vogl, 2013; McCright et al., 2016).

Finally, the $QB2s$ regression shows estimated coefficients with an opposite sign relative to any other regressions. This reflects the contraction in the percentage of respondents who view climate change as *only* a serious problem ($QB2s$) over time. Since there is an overall increase in the percentage of respondents who view climate change *at least* as a serious problem ($QB2$), the increase in the percentage of respondents who view climate change as a very serious problem, i.e. $QB2vs$, is stronger than the contraction in $QB2s$.

As for the results of the omission analysis, as shown in Table A4, we fully confirm the validity of the reduction strategy also for the additional proxy variables assessed in the study. In particular, few country step dummies turn out to be statistically significant at the 5% level (11 cases out of 196 across all the specifications), a deterministic time effect for year 2013 and the Environmental Performance Index (EPI) for $QB1b$, the Political Empowerment Subindex (PEG) for $QB2s$. All these variables were not included in the final specifications, due to their impact on the SC information criterion. Similarly for the already mentioned significant impact of the media coverage variable $MC19$ for $QB2s$ and $QB1a$; $MC17$ for $QB1a$; $MC15$ for $QB2vs$. While also these variables where not included in the final specifications, due to their impact on the SC information criterion, overall they do provide additional support to the view that media coverage of climate change improves environmental attitudes, in relation to both the relative ranking of climate change as a global challenge and its perceived gravity.

7 Conclusions

At current levels of greenhouse gas emissions, the carbon budget for meeting the Paris Agreement target of 2°C will be depleted in less than three decades, while less than a decade is left to limit the increase in global temperature to 1.5°C (IPCC, 2018). Yet these scenarios might even be optimistic, since greenhouse gas emissions are still increasing globally and there might in fact be only time left to contain - not to avoid - large-scale discontinuities in the climate system. International climate *action* is urgently needed. In the light of these considerations, understanding the drivers of climate change attitudes is an important and urgent task, since in democratic systems the legitimacy of political decisions on climate change mitigation actions relies on the support of public opinion. And this will only support measures when there is sufficient awareness of its environmental, economic, human and social implications. Our study contributes to this effort, pinning down some key drivers of climate concern.

Using aggregate figures from the Special Eurobarometer surveys on Climate Change, we find that the evolution of climate change attitudes over time is well described by the "S-shaped" information dissemination model, recently reproposed by Shiller (2017), conditional to various socioeconomic and climatological factors.

Specifically, we find that climate change concern has increased with the level of per capita income. We name this relationship "*climate change/environmental awareness curve*". This curve is theoretically motivated by the public good nature of environmental quality, for which demand increases with the level of income. This curve is also related to the "environmental Kuznets curve", which describes an inverse-U shaped relationship between greenhouse gas emissions and the level of per capita income. Once threshold income level is crossed, economic development becomes sustainable, i.e. higher income levels are associated with lower emissions, and, in our framework, also with higher climate change concern.

Significant effects are also found for social trust and greenhouse gas emissions, which enter the regression function interacted with per capita income. These variables affect the slope of the environmental awareness function, amplifying and dampening the effects of income. Moreover, we find a positive linkage between media coverage, secondary education and climate change concern, but a negative effect for tertiary education. This latter finding surely raises questions about the role of cultural polarization, conflict of interest, cognitive bias and self-denial, in the spreading of a technophilic optimism about humankind's ability to face the climate challenge.

We also detect significant effects from the experience of climate change, in relation to the physical distress associated with hot weather and loss inflicted by extreme weather episodes. Financial loss enters the regression function also once interacted with income and provides a dampening mechanism for the effects of income, by flattening the awareness function. The higher the income of a country, the lower the impact of the same amount of damages on environmental concern.

Finally, we also find a significant impact for two temporal dummies for year 2017 and 2019, accounting for a sizable drop and a sizable increase in environmental concern, respectively, ceteris paribus. While our study cannot establish causal linkages, consistent with the expected role of opinion leaders within our information dissemination model, as well as with robust evidence for the political leader-follower mechanism on environmental issues for the U.S., we are inclined to associate these changes with Donald Trump's denial campaigns and politicization of climate change and Greta Thunberg's environmental activism, respectively. By keeping in mind the above mentioned caveat on causality, in the light of the estimated effects, the positive *Thunberg effect* appears to have prevailed over the negative *Trump effect*. Environmental concern in the EU might have then risen as a consequence of the public controversy on climate change following the election of President Trump. This interpretation is further supported by the significant positive impact detected for the share of young people and media coverage in 2019, and the negative impact of the relative power position of right-wing parties in government, on the ranking of climate change as the most important challenge currently facing humanity.

Two main policy implications follows from our study. Firstly, in the light of the key role played by living standard in the determination of environmental concern, it appears that income levels should be preserved during any transition to a carbon neutral economy. This is even more urgent in the light of the sizable worldwide economic contraction caused by the COVID-19 pandemics, since, as also learned during the Great Recession, public's concern about climate change is negatively affected by economic insecurity (Scruggs and Benegal, 2012).

Secondly, in the light of the contribution of media coverage and education to environmental awareness, it is important that scientific evidence about climate change be disseminated as broadly as possible to citizens, through academic and non-academic channels. Moreover, in the light of the contribution of the appreciation of financial losses caused by extreme weather episodes and the physical distress associated with raising temperatures, citizens should also be guided towards better connecting the "experience" of global warming and extreme weather episodes to climate change.

In this respect, the UK is a leading example for reforms to the education system, aiming to teach young people, at the primary and secondary school levels, about the urgency, severity and scientific basis of the environmental crisis, which can be easily imported in other countries.[12]

The negative impact of tertiary education on climate change attitudes might however be a signal that these efforts should be further pursued at the tertiary education level as well. In this respect, given the sizable economic, financial, social, and political consequences of climate change, the inclusion of climate change education into academic curricula in social sciences

[12] For instance, in the UK, primary school children are taught about how human actions can affect the environment, while in secondary science they are taught about the sources of carbon dioxide emissions, including human activities, and their effects on the climate. Moreover, in GCSE science, they are taught about the evidence for human-made climate change, how greenhouse gases emissions can be reduced, and renewable energy sources. In GCSE geography, they are taught about the causes, consequences and responses to extreme weather disruptions. Finally, since 2017, students have been able to take an environmental science A-level.

appears to be not only sound, but also extremely urgent.

Moreover, a broader coverage and better reporting of climate research findings in the mainstream media is also important. The underreporting of climate findings and natural disruptions around the world appears to be a major impediment to information dissemination, which do require media coverage, in order to foster climate change awareness and counterbalance contrarian arguments, often channeled through nowcast media and electronically spread (Hamilton, 2011). In this respect, citizens should also be helped to question climate change information campaigns, enacted or (openly or hiddenly) sponsored by industries which are highly responsible for greenhouse gas emissions and therefore in conflict of interest.[13] This is also to contrast the politicization of climate change. While the fact that conservative political leaders contribute to climate change skepticism among lay conservatives is a well established fact for the U.S., our findings do provide further empirical evidence for Europe as well.

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[13]See for instance https://www.theguardian.com/business/2020/jan/08/oil-companies-climate-crisis-pr-spending.

See also the Exxon's climate change denial timeline maintained by Greepeace: https://www.greenpeace.org/usa/global-warming/exxon-and-the-oil-industry-knew-about-climate-change/exxons-climate-denial-history-a-timeline/

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Table 1: Cross-sectional distribution of answers (Eurobarometer Climate Change surveys)							
Panel A: Climate change is the most important challenge faced by humanity							
QB1a	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.090	0.183	0.160	0.360	0.070	0.717	-0.287
2011	0.070	0.202	0.190	0.340	0.062	0.366	-0.198
2013	0.060	0.159	0.130	0.390	0.081	1.118	0.477
2015	0.050	0.168	0.150	0.370	0.074	0.813	0.281
2017	0.040	0.126	0.105	0.380	0.077	1.695	2.700
2019	0.100	0.216	0.190	0.500	0.101	1.211	1.091
Panel B: Climate change is the second to fourth most important challenge faced by humanity							
QB1b	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.170	0.331	0.360	0.520	0.089	-0.162	-0.691
2011	0.150	0.302	0.310	0.460	0.076	-0.059	-0.510
2013	0.200	0.334	0.335	0.460	0.065	0.165	-0.710
2015	0.160	0.311	0.330	0.440	0.075	-0.402	-0.874
2017	0.170	0.305	0.300	0.440	0.074	0.006	-1.172
2019	0.260	0.360	0.365	0.440	0.052	-0.349	-0.847
Panel C: Climate change is one of the four most important challenges faced by humanity							
***QB*1**	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.280	0.515	0.500	0.750	0.144	-0.023	-1.217
2011	0.280	0.504	0.510	0.680	0.110	-0.236	-0.569
2013	0.290	0.493	0.460	0.820	0.129	0.727	-0.046
2015	0.240	0.479	0.460	0.760	0.139	0.145	-0.720
2017	0.230	0.432	0.425	0.770	0.140	0.748	-0.214
2019	0.370	0.576	0.575	0.850	0.127	0.297	-0.605
Panel D: Climate change is a serious problem							
QB2s	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.100	0.226	0.230	0.330	0.052	-0.221	0.033
2011	0.080	0.204	0.200	0.320	0.062	-0.071	-0.478
2013	0.120	0.226	0.230	0.360	0.068	0.186	-0.757
2015	0.100	0.231	0.230	0.390	0.066	0.267	0.047
2017	0.090	0.192	0.180	0.300	0.055	0.430	-0.609
2019	0.060	0.155	0.150	0.280	0.054	0.260	-0.488
Panel E: Climate change is a very serious problem							
QB2vs	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.420	0.633	0.660	0.840	0.109	-0.148	-0.769
2011	0.450	0.684	0.690	0.910	0.118	-0.104	-0.639
2013	0.370	0.660	0.675	0.850	0.115	-0.737	0.240
2015	0.340	0.667	0.690	0.870	0.117	-1.078	1.390
2017	0.490	0.721	0.730	0.860	0.094	-0.707	-0.084
2019	0.590	0.772	0.760	0.920	0.082	-0.335	-0.206
Panel F: Climate change is at least a serious problem							
***QB*2**	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.720	0.859	0.880	0.950	0.068	-0.572	-0.887
2011	0.750	0.889	0.900	0.990	0.062	-0.467	-0.496
2013	0.720	0.886	0.905	0.970	0.057	-1.113	0.743
2015	0.700	0.898	0.910	0.970	0.057	-1.893	3.712
2017	0.780	0.913	0.920	0.970	0.045	-1.033	0.810
2019	0.840	0.927	0.930	0.980	0.035	-0.617	-0.193
Panel G: Climate change is one of the four most important challenges faced by humanity and it is at least a serious problem							
***QB*1*QB*2**	**Min**	**Mean**	**Median**	**Max**	**Std. Dev.**	**Skewn**	**Ex-Kurt**
2009	0.200	0.450	0.430	0.670	0.148	-0.061	-1.279
2011	0.240	0.451	0.450	0.650	0.109	-0.189	-0.807
2013	0.210	0.440	0.430	0.750	0.123	0.536	-0.039
2015	0.170	0.435	0.420	0.730	0.142	0.072	-0.763
2017	0.200	0.397	0.390	0.730	0.138	0.736	-0.167
2019	0.340	0.535	0.540	0.820	0.127	0.292	-0.496

The Table reports descriptive statistics for the cross-sectional distributions of the percentage of interviewed that indicated "climate change" as the answer to question "Which of the following do you consider to be the single most serious problem facing the world as a whole?" (*QB*1*a*) and to the question "Which others do you consider to be serious problems? (*QB*1*b*). Similarly for the percentage of interviewed that assigned a score in the range 5-6 (*QB*2*s*) and 7-10 (*QB*2*vs*), respectively, to the question "And how serious a problem do you think climate change is at this moment? Please use a scale from 1 to 10, with '1' meaning it is "not at all a serious problem" and '10' meaning it is "an extremely serious problem" (*QB*2). In the table we also report descriptive statistics for the aggregate of the above percentages, i.e. the percentage of interviewed that indicated "climate change" among the answers provided to either questions *QB*1*a* or *QB*1*b* (the sum of *QB*1*a* and *QB*1*b*), meaning the percentage of respondents that consider climate change one of the four most important challenges; the percentage of interviewed that assigned a score in the range 5-10 to answer Q2, meaning the percentage of interviewed that consider "climate change" *at least* a serious problem, and their interaction (*QB*1*QB*2), meaning the percentage of interviewed that view climate change as one of the four most important challenges and of at least serious gravity. The descriptive statistics are the sample minimum (min) and maximum (max), the sample mean (Mean), median (Median), standard deviation (Std. Dev.), skewness (Skewn) and excess kurtosis (Ex-Kurt).

Table2: Climate change awareness equations – Panel OLS estimation							
	QB1QB2	***QB1***	***QB2***	***QB1a***	***QB1b***	***QB2s***	***QB2vs***
Const	-1.685 (0.251)	-1.374 (0.238)	1.341 (0.133)	-2.227 (0.102)	-1.751 (0.177)	-0.887 (0.089)	0.050 (0.115)
GDP	3.935 (0.667)	3.320 (0.659)	3.278 (0.466)	0.952 (0.297)	3.263 (0.469)	-1.934 (0.252)	3.167 (0.354)
GDP2	-1.944 (0.606)	-1.851 (0.602)	-	-	-2.013 (0.446)	-	-
DT (2017)	-0.228 (0.072)	-0.309 (0.069)	0.098 (0.135)	-0.386 (0.080)	-0.088 (0.052)	-0.220 (0.064)	0.316 (0.075)
GT (2019)	0.343 (0.070)	0.282 (0.067)	0.614 (0.114)	0.285 (0.082)	0.177 (0.051)	-0.486 (0.074)	0.574 (0.083)
GHGGDP	-2.200 (0.601)	-1.930 (0.590)	-2.420 (0.504)	-2.097 (0.387)	-0.704 (0.353)	1.423 (0.272)	-2.398 (0.365)
TRUSTGDP	3.057 (0.473)	3.437 (0.468)	-	3.251 (0.387)	0.970 (0.339)	-	-
TER	-0.730 (0.162)	-0.670 (0.161)	-0.756 (0.185)	-0.354 (0.137)	-0.424 (0.119)	0.526 (0.123)	-0.682 (0.162)
SEC	0.696 (0.236)	0.705 (0.225)	-	-	0.454 (0.166)	-	-
COOL	0.746 (0.188)	0.595 (0.183)	1.257 (0.178)	-	0.304 (0.138)	-0.767 (0.151)	1.078 (0.161)
SOI_	-	-	-0.811 (0.262)	-			
YTH	-	-	-	0.498 (0.172)			
LOSS	1.024 (0.220)	0.841 (0.216)	1.005 (0.242)	-	0.901 (0.155)	-0.781 (0.160)	1.132 (0.198)
LOSSGDP	-2.521 (0.863)	-1.842 (0.825)	-2.702 (0.913)	-	-2.292 (0.584)	2.105 (0.550)	-3.247 (0.721)
EULOSS	-	-	0.350 (0.138)	0.273 (0.095)	-0.138 (0.068)	-0.164 (0.070)	0.239 (0.100)
R2	0.665	0.693	0.514	0.626	0.549	0.546	0.585
Adj.R2	0.641	0.671	0.483	0.607	0.514	0.520	0.561
SC	-1.770	-1.842	-1.251	-1.776	-2.419	-2.163	-1.685
T	166	166	166	166	166	166	166
Normality	[0.2489]	[0.0768]	[0.0094]	[0.4358]	[0.3840]	[0.5842]	[0.9767]
Het	[0.0803]	[0.0335]	[0.0934]	[0.0604]	[0.1229]	[0.0034]	[0.1955]
Het-X	[0.0010]	[0.0035]	[0.0002]	[0.0425]	[0.1280]	[0.1093]	[0.0570]
RESET23	[0.8389]	[0.7114]	[0.3498]	[0.3170]	[0.0012]	[0.9026]	[0.0935]
Cross-Dep	[0.1713]	[0.4090]	[0.6486]	[0.2869]	[0.2787]	[0.3580]	[0.8942]
H-cross	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
H-time	[0. 9129]	[0.7774]	[0.1016]	[0.8531]	[0.9524]	[0.9567]	[0.9008]

The Table reports the estimated final econometric models for the various proxy variables for climate change awareness. i.e. *QB1a*, *QB1b*, *QB2s*, *QB2vs*, *QB1*, *QB2*, *QB1QB2*. Estimation is performed by OLS and heteroskedastic consistent standard errors (HCSE) are reported in round brackets. The regressors are per capita GDP (GDP) and its squared value (GDP2), the Donald Trump (DT, year 2017) and Greta Thunberg (GT, year 2019) dummies, per capita greenhouse gas emissions (GHGGDP) and overall trust (TRUSTGDP) interacted with per capita GDP, secondary (SEC) and tertiary (TER) education, cooling degree days (COOL), the negative component of the Southern Oscillation Index (SOI_-), the ratio of young people in the total population (YTH), cumulated monetary damages (LOSS) also interacted with per capita GDP (LOSSGDP), aggregate EU monetary damages (EULOSS). The reported statistics are the unadjusted (R2) and adjusted (Adj. R2) coefficient of determination, the Schwarz-Bayes information criterion (SC), the sample size (T). Moreover, p-values for the Bera-Jarque Normality Test (Normality), the White LM Heteroskedasticity Tests (Het, Het-X), the Ramsey RESET LM Test (RESET23), the Pesaran Residual Cross-Section Dependence Test (Cross-Dep), and the Honda (H) LM test for omitted random effects (cross-country (cross) and time (time)) are reported in square brackets.

Table 3: Climate change awareness equations – Cross-section Random Effects – Panel EGLS estimation							
	QB1QB2	***QB1***	***QB2***	***QB1a***	***QB1b***	***QB2s***	***QB2vs***
Const	-1.566 (0.340)	-1.280 (0.312)	1.570 (0.150)	-2.199 (0.143)	-1.667 (0.232)	-0.948 (0.115)	0.134 (0.162)
GDP	3.309 (1.054)	3.009 (1.041)	2.399 (0.516)	0.900 (0.545)	2.963 (0.545)	-1.771 (0.382)	2.682 (0.594)
GDP2	-1.512 (0.883)	-1.731 (0.865)	-	-	-1.847 (0.555)	-	-
DT (2017)	-0.184 (0.061)	-0.257 (0.058)	0.075 (0.093)	-0.334 (0.077)	-0.070 (0.045)	-0.188 (0.062)	0.217 (0.082)
GT (2019)	0.355 (0.073)	0.306 (0.069)	0.723 (0.112)	0.318 (0.085)	0.193 (0.049)	-0.460 (0.069)	0.656 (0.095)
GHGGDP	-1.544 (0.646)	-1.254 (0.634)	-1.441 (0.536)	-1.508 (0.604)	-	1.200 (0.390)	-1.735 (0.591)
TRUSTGDP	2.564 (0.841)	3.047 (0.805)	-	3.037 (0.676)	-	-	-
TER	-1.070 (0.235)	-1.055 (0.230)	-1.042 (0.284)	-0.563 (0.199)	-0.530 (0.173)	0.580 (0.167)	-0.890 (0.248)
SEC	0.917 (0.341)	0.881 (0.317)	-	-	0.602 (0.242)	-	-
COOL	0.799 (0.261)	0.664 (0.249)	1.225 (0.343)	-	0.357 (0.203)	-0.715 (0.261)	1.009 (0.320)
SOI_			-1.080 (0.236)	-	-	-	-0.463 (0.228)
YTH	-	-	-	0.613 (0.215)	-	-	-
LOSS	0.464 (0.188)	0.451 (0.176)	0.409 (0.205)	-	0.373 (0.112)	-0.709 (0.237)	0.875 (0.337)
LOSSGDP	-	-	-	-	-	1.921 (0.790)	-2.064 (1.170)
EULOSS	-	-	0.361 (0.124)	0.273 (0.076)	-0.142 (0.060)	-0.158 (0.059)	0.266 (0.086)
MC19	0.441 (0.201)	0.447 (0.192)	-	0.470 (0.120)	-	-0.559 (0.273)	0.462 (0.216)
MC17	-	-	-	-	-	-0.429 (0.231)	-
R2	0.638	0.674	0.490	0.614	0.494	0.553	0.584
R2 w	0.497	0.529	0.383	0.528	0.338	0.485	0.488
Adj.R2 w	0.461	0.496	0.347	0.501	0.300	0.449	0.451
Cross-RD	0.442 (0.254)	0.442 (0.242)	0.336 (0.286)	0.346 (0.218)	0.377 (0.171)	0.337 (0.172)	0.383 (0.240)
Idyo-RD	0.558 (0.286)	0.558 (0.273)	0.664 (0.402)	0.654 (0.300)	0.623 (0.220)	0.663 (0.242)	0.617 (0.305)
SC w	-2.213	-2.311	-1.588	-2.128	-2.800	-2.521	-2.061
T	166	166	166	166	166	166	166
Normality	[0.3129]	[0.2908]	[0.0496]	[0.6087]	[0.1557]	[0.4291]	[0.7929]
Cross-Dep	[0.1754]	[0.0890]	[0.9941]	[0.1014]	[0.3929]	[0.2535]	[0.8292]

The Table reports the estimated final econometric models with cross-section random effects for the various proxy variables for climate change awareness. i.e. $QB1a$, $QB1b$, $QB2s$, $QB2vs$, $QB1$, $QB2$, $QB1QB2$. Estimation is performed by EGLS and heteroskedastic consistent standard errors (HCSE) are reported in round brackets. The regressors are per capita GDP (GDP) and its squared value (GDP2), the Donald Trump (DT, year 2017) and Greta Thunberg (GT, year 2019) dummies, per capita greenhouse gas emissions (GHGGDP) and overall trust (TRUSTGDP) interacted with per capita GDP, secondary (SEC) and tertiary (TER) education, cooling degree days (COOL), the ratio of young people in the total population (YTH), cumulated monetary damages (LOSS) also interacted with per capita GDP (LOSSGDP), aggregate EU monetary damages (EULOSS). The reported statistics are the unadjusted coefficient of determination for unweighted data (R2), the unadjusted (R2 w) and adjusted (Adj. R2 w) coefficient of determination, and the Schwarz-Bayes information criterion (SC w) for weighted data, the sample size (T). Moreover, p-values for the Bera-Jarque Normality Test (Normality) and the Pesaran Residual Cross-Section Dependence Test (Cross-Dep) are reported in square brackets. In the Table we also report Swamy and Arora estimates of component variances and their share. In particular, Cross-RD refers to cross-section random effects, while Idyo-RD to idiosyncratic random effects. The figures reported in the table are the shares of the estimated component variances, while the estimated component standard deviations are reported below in round brackets.

Table 4: Climate change awareness equations, constrained saturated econometric models, Panel OLS estimation							
	QB1QB2	***QB1***	***QB2***	***QB1a***	***QB1b***	***QB2s***	***QB2vs***
Const	-1.589 (0.142)	-0.916 (0.098)	1.589 (0.084)	-2.167 (0.064)	-1.994 (0.096)	-1.043 (0.075)	0.379 (0.082)
GDP	2.016 (0.459)	3.832 (0.441)	2.372 (0.288)	2.038 (0.226)	2.968 (0.183)	-1.845 (0.214)	2.155 (0.265)
GDP2	-0.982 (0.433)	-2.235 (0.426)	-	-	-1.639 (0.172)	-	-
DT (2017)	-0.226 (0.046)	-0.307 (0.052)	0.118 (0.069)	-0.333 (0.047)	-0.084 (0.038)	-0.255 (0.050)	0.268 (0.057)
GT (2019)	0.394 (0.064)	0.248 (0.057)	0.689 (0.071)	0.274 (0.059)	0.151 (0.038)	-0.497 (0.051)	0.500 (0.057)
GHGGDP	-1.595 (0.396)	-2.196 (0.367)	-1.660 (0.313)	-2.141 (0.208)	-	1.324 (0.243)	-1.496 (0.290)
TRUSTGDP	3.702 (0.336)	3.171 (0.324)	-	2.531 (0.241)	-	-	-
TER	-0.633 (0.123)	-0.333 (0.106)	-0.877 (0.109)	-0.575 (0.098)	-0.554 (0.073)	0.717 (0.095)	-0.773 (0.100)
SEC	0.712 (0.141)	-	-	-	0.866 (0.104)	-	-
COOL	0.540 (0.093)	0.569 (0.075)	0.694 (0.082)	-	0.668 (0.078)	-0.633 (0.073)	0.718 (0.087)
SOI_	-	-	-0.823 (0.185)	-	-		
YTH	-	-	-	0.594 (0.100)	-		
LOSS	0.844 (0.150)	0.892 (0.155)	1.518 (0.141)	-	0.479 (0.043)	-0.313 (0.131)	1.121 (0.126)
LOSSGDP	-2.539 (0.550)	-3.658 (0.561)	-2.703 (0.548)	-	-	0.967 (0.476)	-2.142 (0.491)
EULOSS	-	-	0.246 (0.069)	0.247 (0.058)	-	-0.124 (0.053)	0.231 (0.065)
MC19	-	0.490 (0.118)	-	0.453 (0.078)	-	-	0.839 (0.114)
MC17	-	-	-	-	-	-	0.557 (0.099)
GRP	-	-	-	-0.121 (0.044)	-	-	-
FCE	0.531 (0.035)	0.829 (0.034)	-1.485 (0.061)	-0.901 (0.045)	0.620 (0.030)	-0.976 (0.086)	-0.992 (0.049)
R2	0.841	0.859	0.848	0.866	0.814	0.743	0.824
Adj.R2	0.829	0.848	0.838	0.857	0.803	0.726	0.811
SC	-2.487	-2.591	-2.384	-2.711	-3.394	-2.701	-2.598
T	166	166	166	166	166	166	166
Normality	[0.7343]	[0.1999]	[0.8099]	[0.5793]	[0.4699]	[0.8436]	[0.4168]
Hetero	[0.5933]	[0.0605]	[0.4348]	[0.5287]	[0.7001]	[0.1796]	[0.6815]
Hetero-X	[0.9297]	[0.3031]	[0.8761]	[0.8528]	[0.3087]	[0.4971]	[0.3908]
RESET23	[0.3170]	[0.4208]	[0.4530]	[0.5241]	[0.4400]	[0.9611]	[0.9181]
Cross-Dep	[0.4439]	[0.5551]	[0.2614]	[0.1161]	[0.6505]	[0.1466]	[0.3737]
H-cross	[0.9778]	[0.9551]	[0.9135]	[0.9053]	[0.9748]	[0.7347]	[0.9776]
H-time	[0.8646]	[0.7178]	[0.9148]	[0.9336]	[0.7409]	[0.9386]	[0.8540]

The Table reports the estimated final constrained saturated econometric models for the various proxy variables for climate change awareness. i.e. $QB1a$, $QB1b$, $QB2s$, $QB2vs$, $QB1$, $QB2$, $QB1QB2$. Estimation is performed by OLS and heteroskedastic consistent standard errors (HCSE) are reported in round brackets. The regressors are per capita GDP (GDP) and its squared value (GDP2), the Donald Trump (DT, year 2017) and Greta Thunberg (GT, year 2019) dummies, per capita greenhouse gas emissions (GHGGDP) and overall trust (TRUSTGDP) interacted with per capita GDP, secondary (SEC) and tertiary (TER) education, cooling degree days (COOL), the negative component of the Southern Oscillation Index (SOI_-), the ratio of young people in the total population (YTH), cumulated monetary damages (LOSS) also interacted with per capita GDP (LOSSGDP), aggregate EU28 monetary damages (EULOSS), the volume index for climate change media coverage for years 2017 and 2019 (MC17, MC19) , the relative power position of right-wing parties in government (GRP). Moreover, FCE is the overall fixed country effect variable, constructed by aggregating the impulse and step country dummy variables according to the restrictions reported in Table A1, Panel B in the Appendix. The reported statistics are the unadjusted (R2) and adjusted (Adj. R2) coefficient of determination, the Schwarz-Bayes (SC) information criterion, the sample size (T). Moreover, p-values for the Bera-Jarque Normality Test (Normality), the White LM Heteroskedasticity Tests (Het, Het-X), the Ramsey RESET LM Test (RESET23), the Pesaran Residual Cross-Section Dependence Test (Cross-Dep) , and the Honda (H) LM test for omitted random effects (cross-country (cross) and time (time)) are reported in square brackets.

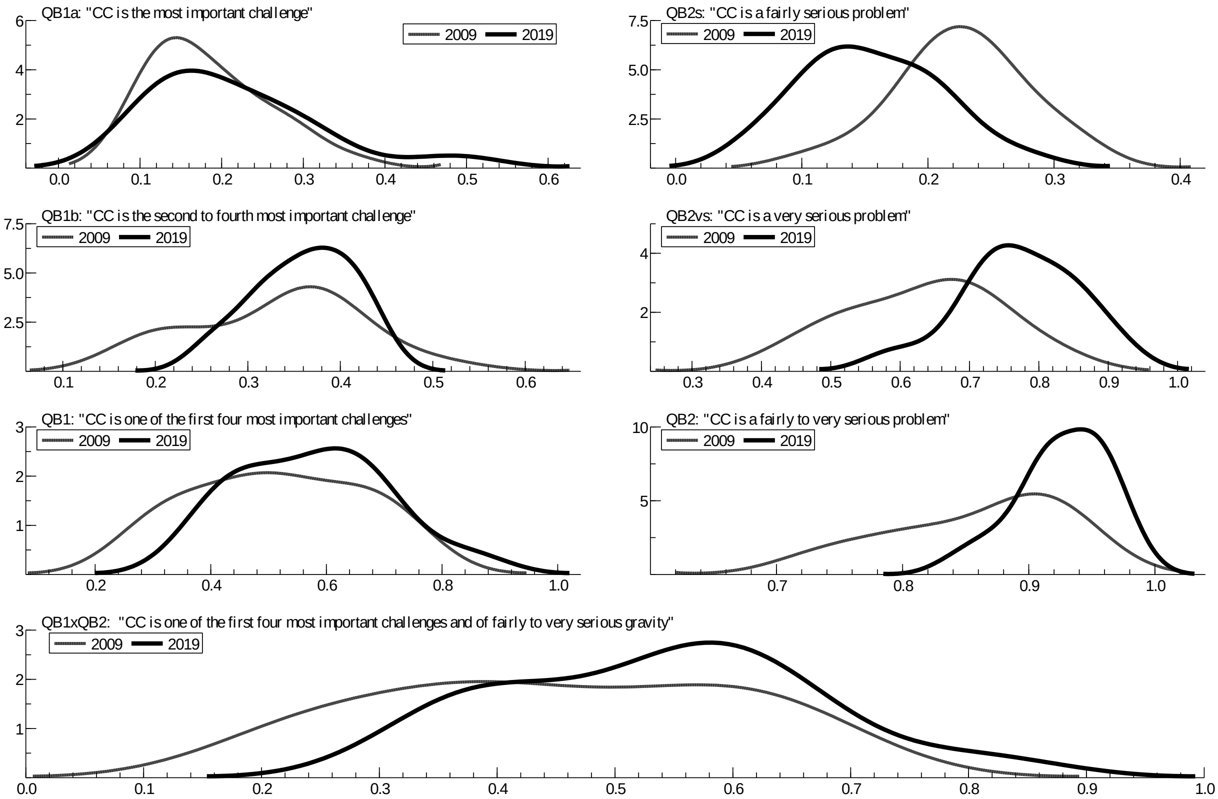

Figure1: Cross-sectional distributions of climate change concern proxy variables: Kernel density estimates

The Figure reports kernel density estimates for the cross-sectional distribution of the answers provided to questions *QB*1*a*, *QB*1*b* and *QB*2, i.e. the percentage of interviewed that indicated "climate change" as the answer to question "Which of the following do you consider to be the single most serious problem facing the world as a whole?" (*QB*1*a*) and to question "Which others do you consider to be serious problems? (*QB*1*b*). Similarly for the percentage of interviewed that assigned a score in the range 5-6 (*QB*2*s*) and 7-10 (*QB*2*vs*), respectively, to the question "And how serious a problem do you think climate change is at this moment? Please use a scale from 1 to 10, with '1' meaning it is "not at all a serious problem" and '10' meaning it is "an extremely serious problem" (*QB*2). In the Figure we also report kernel density estimates for the aggregates of the above percentages, i.e. the percentage of interviewed that indicated "climate change" among the answers provided to either questions *QB*1*a* or *QB*1*b* (the sum of *QB*1*a* and *QB*1*b*), meaning the percentage of respondents that consider climate change one of the four most important challenges, the percentage of interviewed that assigned a score in the range 5-10 to answer *Q*2, meaning the percentage of interviewed that consider "climate change" *at least* a serious problem, and their interaction (*QB*1*QB*2), meaning the percentage of interviewed that view climate change as one of the four most important challenges and at least of serious gravity.

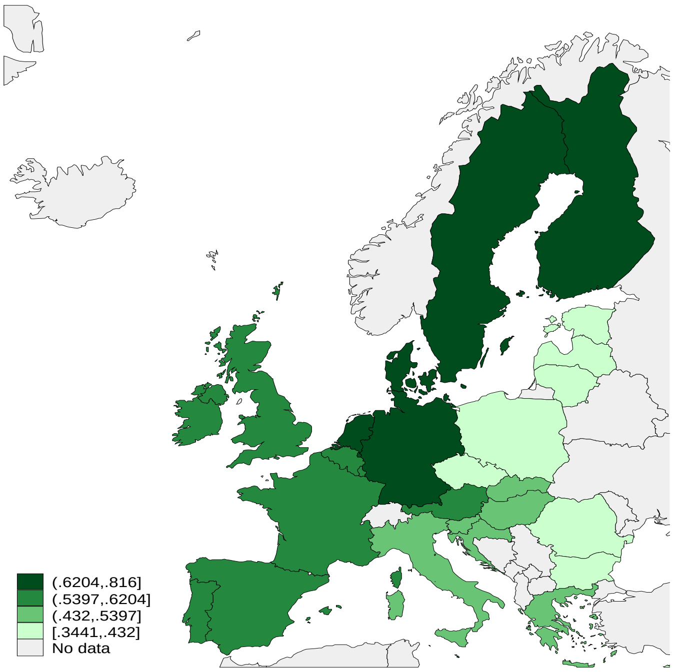

Figure 2: *QB*1*QB*2 in 2019. Shares of respondents who rank climate change as one of the four most important challenges and of at least serious gravity.

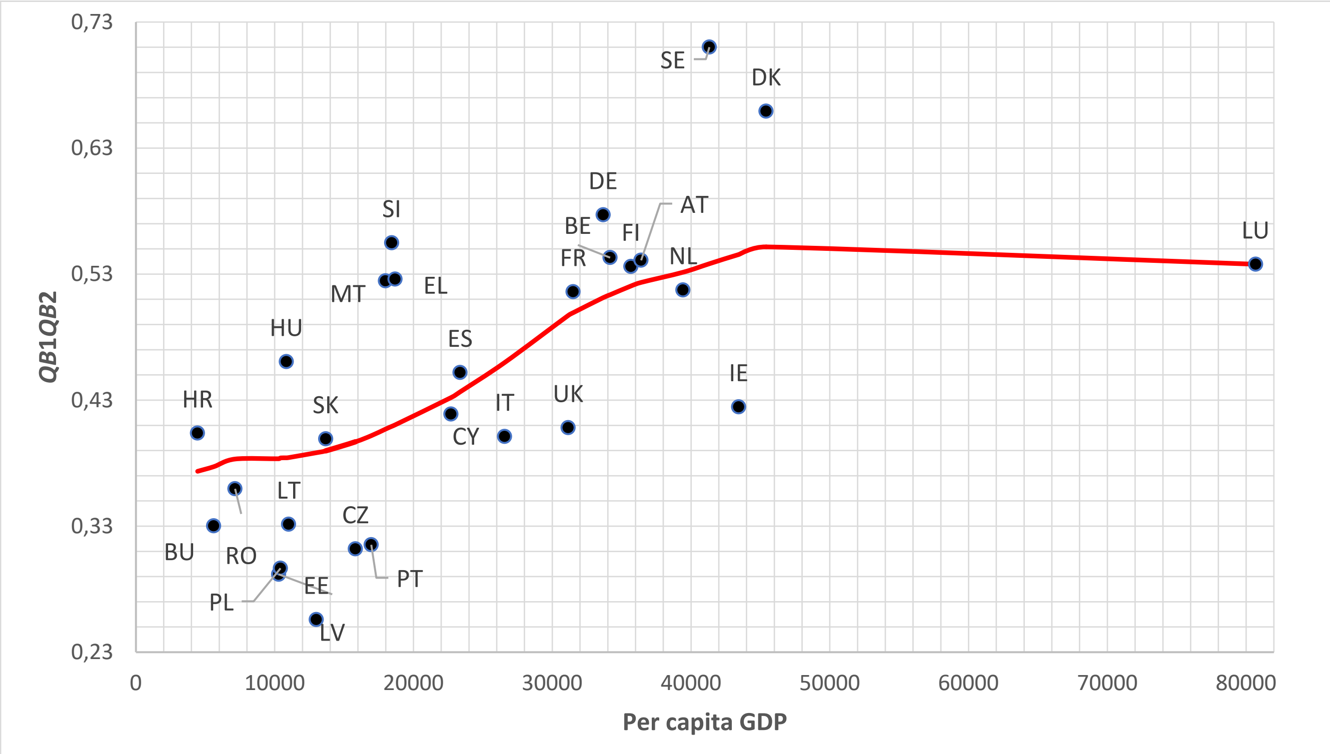

Figure 3, Panel A: The European climate change/environmental awareness curve. Cross plot of temporal averages with (Gaussian) kernel smoothing, under optimal bandwidth selection.

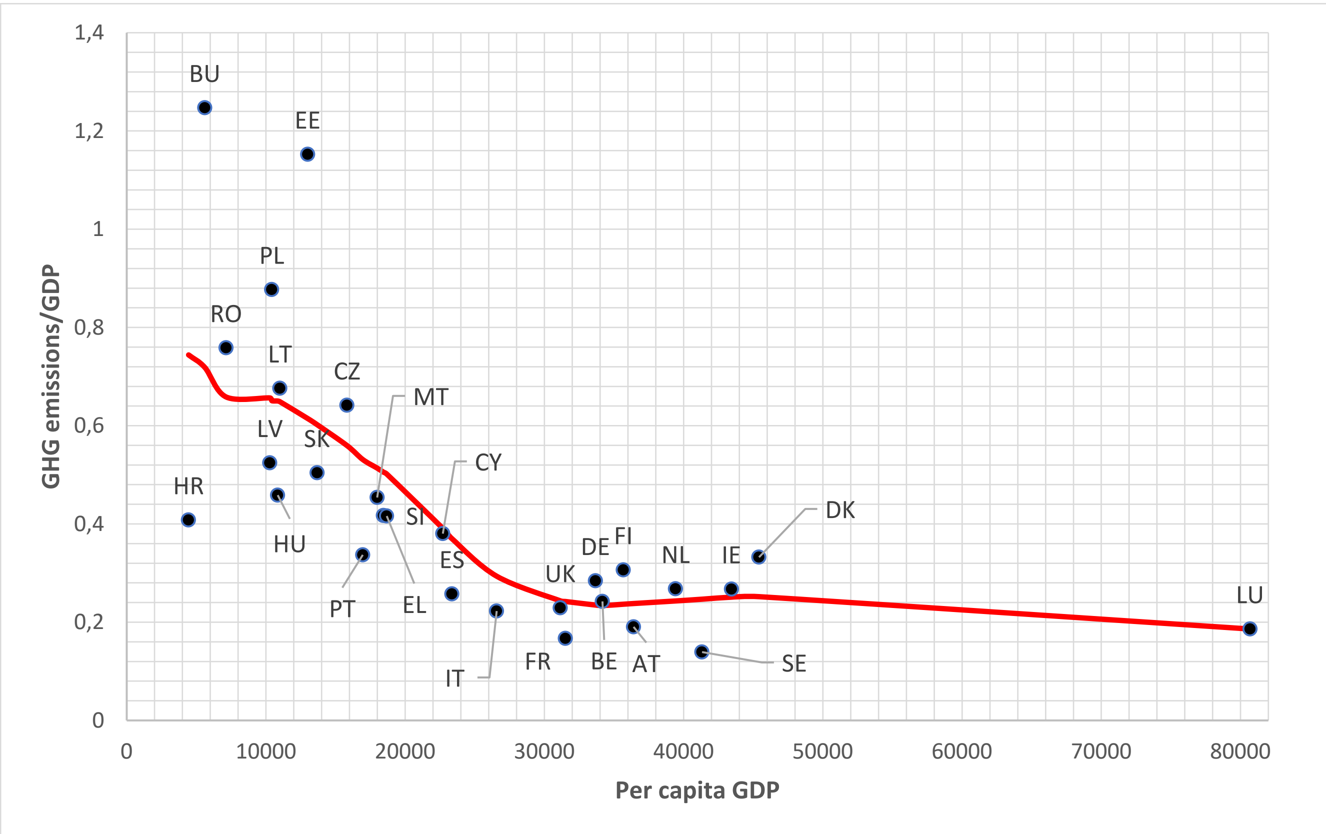

Figure 3, Panel B: The European environmental Kuznets curve (temporal averages). Cross plot of temporal averages with (Gaussian) kernel smoothing, under optimal bandwidth selection.