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Analysis

Raising awareness of climate change: Nature, activists, politicians?

Daryna Grechyna[1]

University of Granada, Departamento de Teoría e Historia Económica, Facultad de Ciencias Económicas y Empresariales, Campus Universitario de Cartuja P.C 18071, Granada, Spain

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ABSTRACT

This paper evaluates the relative importance of natural and human factors in shaping public awareness of climate change. I compare the predictive efficacy of natural factors, represented by air temperature deviations from historical norms, and human factors, encompassing noteworthy political events focused on environmental policies and movements led by environmental activists, in forecasting the salience of climate change topic over weekly and annual horizons using regional European countries' data. The salience of climate change is proxied by the Google search intensity data. The activists' movements are measured by weekly Friday for Future strikes. The best-performing predictor in the short term (weeks), is the size of activists' strikes and in the longer term (years), positive deviations of maximum air temperature from historical norms and political meetings focused on environmental policies. The inter-regional spatial relations, when taken into account, significantly improve the forecasts of the future public interest in climate change.

1. Introduction

Despite growing evidence of the harmful effects of global warming, international and national environmental policy initiatives have struggled to effectively reduce its impact or slow its progress.[2] As discussed by Frantz and Mayer (2009), drawing on Latane and Darley's (1968) "bystander effect" model, this lack of effective action may be attributed to the difficulty in perceiving climate change. Conversely, individual understanding of climate dynamics, pro-environmental social norms, and peer influence strengthen support for climate change mitigation policies (Welsch, 2022; Lipari et al., 2024). Therefore, enhancing public understanding and awareness of climate change is crucial for promoting widespread public engagement and overcoming the barrier to climate action.

Numerous studies demonstrate that natural factors, such as extreme weather events, increase individuals' understanding of climate dynamics (see, for example, Herrnstadt and Muehlegger, 2014; Deryugina, 2013; Owen et al., 2012; Sloggy et al., 2021; Hamilton and Stampone, 2013; Egan and Mullin, 2012; Kalatzi Pantera et al., 2023; Choi et al., 2020; Kahn and Kotchen, 2011). Furthermore, social movements, such as activist protests, and pro-environmental political leadership raise public awareness of climate change (Thiri et al., 2022; Lipari et al., 2024). Nevertheless, there is still insufficient evidence to determine the relative extent to which natural and human factors influence perceptions of climate change and how long their influence lasts.

This paper aims at evaluating the relative importance of natural and human factors in shaping public awareness of climate change. I compare the predictive efficacy of natural factors, represented by air temperature deviations from historical norms, and human factors, encompassing noteworthy political events focused on environmental policies and movements led by environmental activists, in forecasting the salience of climate change over short (weeks) and long (years) horizons. The salience of climate change is measured by Google search intensity for topic "climate change", following Herrnstadt and Muehlegger (2014). By focusing on the predictive efficacy of the factors potentially affecting public awareness of climate change, this paper contributes to the literature without raising any endogeneity concerns. Specifically, it evaluates the relevance of the human and natural factors in forecasting the future public awareness of climate change instead of claiming any causal relationship between these factors and public awareness of climate change.

The contribution of this paper to the literature is threefold. First, I use the assembled weekly-regional panel data from European countries

E-mail address: dgrechyna@ugr.es.

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[2] The evidence on global warming is reported, for example, in Von Schuckmann et al. (2020), Jones and Mann (2004), NASA (2023). The evidence on the lack of effective action against climate change appears in Intergovernmental Panel on Climate Change (IPCC) Reports (https://www.ipcc.ch/).

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to confirm that activists' movements, political events, and air temperature fluctuations are all robust determinants of public awareness of climate change. Second, I evaluate the predictive accuracy of the natural and human factors by comparing the reductions in the out-of-sample root mean square error (RMSE) of a model including each of these factors, as well as their combinations, relative to the baseline "naive" model. Third, I contribute to the discussion on the models relevant for evaluating climate change perceptions by comparing the performance of traditional linear models and models accounting for possible spatial interdependence across regions.

The main results are as follows. The best-performing predictor over weekly horizon in a traditional linear model is the size of activists' strikes. An inclusion of this predictor reduces the RMSE by 1 percent compared to the baseline. In general, the predictive power of the weather indicators, activists' strikes and political meetings in forecasting the search intensity for climate change over weekly horizon is very modest. Specifically, the maximum improvement compared to the baseline model is around 1.25 percent.

The best-performing indicators in a spatial model are political meetings and temperature deviations from historical norms. Intuitively, the spatial models that account for existence of interrelations across regions are more appropriate for capturing the impact of the regional factors that are likely to affect public attention beyond the regional borders, such as heatwaves or political meetings of the European Council focused on the environment. Spatial models provide much more precise predictions over weekly horizon, up to a 6% improvement in forecasting the search intensity for climate change, compared to the baseline.

The best-performing predictors over annual horizon are the annual change in the maximum air temperature deviations from historical norms and indicators for environmentally-related political meetings. In spatial models, an addition of these indicators reduces the RMSE by around 60% compared to the baseline. The results are generally robust when the forecasting performance is estimated for subsets of regions, based on geographical division of European regions into Northern, Southern, Eastern and Western.

Overall, the results suggest that both human and natural factors are relevant predictors of the salience of climate change measured by the Google search intensity for climate change topic. While the activists' strikes are likely to intensify public interest in climate change over the short time horizons, the air temperature fluctuations and the broad political initiatives are more relevant for forecasting public consciousness about climate change over the years. The inter-regional spatial relations are particularly important for spreading the impact of political meetings focused on environmental policies across regions and over time, and, when taken into account, significantly improve the forecasts of the future public interest in climate change.

The paper is structured as follows. Section 2 reviews related studies and discusses the conceptual framework. Section 3 describes the data used in this study. In Section 4, I verify that the natural and human factors analyzed in this study are robust determinants of the search intensity for climate change. I do so, first, using a standard model, and second, using a spatial model accounting for possible interdependencies across regions. In Section 5, I evaluate the predictive performance of the variables analyzed in this study, first, over a very short horizon, a few weeks into the future, and second, based on annual data. Section 6 concludes.

2. Conceptual framework and related literature

2.1. Measuring public perceptions of climate change

Research assessing determinants of climate change perceptions predominantly relies on surveys, case studies, or experiments (Whitmarsh and Capstick, 2018). Surveys have the advantage of generally including questions that directly reveal respondents' beliefs about climate change. Examples of related studies focusing on the impact of weather on perceptions of climate change using surveys include Deryugina (2013), Owen et al. (2012), Egan and Mullin (2012), Hamilton and Stampone (2013), Sloggy et al. (2021), and Kalatzi Pantera et al. (2023). Nevertheless, survey data have several limitations, including small sample sizes, limited geographic coverage, and difficulty in comparisons across different regions or countries.

Recently, research has increasingly relied on Internet search data, such as the Google Trends index (see, for example, (Herrnstadt and Muehlegger, 2014; Choi et al., 2020; Kahn and Kotchen, 2011)). Google Trends index provides a solution to the lack of individual data. The extensive data volumes and nearly universal coverage make it a valuable tool for real-time analysis of societal behavior. Specifically, in seminal papers, Choi and Varian (2009, 2012)) demonstrate that Google search data can be used to forecast near-term values of various economic indicators. Consequently, Google search data has been widely used for the analysis and prediction of various economic phenomena, including migration (Böhme et al., 2020), unemployment (Fondeur and Karamé, 2013), private consumption (Vosen and Schmidt, 2011; Woo and Owen, 2019), trading in financial markets (Preis et al., 2013), tourism demand (Siliverstovs and Wochner, 2018); predictions of epidemics (Ginsberg et al., 2009) and heat-related illness or stress (Adams et al., 2022).

This paper aligns with the recent strand of research by measuring the salience of climate change using weekly Google search intensity data. Specifically, I follow Herrnstadt and Muehlegger (2014), who analyzed the impact of air temperature deviations from historical norms on perceptions of climate change, measured by Google search intensity for climate change topics. Similar to these authors, I consider the air temperature deviations from historical norms as an indicator of natural factors, and Google search intensity for climate change topic as a measure of climate change awareness. Differently from those authors, I consider European rather than US data, and I add the human factors (activists movements and political events) as the potential predictors of public awareness of climate change. Thus, this paper contributes to the literature by evaluating the relative importance of human and natural factors in shaping public awareness of climate change.

2.2. Factors influencing public perceptions of climate change

People's recognition of climate change is enhanced by extreme weather events such as droughts, extreme air temperatures, and floods (see Herrnstadt and Muehlegger, 2014; Booth et al., 2020; Deryugina, 2013; Owen et al., 2012; Sloggy et al., 2021; Hamilton and Stampone, 2013; Egan and Mullin, 2012; Kalatzi Pantera et al., 2023; Choi et al., 2020; Kahn and Kotchen, 2011). Personal experience of climate change is particularly significant: individuals living in areas with rising average temperatures are more likely to perceive global warming (Howe et al., 2013). Additionally, individual socio-economic characteristics such as educational attainment, political ideology, and gender can influence perceptions of climate change (see Lee et al., 2015; Konisky et al., 2016; Weber, 2010).

The fact that awareness of climate change depends on individual characteristics and varies according to geographical factors and the likelihood of experiencing extreme weather events highlights the importance of intergroup interactions and peer pressure. Individuals who are more aware of global warming can transmit their message and convince others of the urgency of the matter. Peer influence, social norms, sociopolitical events, and media coverage have all been shown to shape individuals' awareness of and responses to climate change (Weber, 2010; Welsch, 2022; Lipari et al., 2024). Thiri et al. (2022), in a systematic literature review of social movements contesting fossil fuel projects, conclude that social movements and protests against global warming can effectively constrain the implementation of environmentally damaging projects and raise public awareness. Pro-environmental political leaders also play a crucial role in enhancing public awareness of global warming and promoting pro-environmental behavior (Lipari et al., 2024).

The contribution of this study is to evaluate the relative importance of environmentally-related political events and activist movements compared to the direct impact of climate change on public awareness. In this context, this paper contributes to the debate on the behavioral implications of external actions (nudges) on individual perceptions (see, for example, Collet et al., 2023; Saari et al., 2021; Ohler and Billger, 2014). Specifically, the paper provides an empirical evaluation of Frantz and Mayer's (2009) claims by examining the extent to which people "rely on others for information". This is achieved by comparing how effectively activism, political action, and phenomena demonstrating global warming predict public awareness of climate change.

2.3. Short vs long term and estimation techniques

The impact of natural and human factors on individual awareness of climate change may be short- or long-lasting. A number of studies have examined the durability of weather shocks' impact on public awareness of climate change. For example, Konisky et al. (2016) and Egan and Mullin (2012) find that extreme weather events in recent history shape public awareness of climate change but that their effects diminish over longer periods. Booth et al. (2020) similarly observe that extreme weather shocks mainly affect short-term adaptive behaviors, with their influence fading over time.

This paper aims to re-evaluate the lasting impact of weather events on public awareness of climate change and to assess the enduring significance of human factors, including political events and activist movements. This analysis can help identify factors that can sustain long-term shifts in public consciousness, guiding effective planning and policymaking. Specifically, if weather-related impacts on public perception are short-lived, as suggested by previous studies, this study explores whether social movements or environmentally-related political events could serve as alternative catalysts.

The standard empirical models typically used to evaluate factors influencing public awareness of climate change are linear models. They employ climate change perceptions as the dependent variable and incorporate several explanatory variables. Studies examining the causal impact of these factors often utilize high-frequency data and include fixed effects to address potential spurious geographic and seasonal relationships, as well as common time-varying factors.

This paper contributes to the existing literature by initially adopting a standard linear model similar to studies on the determinants of climate change perceptions and salience (e.g., Herrnstadt and Muehlegger, 2014; Sloggy et al., 2021), while enhancing it with the inclusion of political events and activist movements. I use panel data at weekly and annual frequencies to assess the factors influencing public awareness of climate change in both short-term (weekly) and long-term (annual) perspectives.

Even though a variety of fixed effects included in an estimation of panel data on public awareness of climate change reduces the causality concerns (see Herrnstadt and Muehlegger, 2014), some issues may remain. For instance, the occurrence and size of activist strikes and environmentally-related political meetings can be affected by public consciousness about climate change. This paper overcomes the endogeneity concerns by evaluating the forecasting efficiency of different factors in predicting public awareness of climate change. That is, rather than making causal interpretations from the coefficients estimated in the regression, I evaluate how good are different factors in predicting future public awareness. This approach is similar to that of Ductor et al. (2014) and enables the identification of the best predictors that could influence future public awareness of climate change. In this respect, this study aims at evaluating whether and to what extent weather, political meetings, and activist movements predict perception of climate change, distinguishing, in addition, between short and long term.

A comprehensive examination of the significance and duration of the impact of factors influencing public awareness of climate change requires an empirical framework that considers the complex interactions among these factors and their effects. For instance, weather patterns in one region are likely to resemble those in nearby regions, while the occurrence and scale of activist strikes and political gatherings can influence public opinion not only locally but also in neighboring regions within the same country and abroad. Numerous studies have demonstrated the relevance of spatial models for environmental issues, such as estimating environmental Kuznets curves (Maddison, 2006), assessing pollution impacts on housing prices (Kim et al., 2003), evaluating the relationship between air temperature and economic development (Linsenmeier, 2023), examining the impact of natural disasters on environmental attitudes (Kalatzi Pantera et al., 2023), and analyzing determinants of carbon dioxide emissions by firms (Cole et al., 2013).

This paper contributes to the literature by evaluating the relative significance of weather, political events, and activist movements within a spatial framework that considers potential interdependencies across regions. In addition, I compare the forecasting efficacy of a standard linear model and a spatial model both over short-term and long-term horizons. The findings of this paper underscore the greater relevance of spatial models over standard linear models in predicting public awareness of climate change.

The next section explains the data sources and the structure of the data used in this study. The subsequent section conducts the empirical analysis.

3. Data

For the purpose of this study, I use four different publicly available data sources, as described below.

3.1. Google search intensity data

As a measure of climate change awareness I use the Google Trends index for topic "climate change".[3] Google dominates the search engine market with a significant market share in most European countries, typically over 90% (Siliverstovs and Wochner, 2018; Kennedy and Hauksson, 2012). Since January 2004, the Google Trends index has provided data on user Google search query volumes. It allows researchers to refine their queries by geographical region (such as provinces, states, or countries), categories (like travel, finance, or food), frequency (daily, weekly, or monthly), and choose the data for "keyword" or "topic". "Topics" are collections of terms that share a common concept. According to the description on Google Trends website,[4] topics are generally considered to be more reliable for Google Trends data compared to search terms, because they pull in the exact phrase as well as misspellings and acronyms, and cover all languages.

I download weekly Google Trends data on topic "climate change" for all available regions of European countries (countries from the European Union, Shengen zone, and the UK) for the most recent period including five European summers, from 3 of June 2018 to 30 of July 2023.[5] European regions listed in Google Trends generally coincide with NUTS2 regional classification, which facilitates merging of Google data with other regional data.[6] The selection of the time period is

[3] It is publicly accessible at https://www.google.com/trends.

[4] https://newsinitiative.withgoogle.com/resources/trainings/google-trends/basics-of-google-trends/

[5] The weekly data is reported for Monday–Sunday; thus, 3th of June 2018 corresponds to the first week of June 2018 and 30th of July 2023 corresponds to the last week of July 2023.

[6] NUTS, Nomenclature of territorial units for statistics, is a hierarchical system by Eurostat for dividing up the economic territory of the EU and the UK for statistical purposes.

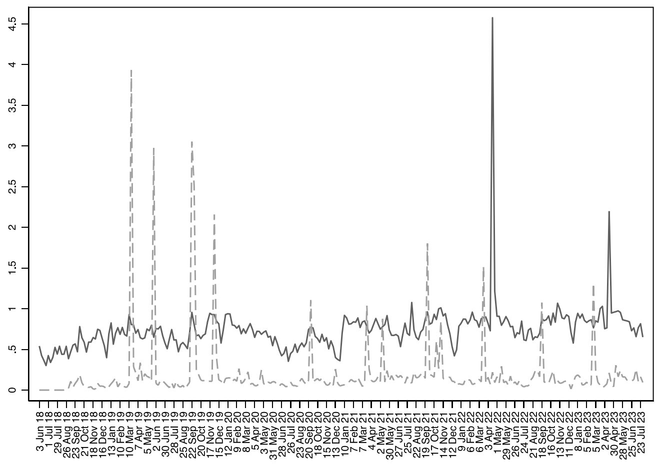

Fig. 1. Google searches for topic "Climate change" and FFF strikes over time.
This figure reports the logarithm of Google Trends index for topic "Climate change", in black, and the logarithm of the number of people participating in Fridays for Future activists' strikes, in dashed gray; both time series measured as averages over all regions for a given week.

motivated by the data availability: first, the objective is to choose the most recent period; second, the data on activists' movements starts in August 2018.

The Google Trends data has two well-known limitations. First, for privacy reasons, Google only provides data for popular queries; if a search query's volume falls below a certain threshold, it is reported as zero. Second, Google aggregates and normalizes data based on a sample of Google search queries to estimate the popularity of search terms or topics relative to the total search volume within a specific time period and geographic location. This normalization allows for a relative comparison of interest over time and across different locations, adjusting for variations in overall search volume. This aspect of the data is advantageous for current research as it automatically adjusts for differences in population size, region size, and other factors that could affect absolute search intensity.

The Google search intensity data lies in the interval [0, 100] where 100 is the maximum search interest for the location during the time period selected. The resulting distribution is skewed towards zero with a very small fraction of searches reaching the index of 100. Specifically, in most of the countries, the maximum was reached during the week corresponding to 22nd of April 2022, where the Google search web contained an animated doodle showing the evolution of Earth surface over time.[7] Therefore, I apply the $ln(y+1)$ transformation to the Google Trend index y to reduce the impact of high-intensity searches on the estimates (see Ductor et al., 2014). Fig. 1 shows the search intensity over time, averaged across all the considered regions.

3.2. Weather data

I use the Meteostat weather and climate database which provides weather observations and long-term climate statistics for individual weather stations around the world. I download the daily weather data for all the available stations for European regions, based on NUTS2 classification, and compute the weekly averages over the stations in a given region. The resulting weekly regional data for the considered period from 3 of June 2018 to 30 of July 2023 is merged with the Google search data. The data merge is conducted by week and region.

In addition, I compute the historical regional weekly weather data, as the averages for a given week and region over the period 1997–2017 or other period for which the information is available prior to 2018. The historical data is used to compute the deviations of the weekly weather indicators from their historical values (similar to Herrnstadt and Muehlegger, 2014). As a baseline weather indicator, I use the positive deviation of the maximum weekly temperature from its historical average (similar to Herrnstadt and Muehlegger, 2014). The Meteostat data also contains precipitation, wind, and snow indicators. However, those variables are not very robust predictors of the search intensity for climate change, as discussed below.

3.3. Data on activists' movements

I use the data on weekly strikes organized by the Fridays for Future movement. Fridays for Future (FFF) is a youth-led and -organized global climate strike movement that started in August 2018.[8] These strikes are set to take place on Fridays. The FFF website reports the strikes data as the number of people that attended the strike at town-date precision. I use the available reported data on strikes and aggregate the town-day data (the days are Fridays) into the weekly-regional data. The FFF town-level data contains special symbols and some town names are non-standard. I apply several data-processing techniques, such as geocoding services and the combination of NUTS, ISO, and HASC regional codes to merge town-level to regional-level data. As a result, I could identify the regions of 85% of the available towns. Finally, I combine the weekly-regional data on FFF activists' strikes with the weekly-regional data on Google searches and weather. Again, the data merge is conducted by week and region.

The total number of strikes during the considered period is 2868 but the number of reported strikes' participants varies from 1 to 250000. Similar to the search intensity data, this data is skewed towards zero. Therefore, I apply the $ln(x+1)$ transformation to the strike size x to reduce the impact of the largest strikes on the estimates. Fig. 1 shows the FFF strikes over time, averages across all the considered regions. The Global Climate strikes appear as the most significant spikes in the data.

3.4. Data on political meetings

From the European Council website, I collect the data on the summits and ministerial meetings that took place between 3 of June 2018 and 30 of July 2023 and that remain when the data is filtered to topics "Environment" and "Climate Neutrality".[9] There were 56 days of meetings in the considered sample of countries ("local meetings") and 60 days of meetings in the countries other than those in the considered sample ("other meetings"). The "local meetings" include the European Council meetings, Environment Council meetings, G7 and COP26 Summits, and Informal meetings of environment ministers. Although the majority of local meetings took place in Brussels (Belgium), there were also meetings in ten other European countries from the sample. The "other meetings" include the UN climate change conference COP27 (Egypt), UN General Assemblies (US), G20 Summit (India), and European meetings that took place in Luxembourg or online.

The resulting indicators for "local meetings" take a value of one for the region and week in which they occurred, and zero otherwise. Meetings that took place outside the regions considered in the sample ("other meetings") are coded as one during the week when they occurred, across all regions, and zero otherwise. The data on political meetings is merged with other sources by region and week.

[7] See Google doodle for 22 of April 2022: https://doodles.google/doodle/earth-day-2022/.

[8] See the FFF website, from which all the information and data was taken, https://fridaysforfuture.org.

[9] The data was downloaded from https://www.consilium.europa.eu/en/meetings/calendar/.

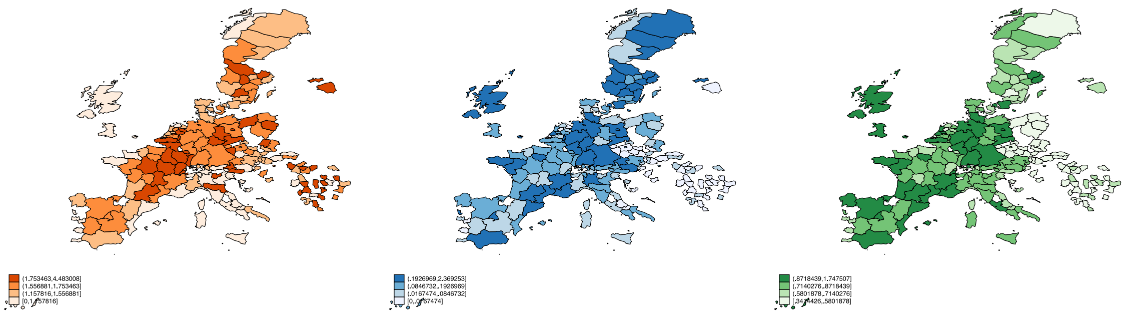

Fig. 2. Average temperature deviations, activists' strikes size, and search intensity for climate change, by region.
This figure reports the average temperature deviations, activists' strikes size (in logarithms), and search intensity for climate change (in logarithms), in the left, middle, and right graph, respectively; all variables are averages over the considered period, 3 of June 2018 to 30 of July 2023, for a given region.

For the spatial models, the geolocation of each region, taken from the Eurostat NUTS data, is added to the final dataset. The resulting panel data contains 194 regions from 21 European country covering 291 week from 3 of June 2018 to 30 of July 2023. Fig. 2 summarizes the average positive maximum temperature deviation from historical norm, the average size of strikes (in logarithms) and the average intensity of google searches for climate change (in logarithms) during the considered period, by region. Table 4 in the Appendix presents the summary statistics.

4. Robust determinants of public attention to climate change

In this section, I verify that the natural and human factors analyzed in this study are robust determinants of the search intensity for climate change. For this purpose, I use, firstly, a standard linear model that includes various fixed effects; and secondly, a spatial model that controls for possible spatial interdependencies across regions.

4.1. Standard model

I use a standard linear model from the studies exploring the factors influencing perceptions of climate change (see, for example, Herrnstadt and Muehlegger, 2014; Sloggy et al., 2021), as follows:

$$y_{ijwt} = \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + \mu_m \times \kappa_j + u_{ijwt}, \tag{1}$$

where y_{ijwt} is the search intensity, measured as the logarithm of (Google trends search index plus one) for topic "climate change" in region i of country j at week w of year t; X_{ijwt} are the potential predictors of the intensity of searches: an indicator of weekly weather, the size of activists' strikes, an indicator for political meetings; u_{ijwt} is a normally distributed error term; and a_{ij}, γ_w, η_t, and $\mu_m \times \kappa_j$ are region, week, year, and month times country fixed effects.

The combination of fixed effects accounts for spurious geographic and seasonal relationships and common time-varying unobservables such as global events attracting public attention in different countries. The FFF activists' strikes are predetermined to take place on Fridays, bringing some exogeneity with respect to the weather conditions. The European political meetings also follow a predetermined schedule set by the European Council. I use the positive deviations of the maximum temperature from its historical norms, which is a proxy for heatwaves, as the main weather indicator (similar to Herrnstadt and Muehlegger, 2014; the other air temperature measures give very similar results). I estimate Model (1) by OLS with standard errors clustered at region level.

Table 1, Columns (1)–(4), reports the results. Each of the three potential predictors of search intensity for climate change has a positive and significant coefficient, the magnitude of each does not change significantly when all three regressors are included in the estimation.[10]

The results reported in Columns (1)–(4) of Table 1 are robust to several modifications of the main explanatory variables. Specifically, activists' strikes remain significant if the size of strike is replaced by a binary indicator taking a value of one for weeks in which any strike occurred, regardless of the size, suggesting that the fact that the activists' strikes happen increases public attention. The weather indicator's coefficient remains positive and significant if other air temperature measures are included instead of the positive deviations of maximum temperature from its historical norms. While the latter variable is the most intuitive measure of heatwaves, which are more relevant for the mild European climate compared to extreme cold weather or extreme snowfalls, using the levels of maximum, average, or minimum weekly temperature, or their deviations from their historical norms, also have positive and significant coefficients when included in the estimation of Model (1). This is not surprising given that the maximum and minimum temperatures are highly correlated (the correlation between any pair of the air temperature measures is above 0.90 in the considered panel). The other weather variables, such as precipitation, speed of wind, or snowfall, appear to be insignificant predictors of the search intensity for climate change when included in Model (1).

Since all estimations include a battery of fixed effects, all three predictors of interest are considered robust. However, the primary aim of this study is to evaluate and compare the predictive capacity of each explanatory variable rather than assert any causal relationship between the independent and dependent variables. The conclusion drawn from this subsection is that all three predictors should be included in the forecasting models.

Model (1) does not take into account the fact that the predictors can potentially influence the search intensity with a lag or a lead or that the impact of each of the predictors of interest can be potentially reinforced by the other. These and other extended specifications are considered in the next section, where I evaluate the predictive efficacy of each of the predictors of interest in forecasting public awareness of climate change proxied by the intensity of google searches for climate change. But before that, I confirm that the natural and human factors analyzed in this study are robust determinants of the search intensity for climate change in a spatial model accounting for potential spillovers across the regions.

[10] The impact of the political meetings held in other countries cannot be estimated in a model with fixed effects; it is analyzed in more detail in the next section.

Table 1
Potential predictors of Google searches for climate change: baseline estimates.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline model: OLS FE				Spatial model: SAC			
TempDev	0.00956***			0.00956***	0.00660**			0.00667**
	(0.00266)			(0.00266)	(0.00274)			(0.00273)
Activists		0.0144***		0.0146***		0.0162***		0.0164***
		(0.00371)		(0.00370)		(0.00376)		(0.00375)
PolitMeetIn			0.139**	0.141**			0.114**	0.117**
			(0.0560)	(0.0562)			(0.0511)	(0.0514)
ρ					0.117***	0.119***	0.118***	0.118***
					(0.0270)	(0.0275)	(0.0272)	(0.0273)
λ					0.108***	0.104***	0.107***	0.103***
					(0.0257)	(0.0250)	(0.0252)	(0.0252)
Constant	0.374***	0.408***	0.410***	0.372***				
	(0.107)	(0.105)	(0.105)	(0.107)				
Observations	52,380	52,380	52,380	52,380	52,380	52,380	52,380	52,380
N regions	194	194	194	194	194	194	194	194

This table reports the results of Model (1) estimation by OLS, in Columns (1)–(4), and Model (SAC) estimation by maximum likelihood, in Columns (5)–(8); time and region fixed effects included in all estimations; ***, **, and * denote statistical significance at 1, 5, and 10% significance level, respectively.

4.2. Spatial model

The purpose of this subsection is to verify that the main explanatory variables remain robust in a spatial model of the search intensity for climate change, given that spatial interactions could be important for propagating the impact of the factors considered in this study. I follow LeSage and Pace (2009), Elhorst (2010), and Belotti et al. (2017) by selecting the appropriate fixed effects spatial model among the following four alternatives, using the notation from Model (1):

- spatial Durbin model:

$$y_{ijwt} = \rho W y_{ijwt} + \beta X_{ijwt} + \theta W X_{ijwt} + a_{ij} + \gamma_w + \eta_t + u_{ijwt}, \quad \text{(SDM)}$$

- spatial autoregressive model:

$$y_{ijwt} = \rho W y_{ijwt} + \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + u_{ijwt}, \quad \text{(SAR)}$$

- spatial error model:

$$y_{ijwt} = \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + v_{ijwt}, \;\; v_{ijwt} = \lambda W v_{ijwt} + u_{ijwt}, \quad \text{(SEM)}$$

- spatial autocorrelation model:

$$y_{ijwt} = \rho W y_{ijwt} + \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + v_{ijwt}, \;\; v_{ijwt} = \lambda W v_{ijwt} + u_{ijwt}, \quad \text{(SAC)}$$

where W is the spatial weighting matrix and v_{ijwt} is spatially autocorrelated error term. The spatial weighting matrix W consists of the inverse distances among the regions, with distances calculated from Eurostat NUTS geolocation data.

Following Belotti et al. (2017), in order to determine the optimal spatial model, I test the significance of coefficients distinguishing between alternative models and compare the goodness of fit across different model alternatives. The model selection procedure, outlined in Table 5 in the Appendix, identifies SAC as the most appropriate model for the weekly panel data considered in this section. The results of this model's estimation by maximum likelihood are presented in Table 1, Columns (5)–(8).[11] Each of the potential predictors has a positive and significant coefficient robust to the inclusion in the model of all three predictors (Column (8) of Table 1). The coefficient on the spatially autocorrelated error term is positive and significant, suggesting that spatial spillovers constitute an important determinant of search intensity for climate change.

The estimation results from Table 1 suggest that public awareness of climate change can be raised by both natural and human factors, such as strikers' and policymakers' activities. It remains to be seen which of the factors is a more powerful predictor of public awareness of climate change. In the next section, I consider different combinations of the three predictors of interest, activists' strikes, temperature variations, and political meetings, and various econometric models to evaluate and compare the forecasting performance of different predictors and models. First, I consider forecasting is very short term, several weeks in advance; second, I evaluate forecast performance of the predictors using annual data.

5. Forecasting public attention to climate change

5.1. Predicting short-term search intensity

The purpose of this subsection is to evaluate and compare the predictive performance of the indicators of weather, activists' strikes, and internal and external political meetings in forecasting climate change over the weekly horizon. For this purpose, out of 291 weeks of data available, I use the first 270 weeks for model estimation, and predict the search intensity for climate change over the following 9 weeks (the additional weeks are used when forward or lagged values of the variables are included in the estimation). The predictive efficacy is measured by the average out-of-sample root mean square error, RMSE (similar to Baltagi et al., 2014; Ductor et al., 2014).

5.1.1. Choosing the baseline "naive" model

As a first step, I choose the best-performing baseline model, by comparing the estimations by OLS of several variations of Model (1):

- (OLS FE WE YE M*C static): the model as it is, containing region, week, year, and month times country fixed effects;
- (OLS FE WE YE M*C dynamic): the model as it is, containing region, week, year, and month times country fixed effects with the lagged dependent variable added;
- (OLS FE WE static): the model without year and month times country fixed effects;
- (OLS FE WE dynamic): the model without year and month times country fixed effects with the lagged dependent variable added;
- (OLS WE static): pooled model — the model without region, year and month times country fixed effects, with week fixed effects;
- (OLS WE dynamic): pooled model — the model without region, year and month times country fixed effects, with week fixed effects and with the lagged dependent variable added;
- (OLS static) pooled model without any time fixed effects;

[11] The estimations of the other three models produce very similar results.

Table 2
Forecasting the search intensity for climate change over the weekly horizon: percentage difference in RMSE compared to baseline.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Individual predictors					Combinations of predictors
Regions	Activ.	TempDev	PolitIn	PolitOut	Best	Composition
Linear model (Pooled OLS)						
(1) All	−1.013	−0.427	−0.053	−0.187	−1.253	l(2/8) Activists TempDev PolitMeetIn
(2) Eastern	−0.037	−0.012	−0.025	−0.050	−0.050	l(0/0) Activists PolitMeetOut
(3) Northern	−0.829	−1.331	0.980	−0.364	−1.908	l(2/8) Activists TempDev
(4) Western	−3.014	0.017	0.050	−0.265	−2.882	l(2/10) Activists PolitMeetIn
(5) Southern	−0.284	−1.027	−0.622	0.041	−1.920	l(2/8) Activists TempDev PolitMeetIn
Spatial model (SDM)						
(6) All	−5.547	−5.960	−6.067	−5.840	−6.267	TempDev PolitIn TempDev × PolitIn

This table reports the percentage difference of the RMSE compared to the baseline, in the OLS-estimated model and the best-performing spatial model, using weekly data, for each of the sole main predictors, in Columns (2)–(5), and for the best-performing combinations of the predictors, in Columns (6)–(7).

- (OLS dynamic) pooled model without any time fixed effects with the lagged dependent variable added.

In this way, I evaluate the role of various fixed effects in model's predictive efficacy. All the variations are estimated without any additional explanatory variables and with an addition of different combinations of explanatory variables (e.g., temperature variations; temperature variations and activists' strikes; temperature variations, activists' strikes, and political meetings; etc.). In all the cases, the best performing model is (OLS WE dynamic), suggesting that while seasonable variations are important, the region-specific time-invariant characteristics do not improve the predictive accuracy. Therefore, the model (OLS WE dynamic) is used as a baseline, "naive" model, in the analysis of forecasting performance over weekly horizon. Table 6 in the Appendix reports the RMSE and AIC criteria for all the considered variations when no additional explanatory variables are included.[12]

5.1.2. Forecasting using a standard model

As a next step, I compare the predictive performance of the various predictors of interest included in the model (OLS WE dynamic) with a baseline model (OLS WE dynamic) in which no predictors are added. Each model's performance is measured by the percentage difference of the average out-of-sample RMSE compared to the average out-of-sample RMSE generated by the baseline model. I include each of the predictors one-by-one (e.g., only activists' strikes, only temperature deviations, only local (internal) political meetings, or only external political meetings), as well as combinations including two-three-four predictors at a time, their interactions, and various leads and lags.

The past and the future values of the predictors can contain useful information about the future changes in search intensity. For example, an announcement of the Friday for Future global strike aimed at raising awareness of climate change can increase the public interest in climate change ahead of the strike. A heatwave experienced in a given week can enhance public interest in climate change in the current and the following week. The expectation of future abnormal climate changes announced in weather forecasts may affect public interest in climate change in the present.

Furthermore, the impact of each of the predictors of interest can be potentially reinforced by the other. For example, political meetings related to the climate change are frequently accompanied by activists' strikes, which can significantly increase the public attention to the issues associated with the meetings, in this case, climate change. The interactions can also be used to evaluate the indirect impact of the political meetings that took place outside the considered countries regardless of a set of fixed effects included in the model.

Fig. 3 in the Appendix presents an example of a set of estimated RMSEs, reported in percentage difference compared to the baseline, for different combinations of the main predictors of interests, their lags, leads, and interactions. After comparison of hundreds of the RMSEs resulting from different variations of the estimated models (similar to those reported in Fig. 3), I conclude that forward values of the main explanatory variables do not contribute to the predictive capacity of the model. Nevertheless, the two to eight or the two to ten weeks lags of the main explanatory variables are important for reducing the out-of-sample prediction error over weekly or monthly horizons.

Table 2 reports the predictive performance of each of the predictors, in row (1), Columns (2)–(5), and the combination of predictors that delivers the largest reduction in RMSE compared to the baseline, in row (1), Columns (6)–(7). The measure of activists' strikes is the best among sole contemporaneous predictors in the OLS estimation and reduces the RMSE of predicting the search intensity of climate change during the upcoming two months by around one percent. The measure of air temperature fluctuations improves the forecasting performance of the model by around half percent. The indicators for political meetings, either internal or external, have the lowest predictive power, reducing the RMSE by 0.05–0.19 percent.

The maximum contribution of the main predictors of interest in predicting the search intensity of climate change over and above the lagged search intensity of climate change is around 1.25% (the RMSEs comparison test suggests that the difference is statistically significant). This best predictive performance is achieved when all three predictors of interest are included, moreover, in their two-to-eight weeks lags (as reported in row (1), Columns (6)–(7) of Table 2).

The results imply that the environmental activists' strikes and temperature variations observed during the last two months contain useful information in forecasting the public interest in climate change in the subsequent two months. The reduction is forecasting error is statistically significant but modest.

5.1.3. Forecasting using spatial models

The OLS model does not take into account possible spatial interrelations across regions. When spatial interactions are important, as it is likely to be the case in the data analyzed in this paper, the inclusion of spatial dependence can significantly improve the out-of-sample forecasts (see Giacomini and Granger, 2004; Hernández-Murillo and Owyang, 2006) .

Therefore, I re-estimate the predictive performance of different combinations of the predictors of interest in four versions of the spatial model described in the previous section (SDM, SAR, SAC, and SEM). Fig. 4 in the Appendix reports the results in terms of percentage improvement in RMSE compared to the baseline, (OLS WE dynamic)

[12] It is impossible to evaluate the forecasting performance of (OLS static): pooled model without any time fixed effects and without the lagged dependent variable added if no other explanatory variables are included; however, the performance of such a model is always below (OLS WE dynamic) for any combinations of the predictors of interest, when these are included.

with no other predictors.[13] The predictive performance of the spatial models varies by model type and predictors included, but in all cases it considerably overperforms any of the OLS estimated models. The lowest RMSEs are achieved in the SDM model.

Differently from the OLS case, the best-performing predictor in the spatial model is the indicator for local political meetings (that take place within the considered sample of countries), which reduces the RMSE by 6%, compared to the baseline. The performance of the remaining predictors is similar, with each of them reducing the RMSE by around 5.5%–6% (see row (6), Columns (2)–(5) of Table 2).

The best combination of predictors includes the indicators of weather fluctuations, local political meetings and their interaction, reducing the RMSE by around 6.3% (see row (6), Columns (6)–(7) of Table 2). Intuitively, the spatial model accounts for the existence of interrelations across the regions and is able to capture the impact of the regional factors that are likely to affect public attention beyond the regional borders, such as the political meetings or the heatwaves.

5.2. Predicting long-term search intensity

It may require some time for the impacts of human and natural factors on the public awareness of climate change to become noticeable. I use annual data, constructed by averaging weekly observations over years, to evaluate the predictive efficacy of the predictors of interest over longer-term horizons.[14] I use the first four years to estimate the model, and forecast the search intensity of climate change in the fifth and sixth years.

5.2.1. Choosing the baseline "naive" model

As a first step, I compare the forecasting performance of different representations of the indicators of interest and the dependent variable, including the levels and growth rates, lags and leads, and different models, including dynamic and static linear models, and the variations of spatial models. The performance is measured by the out-of-sample RMSE corresponding to different variations of the model and different sets of predictors, similar to the analysis done in the previous subsections.

The analysis suggests that, for annual panel, first-differencing of the dependent and explanatory variables significantly improves the prediction precision. Therefore, I use the annual growth rate of the search intensity for climate change (the first difference of the logarithm of search intensity) as the dependent variable and the indicators of interest are first-differenced and lagged (except for the annual indicators of local and external meetings, computed as the average number of meetings during the year) for forecasting over the annual horizon. The OLS-estimated dynamic model with region fixed effects overperforms the static OLS-estimated model with region fixed effects and pooled OLS-estimated models in forecasting annual growth rate of the search intensity (see Table 6 in the Appendix). Among the spatial models, SDM gives the best results (see Fig. 6 in the Appendix).

[13] All spatial models include week and region fixed effects, because this specification over-performs other spatial specifications, such as those with no fixed effects, or annual, monthly, and other additional fixed effects. The lags or leads of explanatory variables do not contribute to the predictive efficacy in the spatial models and therefore, are not considered.

[14] Before constructing the annual panel from the weekly panel, I remove an outlier observation corresponding to the week of April 22, 2022, when a Google doodle about the history of climate change raised public attention to the topic to an unprecedented level.

5.2.2. Choosing the best predictors in the linear and spatial models

As a second step, I choose the best-performing combinations of predictors within the best performing models. Fig. 5 in the Appendix reports the RMSE for different combinations of the predictors (lagged, in first-differences) for the best performing non-spatial and spatial models. Rows (1) and (6) of Table 3 summarize the results, for the sole predictors, in Columns (2)–(5), and the best-performing combinations of predictors, in Columns (6)–(7).

The direct indicator of global warming, the annual change in the average of positive deviations of maximum temperature from its historical norms, and the external political meetings are the best predictors of the growth rate in the search intensity for climate change over the annual horizon in a non-spatial model and reduce the RMSE by 23 and 45 percent compared to the baseline. Differently from the results obtained for weekly data, the information on external political meetings contributes (significantly) to the reduction of forecasting error in the annual data. In particular, external political meetings, together with internal political meetings and temperature fluctuations constitute the best combination of predictors in a non-spatial model, and reduce the RMSE by 45.3% (see row (1), Columns (6)–(7) of Table 3). Intuitively, the impact of such meetings on public interest in climate change occurs through the measures and policies approved during the meetings, and the latter require some time to be implemented.

The forecasting performance of the predictors of interest is significantly better when the spatial models are used (see Fig. 5 in the Appendix and Fig. 7 which presents the kernel densities of the true and predicted growth rates of the search intensity for climate change). Specifically, an addition of the growth rate of past year temperature deviations from historical norms or the data on political meetings focused on environmental issues in the spatial model reduces the RMSE by approximately 61–63 percent compared to the baseline. Nevertheless, the best-performing combination of predictors includes all three predictions of interest (see row (6), Columns (6)–(7) of Table 3), suggesting that activist movements, political meetings, and the weather indicators are important for shaping public awareness of climate change in the long term.

5.3. Robustness checks

Although it can be argued that European regions are relatively homogeneous, they possess some significant differences. One striking difference is the climate, which varies between Northern and Southern Europe. The economic conditions also differ across regions, with Western Europe being relatively richer than Eastern Europe.

These differences in geographical and economic characteristics may affect the relationship between the factors studied in this paper and public perception of climate change. To test this possibility, I consider four subregions of Europe, as defined by the United Nations geoscheme for Europe: Eastern, Northern, Southern, and Western. Conveniently, these subregions differ both in weather and economic conditions. Northern and Western subregions are comparatively affluent and characterized by nordic and oceanic climates, respectively. The Eastern subregion is characterized by lower income levels and a continental climate, while the Southern subregion is characterized by moderate income levels and a Mediterranean climate. They are also represented relatively equally in the data used in this study: the percentage of the data corresponding to the Eastern subregion is 27.32, Northern subregion, 15.46; Southern subregion, 20.10; and Western subregion, 37.11.

I evaluate the forecasting performance of activist strikes, political meetings, and air temperature fluctuations, as well as combinations of these predictors, for each subregion separately, using a standard linear

Table 3
Forecasting the search intensity for climate change over the annual horizon: sole predictors and the best combinations of predictors.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Individual predictors					Combinations of predictors
Regions	Activ.	Temp	PolitIn	PolitOut	Best	Composition
Linear model (OLS FE)						
(1) All	−1.373	−22.971	−1.748	−45.069	−45.318	TempDev PolitMeetIn PolitMeetOut
(2) Eastern	−6.044	−28.242	0	−37.363	−40.659	TempDev × PolitMeetOut
(3) Northern	−10.267	3.938	0	−49.930	−57.525	TempDev PolitMeetIn PolitMeetOut
(4) Western	7.719	−24.912	−2.456	−54.386	−54.386	PolitMeetOut
(5) Southern	−9.836	−31.893	11.624	−36.066	−38.301	TempDev × PolitMeetOut
Spatial model (SDM)						
(6) All	−59.426	−61.423	−63.171	−49.688	−63.296	Activists TempDev PolitMeetIn

This table reports the percentage difference of the RMSE compared to the baseline, in the OLS-estimated model and the best-performing spatial model, using annual data, for each of the sole main predictors, in Columns (2)–(5), and for the best-performing combinations of the predictors, in Columns (6)–(7).

model.[15] The results are reported in rows (2)–(5) of Table 2 and Table 3, for the predictions over weekly and annual horizons, respectively.

There is some variation in the forecasting performance of individual indicators compared to the full sample that includes all the regions. Specifically, over the weekly horizon, forecasting performance is lowest in Eastern regions and highest in Northern and Western regions. This implies that the impact of human and natural factors on public awareness of climate change can depend on geopolitical and economic factors. Further research is needed to clarify the impact of such factors. Nevertheless, the predictive accuracy of combined predictors remains similar across all regions, suggesting that the full forecasting model's performance is robust to subregional divisions.

For the annual horizon, political meetings has no predictive power in Eastern and Northern regions and the inclusion of activists' strikes worsens the forecasting performance in Western regions, compared to the baseline. The differences in forecasting performance across individual predictors can be attributed to variations in the values of these predictors among the subregions. For instance, Eastern subregion did not experience any political meetings during the considered period, and Northern subregion had very few political meetings compared to the Western subregion. Nevertheless, similar to the weekly horizon, when the combinations of predictors are considered, the forecasting performance is similar across regions.

I conduct other robustness checks, not included in this paper. Specifically, I consider different indicators of weather (such as precipitation, snow, wind speed, the maximum temperature levels, minimum or average temperatures or their deviations from historical norms); a binary indicator for activists' strikes; the growth rates of the variables of interest vs the levels; the growth rate vs the level of the dependent variable. The predictors and the models reported in Table 2 and Table 3 remain the most effective in forecasting the search intensity for climate change over weekly and annual horizons.

6. Conclusions

The findings of this paper indicate that public awareness of climate change, as measured by Google search intensity for the topic, is influenced by both human and natural factors. Activist strikes can increase immediate public interest in climate change, but factors like temperature fluctuations and comprehensive political initiatives hold greater relevance in the long term. Inter-regional spatial connections, when taken into account, significantly improve the accuracy of forecasting the future search intensity for climate change.

The findings of this paper justify public funding of activists' movements and public policy initiatives. Increased levels of environmental knowledge is associated with sustainable consumption behavior (Saari et al., 2021). Therefore, raising public awareness of climate change is an important step towards changing public behavior to combat climate change.

This paper has several limitations and suggests several areas for future research. Firstly, it focuses exclusively on activist movements and environmentally-related political meetings as indicators of human factors influencing public awareness of climate change through peer influence. However, another related factor that can affect public perception of climate change is the social media. Social media has become increasingly influential in recent years, serving as a primary source for disseminating information about events such as activist strikes and fostering public discussions on weather, climate change, and potential actions. Analyzing the contribution of social media, in addition to the factors already studied, presents an important avenue for future research. Secondly, this study focuses on regional data from Europe. While this regional focus offers advantages from an econometric perspective due to the relative homogeneity of European regions, extending this research to other countries and regions could provide additional insights on the factors influencing public awareness of climate change from a global perspective.

CRediT authorship contribution statement

Daryna Grechyna: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix

See Tables 4–6 and Figs. 3–7

[15] Using a spatial model for subregions would imply that those subregions are not spatially related, which is not supported by the spatial model estimates presented in Table 1.

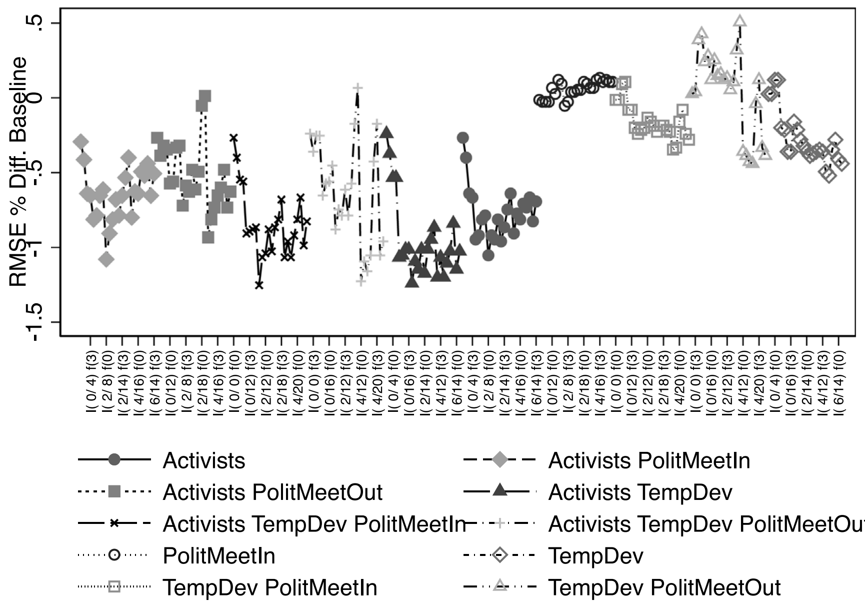

Fig. 3. Predicting the search intensity for climate change over the weekly horizon: comparison of different combinations of predictors.
This figure reports the percentage reduction in the RMSE compared to the baseline short-run model where the only explanatory variables are the lagged dependent variable and weekly fixed effects; all models are estimated by OLS and focus on short term predictions, several weeks in advance; each observation in the figure is associated with an out-of-sample RMSE corresponding to the estimation of the model including a specific combination of the predictors, their past and forward values (for example, the first observation in the figure corresponds to the percentage reduction in the RMSE when the set of explanatory variables included in the estimated model consists of activists' strikes and local political meetings, both variables included in their contemporaneous values, l(0), and in their first four lags, l(1/4), as well as in their future values observed three weeks forward, f(3)).

Table 4
Summary statistics.

Variables	(1) N	(2) Mean	(3) St.Dev.	(4) Min	(5) Max
Activists's strikes (logarithm)	52,380	0.194	0.983	0	12.43
Search intensity for climate change (logarithm)	52,380	0.745	0.842	0	4.615
PolitMeetIn	52,380	0.005	0.069	0	1
PolitMeetOut	52,380	0.133	0.340	0	1
TempDev	52,380	1.475	1.994	0	17.63

This table reports summary statistics for weekly data on 194 regions of 21 European country covering period 3 of June 2018 to 30 of July 2023.

Table 5
Spatial model selection for the estimation reported in Table 1, Columns (4)–(8)

Alternative models hypotheses tests			
Alternative models		Hypothesis	Test p-value
SDM vs	SAR	$\rho = 0$ and $\theta = 0$	0.000 and 0.0734
SDM vs	SEM	$\theta = -\beta\rho$	0.0564
Models' AIC			
SDM	SAR	SEM	SAC
116	110	110	108

This table reports the results of spatial model selection for estimation reported in Table 1. After estimating the SDM model, first, I test the hypotheses that (1) $\rho = 0$ and (2) $\theta = 0$. Hypothesis (1) is rejected, while hypothesis (2) cannot be rejected at 5% significance level. Therefore, SAR rather than SDM is likely to be a more appropriate model for the data analyzed in this paper. Second, I test the hypothesis that (3) $\theta = -\beta\rho$ to evaluate whether SEM or SDM model is more appropriate. Hypothesis (3) is cannot be rejected at 10% significance but is rejected at 5%, thus it is uncertain which model is more appropriate. Finally, I compare the Akaike information criteria (AIC) across all four potential models; SAC model has the lowest AIC for weekly data panel. Given the tests' results and the AIC comparison, the SAC model is used for the estimations based on weekly data.

Table 6
Forecasting: comparison of the potential baseline models' performance.

RMSE	Model	AIC
Short term		
0.833	OLS WE dynamic	115 528.9
0.842	OLS FE WE dynamic	112 299.6
0.858	OLS WE static	117 246.5
0.858	OLS FE WE static	113 119.6
0.903	OLS dynamic	117 105.8
0.977	OLS FE WE YE MxC static	108 033.2
1.017	OLS FE WE YE MxC dynamic	107 423.9
Long term		
0.405	Pooled OLS with lag dep.	389.187
0.748	Pooled OLS without lag dep.	452.298
0.375	OLS FE with lag. dep	195.371
0.748	OLS FE without lag dep.	396.157

This table reports the RMSE and AIC criteria for the competing models estimated by OLS using weekly data, in the top panel, and annual data, in the bottom panel.

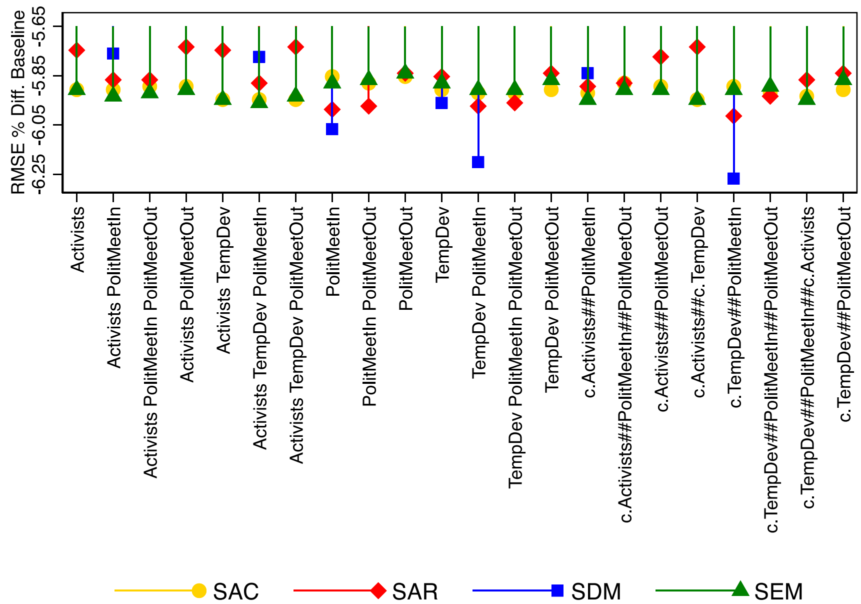

Fig. 4. Forecasting the search intensity for climate change over the weekly horizon: comparison of spatial models.
This figure reports the percentage reduction in the RMSE in different spatial models compared to the baseline short-run OLS-estimated dynamic model with weekly fixed effects; each observation in the figure is associated with an estimation of a particular spatial model, SAC, SAR, SDM, or SEM, in circles, diamonds, squares, and triangles, respectively, including a specific combination of the predictors (for example, the blue square observation above "c.TempDev##PolitMeetIn" on the horizontal axis in the figure corresponds to the percentage reduction in the RMSE when the set of explanatory variables included in the estimated model consists of the temperature deviations from historical norms, local political meetings, and the interaction of these two variables, and the estimated model is SDM).

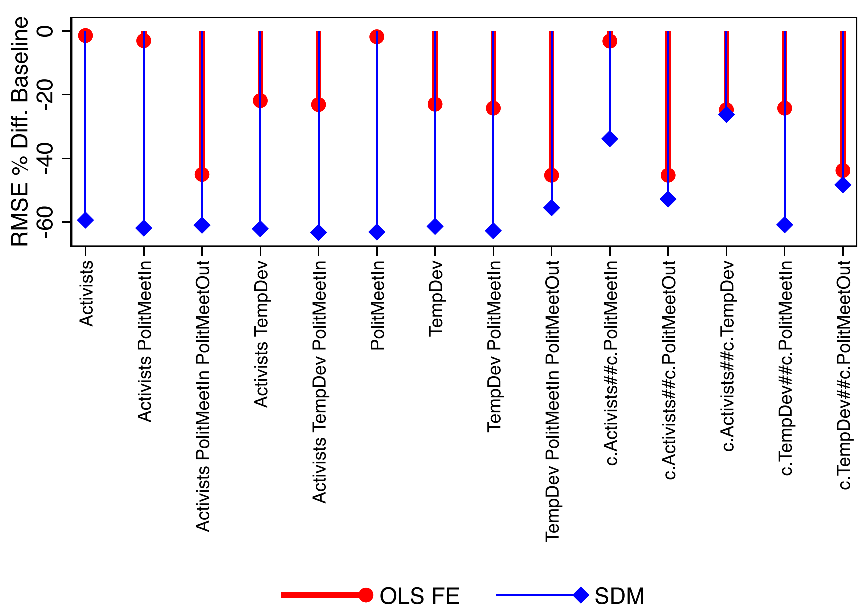

Fig. 5. Forecasting the search intensity for climate change over the annual horizon: comparison of non-spatial and spatial models.
This figure reports the percentage reduction in the out-of-sample RMSE in a linear model estimated by OLS, in circles, and a spatial model estimated by SDM, in diamonds, compared to the baseline long-run model where the only explanatory variables are the lagged dependent variable and region fixed effects; each observation in the figure is associated with an estimation of a particular model including a specific combination of the lagged values of predictors in first-differences.

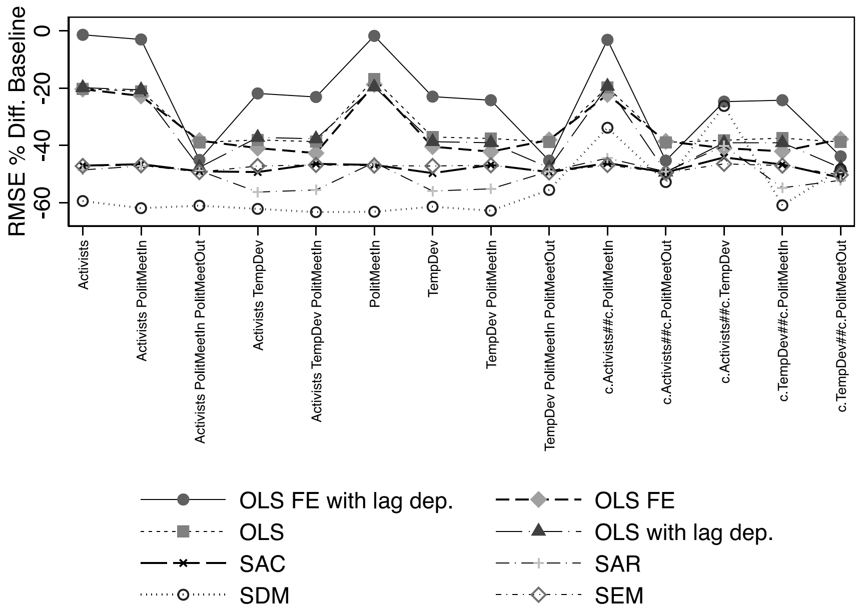

Fig. 6. Predicting the search intensity for climate change over the annual horizon: comparison of different models and combinations of predictors.
This figure reports the percentage reduction in the RMSE compared to the baseline long-run model where the only explanatory variables are the lagged dependent variable and region fixed effects; all models focus on longer term predictions, one-two years in advance; each observation in the figure is associated with an out-of-sample RMSE corresponding to the estimation of a particular model including a specific combination of the lagged values of predictors in first-differences (for example, the first hollow circle observation in the figure corresponds to the percentage reduction in the RMSE when the set of explanatory variables included in the estimated model consists of the lagged value of the growth rate of activists' strikes, and the estimated model is SDM; the first filled circle observation in the figure corresponds to the percentage reduction in the RMSE when the set of explanatory variables included in the estimated model consists of the lagged value of the growth rate of activists' strikes, and the estimated model is dynamic OLS with region fixed effects).

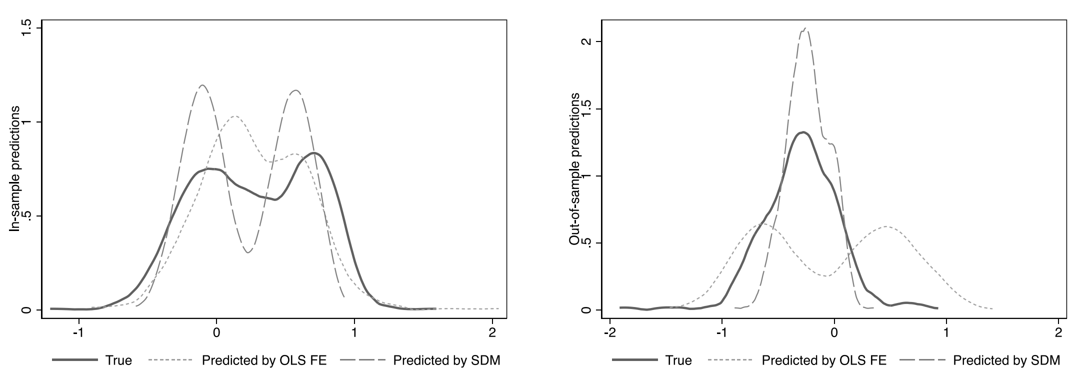

Fig. 7. Forecasting the search intensity for climate change over the annual horizon: kernel densities.
This figure reports the kernel densities of the true data, solid line, and the data predicted by OLS, dotted line, and SDM, dashed line, on the growth rate of search intensity for climate change, for the in-sample prediction, in the left graph, and out-of-sample prediction, in the right graph.

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