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Raising Awareness of Climate Change: Nature, Activists, Politicians?

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.

JEL-Codes: Q010, Q520, Q580, C330.

Keywords: climate change, activists' strikes, political meetings, weather.

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1 Introduction

In the wake of recurrent heat waves that have embraced Europe in recent years, awareness of climate change is growing on the continent. In effect, a number of studies have demonstrated that extreme weather events enhance people's recognition of climate change.[1] Nevertheless, the global international and national environmental policy initiatives have not been able to slow down global warming.[2] Partly in response to the lack of any significant measures undertaken by society to address the climate crisis, various activist movements, consisting mainly of young people, have emerged in an attempt to foster environmental consciousness in the public and among politicians. The question is whether activism and political action can enhance public awareness of global warming, thereby encouraging involvement in climate-protective efforts? Alternatively, is it solely nature's force, demonstrated through natural disasters and unprecedented fluctuations in air temperatures, that can persuade society of the imperative for action?

This paper aims at evaluating the relative importance of natural and human factors in shaping public awareness of climate change. To this end, 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, as well as movements led by environmental activists, in forecasting the salience of climate change topic over short (weeks) and long (years) horizons using regional European countries' data.

The contribution of this paper to the literature is twofold. First, I evaluate the impact of activists' movements and political events on the salience of climate change topic using

[1]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, Böhmelt, and Bakaki, 2023; Choi, Gao, and Jiang, 2020; Kahn and Kotchen, 2011.

[2]According to the politicians themselves, see, for example, the United Nations Climate Change Conference COP26 report at UNEP: "COP26 ends with agreement but falls short on climate action" (https://www.unep.org/news-and-stories/story/cop26-ends-agreement-falls-short-climate-action) or COP28 UN Climate Change press release stating that "..we didn't turn the page on the fossil fuel era.." and "increasing climate finance.. financial pledges are far short of the trillions eventually needed to support developing countries with clean energy transitions.." (UN Climate Press Release 2023. COP28 Agreement Signals "Beginning of the End" of the Fossil Fuel Era. 13 December 2023. https://unfccc.int/news/cop28-agreement-signals-beginning-of-the-end-of-the-fossil-fuel-era).

highly granular weekly-regional data. Second, I evaluate whether these activities can be more effective in raising public awareness of climate change compared to the climate change itself. A better understanding of how human actions influence public awareness of global natural phenomena regardless of these phenomena's inherent manifestations could facilitate the formulation of effective policies. For instance, if activist movements prove effective in raising public awareness about climate change, governments should consider providing increased support to these movements. Conversely, if political events emphasizing environmental policies are more successful in capturing public attention, the considerable expenses associated with organizing these gatherings could be considered justified.

This research is closely related to the extensive literature on the impact of weather conditions on personal choices. Climate changes and extreme temperatures have been shown to affect various aspects of human life, including economic growth rates (Dell, Jones, and Olken, 2012), behavior in financial markets (Cao and Wei, 2005; Peillex et al., 2021; Choi, Gao, and Jiang, 2020), academic achievement (Cho, 2017), migration (Cattaneo and Peri, 2016; Cattaneo et al., 2019; and Berlemann and Steinhardt, 2017) and mortality (Deschenes and Moretti, 2009; Barreca et al., 2016); see also a review by Dell, Jones, and Olken (2014). The contribution of this study is to evaluate the role of other factors, specifically, political events and activists' movements, over and above the impact of climate itself, on individual awareness of climate change.

Traditionally, the source of data on climate beliefs has been surveys (related studies that use surveys include Deryugina; 2013; Owen et al., 2012; Egan and Mullin, 2012; Hamilton and Stampone, 2013; Sloggy et al., 2021; Kalatzi Pantera et al., 2023). But recently, research relies more frequently on Internet search data, such as Google Trends, which provide a solution to the lack of individual data (see, for example, Herrnstadt and Muehlegger, 2014; Choi, Gao, and Jiang, 2020; Kahn and Kotchen, 2011). 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.[3]

[3] 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.,

Therefore, following Herrnstadt and Muehlegger (2014), I proxy the salience of climate change by weekly Google search intensity data. I use Meteostat for regional data on weather indicators. The data on noteworthy political events focused on environmental policies is collected from the European Council website. I distinguish between "local meetings" that took place in some of the considered countries (such as, for example, the European Council meetings and Environment Council meetings) and "other meetings," that took place outside Europe (such as, for example, COP27, Egypt and UN General Assemblies, US). As a measure of environmental activists' movements, I use weekly regional data on Fridays for Future strikes. Fridays For Future (FFF) is a youth-led international movement that have organized various protests in the locations around the world to demand action from political leaders to prevent climate change.[4] The studies that have analyzed the impact of Fridays for Future movement on public attention focused on the main twelve global strikes (see, for example, Schuster et al., 2023). Another contribution of this paper is an analysis of highly granular activists' data, which permits an evaluation of a marginal impact of environmental activists' initiatives on the public. I use all available strikes and apply data-processing techniques to combine weekly regional data on Google searches for topic "climate change" with weekly town-level data on activists' strikes and political events during five years starting from 2018, when the Friday for Future activists' movement was initiated.

First, I use the assembled weekly-region panel data to confirm that activists' movements, political events, and temperature fluctuations are all robust determinants of the intensity of Google searches for climate change, even after controlling for a wide variety of fixed effects to account for spurious geographic and seasonal relationships and common time-varying factors. Second, I use the traditional econometric models and models accounting for possible spatial interdependence across regions to predict the intensity of Google searches for climate change using each of these determinants, as well as their combinations, as potential predictors. I consider a selection of estimation techniques: static and dynamic models, pooled OLS, OLS controlling for fixed effects, spatial autoregresive (SAR), autocorrelation (SAC), Durbin (SDM) models, and spatial error (SEM)

2009) and heat-related illness or stress (Adams et al., 2022).

[4]It began in August 2018, after 15-year-old Greta Thunberg and other young activists sat in front of the Swedish parliament every schoolday for three weeks, to protest against the lack of action on the climate crisis. See https://fridaysforfuture.org/.

model. The predictive power of each of the potential predictors of interest is evaluated by comparing the out-of-sample root mean square error (RMSE) against the out-of-sample RMSE obtained from the baseline non-spatial model that includes a lagged dependent variable.

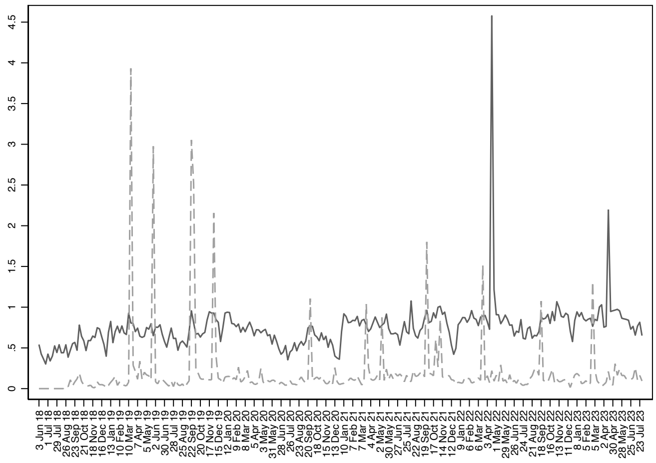
The best-performing predictor in the short term (two months in advance) in a non-spatial model is the size of activists' strikes. An inclusion of this predictor reduces the RMSE by 0.6 percent compared to the baseline. In general, the predictive power of the weather indicators, activists' strikes and political meetings in forecasting the search intensity for climate change in the following two months is very modest. Specifically, the maximum improvement compared to the baseline model is around 1.5 percent. Spatial models provide much more precise predictions. In particular, an SDM model provides a 6% improvement in forecasting the search intensity for climate change, compared to the baseline.

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.

For the longer-term horizon (one-two years in advance), I use the growth rate of Google search intensity for climate change as the dependent variable and the growth rates or the first differences of the main predictors of interest as explanatory variables. The best-performing predictor in the longer term in a non-spatial model is the annual change in the maximum air temperature deviations from historical norms. In spatial models, an addition of the data on political meetings focused on environmental issues reduces the RMSE by around 60% compared to the baseline.

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

Figure 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 grey; both time series measured as averages over all regions for a given week.

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 describes the data. In Section 3, 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 4, 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 5 concludes.

2 Data

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

Google search intensity data: as a measure of climate change awareness I use the Google Trends index for topic “climate change.” In Google Trends, topics are a group of terms that share the same concept in any language. According to the description on Google Trends website,[5] topics are generally considered to be more reliable for Google

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

Trends data compared to search terms, because they pull in the exact phrase as well as misspellings and acronyms, and cover all languages. I use weekly regional data for European countries (countries from the European Union and/or Shengen zone and the UK) for the most recent period including five European summers, from 3 of June 2018 to 30 of July 2023.[6] For Europe, regions listed in Google Trends generally coincide with NUTS2 regional classification, which facilitates merging of Google data with other regional data.[7] The selection of the time period is motivated by the data availability: first, the objective is to choose the most recent period; second, if the time period is further extended, the data reported by Google trends is monthly rather than weekly; finally, the data on activists' movements starts in August 2018.

Google Trends data is pulled from a random, unbiased sample of Google searches, and computed as a proportion of all searches at that time and location, so that the data lies in the interval [0,100] where 100 is the maximum search interest for the location during the time period selected (low volume searches are censored to zero). The resulting distribution is skewed toward 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.[8] 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). Figure 1 shows the search intensity over time, average across all the considered regions.

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 countries 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 combined with the Google search data. Besides, I compute the historical regional weekly data, as the averages for a given week and region over the period 1997–

[6]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.

[7]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.

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

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 data from its 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.

Activists' data: I use the data on weekly strikes organized by the Fridays for Future movement. Fridays for Future (FFF) is a youth-led and -organised global climate strike movement that started in August 2018.[9] 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 to combine it with the weekly-regional data on Google searches and weather. The FFF town-level data contains special symbols and some town names are non-standard. I apply various data-processing techniques, including geocoding services and the combination of NUTS, ISO, and HASC regional codes to merge town-level FFF data to regional-level Google search data. As a result, I could identify the regions of 85% of the available towns.

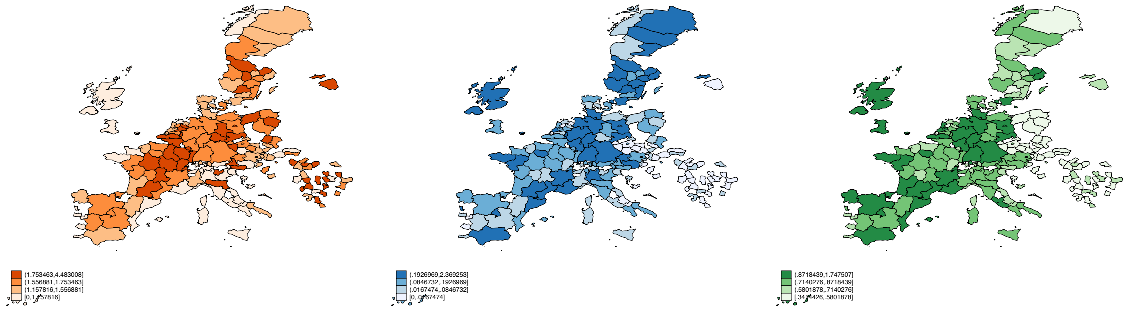
The total number of strikes during the considered period is 2,868 but the number of reported strikes' participants varies from 1 to 250000. Similar to the search intensity data, this data is skewed towards zero. Therefore, I apply the $ln(x + 1)$ transformation to the strike size x to reduce the impact of the largest strikes on the estimates. Figure 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.

Political meetings data: 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."[10] 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

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

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

Figure 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.

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 conferences COP27 (Egypt) and COP26 (Scotland), UN General Assemblies (US), G20 Summit (India), and European meetings that took place in Luxembourg or online.

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 22 European countries covering 291 week from 3 of June 2018 to 30 of July 2023. Figure 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.

3 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.

3.1 Standard Model

I use a standard linear model from the studies of the determinants of perceptions and salience of climate change (see, for example, Herrnstadt and Muehlegger, 2014 and 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.[11]

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'

[11]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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		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.

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).

Given that all the estimations include a battery of fixed effects, all three predictors of interest can be considered robust. Although causal inferences can be made for the specification considered, the primary goal of this study is to evaluate and compare the predictive capacity of each of these explanatory variables. 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.

3.2 Spatial Model

The weather in a given region is likely to be similar to the weather in geographically close regions. The weather, the number and size of activists' strikes and political meetings occurring in a given region are likely to influence the public opinions not only in a given region, but also in other regions, more so in geographically close regions of the same country. Therefore, spatial interactions could be important for propagating the impact of the factors considered in this study on the public awareness of climate change.

Spatial models are particularly relevant for studies focused on environmental issues and have been used, for example, to estimate environmental Kuznets curves (Maddison, 2006); the impact of pollution on house prices (Kim, Phipps and Anselin, 2003); the impact of air temperature on economic development (Linsenmeier, 2023); the impact of natural disasters on environmental attitudes (Kalatzi Pantera et al., 2023); and the determinants of carbon dioxide emissions by firms (Cole et al., 2013).

I verify that the main explanatory variables remain robust in a spatial model of the search intensity for climate change. I follow LeSage and Pace (2009), Elhorst (2010), and Belotti, Hughes and Mortari (2017) by selecting the appropriate fixed effects spatial model among the following four alternatives, using the notation from Model (1):

- spatial Durbin model:

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

- spatial autoregressive model:

$$y_{ijwt} = \rho W y_{ijwt} + \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + u_{ijwt}, \tag{SAR}$$

- spatial error model:

$$y_{ijwt} = \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + v_{ijwt},\ v_{ijwt} = \lambda W v_{ijwt} + u_{ijwt}, \tag{SEM}$$

- spatial autocorrelation model:

$$y_{ijwt} = \rho W y_{ijwt} + \beta X_{ijwt} + a_{ij} + \gamma_w + \eta_t + v_{ijwt},\ v_{ijwt} = \lambda W v_{ijwt} + u_{ijwt}, \tag{SAC}$$

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.

The model selection procedure, outlined 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).[12] 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.

4 Forecasting public attention to climate change

The impact of the natural and human factors on individual awareness of climate change may be short- or long-lasting. An efficient planning and policymaking requires a better understanding of the role and relative importance of these factors in shaping social perceptions of the environment. One way to improve this understanding is to evaluate which factors contribute more to predicting the salience of climate change. 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.

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

4.1 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 monthly 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 and Ductor et al., 2014).

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;

- (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

Table 2: Forecasting the search intensity for climate change over the weekly horizon: sole predictors and the best combinations of predictors

RMSE % Diff. compared to baseline, by potential predictor		
OLS	Spatial	Variables
-0.596	-5.777	Activists
-0.169	-5.900	TempDev
-0.004	-5.947	PolitMeetIn
+0.060	-5.843	PolitMeetOut

Best predictions compared to baseline, by sets of predictors		
% Diff	Variables	Model
-1.253	L.(2/8).(Activists TempDev PolitMeetIn)	Pooled OLS
-1.213	L.(2/8).(Activists TempDev)	Pooled OLS
-6.267	TempDev PolitMeetIn TempDev×PolitMeetIn	Spatial SDM
-6.067	PolitMeetIn	Spatial SDM

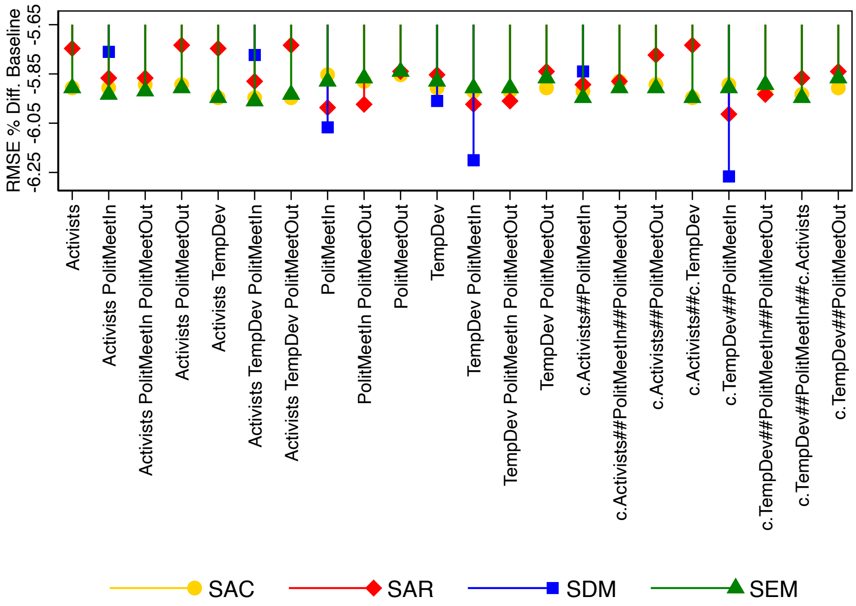
This table reports the percentage difference of the RMSE compared to the baseline, in the OLS-estimated model and the best-performing spatial model, using weekly data, for each of the sole main predictors, in the top panel, and for the best-performing combinations of the predictors, in the bottom panel.

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 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.[13]

As a second step, I compare the predictive performance of the various predictors of interest in the model (OLS WE dynamic) with a baseline model (OLS WE dynamic) in

[13]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.

Figure 3: 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).

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.

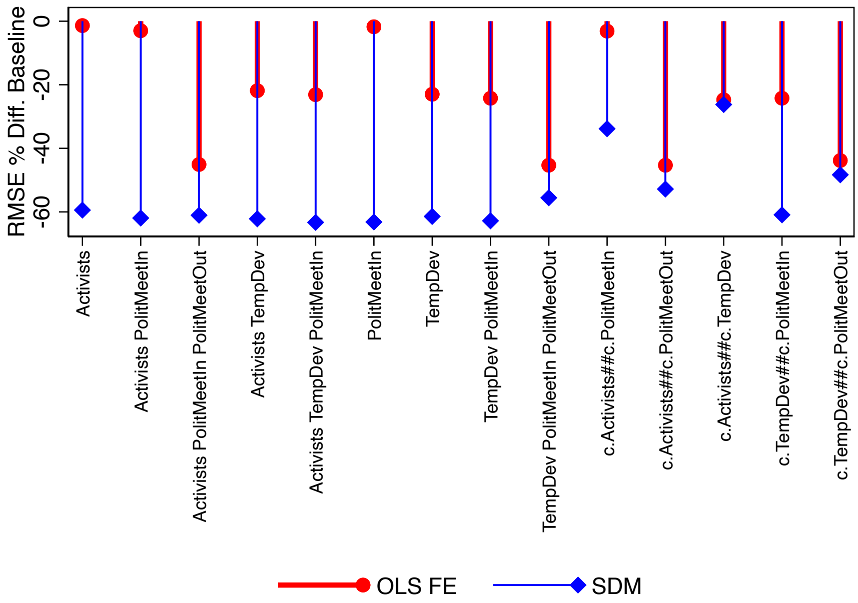
Furthermore, the impact of each of the predictors of interest can be potentially reinforced by the other. For example, political meetings related to the climate change are frequently accompanied by activists' strikes, which can significantly increase the public attention to the issues associated with 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.

Figure 5 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 Figure 5), 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 the top panel, and the combinations of predictors that deliver the largest reduction in RMSE compared to the baseline, in the bottom panel. 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 half percent. The political meetings, either internal or external, have no predictive power when included in the OLS estimation. 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 only around 1.5% (the RMSEs comparison test suggests that the difference is statistically significant). The best predictive performance is achieved when all three predictors of interest are included, moreover, in their two-to-eight weeks lags. The second best performing combination of predictors consists of activists' strikes and temperature variations, in their two-to-eight weeks lags.

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 very modest.

Figure 4: 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.

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 analysed in this paper, the inclusion of spatial dependence can significantly improve the out-of-sample forecasts (see Giacomini and Granger, 2004 and 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). Figure 3 reports the results in terms of percentage improvement in RMSE compared to the baseline, OLS WE dynamic with no other predictors.[14] 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 esti-

[14]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.

mated models. The lowest RMSE, 6.27% less that in the baseline, is achieved in the SDM model. Differently from the OLS case, the best-performing predictor in the spatial model is local political meetings (that take place within the considered sample of countries) and the best combinations of predictors is the interaction of weather fluctuations with local political meetings, see 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.

Finally, I confirm that the models and the predictors considered in this subsection produce the best forecasts given the available data. 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 instead of the levels; the growth rate of the dependent variable; and different estimation horizons. The predictors and the models reported in Table 2 remain the most effective in forecasting the search intensity for climate change over weekly or monthly horizons.

4.2 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.[15] I use the first four years to estimate the model, and forecast the search intensity of climate change in the fifth and sixth years.

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 subsection.

[15] 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.

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 Figure 6 in the Appendix).

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

	RMSE % Diff. compared to baseline, by potential predictor	
OLS FE	Spatial	Variables
-1.373	-59.426	Activists
-1.748	-63.171	PolitMeetIn
-22.97	-61.423	TempDev

	Best predictions compared to baseline, by sets of predictors	
% Diff	Variables	Model
-45.318	TempDev PolitMeetIn PolitMeetOut	OLS FE dynamic
-45.318	Activists PolitMeetOut Activists×PolitMeetOut	OLS FE dynamic
-63.296	Activists TempDev PolitMeetIn	SDM
-63.171	PolitMeetIn	SDM

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 the top panel, and for the best-performing combinations of the predictors, in the bottom panel.

As a second step, I choose the best-performing combinations of predictors within the best performing models. Figure 4 reports the RMSE for different combinations of the predictors (lagged, in first-differences) for the best performing non-spatial and spatial models. Table 3 summarizes the results, for the sole predictors, in the top panel, and the best-performing combinations of predictors, in the bottom panel. The direct indicator of global warming, the annual change in the average of positive deviations of maximum temperature from its historical norms, is the best predictor of the growth rate in the search intensity for climate change over the annual horizon in a non-spatial model and reduces the RMSE by 23 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 form part of the best combination of predictors in a non-spatial model. 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.[16] 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 SDM model reduces the RMSE by approximately 60 percent compared to the baseline.

5 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.

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Appendix

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

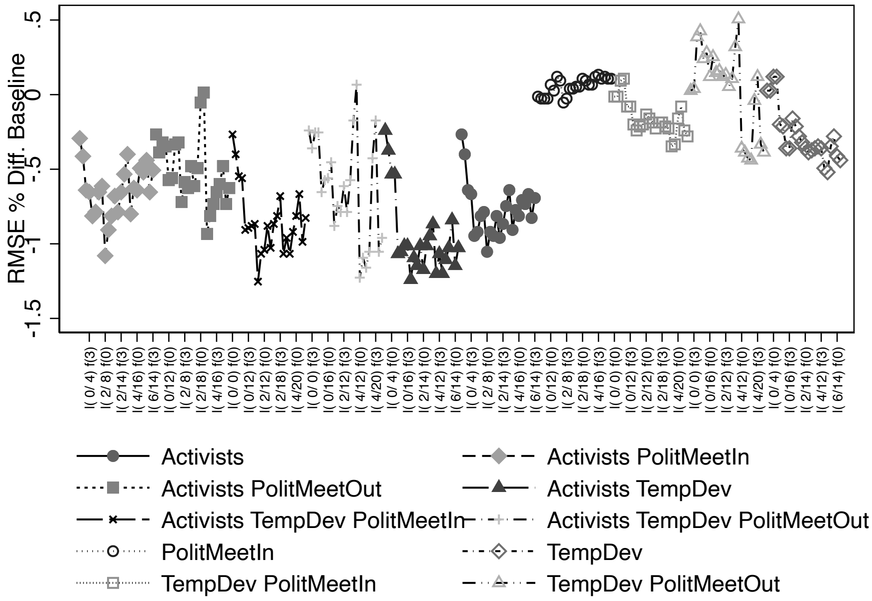
This table reports summary statistics for weekly data on 194 regions of 22 European countries covering period 3 of June 2018 to 30 of July 2023.

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 analysed 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.

Figure 5: Predicting the search intensity for climate change over the weekly horizon: comparison of different combinations of predictors



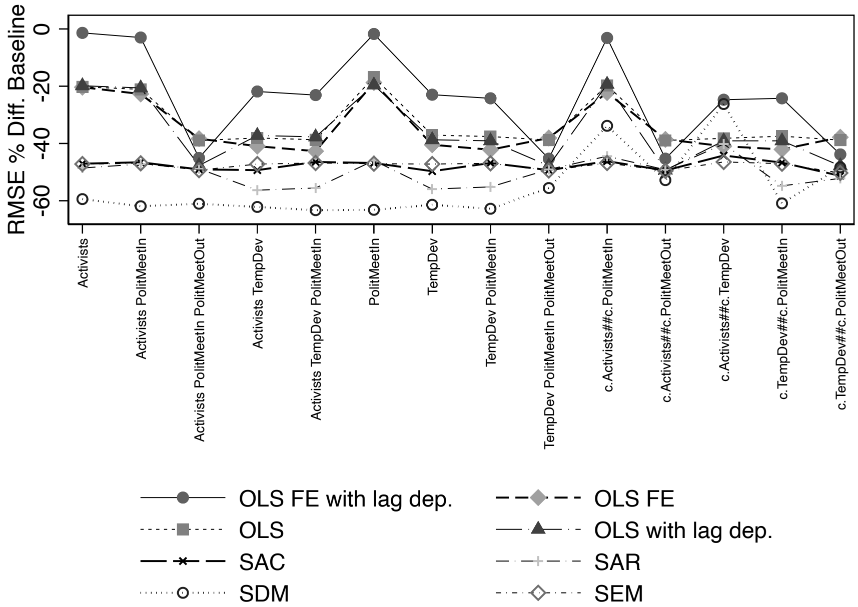
This figure reports the percentage reduction in the RMSE compared to the baseline short-run model where the only explanatory variables are the lagged dependent variable and weekly fixed effects; all models are estimated by OLS and focus on short term predictions, several weeks in advance; each observation 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 6: Forecasting: comparison of the potential baseline models' performance.

RMSE	Model	AIC
	Short term	
0.833	OLS WE dynamic	115528.9
0.842	OLS FE WE dynamic	112299.6
0.858	OLS WE static	117246.5
0.858	OLS FE WE static	113119.6
0.903	OLS dynamic	117105.8
0.977	OLS FE WE YE MxC static	108033.2
1.017	OLS FE WE YE MxC dynamic	107423.9
	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

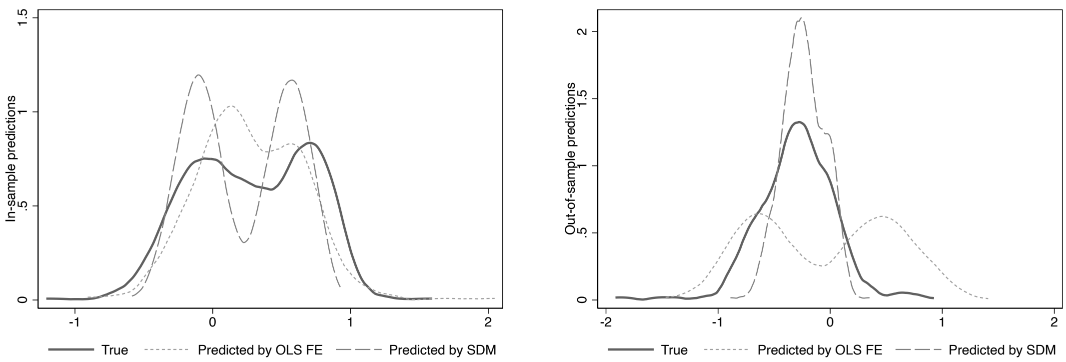
This table reports the RMSE and AIC criteria for the competing models estimated by OLS using weekly data, in the top panel, and annual data, in the bottom panel.

Figure 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).

Figure 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.