The role of news and social pressure in shaping U.S. public opinion on climate change

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Abstract: We explore how news and social pressure affect public opinion on climate change in the USA, based on county-level data over the period 1990–2024. Social pressure turns out to be the key factor that shapes public opinion on climate change, much more so than media. Policies that increase the overall level of educational achievement will create more awareness of climate change, but only if these policies don't change the shape of the education distribution. If only right-wing news is available and republicans have complete control over all media, public opinion about climate in democratic counties will not decrease; in fact, it will increase, although only marginally.

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1 Introduction

There are two main views on how media influence opinion. The first view, sometimes called the 'hypodermic needle theory,' claims that the media have a direct influence on people's opinions. The theory suggests that the media 'inject' their messages directly into a passive audience, which is immediately affected by these messages (Lasswell, 1927; Lubken, 2008). This view was the dominant theory, until Lazarsfeld et al. (1944) showed that the direct effects of the media are in fact rather limited, and that most people are not as passive and helpless as assumed—in fact, they are perfectly able to select which messages affect them and which don't.

The current view is a compromise between these two extremes. Our opinions are reinforced, not changed, by the media, because we tend to expose ourselves to information that is consistent with our opinions while shielding from dissenting views. News may have an impact on what we think about (McCombs and Shaw, 1972) and how we think about it (Entman, 1993), but it does not determine *what* we think. Exposure to newspaper or TV news has very limited effect on our political and other attitudes (Huckfeldt et al., 2004; Gerber et al., 2009), which are largely determined but partisanship, ideology, and the social environment.

If we investigate our own behavior, we see that we watch the TV channels, read the newspapers, and listen to the podcasts that are close to our own moral and political view of the world. It would be more instructive if we read newspapers that were opposite to our views—then we might learn something new and perhaps change our minds. But we don't. Our views are determined by our social group, our education, our religion, and other demographic and political factors. The news simply reinforces those views, leading to political polarization (Stroud, 2010).

If the media only have a limited effect on what we think and are largely unable to change our minds, then what tools do news providers have to make an impact? Suppose you are a democrat. You read the New York Times and the Washington Post, and you watch MSNBC and CNN. These news providers report frequently on natural diasters, and they tell you that global warming is a serious threat and that the IPCC is an important and trustworthy organization. But suddenly the tone of these news providers changes. They now tell you that global warming is not really a threat, just a normal fluctuation of temperatures, and they quote scientists from respectable universities to back this up. Then, you might be challenged to change your mind. The counterforce has to come from your own camp, not from the opposite camp. This idea is not new, and it is sometimes known as the 'Nixon goes to China' effect (Cukierman and Tommasi, 1998). In 1972

Richard Nixon visited China, where he met with Chairman Mao Zedong. Nixon was a well-established anti-communist, and precisely this fact gave him the political cover against domestic criticism.

The current paper, reexamines the role of news versus social pressure in the USA in the context of climate change, and the potential policy instruments that politicians and news providers have to influence public opinion. Our main conclusions can be summarized as follows. Social pressure is the primary force shaping public opinion on climate change—more influential than media exposure. Although the media do play a role, their impact is generally weaker than that of education, group identity, and social networks. We conceptualize social pressure in terms of diversity (inequality): lower inequality leads to stronger social pressure. While reducing inequality is often regarded as a desirable goal, it may have unintended consequences. In our analysis, lower diversity increases social pressure, which in turn reduces public concern about climate change.

We also find that education inequality has a stronger effect than racial inequality, and we see no evidence of partisan differences in the effect of education: higher levels of education are associated with greater climate concern among both democrats and republicans. A policy simulation further suggests that policymakers should focus on raising overall educational attainment, rather than altering the distribution of education, as distributional changes may produce counterproductive effects. In another policy experiment, we examine a hypothetical information environment with only one TV station affiliated with the ruling party (a 'dictatorship'). Surprisingly, under a democratic dictator, public opinion in republican counties would not increase, and under a republican dictator, opinion in democratic counties would not decrease; in fact, the opposite pattern emerges.

The paper is organized as follows. In Section 2 we analyze and quantify the national power balance, based on the political color of the president and the majority in the House and Senate. In our stylized world there are two news providers, labeled 'left' and 'right.' How the national political color influences the operation of these two stations is investigated in Section 3. In Section 4 we make a bold attempt to model the national news from these two stations, based on the assumption that the two stations share the same three (objective) news ingredients: importance, reliability, and positivity. What distinguishes the two stations is how they choose from these objective ingredients, that is, how they transform objective news to subjective news. Our study is not at the national but at the local level, where the local level is defined by the 3,111 counties that divide the USA Geographics matters: 63% of Americans believe in global warming, but at the county level this ranges from 43 to 80% (Howe et al., 2015). The transition from national to local level is discussed in Section 5. In Section 6 we present our model. We discuss our empirical results in Section 7, perform robustness tests in Section 8, and outline policy implications in Section 9. Section 10 concludes. There are three appendices and an extensive online appendix.

2 The national power balance

Presidential elections in the USA take place every four years, congressional elections every two years. The U.S. Congress is composed of two chambers: the House of Representatives and the Senate. Every two years, one-third of the Senate and every seat in the House of Representatives is up for election. Midterm congressional elections take place halfway between presidential elections. Members of the House of Representatives serve two-year terms. All 435 House seats are up for election every midterm and presidential election year. Senators serve six-year terms, so they will not all be up for election at the same time. Every two years, during each midterm and presidential election year, a different third of the 100 Senate seats is elected.

Political power in the USA depends primarily on the president, majority in the House, and majority in the Senate. In Table 1 we report the presidency and the division of seats in both chambers at two-year intervals 1989–2025. We then define indices I_p, I_h, and I_s (president, house, senate) which take the value $+1$ if there is a republican president or a republican majority in House or Senate, and the value -1 if there is a democratic majority. (When there is no majority for either in the House or Senate, we set the index to 0.) We then define the power balance as

$$B(t) = \frac{6I_p(t) + 3I_h(t) + 2I_s(t)}{11}, \tag{1}$$

which therefore takes values between -1 (full power to the democrats) and $+1$ (full power to the republicans). The weights are chosen such that the weight for the president is larger than the weight for the House, which in turn is larger than the weight for the Senate ($6 > 3 > 2$), and also such that the weight for the president is larger than the sum of the two weights for House and Senate ($6 > 3 + 2$). We could have refined (1) by taking the *size* of the majority into account, but we decided not to do this because the political balance would then be smoothed, while we wish to emphasize the discontinuity of regime changes. This discontinuity is further emphasized by keeping the balance constant over each two-year period rather than attempt to smooth it out.

Table 1: The power balance 1989–2025

		House		Senate		Power balance	
Year	President	Dem	Rep	Dem	Rep	P/H/S	$B(t)$
1989	G.H.W. Bush (R)	260	175	55	45	$+--$	0.09
1991	G.H.W. Bush (R)	267	167	56	44	$+--$	0.09
1993	Clinton (D)	258	176	57	43	$---$	-1.00
1995	Clinton (D)	204	230	48	52	$-++$	-0.09
1997	Clinton (D)	207	226	45	55	$-++$	-0.09
1999	Clinton (D)	211	223	45	55	$-++$	-0.09
2001	G.W. Bush (R)	212	221	50	50	$++0$	0.82
2003	G.W. Bush (R)	205	229	48	51	$+++$	1.00
2005	G.W. Bush (R)	201	233	44	55	$+++$	1.00
2007	G.W. Bush (R)	233	202	49	49	$+-0$	0.27
2009	Obama (D)	257	178	57	41	$---$	-1.00
2011	Obama (D)	193	242	51	47	$-+-$	-0.45
2013	Obama (D)	201	234	53	45	$-+-$	-0.45
2015	Obama (D)	188	247	44	54	$-++$	-0.09
2017	Trump (R)	194	241	47	51	$+++$	1.00
2019	Trump (R)	235	199	45	53	$+-+$	0.45
2021	Biden (D)	222	212	48	50	$--+$	-0.64
2023	Biden (D)	213	222	47	49	$-++$	-0.09
2025	Trump (R)	215	220	45	53	$+++$	1.00

[a] Sources: www.senate.gov/pagelayout/history/one_item_and_teasers/partydiv.htm and history.house.gov/Institution/Party-Divisions/Party-Divisions/

3 Political color at the national level

In our stylized world there are two news providers, say TV stations, at the national level. These TV stations differ by their political color $\bar{c}_j(t)$, and we label these colors as democratic and republican, respectively $(j = d, r)$. The political colors of the 'left-wing' (democratic) and 'right-wing' (republican) stations are determined by a constant β_{0j}, but the color may change over time, and this change is determined by the power balance:

$$\bar{c}_j(t) = \beta_{0j} + \beta_{1j} B(t) \qquad (j = d, r). \tag{2}$$

A priori it is not clear whether the left- and right-wing TV stations will move with the political climate or against it, in other words, whether β_{1d} and β_{1r} are positive or negative. We allow for both possibilities.

While the arrival of a new president of a different party creates a discontinuity, it seems likely that this discontinuity has been particularly strong under Donald Trump. Hence, we introduce a Trump effect $I_T(t)$, which is a dummy taking the value 1 when Trump is in power and 0 otherwise. Equation (2) then becomes

$$\bar{c}_j(t) = \beta_{0j} + \beta_{1j}\big(B(t) + \beta_2 I_T(t)\big) \qquad (j = d, r), \tag{3}$$

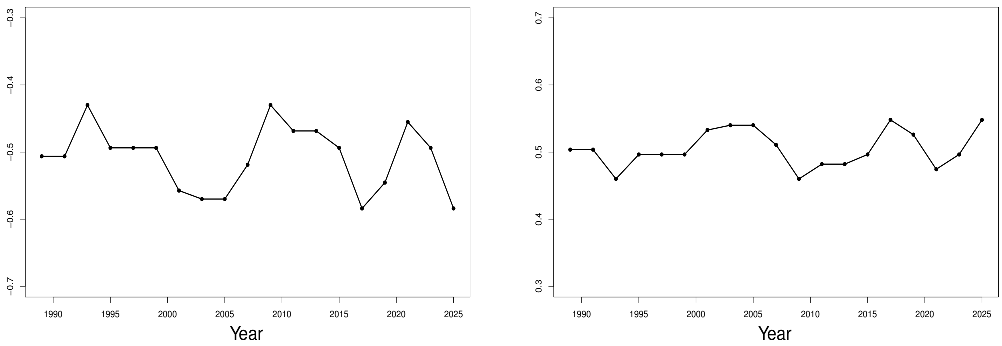
where $\beta_2 \geq 0$ does not depend on j. Plausible values for the parameters are

$$(\beta_{0d}, \beta_{1d}) = (-0.5, -0.07), \qquad (\beta_{0r}, \beta_{1r}) = (0.5, 0.04), \qquad \beta_2 = 0.2 \tag{4}$$

for the left-wing and right-wing stations, respectively, but we shall also experiment with other values of the parameters. Notice that we have assumed that $|\beta_{1d}| > |\beta_{1r}|$, based on the idea that the left-wing channel responds more sharply to a change in government (both from democratic to republican and vice versa) than the right-wing channel; see Mitchell et al. (2014), Jost (2017), and Kim et al. (2022).

In Figure 1 we plot the development of the political color for the left- and right-wing stations. Given the fact that $\beta_{1d} < 0$ and $\beta_{1r} > 0$, we see that a republican government pushes the left-wing station further to the left and the right-wing station further to the right: polarization increases. This behavior is based on Dunlap and McCright (2008)—in the context of climate change—and Kim et al. (2022). The political color of the left-wing channel is not constant, because it is influenced by political power; it moves between -0.43 and -0.58. Similarly, the political power of the right-wing party moves (slightly less) between 0.46 and 0.55.

The increase in polarization between the two channels is plotted in Figure 2. This increase is defined as $\bar{c}_r(t) - \bar{c}_d(t)$ and, as expected, it takes a



(a) democratic channel (b) republican channel

Figure 1: Political color $\bar{c}_d(t)$ and $\bar{c}_r(t)$

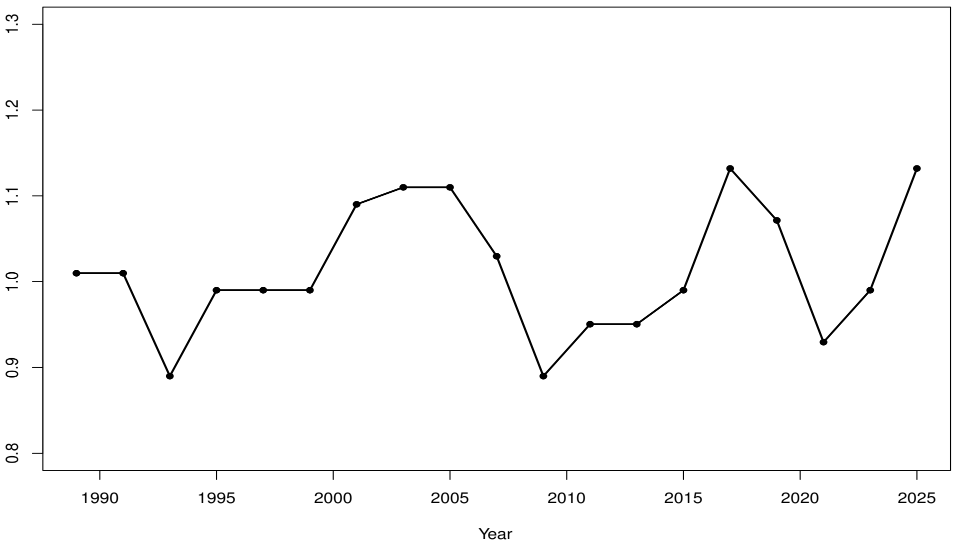


Figure 2: Political distance $\bar{c}_r(t) - \bar{c}_d(t)$ between republican and democratic channels

maximum in the periods 2017–2019 (first half of Trump-1) and 2025–2027 (first half of Trump-2), although polarization was also high under G. W. Bush.

4 National news

While the political balance changes every two years (indexed by $t = 1, \dots, T$), other information arrives at shorter intervals (indexed by $\tau = 1, \dots, N$). At the beginning of each period τ, the two editors of the national TV stations are confronted with q news items of climate-related issues. These news items are *objective* pieces of information depending on three ingredients: importance, reliability, and positivity. Importance $\bar{m}(\tau)$ is to be interpreted as importance for the planet Earth, reliability $\bar{r}(\tau)$ indicates how confident the scientific community is that the information is correct, and positivity $\bar{p}(\tau)$ indicates whether the issue emphasizes a positive feature (some action has resulted in a reduction of greenhouse gas) or a negative feature (another iceberg has melted). These three ingredients are $q \times 1$ vectors, and they serve as our inputs. Importance and reliability are measured on a scale from 0 to 1, positivity on a scale from -1 to $+1$. How these ingredients are generated is discussed in Appendix A. Notice that we have assumed that q is fixed, that is, it does not depend on τ. This involves no loss of generality, since we can always set some components of $\bar{m}(\tau)$ equal to 0.

At the beginning of period τ, the editors of the two TV stations are faced with the same q inputs, defined by the triple $(\bar{m}(\tau), \bar{r}(\tau), \bar{p}(\tau))$. Their task is to rank these inputs into one *subjective* measure $\bar{m}_j(\tau)$, which reflects the importance from the point of view of the jth TV station. This ordering will depend on the political color $\bar{c}_j(\tau)$ of the TV station. Symbolically we write, for the hth news item,

$$\bar{m}_j^{(h)}(\tau) = f\big(\bar{m}^{(h)}(\tau), \bar{r}^{(h)}(\tau), \bar{p}^{(h)}(\tau), \bar{c}_j(\tau)\big) \qquad (j = d, r), \tag{5}$$

which we specify as a two-step process:

$$\bar{m}_j^{(h)}(\tau) = f_1\big(\bar{m}^{(h)}(\tau), \bar{c}_j(\tau)\big) \cdot f_2\big(\bar{r}^{(h)}(\tau), \bar{p}^{(h)}(\tau), \bar{c}_j(\tau)\big), \tag{6}$$

so that the editor in station j first adjusts the importance of an item according to the political color of the station, and then adjusts the resulting channel-specific importance further by taking into account the reliability as perceived by the station and the positivity conforming the political color.

We specify the functions f_1 and f_2 as

$$f_1\big(\bar{m}^{(h)}(\tau), \bar{c}_j(\tau)\big) = \alpha_{1j}(\tau)\bar{m}^{(h)}(\tau) \tag{7}$$

and

$$f_2\big(\bar{r}^{(h)}(\tau), \bar{p}^{(h)}(\tau), \bar{c}_j(\tau)\big) = \alpha_{2j}(\tau)\bar{r}^{(h)}(\tau) + \alpha_{3j}(\tau)\bar{p}_+^{(h)}(\tau) + \alpha_{4j}(\tau)\bar{p}_-^{(h)}(\tau), \quad (8)$$

where we write $|\bar{p}^{(h)}| = \bar{p}_+^{(h)} + \bar{p}_-^{(h)}$ with

$$\bar{p}_+^{(h)} = \begin{cases} 0 & \text{if } \bar{p}^{(h)} \leq 0, \\ |\bar{p}^{(h)}| & \text{if } \bar{p}^{(h)} > 0, \end{cases} \qquad \bar{p}_-^{(h)} = \begin{cases} |\bar{p}^{(h)}| & \text{if } \bar{p}^{(h)} \leq 0, \\ 0 & \text{if } \bar{p}^{(h)} > 0. \end{cases} \quad (9)$$

The weights $\alpha_{1j}, \ldots, \alpha_{4j}$ depend linearly on the political color

$$\alpha_{\ell j}(\tau) = \phi_{\ell j} + \theta_{\ell j}\bar{c}_j(\tau) \qquad (\ell = 1, \ldots, 4). \quad (10)$$

Letting $B^*(\tau) = B(\tau) + \beta_2 I_T(\tau)$, we obtain

$$\bar{c}_d(\tau) = \beta_{0d} + \beta_{1d}B^*(\tau), \qquad \bar{c}_r(\tau) = \beta_{0r} + \beta_{1r}B^*(\tau), \quad (11)$$

and hence

$$\alpha_{\ell d}(\tau) = \phi^*_{\ell d} + \theta^*_{\ell d}B^*(\tau), \qquad \alpha_{\ell r}(\tau) = \phi^*_{\ell r} + \theta^*_{\ell r}B^*(\tau), \quad (12)$$

where

$$\begin{aligned} \phi^*_{\ell d} &= \phi_{\ell d} + \theta_{\ell d}\beta_{0d}, \qquad & \theta^*_{\ell d} &= \theta_{\ell d}\beta_{1d}, \\ \phi^*_{\ell r} &= \phi_{\ell r} + \theta_{\ell r}\beta_{0r}, \qquad & \theta^*_{\ell r} &= \theta_{\ell r}\beta_{1r}. \end{aligned} \quad (13)$$

This gives

$$\begin{aligned} f_1\big(\bar{m}^{(h)}(\tau), \bar{c}_j(\tau)\big) &= \phi^*_{1j}\bar{m}^{(h)}(\tau) + \theta^*_{1j}\bar{m}^{(h)}(\tau)B^*(\tau) \\ f_2\big(\bar{r}^{(h)}(\tau), \bar{p}^{(h)}(\tau), \bar{c}_j(\tau)\big) &= \Phi^{(h)}_{2j}(\tau) + \Theta^{(h)}_{2j}(\tau)B^*(\tau), \end{aligned} \quad (14)$$

where

$$\begin{aligned} \Phi^{(h)}_{2j}(\tau) &= \phi^*_{2j}\bar{r}^{(h)}(\tau) + \phi^*_{3j}\bar{p}_+^{(h)}(\tau) + \phi^*_{4j}\bar{p}_-^{(h)}(\tau) \\ \Theta^{(h)}_{2j}(\tau) &= \theta^*_{2j}\bar{r}^{(h)}(\tau) + \theta^*_{3j}\bar{p}_+^{(h)}(\tau) + \theta^*_{4j}\bar{p}_-^{(h)}(\tau). \end{aligned} \quad (15)$$

Inserting (14) in (6) gives

$$\frac{\bar{m}_j^{(h)}(\tau)}{\bar{m}^{(h)}(\tau)} = \delta^{(h)}_{0j}(\tau) + \delta^{(h)}_{1j}(\tau)B^*(\tau) + \delta^{(h)}_{2j}(\tau)(B^*(\tau))^2, \quad (16)$$

where

$$\begin{aligned} \delta^{(h)}_{0j}(\tau) &= \phi^*_{1j}\Phi^{(h)}_{2j}(\tau), \\ \delta^{(h)}_{1j}(\tau) &= \phi^*_{1j}\Theta^{(h)}_{2j}(\tau) + \Phi^{(h)}_{2j}(\tau)\theta^*_{1j}, \\ \delta^{(h)}_{2j}(\tau) &= \theta^*_{1j}\Theta^{(h)}_{2j}(\tau). \end{aligned} \quad (17)$$

Table 2: Values of the hyperparameters

β_{0d}	β_{1d}	ϕ_{1d}	θ_{1d}	ϕ_{2d}	θ_{2d}	ϕ_{3d}	θ_{3d}	ϕ_{4d}	θ_{4d}
-0.50	-0.07	0.10	-1.20	0.07	-1.10	0.03	-0.60	0.04	-0.70
β_{0r}	β_{1r}	ϕ_{1r}	θ_{1r}	ϕ_{2r}	θ_{2r}	ϕ_{3r}	θ_{3r}	ϕ_{4r}	θ_{4r}
0.50	0.04	1.10	-1.05	0.90	-0.87	0.46	-0.45	0.50	-0.48

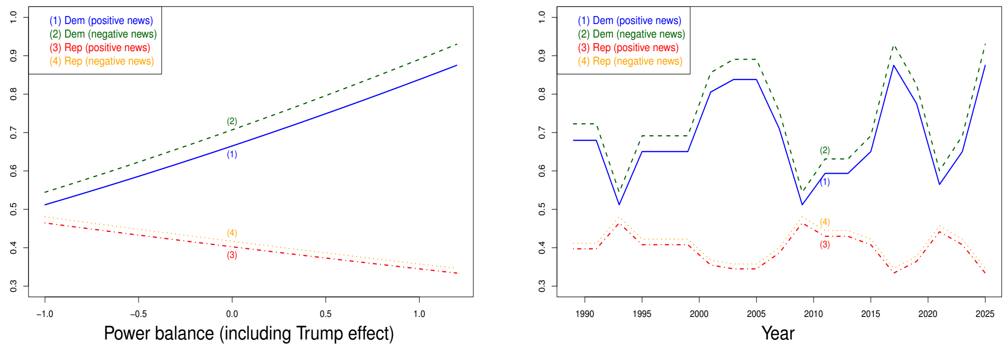
In order to find plausible values for the hyperparameters, we work both forwards and backwards. In the forward process we provide values for the basic parameters and then compose and judge the implied (composed) parameters; in the backward process we start with the composed parameters and work towards the basic parameters. After a series of experiments we arrive at the parameter values in Table 2, based on the following considerations:

- Regarding democratic media we assume that $\phi_{\ell d} > 0$, $\theta_{\ell d} < 0$, and $-1 \leq \bar{c}_d(\tau) < 0$, which implies that as the democratic media move to the left, the weights $\alpha_{\ell d}(\tau)$ increase. In contrast, regarding republican media, we assume that $\phi_{\ell r} > 0$, $\theta_{\ell r} < 0$, and $0 < \bar{c}_r(\tau) \leq 1$, so that as the republican media move to the right, the weights $\alpha_{\ell r}(\tau)$ decrease. Specifically, when the national power balance moves to the right, the left-wing station becomes more left-wing and puts more weight on events related to climate change, while the right-wing station becomes more right-wing and downplays climate change related events.

- Democratic media are more sensitive to changes in political color than republican media: $|\theta_{\ell d}| > |\theta_{\ell r}|$.

- For the editors, subjective importance depends primarily on objective importance, followed by reliability, and then positivity. Moreover, for two events with same absolute positivity value, negative events attract more attention than positive events: $\phi_{1j} > \phi_{2j} > \phi_{4j} > \phi_{3j}$.

Figure 3 illustrates the trend of the subjective importance ratio for events with 1 unit reliability and 1 unit absolute positivity, where power balance including the Trump effect is defined as $B^*(\tau) = B(\tau) + \beta_2 I_T(\tau)$, and we have taken $\bar{r}^{(h)}(\tau) = 1$, $\bar{p}_+^{(h)}(\tau) = 1$, and $\bar{p}_-^{(h)}(\tau) = -1$. Panel (a) shows that, when the power balance increases, the subjective importance of a news item increases for democratic media, but decreases for republican media. Also, the slope of the democratic media curve is larger (in absolute value) than the slope of the republican media curve. In panel (b) we plot the annual



(a) by power balance (b) by year

Figure 3: Ratio $\bar{m}_d/\bar{m}$ and $\bar{m}_r/\bar{m}$ of subjective to objective importance

subjective importance ratio by using the power balance at two-year intervals. The figure shows that subjective importance is sensitive to changes in the power balance in our model, that media respond stronger to negative news than to positive news, and that negative news is given relatively greater subjective importance.

We also need to set the thresholds. There are 1539 climate-related news items over 420 months in our data set. Associated with news item h is an (objective) importance value $\bar{m}^{(h)}(\tau)$, which is a number between 0 and 1. If $\bar{m}^{(h)}(\tau) > 0.7$ we call the event 'severe.' There are 94 severe items, and these are broadcast by both stations, irrespective of their political color.

This leaves 1445 news items with an importance value less than 0.7. The two TV stations assign subjective importance to these news items, and we let $\bar{M}_d(\tau)$ and $\bar{M}_r(\tau)$ denote the average subjective importance of the 'non-severe' items at time τ for the democratic and republic channel, respectively. Then we set the thresholds for the two TV stations at $\bar{M}_d(\tau) - 0.03$ and $\bar{M}_r(\tau) + 0.02$ respectively, based on the fact that democratic media are covering many more climate-related events than republican media. These thresholds lead to 1196 news items being broadcast on the democratic channel, and 360 on the republican channel.

5 The local level

The above development is at the national level. But we shall work at the county level. The USA is divided into 3,244 counties, including the 237 county equivalents.[1] An average county has about 100,000 inhabitants, although there are counties which are much larger: The county of Los Angeles has 10 million inhabitants.

5.1 Power balance

To define the power balance at the local (county) level, let $R_k(t)$ and $D_k(t)$ denote the number of votes in county k for the republican and democratic presidential candidate, respectively. We only observe these variables at four-year intervals, not two-year intervals, so we need to approximate the missing values, and we do so by considering the election results for the House of Representatives—these take place every two years. The election results are available at the state level and at the district level, but not at the county level. We shall use the data at the state level.[2]

In order to approximate the results of the missing presidential elections per county, let d_t denote the percentage of democratic votes and $1 - d_t$ the percentage of republican votes at time t in the presidential elections (observed at times $t-1$ and $t+1$, but not at time t). Also, let e_t denote the percentage of democratic votes and $1 - e_t$ the percentage of republican votes at time t in the House of Parliament elections (observed at times $t-1$, t, and $t+1$). Let

$$\bar{d}_t = \frac{d_{t-1} + d_{t+1}}{2}, \qquad \bar{e}_t = \frac{e_{t-1} + e_{t+1}}{2}, \tag{18}$$

both of which are observed. We approximate d_t in two different ways, labeled $d_t^{(a)}$ and $d_t^{(b)}$, in order to increase the stability of the approximation, namely as

$$\bar{e}_t d_t^{(a)} = \bar{d}_t e_t \tag{19}$$

and as

$$(1 - \bar{e}_t)(1 - d_t^{(b)}) = (1 - \bar{d}_t)(1 - e_t). \tag{20}$$

If $\bar{d}_t = \bar{e}_t$, then $d_t^{(a)} = d_t^{(b)} = e_t$, and if $e_t = \bar{e}_t$, then $d_t^{(a)} = d_t^{(b)} = \bar{d}_t$. But, in general, $d_t^{(a)}$ and $d_t^{(b)}$ will not be equal. We then let

$$\hat{d}_t = \frac{d_t^{(a)}}{d_t^{(a)} + (1 - d_t^{(b)})} = \frac{\bar{d}_t(1 - \bar{e}_t)e_t}{\bar{d}_t(1 - \bar{e}_t)e_t + (1 - \bar{d}_t)\bar{e}_t(1 - e_t)} \tag{21}$$

[1] The 237 county equivalents include the District of Columbia and 100 equivalents in U.S. territories, such as those in Puerto Rico.

[2] There are 435 districts associated with the 435 seats in the House. On average, one district thus contains about seven counties, but there are many counties that lie in two districts. Hence, using district data to approximate the counties is problematic.

be our approximation for d_t. Unlike $d_t^{(a)}$ and $d_t^{(b)}$, $\hat{d}_t$ always lies between 0 and 1.

Next, we define the local power balance in county k as

$$B_k(t) = \frac{R_k(t) - D_k(t)}{R_k(t) + D_k(t)}. \tag{22}$$

Assuming that the same trend applies in each county within a given state, we obtain $B_k(t) = 1 - 2\hat{d}_t$, which will be constant during each two-year period and, like its national equivalent $B(t)$, it is a number between -1 and 1.

5.2 Political color

Based on the local power balance defined in (22), we define the average power balance in county k over the observed T time periods as

$$\bar{B}_k = \frac{1}{T} \sum_{t=1}^{T} B_k(t), \tag{23}$$

which provides an ordering of the counties from very red (republican, close to $+1$) to very blue (democratic, close to -1). The political color in county k at time t is now defined as

$$c_k(t) = \beta_0^* + \beta_1^* \bar{B}_k + \beta_2^* \left(B_k(t) - \bar{B}_k \right) + \beta_3^* B(t), \tag{24}$$

which thus contains both a local (B_k) and a national (B) component. The following values are assumed for these hyperparameters:

$$\beta_0^* = 0.00, \quad \beta_1^* = 0.98, \quad \beta_2^* = 0.49, \quad \beta_3^* = 0.02.$$

Notice that we do not include a Trump effect at the local level.

5.3 Local news

In our stylized world, a typical individual living in county k will be exposed to the two national channels, and also to one local channel. The local channel will reflect the political balance in the county, while the choice of channel by the individual will depend on the same political balance. So, in practice, we may ignore the local channel and simply assume that a typical individual receives news through the two national channels. At this point, we could assume that a county-k individual watches either of the two channels depending on their political preference, which would lead to a weighted average depending on the political color $c_k(t)$ in the county.

We take a different approach by assuming that *all* individuals in county k are exposed to only *one* TV station, either democratic or republican, depending on the political color of the county. This, somewhat bold, assumption emphasizes the polarization in the USA and also gives news the maximum possibility of being effective, something that will prove to be important when we discuss our results.

Recall that, at the beginning of period τ, the editors of the two national TV stations are faced with the same q inputs, defined by the triple $(\bar{m}(\tau), \bar{r}(\tau), \bar{p}(\tau))$. Let $v^{(h)}(\tau)$ denote the vector of objective inputs (importance, reliability, positivity) of item h at time τ. The information flowing to a typical individual in county k is then given by the vector

$$v_k^{(h)}(\tau) = v^{(h)}(\tau) \tag{25}$$

if item h is selected by the TV station whose political color corresponds to the political color of county k at time τ; and 0 if item h is not selected by that station.

6 The model

We wish to model the public opinion about climate change of a typical individual in county k at time τ. This is our dependent variable, denoted by $y_k(\tau)$. The public opinion of the neighboring counties (averaged) is denoted by $y_k^*(\tau)$. Letting $x_k(\tau)$ denote a vector of regressors to be specified below, we write our regression equation as

$$y_k(\tau) = \gamma_0 y_k^*(\tau) + x_k'(\tau - 1)\,\gamma + \epsilon_k(\tau). \tag{26}$$

Thus, we model public opinion in county k at time τ as a linear function of county characteristics in the previous period, and public opinion in neighboring counties. The county characteristics include:

- news characteristics: number of news items, importance of news, reliability of news, positivity of news;
- social pressure: race diversity, age diversity, education diversity;
- political color: political diversity; and
- local characteristics: voter turnout, population density, household median income, median house price, unemployment rate.

Let S denote the symmetric matrix with $S_{kh} = 1$ if counties k and h are neighboring counties, and zeros elsewhere, where we note that the diagonal elements S_{kk} of S are also zero. Further, let λ_k denote the number of counties neighboring county k, and let Λ denote the diagonal matrix containing $\lambda_1, \lambda_2, \dots$ on the diagonal. Then,

$$y_k^*(\tau) = \Lambda^{-1} S y_k(\tau), \tag{27}$$

so that we can write (26) as

$$A(\gamma_0) y_k(\tau) = x_k'(\tau - 1)\,\gamma + \epsilon_k(\tau), \qquad A(\gamma_0) = I - \gamma_0 \Lambda^{-1} S, \tag{28}$$

or, in vector form,

$$A(\gamma_0) y(\tau) = X(\tau - 1)\,\gamma + \epsilon(\tau). \tag{29}$$

Premultiplying by A^{-1} gives

$$y(\tau) = A^{-1}(\gamma_0) X(\tau - 1)\,\gamma + A^{-1}(\gamma_0)\epsilon(\tau). \tag{30}$$

Since we have no observations on public opinion at the local (county) level, we cannot estimate (30) directly, but we can aggregate to

$$\omega' y(\tau) = \omega' A^{-1}(\gamma_0) X(\tau - 1)\,\gamma + \omega' A^{-1}(\gamma_0)\epsilon(\tau) \tag{31}$$

for some weighting vector ω, accounting for the (average) population size of the county. We assume that ω does not depend on τ, so that $\omega' A^{-1}$ also does not depend on τ (although it depends on the unknown parameter γ_0).[3] We write (31) in vector form as $\bar{y} = Z\gamma + u$, where $Z = Z(\gamma_0)$.

The estimation of the parameters is complicated by the fact that Z depends on a parameter, which is slightly unusual. Assuming that $\mathrm{E}(u) = 0$ and $\mathrm{var}(u) = \sigma^2 I_n$, we can estimate the parameters $(\gamma_0, \gamma, \sigma^2)$ jointly using the maximum likelihood procedure developed in Ikefuji et al. (2022). While it is possible to estimate γ_0 and its (asymptotic) precision, it turns out to be difficult to estimate γ_0 precisely. Moreover, the estimates of the γ parameters appear to be robust with respect to different values of γ_0 (within reasonable bounds); see Section 8 below. To simplify matters, we set $\gamma_0 = 0.5$. With γ_0 fixed, we estimate the parameters (γ, σ^2) by least squares.

[3] A small computational problem occurs as the diagonal matrix Λ contains some zero diagonal components, so that Λ^{-1} is not defined. This problem can be resolved by either deleting the zero elements or by using the Moore–Penrose inverse—the result is the same.

7 Empirical results

We discussed some of the relevant literature on media and public opinion in the Introduction, but this was a general review and not specialized to climate change. In the current section where we present our empirical results, we wish to confront our results with the more specialized literature. The main conclusions from this specialized literature are the same as from the general literature. In particular, there have been a number of meta-analyses (Brulle et al., 2012; Hornsey et al., 2016, among others), attempting to find common ground from many different studies, and these analyses conclude that political mobilization by elites and advocacy groups (so-called elite cues) is critical in influencing climate change concern. Values, ideologies, and political orientation are far more important than the media—at least, that seems to be the current consensus.

That more unemployment leads to more climate skepticism (Meyer, 2022) is not surprising, but that the opinion on climate change is less polarized among African Americans and Hispanics/Latinos (Ballew et al., 2021) is less obvious. The most intriguing finding concerns education. It appears that concern about climate change increases with education among democrats but decreases among republicans (Malka et al., 2009; Hamilton, 2011), so that more education does not necessarily lead to more concern about climate change; instead, it leads to more cultural polarization. We shall see that our conclusions do not always agree with these earlier findings.

Within the above framework we model public opinion in county k at time τ as a linear function of county characteristics at time $\tau - 1$ and public opinion (at time τ) in neighboring counties. The county characteristics include eleven variables: importance of news, reliability of news, positivity of news, number of news items, voter turnout, household median income, unemployment rate, population density, median house price, education level, and political color; and four diversity measures: race diversity, education diversity (in contrast to the *level* of education), age diversity, and political diversity (in contrast to political color).

Our focus variables (present in almost every model) are public opinion (at time τ) in neighboring counties and a constant, and in addition: news importance, news number, voter turnout, median income, and unemployment (all at time $\tau - 1$). Our auxiliary variables (not present in every model) are the four diversity measures, the level of education, the political color, and a cross term allowing us to test whether concern about climate change increases with education among democrats, but decreases among republicans.

The following analysis does not include population density and house price, but we will consider their (lack of) relevance in the online appendix.

Since we have no data on the reliability and positivity of news, these will be ignored for the time being, but they will play a role later when we present our policy experiments in Section 9.

The diversity regressors are computed from our data as follows. For race, education, and age we follow Wang et al. (2021) and define

$$s_{gk}(\tau) = 1 - \sum_i \left(\frac{g_{ik}(\tau)}{pop_k(\tau)}\right)^2 \qquad (g = r, e, a), \tag{32}$$

where r, e, and a represent race, education, and age, respectively, i denotes the group within variable g, and pop denotes total population. This is essentially the Simpson index (Simpson, 1949), which measures the level of diversity when individuals are grouped into categories. The definition implies that s_{gk} lies between 0 and 1, and that the larger is s_{gk} the more diverse is county k with respect to the variable g.

Political diversity is defined as

$$s_{pk}(\tau) = 1 - 2|d_k(\tau) - 0.5|, \tag{33}$$

where $d_k(\tau)$ represents the percentage of democratic votes at time τ, as defined in Section 5.1. Local political diversity is maximized when $d_k = 0.5$ and $s_{pk} = 1$, and minimized when $d_k = 0$ or 1 and $s_{pk} = 0$.

7.1 The baseline model

We summarize our model selection search by concentrating on five models. The first three models contain all focus regressors and a subset of the diversity regressors, where the subsets are chosen such that multicollinearity is avoided, as far as possible and reasonable. Since race diversity, age diversity, political diversity, and also the *level* of education are highly correlated—the absolute value of the pairwise correlations exceeds 0.9 in each case—we do not combine them in one regression. In model (4) we add the level of education, political color, and a cross term.[4] Since the cross term and also median income turn out to be not significantly different from 0, we delete them and arrive at model (5), our baseline model. In Section 7.2 we introduce social pressure, and will discuss model (6).

Least-squares estimates of the parameters in models (1)–(6) are presented in Table 3, where γ_0 is set to 0.5. Let us first consider the importance of the news and the number of news items presented to the public. One would

[4]The cross term is defined as $(x - \bar{x})(y - \bar{y})$, not as xy, thus measuring the joint variability of the two regressors x and y.

Table 3: Comparison of six models for $\gamma_0 = 0.5$

	(1)	(2)	(3)	(4)	(5)	(6)
Focus variables						
constant	-63.6^{***}	-696.5^{***}	-29.6^{***}	-58.4^{***}	-65.3^{***}	119.4^{***}
	(10.9)	(119.8)	(8.5)	(12.2)	(11.6)	(13.1)
news importance	0.55	0.77	0.36	1.49^{**}	1.59^{***}	1.40^{**}
	(0.55)	(0.56)	(0.56)	(0.56)	(0.56)	(0.55)
news number	0.15	0.07	0.20	-0.16	-0.19	-0.14
	(0.16)	(0.16)	(0.16)	(0.17)	(0.16)	(0.16)
voter turnout	0.18^{***}	0.20^{***}	0.23^{***}	0.20^{***}	0.23^{***}	0.27^{***}
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
median income	0.76^{*}	1.02^{**}	1.12^{***}	-0.50		
	(0.40)	(0.41)	(0.43)	(0.40)		
unemployment	-0.75^{***}	-0.69^{***}	-0.68^{***}	-0.84^{***}	-0.79^{***}	-0.90^{***}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Auxiliary variables: diversity and social pressure						
race	33.1^{***}					
	(5.3)					
education	139.8^{***}	143.0^{***}	114.3^{***}	145.4^{***}	149.9^{***}	
	(16.7)	(18.2)	(15.8)	(20.3)	(20.2)	
age		681.1^{***}				
		(119.8)				
political			-21.1^{***}			
			(4.3)			
social pressure						-282.2^{***}
						(37.1)
Auxiliary variables: levels						
education level				0.37^{***}	0.36^{***}	0.02
				(0.07)	(0.07)	(0.04)
political color				-21.4^{***}	-19.6^{***}	-15.6^{***}
				(3.1)	(3.0)	(2.9)
edu level $\times$ political color				-0.62		
				(0.48)		
Observations	420	420	420	420	420	420
Res. SE	3.41	3.44	3.48	3.34	3.34	3.33

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

expect that if a news item is more important or when more climate-related news items are being broadcast, then this has a positive effect on public opinion. This expectation is confirmed by our results, at least regarding news importance, which has a positive sign and is even significantly different from 0 in models (4)–(6). The estimated parameter value is, however, small so that the effect is also small. Apparently, news is less important than one might think. If this is indeed the case, then perhaps there is something else that is more important, and indeed there is. Social pressure turns out to be more important than news, which is broadly in line with the current view on media and opinion changes. We shall elaborate on this claim in Section 7.2 below.

Surprisingly perhaps, our results cannot identify any effect (positive or negative) of the number of news items. In other words, whether the public receives little or much information about climate-related issues does not seem to matter in forming their opinions. Higher voter turnout corresponds to higher political engagement, leading to more people being concerned with public issues, including climate change. When the unemployment rate increases, people are under greater economic pressure and this leads to more concern about economic issues and less concern about climate. More income has the opposite effect: less economic pressure and (in general) more concern about climate change.

The four diversity parameters in models (1)–(3) are all statistically significant in explaining public opinion. The effect of these variables is positive with the exception of political diversity, where the effect is negative. Whereas all four diversity variables range from 0 to 1 in theory, their ranges in practice are much smaller:

$$0 \leq s_r \leq 0.75, \quad 0.19 \leq s_e \leq 0.78, \quad 0.84 \leq s_a \leq 0.94, \quad 0 \leq s_p \leq 1.$$

Since the lengths of the ranges are quite different (0.75, 0.59, 0.10, and 1.00, respectively), we compare relative rather than absolute changes when assessing the effects of the four diversity regressors. Using the estimates reported in Table 3, we thus compute

$$33.1 \times 0.75 = 25 \text{ (race)}, \qquad 114\text{-}143 \times 0.59 = 67\text{-}84 \text{ (education)},$$

and

$$681.1 \times 0.10 = 68 \text{ (age)}, \qquad -21.1 \times 1.00 = -21 \text{ (political)},$$

so that a 1% increase in education (age, race) diversity raises public concern by around 0.67–0.84% (0.68%, 0.25%), while a 1% increase in political diversity reduces public concern on climate change by 0.21%. Overall, the impact of education diversity is more important than age, race, and political diversity, in line with the findings of Case and Deaton (2021) and Muller and Roehrkasse (2025).

In models (4) and (5) we introduce the level of education, political color, and the cross term as additional explanatory variables. As expected, highly-educated people tend to be associated with better scientific knowledge about climate change, while climate doubters are more numerous among republicans than among democrats. But there is no indication of an interaction effect, as the cross term is not significantly different from 0. Hence there is no evidence that concern about climate change increases with education among democrats but decreases among republicans, as claimed by Malka et al. (2009) and Hamilton (2011). Since median income and the cross term are not significantly different from 0, we delete these two regressors from model (4) and arrive at model (5): our baseline model.

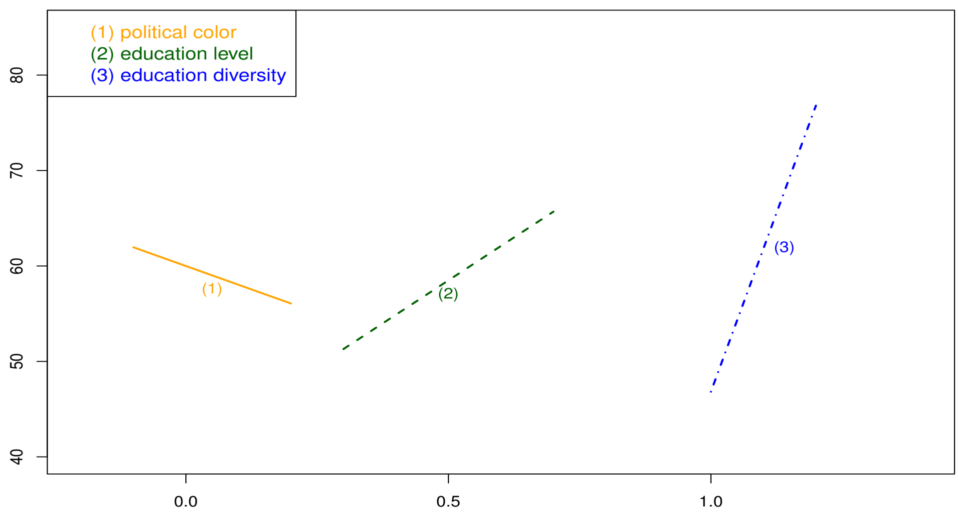


Figure 4: Opinion on climate change as a function of education level, education diversity, and political color

The difference between education level and education diversity is subtle. In our baseline model, both are significantly positive. What this means is that if the overall level of education increases then people become more aware of the dangers of climate change. This is as one would expect, although the impact is small and not very robust as further sensitivity tests reveal. But it also means that if the educational gap narrows, then climate awareness *decreases.* From a climate-policy viewpoint one should therefore aim to shift the overall *level* of educational achievement to the right, but one should not aim to change the *shape* of the distribution. The dependence of climate-related opinion on education level and diversity (and political color) is plotted in Figure 4. A small change in education diversity has a big impact, much bigger than a small change in the level of education. Also, if the political color moves from blue to red (more republican) then there will be less interest in climate issues, and the figure illustrates the effect of a small change in the political spectrum on this opinion.

One can argue (with reason) that there is considerable inertia in political beliefs and public opinion. The political shift among counties at 2-year intervals is 6.7% on average. It was largest (12.4%) at the 1994 elections (midterm election during Clinton's first term) when both the House and the Senate changed from democratic to republican. It was also large (9.4%) in the 2010 elections (midterm election during Obama's first term). In the more recent Trump-Biden years the percentages have been low, especially in the 2020 presidential elections (2.2%) when Biden defeated Trump.

Such small percentages in political shifts are directly related to small shifts in opinions. Today's opinion is to a large degree equal to yesterday's opinion. If we add last month's opinion to our regression, that is, if we consider the regression results when the dependent variable $\bar{y}(\tau)$ is replaced by $\bar{y}(\tau) - \bar{y}(\tau - 1)$, then all effects become (much) smaller, as expected. But, apart from the fact that these results show that there is considerable inertia in opinion, such an analysis does not reveal the structural ingredients that shape the opinion. Hence, we choose for an analysis in levels rather than first differences.

7.2 Social pressure

We define social pressure as the opposite of diversity. More diversity leads to less social pressure, and less diversity leads to more social pressure. More specifically, we define social pressure as

$$P_k(\tau) = 1 - \frac{2s_{rk}(\tau) + 6s_{ek}(\tau) + 5s_{ak}(\tau) + s_{pk}(\tau)}{14}, \tag{34}$$

which is based on a weighted average of the four diversity regressors, and the weights $(2, 6, 5, 1)$ are based on the results of Table 3 and the calculations in Section 7.1.

Social pressure thus combines all four diversity measures into one variable. In Table 3, model (6) is the same as our baseline model, but with education diversity replaced by social pressure. The effect on the parameters of interest is small, except that the level of education is no longer significantly different from 0.

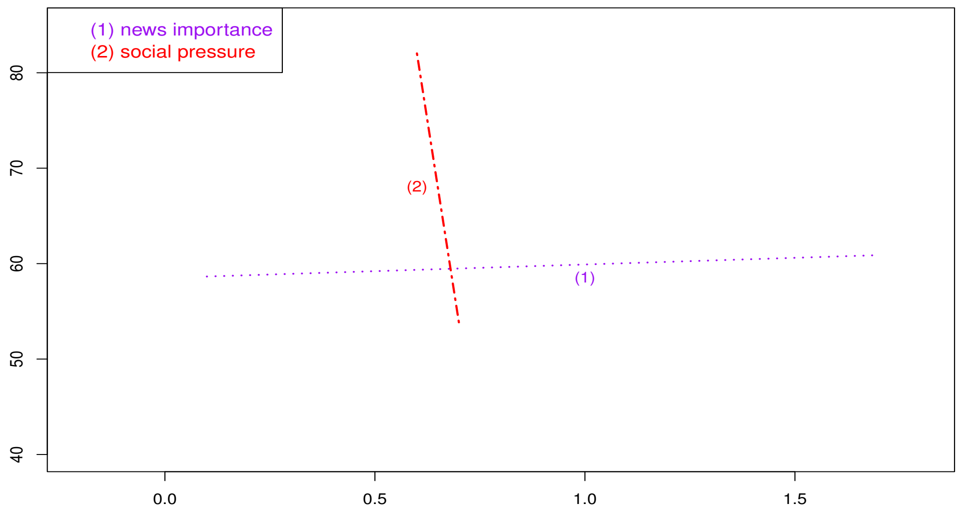
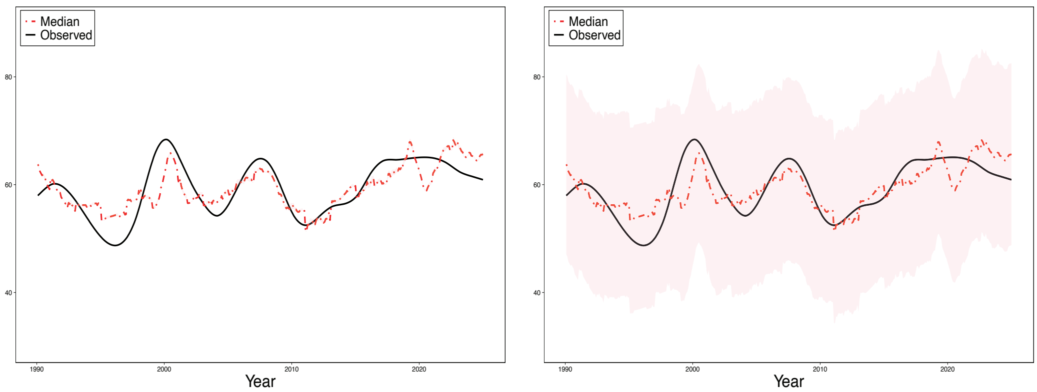


Figure 5: Opinion on climate change as a function of news importance and social pressure

Figure 5 visualizes the effects of our two variables of primary interest (news importance and social pressure) on opinion, and the figure illustrates very clearly that a small change in news importance does very little, but that a small change in social pressure does a lot to shift public opinion on climate change.

To push the argument one step further, let us consider the uncertainty of the parameter estimates by considering the quartiles of the distribution. If the estimate of a parameter μ is denoted by $\hat{\mu}$ with standard deviation σ (estimated by $\hat{\sigma}$), then we can approximate the first and third quartile of this estimate by $\hat{\mu} \pm 0.6745\hat{\sigma}$. Figure 6 shows that the effect of changing the parameter value of news importance is very small, because the parameter estimate and the standard error are both small. In contrast, the effect of changing the parameter value of social pressure is large even though the standard error is relatively small, because the parameter estimate itself is large. In both cases, the estimated parameter (the median) approximates the observed opinion rather well.



(a) news importance (b) social pressure

Figure 6: Observed versus predicted public opinion with interquartile range

7.3 Polarization

We observe opinion at the national level, not at the county level. But we can predict county opinions based on the estimation results of our baseline model. This gives 3,111 county opinions in each month of our observation period. Since we also know whether a county has a democratic or republican majority, we can study the development of public opinion for democratic and republican counties separately.

In Figure 7 we plot at each point in time (each month) the median public opinion for the democratic and republican counties respectively, together with the associated interquartile ranges. The median ranges from 48.5 to 69.8 percentage points in democratic counties and from 26.0 to 50.6 percentage points in republican counties. Clearly, there is a large gap of about 22 percentage points, and the gap increases over time showing a deepening polarization. But there is no indication that news items have opposite effects for the two groups.

Briefly summarizing, we find that social pressure is the key factor that shapes public opinion on climate change, more so than the media. The media do matter, but often less than education, group identity, and social networks. The role of education in forming opinions on climate change is subtle and intriguing. We shall comment on our findings in more detail in our concluding section.

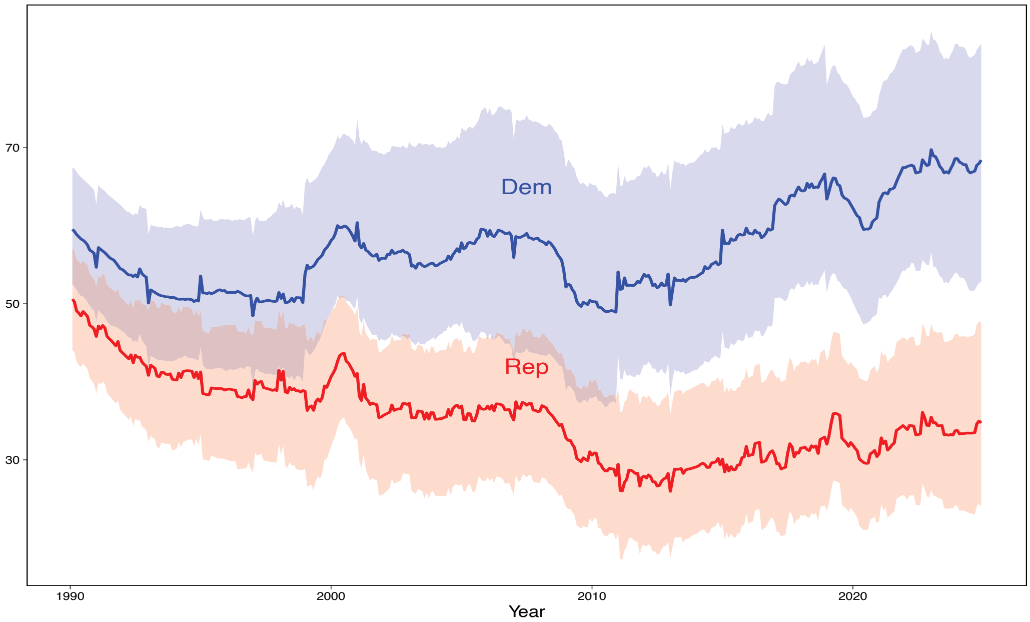


Figure 7: County-level median opinion on climate change by party affiliation with interquartile range

8 Sensitivity analysis

All models are approximations and we believe that our baseline model presented in Section 7 provides the best approximation to the true process. We chose values for our hyperparameters and, based on these values, we looked at various model specifications. This model selection exercise can be viewed as one aspect of sensitivity analysis. Now we consider other aspects, in particular sensitivity with respect to the hyperparameters. Below we report sensitivity analyses on the following items:

- γ_0 refers to the interaction between neighboring counties (Table 4).
- The definition of severe events affects how many non-severe events enter the filtering process, and the threshold values (Table 5) determine which news is selected for broadcasting.
- Positivity and reliability determine the objective characteristics of news items (Table 6).

More sensitivity analyses are provided in the online appendix, in particular:

- β_{0j}, β_{1j}, and β_2 are related to the value of national political color: β_{0j} represents the long-term level of national political color, β_{1j} the effect of changes in the national power balance, and β_2 the effect brought by the Trump administration.

- $\phi_{\ell j}$ and $\theta_{\ell j}$ ($\ell = 1, \ldots, 4$) determine the subjective weights that national TV stations assign to the components of news items. In particular, the subjective weight to importance (ϕ_{1j}, θ_{1j}), to reliability (ϕ_{2j}, θ_{2j}), to positivity (ϕ_{3j}, θ_{3j}), and to negativity (ϕ_{4j}, θ_{4j}).

The parameters can be divided into three aspects that affect the estimation results: (a) input of news, (b) selection of news, and (c) spatial spread effect (neighboring counties). We shall report on the sensitivity of one representative item of each of these three aspects, namely the sensitivity with respect to γ_0, thresholds, and positivity/reliability.

Table 4: Sensitivity to γ_0

γ_0	0.0	0.2	0.5	0.7
Focus variables				
constant	-154.6^{***}	-117.4^{***}	-65.3^{***}	-34.1^{***}
	(21.6)	(17.7)	(11.6)	(7.2)
news importance	3.41^{***}	2.69^{***}	1.59^{***}	0.87^{**}
	(1.08)	(0.87)	(0.56)	(0.34)
news number	-0.47^{*}	-0.36	-0.19	-0.08
	(0.28)	(0.24)	(0.16)	(0.10)
voter turnout	0.50^{***}	0.39^{***}	0.23^{***}	0.14^{***}
	(0.08)	(0.07)	(0.04)	(0.03)
unemployment	-1.62^{***}	-1.28^{***}	-0.79^{***}	-0.47^{***}
	(0.11)	(0.09)	(0.05)	(0.03)
Auxiliary variables: diversity				
education	336.8^{***}	260.0^{***}	149.9^{***}	81.6^{***}
	(37.3)	(30.7)	(20.2)	(12.5)
Auxiliary variables: levels				
education level	0.56^{***}	0.50^{***}	0.36^{***}	0.23^{***}
	(0.11)	(0.09)	(0.07)	(0.05)
political color	-43.4^{***}	-33.7^{***}	-19.6^{***}	-10.8^{***}
	(5.6)	(4.6)	(3.0)	(1.8)
Observations	420	420	420	420
Res. SE	3.23	3.27	3.34	3.41

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Since γ_0 turns out to be difficult to estimate precisely, we investigate how the estimates are affected when γ_0 changes between 0 and 1. We see from

Table 4 that all estimates (in absolute value) become smaller as γ_0 becomes larger. This, of course, is not surprising because if we assume stronger spatial interactions then these will account for more of the variation in public opinion. But the pattern and the relative sizes of the estimates remain the same. The estimated parameters of news importance, voter turnout, unemployment, education diversity, education level, and political color remain significant, and the direction of their impact does not change. The effect of news number remains insignificant when $\gamma_0 > 0.0$. We conclude therefore that the effect of γ_0 is robust.

Table 5: Sensitivity to national media thresholds

	Deviation from mean				
democratic	-0.03	-0.04	-0.02	-0.03	-0.03
republican	$+0.02$	$+0.02$	$+0.02$	$+0.01$	$+0.03$
Focus variables					
constant	-65.3^{***}	-64.2^{***}	-65.4^{***}	-66.3^{***}	-65.9^{***}
	(11.6)	(11.6)	(11.6)	(11.5)	(11.5)
news importance	1.59^{***}	1.25^{**}	1.40^{***}	1.93^{***}	1.91^{***}
	(0.56)	(0.57)	(0.50)	(0.56)	(0.49)
news number	-0.19	-0.05	-0.15	-0.11	-0.48^{***}
	(0.16)	(0.16)	(0.17)	(0.10)	(0.18)
voter turnout	0.23^{***}	0.23^{***}	0.23^{***}	0.23^{***}	0.24^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
unemployment	-0.79^{***}	-0.79^{***}	-0.79^{***}	-0.79^{***}	-0.79^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Auxiliary variables: diversity					
education	149.9^{***}	148.1^{***}	149.6^{***}	151.8^{***}	150.7^{***}
	(20.2)	(20.2)	(20.2)	(20.1)	(19.9)
Auxiliary variables: levels					
education level	0.36^{***}	0.35^{***}	0.36^{***}	0.35^{***}	0.37^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
political color	-19.6^{***}	-18.8^{***}	-19.0^{***}	-18.9^{***}	-21.3^{***}
	(3.0)	(3.0)	(2.9)	(2.8)	(3.0)
Observations	420	420	420	420	420
Res. SE	3.34	3.35	3.34	3.33	3.32

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Our second sensitivity test concerns the thresholds of the two national TV stations, which determine the number of news items. These thresholds were assumed, not estimated, and we can test their robustness by slightly raising or lowering their values. In Table 5, the column (−0.03, +0.02) represents our default. The parameter estimates of voter turnout, unemployment, education diversity, education level, and political color are all quite stable in terms of sign, value, and significance level. In contrast, the effects of news (both the importance and the number) appear sensitive to changes in the thresholds. Specifically, the effect of news importance, while always positive and significant, varies a lot across different sets of threshold values. The effect of news number is negative, but not convincingly so, unless we raise the threshold of republican media (last column). Overall, the estimated impact of news is sensitive to how the thresholds are specified, and we shall employ this sensitivity when we describe our experiments in Section 9.

Table 6: Sensitivity to positivity and reliability

positivity	±0.5	±0.3	±0.7	±0.5	±0.5
reliability	0.5	0.5	0.5	0.3	0.7
Focus variables					
constant	-65.3^{***}	-64.2^{***}	-66.8^{***}	-64.2^{***}	-67.2^{***}
	(11.6)	(11.6)	(11.5)	(11.6)	(11.5)
news importance	1.59^{***}	1.39^{**}	2.05^{***}	1.59^{***}	2.04^{***}
	(0.56)	(0.57)	(0.55)	(0.56)	(0.54)
news number	-0.19	-0.21	-0.33^{**}	-0.34^{*}	-0.34^{**}
	(0.16)	(0.17)	(0.16)	(0.19)	(0.15)
voter turnout	0.23^{***}	0.23^{***}	0.24^{***}	0.23^{***}	0.24^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
unemployment	-0.79^{***}	-0.78^{***}	-0.80^{***}	-0.78^{***}	-0.80^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Auxiliary variables: diversity					
education	149.9^{***}	147.9^{***}	151.7^{***}	147.7^{***}	152.4^{***}
	(20.2)	(20.2)	(20.0)	(20.1)	(20.0)
Auxiliary variables: levels					
education level	0.36^{***}	0.36^{***}	0.37^{***}	0.37^{***}	0.38^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
political color	-19.6^{***}	-19.5^{***}	-20.9^{***}	-20.2^{***}	-20.8^{***}
	(3.0)	(2.9)	(3.0)	(3.0)	(2.9)
Observations	420	420	420	420	420
Res. SE	3.34	3.35	3.32	3.35	3.32

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Our third and final sensitivity test concerns the (objective) positivity and reliability of the news items. We possess no information on these two variables, and our default is that all news items share the same, numerically neutral, values of positivity and reliability. In Table 6, we experiment with different values of these two news ingredients. The column (±0.5, 0.5) represents our default, while the other four columns represent deviations from this default. The conclusions of this sensitivity test are similar to the conclusions of the previous test relating to thresholds. The parameter estimates of voter turnout, unemployment, education diversity, education level, and political color are again robust. But the effects of news importance and number are somewhat sensitive to changes in positivity and reliability. When the positivity or reliability of all news items increases, the positive effect of news importance becomes much stronger, while the negative effect of news number is estimated more precisely and becomes marginally stronger. In Section 9 we shall further experiment with different values of the objective positivity and reliability of news items.

Summarizing, the magnitude of the spatial spread effect does affect the estimates, but uniformly and according to our expectation, which we interpret as a sign of robustness. The effects of news importance and news number appear to be sensitive to changes in national media thresholds and news ingredients. However, the impact of news number remains insignificant in most cases.

Other sensitivity results generally confirm the above conclusions. In particular, the estimated parameters are robust to changes in the magnitude of the Trump effect, the definition of severe events, the speed and direction of the response of the two TV stations to shifts in the national power balance, and the subjective weights assigned to news ingredients.

If we change the values of β_{0d} and β_{0r} which determine the long-term levels of national political color (set to -0.5 and $+0.5$, respectively, in the baseline model), then we find that if republican media move to the right (β_{0r} becomes larger so that polarization increases compared to the baseline model), then the parameter estimate of news importance increases a lot, and the originally statistically insignificant parameter estimate of news number becomes significant.

9 Policy implications

Having determined our baseline model in Section 7, we can now use the estimated parameters to investigate the effects of various policies. In these policy exercises the parameters are fixed at their estimated values presented in Table 3, column (5), while we change the input of county-level data to simulate a series of policies.

We distinguish between two types of policies: those that can be controlled by the government and those that can be controlled by the media. Examples of government-controlled policies are:

(A1) Investment in public education, which may affect both its level and its diversity.

(A2) Only one national TV station exists, either democratic or republican, so that all individuals receive the same information regardless of their political convictions.

(A3) Funding institutions so that the (objective) reliability of the news increases.

(A4) Measures to reduce unemployment.

Examples of media-controlled policies include:

(B1) The TV stations broadcast more positive news on climate change.

(B2) The TV stations adjust their news filtering thresholds to broadcast either more or fewer news.

(B3) Local TV stations broadcast news from the national TV station holding the opposite political views.

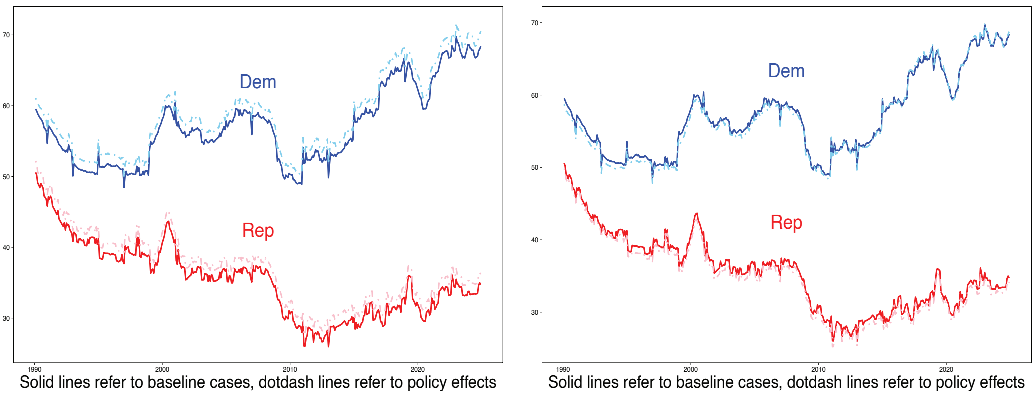
(B4) The political distance between the two national TV stations increases, implying more polarization.

Below we report on (A1) and (A2), which we consider the most intriguing items, while the results of the other experiments are only briefly summarized. A full report of all experiments is provided in our online appendix.

Recall that while we have no information on county-level opinions, we can predict these opinions given our parameter estimates. In addition, we have information on county-level political colors. In our policy experiments we divide the counties into two groups, democratic and republican, depending on the political color at the time of observation. This division is important, because the trends in public opinion in democratic and republican counties are not necessarily the same. In fact, they may work in opposite directions in which case the aggregate would show no effect, while two separate effects exist.

9.1 Investment in education

Suppose that the federal government implements a nationwide policy to improve the level of education. To allow for possible differences between counties, we compute the 50% (median) and 75% quartiles of education level for each county across all months, and then assume that the nationwide policy succeeds in improving the education level of each county by pushing the level up from the median to the 75% quartile.



(a) education level ↑ (b) education level ↑ and diversity ↓

Figure 8: The effect of changes in education level and education diversity

Such a policy represents a nontrivial educational shock, which should have an effect on people's opinion on climate change. As shown in Figure 8a, a 25% interquartile increase in the education level of all counties leads to a 1.6 percentage point increase of public opinion in democratic counties, and a slightly lower but still substantial 1.5 percentage point increase in republican counties.

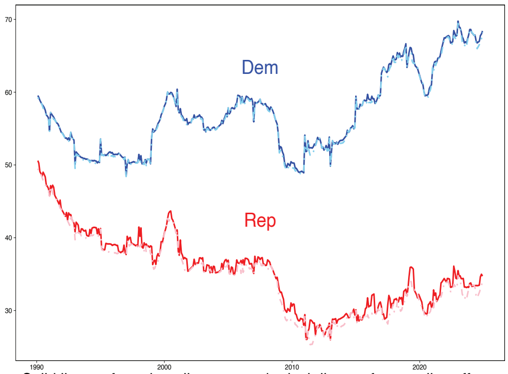
In this first experiment, only the level of education is affected, not the diversity. Now we consider a scenario where there are various levels of education—say: low, medium low, average, medium high, and high—and the government initiates a program that is intended to push the average group to medium high. This will increase the overall level of education, but it will decrease the diversity since more people are now concentrated in one group. To study the effect of such an initiative, we assume that the decrease in education diversity is 10 percentage points (from 50% to 40%), hence smaller than the increase in education level.

Figure 8b shows that even a small decline in education diversity can greatly impede the positive effect of improving the level of education. The positive effect of investing in education can even become negative, as it does in our scenario where public opinion decreases by 0.34 percentage points for democratic counties and quite a bit more (0.73 percentage points) for republican counties.

Our result suggests that investment in education should apply equally to all levels so that the diversity is not affected; otherwise, education investment may backfire and reduce public opinion on climate change.

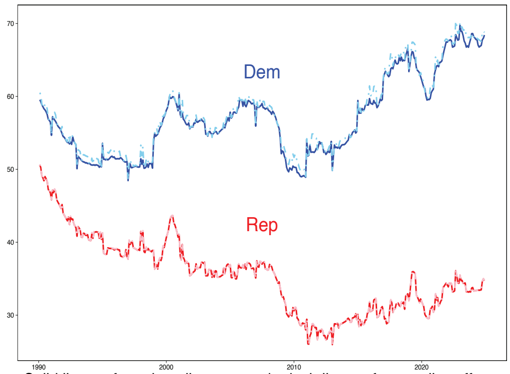
9.2 Dictatorship

In our second experiment, we assume that the President has become a dictator and has decided to abolish the TV station of the opposition. Under a democratic dictator, the republican channel is abolished, and under a republican president the democratic channel is abolished. Either way, the public has only access to one TV station.



Solid lines refer to baseline cases, dotdash lines refer to policy effects

(a) democratic



Solid lines refer to baseline cases, dotdash lines refer to policy effects

(b) republican

Figure 9: The effect if only one national TV station exists

Under a democratic dictator, Figure 9a shows that public opinion decreases by 0.70 percentage points on average in republican counties and by 0.21 percentage points in democratic counties. Under a republican dictator, as shown in Figure 9b, public opinion increases by 0.54 percentage points on average in democratic counties and by 0.04 percentage points in republican counties.

One might expect that under a dictator nothing changes in counties that have the same political color as the dictator, since they continue to watch the same TV station as before. This is more or less true under a republican dictator, but not under a democratic dictator, which is explained in part by the spatial interaction in our model: a change in one county affects all neighboring counties.

More importantly, one might expect that under a democratic dictator with democratic-controlled news, the opinion in republican counties is pushed in the democratic direction. And, vice versa, that under a republican dictator the opinion in democratic counties is pushed in the republican direction. That would be in line with one strand of the literature on media effects, which argues that sustained exposure to opposing media enables people to learn about alternatives, which would moderate their attitudes; see Broockman and Kalla (2025) for a recent experiment.

Our results do not support this view. Under our assumptions, opponents become even more convinced of their own right under a news dictatorship, and polarization will become even larger. While such a result may not be the common or even the common sense view, there is some support from another strand of the literature which suggests that cross-cutting media may elicit counterarguments, which in turn reinforce prior attitudes due to the theory of 'motivated reasoning' (Taber and Lodge, 2006; Hart and Nisbet, 2012; Levendusky, 2013).

9.3 Other policy experiments

We briefly summarize our other policy experiments. An increase in the reliability or the positivity of news items has only a slight effect on public opinion (A3, B1), but lowering unemployment can significantly improve public opinion on climate change (A4). Lower thresholds lead to lower public opinion for both democratic and republican counties, which is caused by the effect of news importance in our model, since broadcasting more news items results in a lower average importance of the items. The concern of individuals may then decrease due to information dilution. Thus, there is a trade-off between news quality and quantity, suggesting that fewer but more important news items can actually push up public concern (B2). When individuals are exposed to cross-cutting media, democratic (republican) counties become more (less) concerned about climate change (B3). A larger political distance between national TV stations intensifies the polarization in public opinion between democratic and republican counties, although the effects are small (B4).

10 Conclusions

Our aim in this paper has been to explore how news and social pressure affect public opinion on climate change in the USA, based on county-level data over the period 1990–2024. Our data exhibit several novel features. In particular, we include not only the number but also the quality of news items, we introduce social pressure as the opposite of four types of diversity (race, education, age, and political), and we allow for spatial correlation. The use of county-level data allows us to preserve the heterogeneity among the 3,111 counties, thus avoiding the limitations imposed by using national-level data only.

Summarizing our findings we offer three conclusions. First, social pressure (group identity) is the key factor that shapes public opinion on climate change, more so than the news. Greater demographic diversity (race, education, age) reduces social pressure and leads to a more heterogeneous social environment, which in turn increases interpersonal contact and the spread of climate-related information, thereby making more people concerned about climate change. Conversely, greater political diversity leads to more balanced partisan affiliations, which in turn intensifies partisan conflict.

Second, news does matter but often less than education, group identity, and social networks. News influences public opinion through the importance of its content, but the effect is small—much smaller than the effect of social pressure. The effect of presenting more news on climate change is negligible. Media effects are often indirect (shaping the agenda, telling us what issues are salient) rather than directly changing our opinions, and long-term predispositions and social context anchor political attitudes more firmly than media exposure alone.

Third, the role of education in forming opinions on climate change is important and intriguing. We find evidence that the impact of education inequality dominates the impact of race inequality. But we find no evidence that education has a different effect on republicans than on democrats: higher education leads to more concern about the climate for both democrats and republicans.

In the policy experiments, we predict county-level public opinions based on our estimated parameters, and we divide the counties into two groups, democratic and republican, depending on their political color at each point in time, thus allowing us to identify different responses to policies across democratic and republican counties. We find that policy makers, if they wish to raise awareness of the dangers of climate change, should aim to increase the overall level of educational achievement, but they should not aim to change the shape of the distribution as this may have the opposite effect. Public education investment should therefore be applied equally to all educational levels rather than to one specific level, because decreasing educational diversity will increase social pressure, which leads to an unintentional decrease in public opinion.

Under dictatorship there would be one TV station only, namely the TV station of the party in power. In the case of a democratic dictator, public opinion in republican counties does not increase, and under a republican dictator, public opinion in democratic counties does not decrease. In fact, the opposite happens, although the effects are small. This may seems counterintuitive and counterfactual, but it does align with the argument that exposure to cross-cutting media elicits counterarguments and reinforces predisposition.

Finally, this study has required a fair amount of assumptions, and each of these can be challenged. For example, we need to impose a structure on how the political color of national TV stations shifts and how local TV stations rate the subjective importance of news. We guard ourselves, to a certain extent, by conducting extensive sensitivity tests, where we find that most estimation results are quite robust. But the news variables and education level still show some sensitivity to our choice of model and the values of the hyperparameters. The data at county level, while rich, suffer from one serious constraint, namely that no data on public opinion at the county level are available. This means that we had to restrict our model and our assumptions about random errors in such a way that we can still use county-level data but only national-level opinions.

Appendix A Objective news: importance, positivity, and reliability

Recall that we distinguish between three objective ingredients underlying the national news: importance, reliability, and positivity. This appendix only discusses importance. News coverage on climate change depends primarily on two ingredients: the occurrence of climate-related diasters and the occurrence of major climate-related policy events (Anderson, 2009). Thus, we link the objective importance of news to influential climate-related events, including both severe disasters and policy events.

Based on the data provided by the National Centers for Environmental Information (NCEI), Figure 10 shows the number (solid line) and total CPI-adjusted losses (dashed line) of annual billion-dollar climate disasters. We denote the current intensity of the ith disaster at time τ by $\nu_i^{d-}(\tau)$, which captures the instantaneous impact of the disaster on news coverage, and we assume that the impact of a climate disaster lasts for 6 to 12 months with diminishing intensity. The initial intensity $\nu_i^{d-}(\tau)$ is determined by the economic loss $l_i(\tau)$ it incurred:

$$\nu_i^{d-}(\tau) = 0.03\, l_i(\tau) + 6, \tag{35}$$

where the value of ν_i^{d-} is rounded to the nearest integer. Since $1.1 \leq l_i \leq 201.3$ (the largest disaster was Hurricane Katrina in August 2005, causing

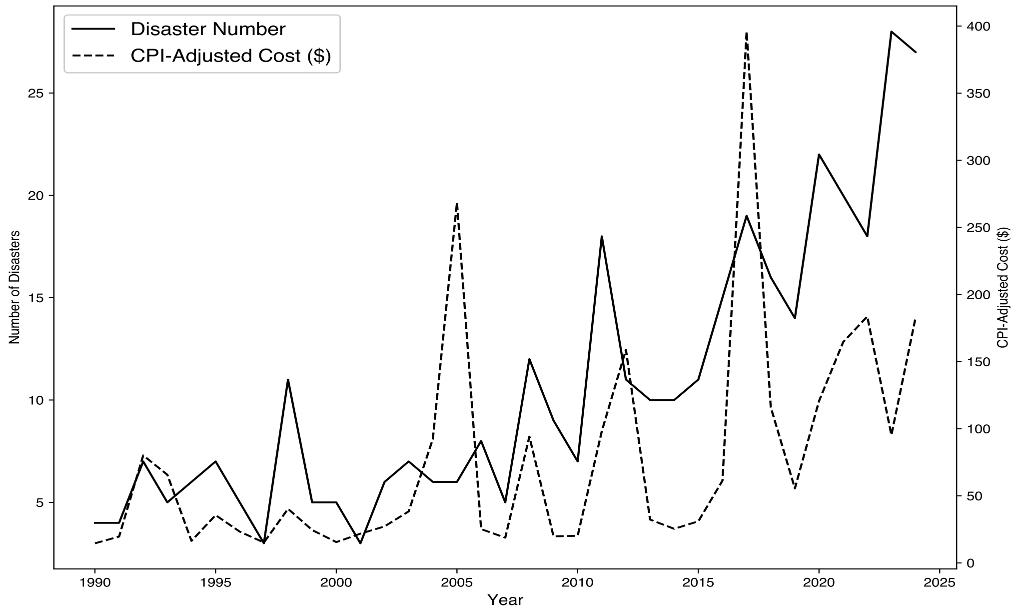


Figure 10: Number and losses of the U.S. billion-dollar disasters

1,833 deaths and approximately \$201.3 billion in damages), it follows (after rounding) that $6 \leq \nu_i^{d-}(\tau) \leq 12$. The monthly depreciation in intensity is set to 1 unit, so that the duration of impact ranges from 6 to 12 months. The total disaster intensity at time τ is then given by the sum of the current diminished intensities of all climate disasters affecting that month:

$$\nu^{d-}(\tau) = \sum_i \nu_i^{d-}(\tau). \tag{36}$$

In addition to climate-related disasters, we also consider major climate-related policy events. Unlike disasters, which are always negative, policy events can be either positive or negative. We use data from the Media and Climate Change Observatory (MeCCO), and consider the news coverage on climate change by two representative TV stations: CNN and FOX.

This TV coverage is shown in Figure 11, and it is clear that CNN reports much more frequently on climate events than FOX. We focus on the main fluctuations and peaks, and investigate what influential climate-related policy events occurred around those points in time.

The main climate-related policy events that had serious impact on the USA since 1990 are listed in Table 7. Since policy events typically receive much longer news coverage than disasters (Houston et al., 2012), we assume that the initial intensity of a policy event is equal to the initial intensity of

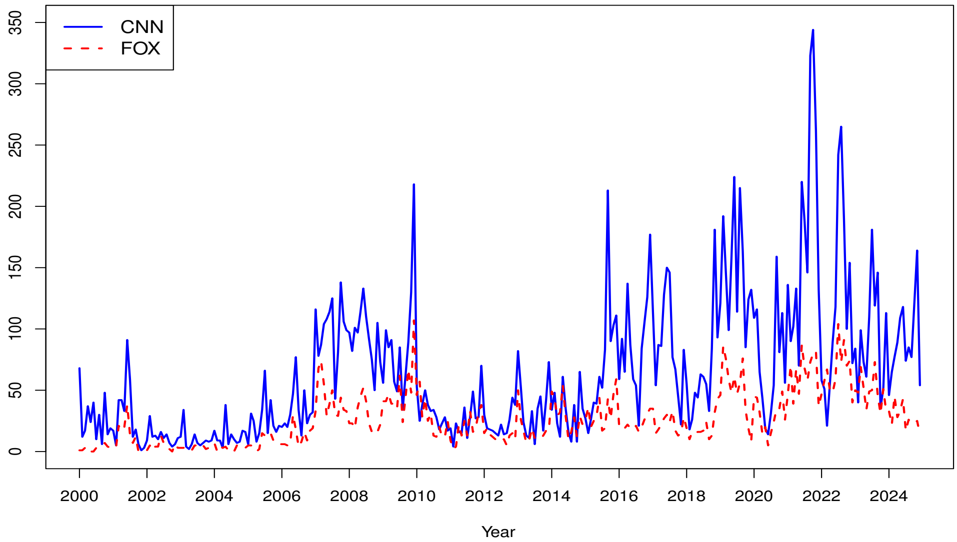


Figure 11: Monthly TV news coverage of climate change in the USA

Table 7: Major climate-related events, 1990–2024

Event	Date	ν_i^{e+}	ν_i^{e-}
UNFCCC Adoption	1992/06	12	0
Kyoto Protocol	1997/12	12	0
Withdraw from Kyoto Protocol	2001/03	0	12
An Inconvenient Truth	2006/05	12	0
American Recovery and Reinvestment Act	2009/02	12	0
American Clean Energy and Security Act	2009/06	12	0
Copenhagen Climate Summit	2009/12	12	0
White House Office of Energy and Climate Change Policy eliminated	2011/04	0	12
Pope Francis emphasized climate change in his speech in Washington	2015/09	12	0
Paris Agreement	2015/12	12	0
Withdraw from Paris Agreement	2017/06	0	12
Global Climate Action Summit	2018/09	12	0
Green New Deal Resolution	2019/02	12	0
Rejoin Paris Agreement	2021/01	12	0
Inflation Reduction Act	2022/08	12	0

the most severe disaster:

$$\nu_i^{e+}(\tau) = \nu_i^{e-}(\tau) = 12. \tag{37}$$

As before, the total policy events intensities for positive and negative events at time τ are given by the sum of the current diminished intensities of all climate-related policy events affecting that month:

$$\nu^{e-}(\tau) = \sum_i \nu_i^{e-}(\tau), \qquad \nu^{e+}(\tau) = \sum_i \nu_i^{e+}(\tau). \tag{38}$$

Consequently, we arrive at the total positive and negative climate events intensities:

$$\nu^{+}(\tau) = \nu^{e+}(\tau), \qquad \nu^{-}(\tau) = \nu^{d-}(\tau) + \nu^{e-}(\tau), \tag{39}$$

which are visualized in Figure 12.

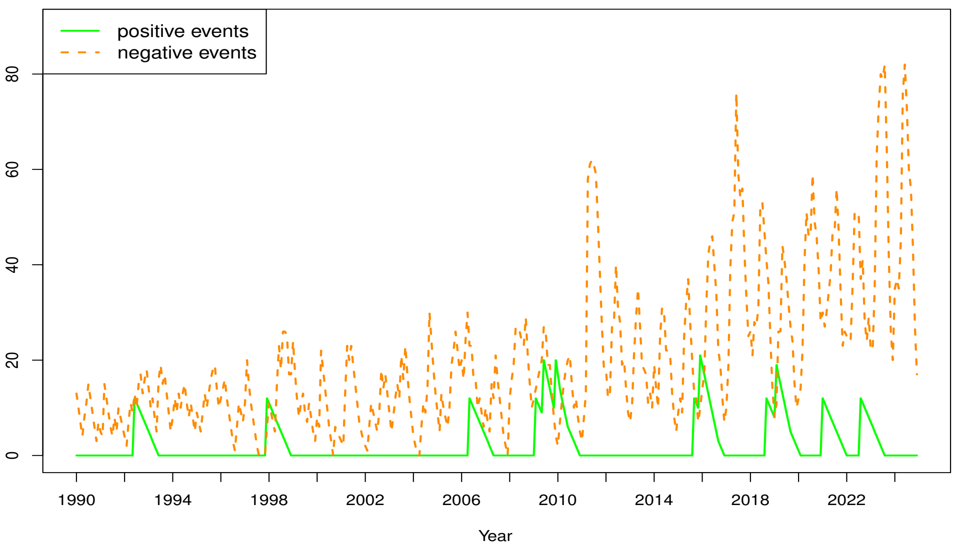


Figure 12: Monthly climate-related events intensity

Similar to the definition of initial intensity, we assign importance values m_i^d and m_i^e to each disaster and policy event as follows:

$$m_i^d = 0.003\, l_i + 0.4, \qquad m_i^e = 1, \tag{40}$$

where the value of m_i^d is rounded to one decimal place. Unlike intensity, the importance of each climate event remains constant over time.

The previous discussion provides us with the (constant) importance and the (decreasing) intensity of each climate event, and we consider these pieces of information as objective facts that are made available to the two news providers.

To facilitate the transformation from climate-related objective news to news *blocks* we define the number of positive and negative news items in each month as

$$n^{+}(\tau) = \left\lfloor \frac{\nu^{+}(\tau)}{s} \right\rfloor + 1, \qquad n^{-}(\tau) = \left\lfloor \frac{\nu^{-}(\tau)}{s} \right\rfloor + 1, \tag{41}$$

where $\lfloor x \rfloor$ denotes the floor function, which rounds x down to the nearest integer less than or equal to x. The addition of 1 ensures that at least one positive and one negative news block exists in each month. Since $\nu^{+}_{max} = 21$ and $\nu^{-}_{max} = 82$, we set $s = 10$, so that

$$n^{+}_{max} = \lfloor 2.1 \rfloor + 1 = 3, \qquad n^{-}_{max} = \lfloor 8.2 \rfloor + 1 = 9, \tag{42}$$

and we have a maximum number of $q = n^{+}_{max} + n^{-}_{max} = 12$ news blocks per month.

Taking the importance and intensity of each news event into account, we now bundle the news events into news blocks, where for each block we know its importance and whether it is positive or negative news (and ideally also its reliability, although we shall only use reliability in the simulations, not in the estimations due to lack of information).[5] In our stylized world, the news providers then choose the number and the type (positive or negative) of these objective blocks depending on how much time they want to spend on climate news and whether they wish to emphasize positive or negative news.

Appendix B Climate change opinions at the national level

There are several surveys that investigate public opinion in the USA on climate change. We shall use the data provided by the Gallup Poll Social Series (GPSS), because these data include the climate-related survey questions that are most relevant to us. The four most closely-related survey questions in the GPSS cover the following aspects:

[5] We explain in detail how the news blocks are constructed and provide an example in our online appendix.

- How worried are you personally about climate change,
- When do you think the effects of global warming will begin to happen,
- Is global warming caused by human activities or not, and
- Do you think global warming is a threat.

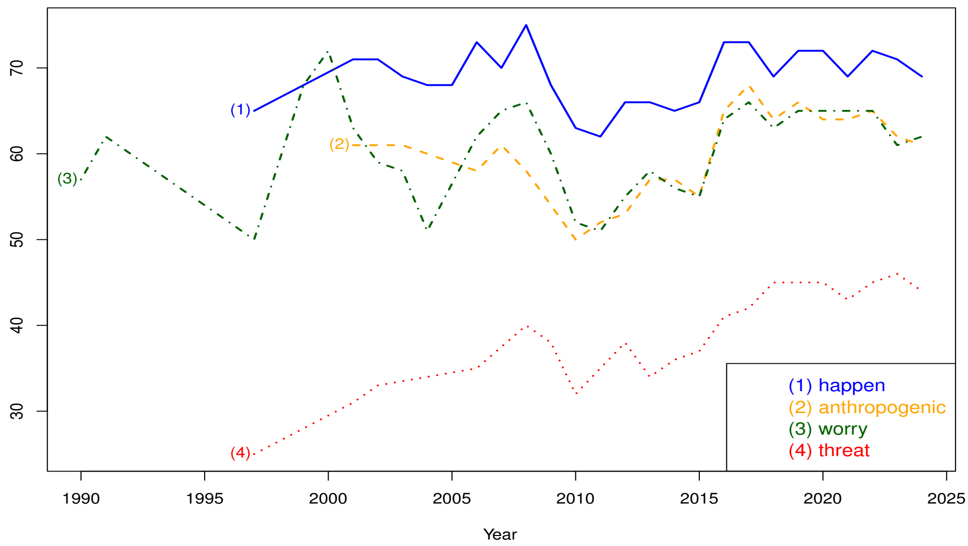


Figure 13: Trends in public opinion on climate change (Source: GPSS)

The long-term trends in national public opinion on climate change based on these four questions are graphed in Figure 13. We choose the green line ('worry') as our indicator of national climate-change opinion, because the trends in the four survey questions are highly correlated (ignoring the levels) and the survey question on personal worries about climate change covers the longest time span with the largest number of observations.

Appendix C County characteristics

We shall employ different types of county characteristics: political, demographic, economic, and geographic, as detailed in Table 8.

Some counties have been merged or have been eliminated during this period. In order to achieve consistency and comparability, we choose the

Table 8: County-level raw data

Item	Year
Political	
General presidential election votes	1990 to 2024, at four-year intervals
Demographic	
Total population	1990 to 2024, annually
Population by age group	1990 to 2024, annually
Population by race group	1990 to 2024, annually
25+ population by education group	1990 to 2005, 2010 to 2023, annually
Economic	
Median household income	1990, 1999, 2010 to 2023, annually
Median house price	1990, 2000, 2010 to 2023, annually
Labor force	1990 to 2024, annually
Geographic	
Land area	almost constant
Contiguity	constant

year 2020 as our benchmark, and adjust (if necessary) the data from the other years. Thus we obtain 3,111 counties and county equivalents.

The data come from various data sources. Using the items in Table 8, we construct the following set of county characteristics:

- Voter turnout: We divide the total number of valid votes by the total population per county as a proxy to the (relative) voter turnout.

- Party share: Excluding the negligible third parties' votes, we define party share as the percentage of votes received by the democratic (or republican) party relative to the total number of votes for the two major parties.

- Population density: Population density is measured by population per square miles, that is, total population divided by land area.

- Household median and mean income: Income data have to be adjusted for inflation, and we adjusted all income-related data to 2020 dollars using the appropriate CPI-U-RS (Consumer Price Index) adjustment factor.

- Median house price: Unlike income, house prices are usually not adjusted for inflation, as a house is not only a consumption good but also an asset. House prices are typically influenced by both inflation and other factors such as demand and the interest rate. Therefore, we use nominal house prices.

- Unemployment rate: Unemployment rate is measured as the share of the labor force without work.

- County adjacency: For each county we can identify the adjacent counties.

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Online material

The online appendix is available at

www.janmagnus.nl/papers/zhehao-app.pdf

Here we

- show the forward and backward processes in detail when assigning plausible values for the hyperparameters that determine subjective importance,
- explain how we link climate disasters and climate-related policy events with the generation of news number and news objective importance,
- list all potential models and regression results,
- provide a complete version of sensitivity analysis, and
- provide a complete version of policy experiments.

The data appendix is available at

www.janmagnus.nl/papers/zhehao-app-data.pdf

In the data documentation, we

- carefully explain how we select the 3,111 counties and county equivalents,
- provide all data sources that we refer to, and present the summary statistics,
- explain how we use Kalman filter to interpolate monthly data, and take the biggest county Los Angeles as an example to show the interpolation results for each variable.