Man Bites Dog? Editorial Choices and Biases in the Reporting of Weather Events^{*}

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Abstract

Every day, editors of media outlets decide what is news. In this paper, we unpack the process of news production by looking at US local TV newscasts' coverage of weather events, which we define as deviations in temperatures from the historical mean. We show that large deviations receive substantially more coverage than typical temperatures, and the greater the deviation, the higher the coverage. We document a clear publication bias in the coverage of these events. In summer, the increase in coverage of deviations above (below) the historical mean is more pronounced in TV stations operating in Democratic-leaning (Republican-leaning) media markets. We further study how much emphasis weather news receives, whether stations engage in presentation bias, and offer empirical and theoretical evidence that demand rather than supply forces drive coverage.

Keywords: Local News, Climate Change, Publication Bias, Presentation Bias, Editorial

Strategies

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We address these questions by studying how US local TV stations cover weather events, which we define as temperature deviations from the historical mean. These events are particularly suitable to study editorial choices and biases. First, weather events are verifiable, allowing us to establish a ground truth to which we can compare coverage decisions. Second, we can establish how rare a weather event is using historical data, which allows us to test the "man bites dog" hypothesis that infrequent events receive more coverage.¹ Third, while weather events may appear to be ideologically neutral, they are actually closely intertwined with climate change—a deeply polarized topic in American public discourse. This makes weather events ideal for determining whether editors truly base their editorial choices solely on newsworthiness.

We begin by estimating the newsworthiness of different weather events by linking coverage of local weather in TV newscasts and the occurrence of the events themselves, separately in the summer and in the winter. Exploiting close to the universe of newscast transcripts of local TV stations, we first document a clear "man bites dog" effect: Days that experience infrequent weather events, which happen to be large deviations from the historical mean, see substantially more coverage of local weather than days in which temperatures are in line with the norm. The difference is substantial. For example, a summer day with temperatures in the bottom (top) 10% of the within-media market deviation distribution presents 10% (5%) more coverage of local weather relative to days with a close to zero deviation. We also

¹Specifically, for each media market and day in the 2013-2019 period, we calculate the deviation of the maximum temperature from the mean temperature recorded on the same calendar day from 2000 to 2012 (the historical mean). We assign to each temperature deviation its percentile in the within-media market deviation distribution, separately in the summer and in the winter. We then aggregate these percentiles in different bins, that become our weather events.

show that local TV news also cover moderate deviations more than weather in line with the norm. Hence, "big dog's bites" are also sometimes news.

Next, we examine how media outlets tailor their publication strategies based on the political leaning of the markets they serve (also known as Designated Market Areas or DMAs). We find clear evidence of publication bias: coverage of weather events in Democratic- and Republican-leaning media markets is markedly distinct. This difference is especially visible when it comes to uncommon events in summer. Relative to the baseline of temperatures in line with the historical norm, coverage of local weather in unseasonably cold days increases significantly more in Republican- than Democratic-leaning markets, whereas the reverse holds true in unseasonably hot days. Hence, newsworthiness is not the only factor entering into editors' coverage decisions. In other words, editorial choices are biased.

While the first choice any editor makes is whether to broadcast (or publish) a story, editorial decisions do not stop there. Editors must choose how much salience to give to a story (i.e., where to place it in a newscast or a newspaper) and how to present it (i.e., the slant of the story). We find that the salience of weather stories presents the same direction of bias as the number of weather stories. We then look at the framing of these stories and, in particular, whether they are explicitly linked to climate change or global warming. Our results are striking: the terms "climate change" and "global warming" are barely mentioned no matter the temperature of the day. We also train a topic model on our local weather stories and, again, find no topic that explicitly relates to climate change.

Having determined the existence of editorial bias when it comes to coverage and salience of weather events, we also study its possible causes. In particular, we are interested in understanding whether demand-side factors (TV stations responding to the preferences of their potential audience) or supply-side factors (TV stations choosing coverage so as to influence citizens' belief on climate change) are likely to be at play. We begin by studying whether acquisitions by a conservative broadcast group, Sinclair, impact coverage of weather events. As Sinclair is well-known for its conservative bent, we would expect a change in coverage when Sinclair takes control of a station if supply-side factors drive broadcasting decisions. If coverage is demand-driven, instead, we would expect to observe little change. Using the staggered timing of the acquisitions in both a differences-in-differences and a triple differences design, we provide evidence more consistent with demand-driven than supplydriven coverage.

In the final part of the paper, we present a formal model of coverage decisions and media consumption to make sense of the main empirical patterns we uncover. An outlet faces an audience which is constituted in part of Democratic citizens and for the rest of Republican citizens. All citizens like to learn about uncommon events as they value surprises. They also all suffer from a form of confirmation bias: their utility depends on what they learn about climate change from weather news.² While Democrats receive a payoff gain from holding higher beliefs in climate change following news, Republicans suffer a loss from increased beliefs. Citizens consider their expected utility from watching local news versus the utility from their outside option, which could include watching different, entertainment shows on TV. This expected utility is a function of the time allocated to weather news and other news by the local TV station times the consumption value of each type of news. This consumption value is fixed for non-weather news. It depends on the size of the weather events for weather news. Larger events are more unexpected and deviations above the mean also indicate that climate change is happening.

We compare the coverage decisions of a profit-maximizing outlet and of biased outlets which seek to minimize or maximize belief in climate change. The first type captures demand-driven coverage, the second corresponds to supply-driven coverage. We show that the strategy of a profit-maximizing outlet matches most of our empirical findings. Larger events receive more coverage. Events above (below) the norm, that increase (decrease) beliefs in climate change, see a greater increase in coverage when the TV station operates in a market with many Democratic (Republican) citizens. In contrast, supply-driven coverage fails to match any of our empirical results. In fact, even if a biased TV station can commit to a coverage strategy, it either hides events or spends as much time as possible covering them, generating either no or very stark variations in coverage as events become more extreme as opposed to the smooth increase we observe empirically.

²In the Online Appendix, we use individual-level survey data from the Cooperative Congressional Election Survey to show that, indeed, individuals' stated beliefs about climate change depend on weather events.

Related Literature

With this paper, we contribute to several strands of literature within the economics of media. First and foremost, we contribute to an extensive theoretical and empirical literature that studies media bias. The theoretical literature (see, for example, Gentzkow et al., 2015) broadly considers two non-mutually exclusive types of bias: filtering or publication bias (bias in *what* events are covered) and presentation bias (bias in *how* events are covered). In this paper, we primarily focus on the former—that is, on editors' decisions of what events to cover and what events not to cover. Recently, Armona et al. (2024) have noted that, to be able to identify publication bias, it is important to determine an unbiased reporting benchmark, to which to compare coverage against. In their paper, they focus on national media outlets and determine unbiased reporting based on a scoring rule (a statistical measure of the amount of "news" in the realization relative to the consumer's prior). Instead, thanks to our focus on local media outlets, we are able to determine the benchmark of unbiased reporting empirically, by looking at reporting of the closely related events in markets with a neutral political leaning. Our investigation also extends the empirical literature on publication bias in media coverage. Most of this literature has focused on explicitly political topics or events (e.g., scandals as in Puglisi and Snyder Jr, 2011 or economic news that are likely to impact voting behavior as in Larcinese et al., 2011). Instead, we show that media bias is also present when studying a topic, weather, that is not explicitly political, although it connects to the politically charged issue of climate change.

Our focus on an environmental issue also connects our work to a few recent advances in the literature on media strategies. Closest to us is Pianta and Sisco (2020), who focus on coverage of extreme temperatures for a sample of European newspapers. Their analysis, however, does not address the determinants of coverage and does not examine how coverage varies with ideological leaning. Ash et al. (2023) and Djourelova et al. (2024) study the media coverage of climate change with a focus on presentation bias and its consequences for political preferences. Relative to these papers, we find only limited evidence of presentation bias being at play in the closely related domain we analyze, weather event. While this might appear to be surprising at first glance, recent studies have documented variation in coverage even across different natural disasters (see Fetzer and Garg, 2025).

After documenting media bias in weather events coverage, we conduct a comprehensive examination of its drivers. In particular, we contribute both theoretically and empirically to work in the economics of media literature highlighting supply-side explanations (see, among many others, Strömberg, 2004; Baron, 2006; Wolton, 2019) and demand-side explanations (see, among others, Gentzkow and Shapiro, 2006; Anand et al., 2007; Mullainathan and Shleifer, 2005). Our evidence suggests that the empirical patterns are more likely driven by demand-side than supply-side factors, extending the findings of Gentzkow and Shapiro (2010) to a different, more mundane issue. From a theoretical perspective, we enhance existing models of media bias by highlighting how learning and belief updating might play a fundamental role in determining the demand for news, thus adding to the experimental findings in Chopra et al. (2024).

In summary, our paper sheds light on the daily operations of news production, focusing on routine events like weather. We find that extreme weather deviations receive more coverage, and local TV stations' weather reporting is influenced by the political leanings of their audience, rather than supply-side forces. This has two broad implications. Newsworthiness cannot on its own explains the editorial choices we observe. Weather reporting may inadvertently shape climate change beliefs through daily coverage decisions.

1 Background

Each local TV station is licensed to operate in a specific media market (also referred to as Designated Market Area or DMA), which effectively represents the geographic reach of the station. More precisely, media markets are regions whose residents have access to the same television and radio broadcasts, and are defined by Nielsen based on household viewing patterns, which makes them non-overlapping geographies.³ Within each market, our focus

 $^{^{3}}$ A county is assigned to a specific media market if the majority of its television audience watches stations from that market (Nielsen, 2019). Although counties can sometimes be divided between multiple media markets, this is relatively rare. According to Moskowitz (2021), only 16 out of 3,130 counties fall into this category. Additionally, while Nielsen updates media market boundaries annually, only 30 counties changed their market affiliation between 2008 and 2016.

is on stations affiliated with the four major broadcast networks (ABC, CBS, FOX, and NBC), as they tend to have the highest viewership and produce their own newscast (Papper (2017)).⁴

Local TV newscasts, which are locally produced by each station, feature a mix of national and local stories. Mastrorocco and Ornaghi (Forthcoming) show that the most common topics of local stories are crime, politics, weather, and sports. Despite a gradual decline in viewership, these TV newscasts remain a significant source of information for many Americans. A 2017 report by the Pew Research Center found that 50% of U.S. adults regularly consume news from television, surpassing the share who rely on online sources (43%), radio (25%), or print newspapers (18%) (Gottfried and Shearer (2017)). Among television news sources, local stations attract larger audiences than both cable networks and national broadcasters (Matsa (2018)). This makes studying local TV news particularly relevant.

2 Data & Measurement

This paper combines several data sources, which we detail below.

Local TV Stations. Our starting sample includes all local TV stations affiliated to one of the big-four networks (ABC, CBS, NBC, and FOX) in the continental United States. Information on the market served by each station and yearly affiliation is from BIA/Kelsey, an advisory firm focusing on the media industry. Additionally, we track historical call sign changes over our study period using data scraped from the Federal Communications Commission (FCC) website.

Newscast Transcripts. To measure coverage of local weather, we rely on comprehensive transcripts of (close to) the universe of all local TV newscasts 2013-2019. In particular, our sample includes 691 TV stations, active in 205 media markets. The transcripts are originally collected by TVEyes and archived by Harmony Labs. We segment each transcript into

⁴Broadcast networks create and distribute content under a unified brand, while affiliated stations, which are independently owned, carry the network's programming alongside their own locally produced content. Typically, each media market has only one affiliate per network.

separate stories using chunks of 150 words.⁵ A segment is classified to be about local weather if it meets two criteria: (i) it contains at least two terms from a weather-related lexicon compiled by Baylis et al. (2018); and (ii) it references at least one county or municipality within the station's media market.⁶ We aggregate this information at the station-by-day level and define our main outcome as the number of segments about local weather appearing in the station's local newscasts on a given day. To maintain consistency, we focus exclusively on weekday broadcasts, as weekend programming structures vary significantly across stations.

Weather Data. We define weather events using data from the AN81d dataset of the PRISM Climate Group. Our starting point are daily maximum temperatures measured in degree Celsius at the 4km-by-4km cell level from 2000 to 2019, which we aggregate at the media market level using population-weighted averages.⁷ We construct weather events proceeding in three steps. First, we use data from 2000 to 2012 to calculate the historical mean for each calendar date and media market. Second, we compute the difference between the temperature recorded in each day and media market 2013-2019 and the historical mean for the same calendar date and media market. We call this difference the deviation from the historical mean (or deviation in short). Third, we look at how this deviation compares with the deviations in a given season in media market *m* over the 2013-2019 period and record its percentile in the within-media market distribution of season-specific deviations. We aggregate these percentiles in different bins, that become our weather events.

Several methodological choices warrant discussion. First, we focus on maximum temperatures, as they are more noticeable to the public and occur during waking hours, unlike minimum temperatures, which often materialize overnight.⁸ Second, we limit our analysis to winter and summer, where temperature patterns exhibit greater stability, excluding the

 $^{^{5}}$ We choose 150 words as it corresponds approximately to the number of words per minute spoken by a TV news anchor (e.g., Jensema et al. (1996)), but our results are robust to using segments of 300 words.

⁶See Appendix C for further information and a detailed discussion of the classification procedure.

⁷To perform the weighting we use information on population for 1km by 1km cells from the 2000 population census, which is made available by the Socioeconomic Data and Applications Center (SEDAC).

⁸An additional reason that justifies the focus on maximum temperatures requires getting into the details of how a day is defined in PRISM. PRISM defines each day as covering the 1200 UTC-1200 UTC interval, corresponding for example to 7 AM-7AM in EST (note that we align our day definition in the content data for consistency). Considering that most local newscasts take place in the afternoon/evening, focusing on maximum temperatures allows us to study a day's news coverage of the day's weather event.

transitional and more volatile seasons of spring and fall. Finally, we define weather events looking at the within-media market distribution of deviations in each season. This means that our definition of weather event consists of a double comparison. First, we compare the temperature in a given date in a media market relative to its historical mean. Second, we look at whether the difference in temperature corresponds to a large deviation relative to all possible deviations from the mean during the same season within a specific media market.⁹ As a result, a weather event is large if (i) the distance between the experienced temperature and its historical mean is big and (ii) this difference is substantial relative to the expected variation experienced during the season in the area. Our key assumption is that individuals experience and care about how daily temperatures compare to the usual local means, not some national means. Yet, our measure is such that weather events are comparable across media markets as they are all measured on the same scale: how uncommon they are relative to the usual within-media market temperature deviations (their percentile in the distribution of deviations).

DMAs' Political Leaning. We use county-level results for the 2008 Presidential elections from the MIT Election Lab, which we aggregate to the media market level, to define each media market's political leaning. Specifically, we define a media market to be Republican-leaning if the Republican vote share is in the top quartile (the average Republican vote share is 65% in these media markets); Democratic-leaning if the Republican vote share is in the bottom quartile (average of 38%); and "swing" otherwise (average of 52%).

Sinclair Ownership. We collect information on the date of each Sinclair acquisition 2013-2019, in addition to the name of stations controlled by the group at the beginning of the period, from the group's yearly company reports to shareholders and 10-K forms. Following Martin et al. (2024), we consider a station to be under Sinclair control if it is directly owned and operated by Sinclair or has a local marketing agreement (LMA) with the group (which

⁹In theory, large deviations need not be rare events (e.g., if the distribution of deviations is double peaked at its extremes). In practice, the distribution of deviations assume a close approximation of a (truncated) Normal distribution. Hence, large deviations are also rare weather events.

effectively gives Sinclair control over the station's programming). We use the same data source to identify starting dates of LMAs.

CCES. We proxy attitudes towards climate change using the Cooperative Congressional Election Study (CCES) waves from 2009 to 2012.¹⁰ We use these data to study how weather events impact stated climate change beliefs (see Online Appendix F), but also to check whether our estimation of publication bias is robust to using heterogeneity in beliefs about climate change directly. To do so, we aggregate these responses at the media market level to create an alternative proxy of climate change scepticism. That is, we define a media market to be climate change sceptic if the share of respondents stating that climate change requires immediate action is in the bottom quartile (the average share of respondents reporting that climate change requires immediate action is 43% in these media markets); non-sceptic if it is in the top quartile (average of 61%); and neutral otherwise (average of 51%).

Additional Data Sources. In Appendix D, we provide information on the data sources that we use to perform robustness checks and analyses only presented in the Online Appendix.

2.1 Descriptives

We begin by showing the variation in temperature deviations and local weather coverage that we use to identify editorial strategies. Figures 1 and 2 show the distribution of temperature deviations from the historical mean in each weather event, on average and by media market political leaning. The x-axis reports our weather events, that is, the different bins of the within-media market deviation distribution that we use throughout the analysis. Days that fall between the 40th and 60th percentile of the distribution are days in which temperatures are in line with the historical mean: deviations are close to zero. To the left, we have weather events that correspond to unseasonably cold days (days in which temperatures are below the

¹⁰Specifically, we measure stated beliefs about climate change using the question "From what you know about global climate change or global warming, which of the following statements comes closest to your opinion?" We then define an indicator equal to one if the respondent answers "Global climate change has been established as a serious problem, and immediate action is necessary" or "There is enough evidence that climate change is taking place and some action should be taken."

Figure 1: Distribution of Deviations



Notes: This figure shows the distribution of deviations for different weather events. In particular, we show the boxplot (5th percentile, 25th percentile, median, 75th percentile, 95th percentile) of the deviation from historical mean falling in each bin of the within-media market deviation distribution, separately for summer (panel (a)) and for winter (panel (b)).

historical mean), with increasing levels of severity. Instead, as we move to the right, we have weather events that correspond to unseasonably hot days (days in which temperatures are above the historical mean), again with increasing levels of severity.

Three notable patterns emerge. First, deviations from historical temperatures are more pronounced in winter than in summer, suggesting greater variation in cold-season weather anomalies. Second, extreme deviations—those in the bottom or top 5%—exhibit substantially larger temperature fluctuations than those in intermediate bins. Third, while there is some overlap in temperature distributions across media markets, deviations remain relatively well-demarcated. This ensures that extreme deviations in one media market generally correspond to similarly extreme deviations in others, allowing for meaningful cross-market comparisons. Importantly for our strategy, weather events do not systematically refer to different deviations in media markets with different political leanings.

Appendix Figures A.1 and A.2 similarly show the average number of local weather stories in different weather events, again on average and by media market political leaning. The coverage–weather events relationship follows a U-shape in the raw data, a pattern that is more pronounced in the winter than in the summer. Also, stations in Democratic-leaning markets tend to have higher coverage of local weather, for every weather event, relative



Figure 2: Distribution of Deviations by DMA Political Leaning

Notes: This figure shows the distribution of deviations for different weather events, by the political leaning of the media market. In particular, we show the boxplot (5th percentile, 25th percentile, median, 75th percentile, 95th percentile) of the deviation from historical mean falling in each bin of the within-media market deviation distribution for media markets that are Democratic-leaning, swing, and Republican-leaning, separately for summer (panel (a)) and for winter (panel (b)).

to both swing and Republican-leaning media markets. This hints to the importance of estimating proportional effects to take into account different base levels in coverage.

3 Publication Strategies

In this section, we investigate the average publication strategy of local TV stations. This allows us to understand what events are considered newsworthy on average across all stations.

3.1 Empirical Approach

To uncover the average publication strategy of local TV stations, we estimate the following regression:

$$Y_{st} = \sum_{\rho} \sum_{k \in \{-1,0,1\}} \beta_k^{\rho} \mathbb{I}\{\rho^{th} bin\}_{m(s)t+k} + \delta_s + \delta_t + \delta_{\eta(st)} + \epsilon_{st},\tag{1}$$

where Y_{st} is the number of segments about local weather in the newscasts of station s on date t, $\mathbb{I}\{\rho^{th}bin\}_{m(s)t}$ are indicator variables equal to one if the deviation in temperatures from the historical mean of media market m(s) on date t falls within the ρ_{th} bin of the within-market deviation distribution, δ_s are station fixed effects, δ_t are date fixed effects, and $\delta_{\eta(st)}$ are

number of segments decile fixed effects. We estimate the specification separately for summer and winter, using a Poisson regression.¹¹ Standard errors are clustered at the media market level.

We estimate two versions of the regression that allow different degrees of flexibility in the relationship between coverage of local weather and weather events. We begin by estimating a fully-flexible specification in which we separate the within-media market deviation distribution into eleven different bins and allow each weather event (each bin) to have a different effect on coverage. Specifically, we split weather events as follows: bottom 5%, 5-10%, 10-20%, 20%-30%, 30%-40%, 40%-60%, 60%-70%, 70%-80%, 80-90%, 90-95%, and top 5%. The first five bins correspond to weather events with temperatures below the historical mean (unseasonably cold days), with decreasing degree of severity. The middle bin, 40%-60%, corresponds to days in which temperatures are approximately in line with the historical mean and is our omitted category. The last five bins capture events with temperatures higher than the historical mean (unseasonably hot days), now with increasing degree of severity. The estimates from this specification are reported in our figures. In addition, we estimate a more parsimonious specification in which we split weather events according to five categories only: bottom 10%, 10%-40%, 40%-60%, 60%-90%, and top 10%. The estimates from this specification are reported in our tables.

In our analysis, we include the weather event of the same day as news coverage (k = 0 in Equation 1), the weather event of the day before news coverage (k = -1) and the weather event of the day after news coverage (k = 1). This is to avoid attributing daily coverage to past or future weather events, especially given the correlation between weather events over time. In other words, this allows us to isolate the effect we are interested in estimating: the contemporaneous effect of weather events on coverage of local weather. We also add day fixed effects (δ_t) , which control for differences in deviations or reporting that affect all stations equally such as national events happening on the same date, station fixed effects (δ_s) , which

¹¹Different stations have different baseline propensities to cover local weather, which means that results are best estimated as proportional effects. We chose a Poisson model over a log transformation since (i) our outcome variable is a count and (ii) our dataset includes a few days when the local weather is not talked about, so that using a log transformation would have required ad hoc adjustments (such as, using the log+1 transformation, or dropping these instances). We show that our results are robust to using OLS and outcomes in logs or shares in Online Appendix E.

Figure 3: Publication Strategies



Notes: This figure shows the relationship between news coverage of local weather and weather events. We regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, one lead and one lag of the same indicators, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 1). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (panel (a)) and for winter (panel (b)), using a Poisson model. Standard errors are clustered at the media market level.

allow different stations to have a different baseline propensity to cover local weather, and fixed effects for different deciles of the number of segment distribution across all stations $(\delta_{\eta(s)t})$, which control for the space allotted to local newscasts by station s in date t.

The β_0^{ρ} are our coefficient of interest. Given that we estimate a Poisson model and that the omitted category is always the 40-60% bin, the β_0^{ρ} coefficients correspond to the average percentage change in the coverage of local weather events when the deviation from the historical mean falls into the ρ^{th} bin (e.g., the bottom 5% bin) of the within-market deviation distribution relative to the coverage when temperatures are close to the norm (i.e., the deviation falls in the reference bin of 40-60%).

3.2 Results

Figure 3 reports the average publication strategy that we estimate using Equation 1, separately for summer (panel (a)) and winter (panel (b)). In turn, Table 1 displays the summary estimates (column (1) for summer and column (3) for winter).

In summer, both unseasonably cold and unseasonably hot days see higher coverage of local weather relative to days with deviations in the 40% to 60% range of the deviation

distribution. When temperatures are below the historical mean—that is, in unseasonably cold summer days—deviations have to be large to induce an increase in coverage of local weather. Instead, unseasonably hot days induce stations to increase their coverage of local weather also when the deviations are small. We again see that the larger the deviation the larger the increase, although the largest deviations above the mean induce smaller increases than the larger deviations below the mean. Specifically, days in the bottom 10% of the deviation distribution display 5.9% higher coverage than days in which temperatures are in line with the usual, while days in the top 10% of the deviation distribution increase coverage by 4.5% (Table 1 column (1)).

In winter, unseasonably cold days receive more attention relative to days in which temperatures are in line with the norm and, the larger the size of the deviation, the higher the increase in coverage. Table 1 column (3) shows that days in the top 10% of the deviation distribution see a 10.2% increase in coverage of local weather relative to days with temperatures in line with the historical mean. Smaller deviations also experience higher coverage, with an increase of 2.5%. Instead, coverage of local weather in unseasonably hot days only increases when temperatures are well above the historical mean (top 5% of the deviation distribution) and is otherwise constant or even lower for deviations of smaller magnitudes. The asymmetry in these patterns might be surprising at first glance. These weather events, however, may be less "remarkable." For example, Moore et al. (2019) use social media data for the United States and show that in cold periods, people tweet more (and more negatively) about the weather when temperatures are below the historical mean and less (and using more positive sentiment) when temperatures are above the mean.

Taken together, these results show that severe weather events are treated as fundamentally newsworthy—that is, "man bites do" is indeed news—, but intermediate temperature deviations are also sometimes covered—"big dog's bites" can also be news.

4 Publication Bias

In this section, we begin to entertain the possibility of factors other than newsworthiness influencing coverage of weather events. We ask whether coverage patterns vary with the political leaning of the media market in which stations operate. This is particularly compelling because weather—unlike elections, social issues, or economic policies—is at first glance a less explicitly political topic. Still, weather events carry a political connotation to the extent that they intersect with climate change, which suggests that media coverage of weather events could potentially vary based on political ideology. As above, before presenting our results, we describe our empirical strategy.

4.1 Empirical Approach

To test for the presence of publication bias, we estimate separate editorial strategies for stations that operate in Democratic-leaning, swing, or Republican-leaning media markets. We do so by including interactions between the indicators capturing the weather events and our measure of media market's political leaning. Our baseline specification to estimate publication bias is the following:

$$Y_{st} = \sum_{\rho} \sum_{k \in \{-1,0,1\}} \beta_k^{\rho} \mathbb{I}\{\rho^{th} bin\}_{m(s),t+k}$$

+
$$\sum_{i \in \{D,R\}} \sum_{\rho} \sum_{k \in \{-1,0,1\}} \beta_{i,k}^{\rho} \mathbb{I}\{\rho^{th} bin\}_{m(s),t+k} \times \mathbb{I}\{ideology_{m(s)} = i\}$$

+
$$\delta_s + \delta_t + \delta_{\eta(st)} + \epsilon_{st},$$
(2)

where $\mathbb{I}\{ideology_{m(s)} = i\}$ are indicator variables equal to 1 if media market m(s) has political leaning *i* and all other variables are defined as before. Similarly, weather events can be either finely or coarsely defined, the specification is estimated through a Poisson regression, and standard errors are clustered at the media market level.

4.2 Results

Figure 4 reports the estimates we obtain from the fully flexible version of Equation 2. Specifically, the figure reports publication strategies for stations that operate in different media markets. That is, for each weather event we show β_k^{ρ} for swing media markets, $\beta_k^{\rho} + \beta_{R,k}^{\rho}$ for Republican-leaning media markets, and $\beta_k^{\rho} + \beta_{D,k}^{\rho}$ for Democratic-leaning media markets.





Notes: This figure shows the relationship between news coverage of local weather and weather events by media market political leaning. We regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with indicators for the market being either Democratic- or Republican-leaning, one lead and one lag of the same variables, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 2). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (panel (a)) and for winter (panel (b)), using a Poisson model. Standard errors are clustered at the media market level. Note that the figure reports the overall effect in each type of media market (that is, β_0^{ρ} for Swing media markets and $\beta_0^{\rho} + \beta_{i,0}^{\rho}$ for Democratic- and Republican-leaning DMAs).

Instead, Table 1 columns (2) and (4) report estimates from the summary specification. The table reports the $\beta_{i,k}^{\rho}$ coefficients directly.

Figure 4 and Table 1 provide clear evidence of publication bias: stations that operate in Republican- and Democratic-leaning media markets follow drastically different publication strategies in their reporting of the same weather events. We begin by discussing the results for summer (reported in panel (a) in the figure and column (2) in the table).

No matter the media market, we observe that unseasonably cold and unseasonably hot days receive more coverage than days in which temperatures are in line with the historical mean. A more interesting pattern emerges when we compare by how much coverage increases. In days with temperatures below the historical mean, coverage increases more in stations in Republican-leaning markets than in stations in Democratic-leaning markets (with the difference just reaching statistical significance at the 5% level). Stations in swing media markets are somewhat in-between. The pattern is exactly reversed in days with temperatures above the historical mean. There, we see a greater increase in coverage in stations operating in Democratic-leaning media market than in those with a Republican-leaning audience with,

	Local Weather Segments						
	Sun	nmer	Wii	nter			
	(1)	(2)	(3)	(4)			
Bottom 10%	0.059***	0.061***	0.102***	0.096***			
	(0.007)	(0.012)	(0.009)	(0.012)			
Bottom $10\% \times \text{D-Leaning}$		-0.015		-0.012			
		(0.016)		(0.019)			
Bottom $10\% \times \text{R-Leaning}$		0.018		0.070^{***}			
		(0.018)		(0.020)			
10%-40%	0.001	-0.001	0.025^{***}	0.018^{***}			
	(0.003)	(0.004)	(0.005)	(0.006)			
$10\%-40\% \times D$ -Leaning		0.004		0.009			
		(0.007)		(0.010)			
$10\%-40\% \times \text{R-Leaning}$		0.008		0.021^{**}			
		(0.008)		(0.011)			
60%-90%	0.018^{***}	0.012^{***}	-0.011^{***}	-0.015^{***}			
	(0.003)	(0.004)	(0.004)	(0.006)			
60%-90% × D-Leaning		0.017^{**}		-0.001			
		(0.007)		(0.009)			
60%-90% × R-Leaning		0.000		0.030^{***}			
		(0.007)		(0.008)			
Top 10%	0.045^{***}	0.032^{***}	0.007	0.003			
	(0.006)	(0.008)	(0.005)	(0.007)			
Top $10\% \times D$ -Leaning		0.035^{***}		0.001			
		(0.012)		(0.011)			
Top $10\% \times \text{R-Leaning}$		-0.005		0.022^{*}			
		(0.011)		(0.013)			
Observations	297659	297659	288726	288726			
Stations	698	698	699	699			
DMAs (Clusters)	204	204	204	204			
Mean Dep. Variable	27.905	27.905	27.915	27.915			
Bottom $10\% \times D = Bottom 10\% \times R$		0.050		0.000			
$10\%-40\% \times D = 10\%-40\% \times R$		0.629		0.328			
60%-90% × D = 60%-90% × R		0.023		0.001			
Top 10% × D = Top 10% × R		0.001		0.155			

Table 1: Publication Strategies and Bias

Notes: This table shows the relationship between news coverage of local weather and weather events, on average and by media market political leaning. In columns (1) and (3), we regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, one lead and one lag of the same indicators, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 1). Columns (3) and (4) additionally include the weather events indicators interacted with interacted with dummies for the market being either Democratic- or Republican-leaning, with one lead and one lag of the same variables (see Equation 2). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (columns (1) and (2)) and for winter (columns (3) and (4)), using a Poisson model. Standard errors are clustered at the media market level.

again, TV stations in swing media markets in-between. For those unseasonably warm days, the difference is statistically significant both for medium-sized deviations, falling within the 60th and 90th percentile, and large deviations, in the top 10% (*p*-value = 0.023 and 0.001 respectively).

Patterns are slightly different in winter. In particular, we observe larger increases in coverage of weather for both unseasonably cold and unseasonably hot days in stations located in Republican-leaning media markets than in stations operating in Democratic-leaning media markets. Again, the estimates for swing media markets are generally in-between. Below the mean, the difference in coverage increase is only statistically significant between Republican and Democratic media markets for very cold day (bottom 10% deviation). Above the mean, the difference is only statistically significant for intermediate shocks (deviations falling between the 60th and 90th percentile).

Overall, stations that operate in Republican- and Democratic-leaning media markets follow different publication strategies in their reporting of similar weather events. Editors do not just take into account the newsworthiness of an event (its rarity) in their coverage choices, political factors appear to also matter. In short, coverage decisions are biased.

5 Beyond Publication Bias

Editors do not just decide whether to cover an event, they also choose how much emphasis to give to a story and how to talk about it. In this section, we look at other aspects of outlets' editorial strategies: salience (that is, how prominently a weather event is featured) and framing (that is, how explicitly it is connected to the broader climate crisis).

Salience. To study the salience of weather news, we adopt the approach used for newspapers. Rather than the page in which the story appears (e.g., Wasow, 2020), we look at the rank of a segment in a newscast. More precisely, our dependent variable is the log of the average minimum rank in which a weather story appears in a given day. The specification is the same as Equation 2, but we now estimate it using OLS as the average rank can be non-integer.¹²

Figure 5 displays the results from this analysis.¹³ Note that, for consistency with our previous exhibits, we have inverted the y-axis so that estimates visually above zero corresponds to higher salience of the news story. The patterns we observe match our findings for publication bias. Overall, the more extreme the weather event, the higher its salience in the

¹²Using a log transformation of the outcome allows us to be consistent with our approach in the rest of the paper and estimate proportional effects.

¹³Appendix Table B.1 reports the corresponding estimates from our summary specification. We also report for specifications that control for local weather story decile fixed effects to avoid mechanical effects whereby the ranking of local weather story diminishes because there are simply more stories reported in the newscast. Our results remain the same.





Notes: This figure shows the relationship between the salience of news coverage of local weather and weather events by media market political leaning. We regress the log minimum rank of segments about local weather (averaged across the different newscasts) on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with indicators for the market being either Democratic- or Republican-leaning, one lead and one lag of the same variables, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 2). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (panel (a)) and for winter (panel (b)), using OLS. Standard errors are clustered at the media market level. Note that the figure reports the overall effect in each type of media market (that is, β_0^{ρ} for Swing media markets and $\beta_0^{\rho} + \beta_{i,0}^{\rho}$ for Democratic- and Republican-leaning DMAs).

newscast (with the exception of above the mean events in winter). In summer, stations in Republican-leaning media markets increase the salience (that is, decrease the mean rank) of local weather news in unseasonably cold days more than stations in swing or Democraticleaning media markets. Instead, unseasonably hot days in summer see a larger increase in the salience of local weather news in Democratic-leaning versus Republican-leaning markets. In winter, we see higher responsiveness of stations in Republican-leaning markets both in unseasonably cold and unseasonably hot days. Combining the results of Section 4 with those of this subsection, we observe that when weather events receive more coverage, they are also given more prominence. Salience bias and publication bias go hand-in-hand.

Framing. We also examine the framing of weather news by analyzing how local broadcasts present temperature deviations relative to historical norms. To do so, we take a straightforward approach and measure the frequency with which the terms "climate change" and "global warming" appear in stories about local weather. Figure 6 illustrates the extent to which these terms are mentioned in relation to contemporaneous weather events, separately by the political leaning of the media market. The most striking finding is the sheer scarcity



Figure 6: Climate Change in Local Weather Coverage, by DMA Political Leaning

Notes: This figure shows climate change references in coverage of local weather in different weather events, by the political leaning of the media market. In particular, we show the average share of segments about local weather that mention climate change or global warming in each bin of the within-media market deviation distribution, separately for summer (panel (a)) and for winter (panel (b)).

of such references: only 0.1% to 0.3% of the local weather stories we identify mention climate change.

To systematically investigate the thematic focus of weather coverage and the extent to which it engages with climate discourse, we also train a topic model on our local weather segments (see Appendix G for details on the methodology and text inputs). The topic distributions across winter and summer, presented in Appendix G, reveal that, regardless of the season, local weather segments overwhelmingly concentrate on immediate, short-term conditions, emphasizing terms such as "snow," "rain," "temperatures," "morning," "cold," and "heat." While extreme events such as hurricanes, floods, or tornadoes occasionally feature in these reports, broader contextualization is rare (see Appendix Tables G.1 and G.2).

These findings highlight a crucial pattern: day-to-day deviations from historical temperature means are rarely framed as evidence of climate change. Instead, local weather newscasts remain focused on short-term, practical concerns, with no discussions of climate largely. This suggests that local news media, even when covering abnormal weather patterns, do not explicitly integrate them into broader discussions of climate change.

6 Understanding Publication Bias

Our results so far point to the presence of publication bias in the coverage of weather events. Stations that operate in Republican-leaning and Democratic-leaning media markets follow different editorial strategies. In this section, we discuss several possible explanations for the patterns we uncover.

6.1 Is This Really Publication Bias?

To start with, we have to entertain the possibility that stations in Republican-leaning and Democratic-leaning media markets follow different publication strategies for reasons that have nothing to do with politics. In this subsection, we briefly discuss, and one by one present evidence against, several alternative explanations. We provide more details for each of the empirical tests we implement in Appendix E.

Demand for Weather Coverage. First, it is possible that the patterns we uncover are simply explained by higher demand for reporting on rare weather events (deviations falling in the top or bottom of the distribution) in Republican-leaning markets. However, if it were so, the increase in coverage should be universally larger in Republican-leaning market than in Democratic-leaning markets, which is not what we observe for weather events above the norm in the summer. Also, the fact that on average local weather coverage is higher in Democratic- relative to Republican-leaning markets (see Appendix Figure A.2) provides additional suggestive evidence against this explanation.

Differences in Weather Events. Second, it is possible that these patterns could be explained by Republican- and Democratic-leaning media markets experiencing substantively different weather events. Again, this is unlikely to be the case. Figure 2 already shows that the distribution of deviations within each weather event in the three types of media market is overlapping. And even if we were to take any differences at face value, they would be too small to explain our effects (see Appendix Table E.1). In addition, our results are robust to only comparing media markets that are broadly exposed to similar weather patters, as we can show by estimating specifications with climate region and year fixed effects (see Appendix Table E.2).

Confounding Market Characteristics. Third, we show that the patterns we documented above are not driven by media market's characteristics that are different than political leaning, but happen to correlate with it. In fact, our estimates of publication bias survive controlling for weather shocks interacted with media market's area, population, the share of urban population, and industry shares (Appendix Table E.3). In addition, they are also not driven by natural disasters or wildfires, than might both receive media attention and correlate with weather (Appendix Table E.4).

Measurement and Model Choices. Finally, they are not driven by specific measurement and modeling choices that we made in the estimation, as they are robust to using longer segments, estimating an OLS specification with the outcome in logs or in share, and splitting markets by ideology using the 20th and 80th percentiles and the 30th and 70th percentiles (Appendix Table E.5). No matter how we slice the data, publication bias persists.

6.2 Sinclair Acquisitions

If the political leaning of a media market is indeed behind the publication bias we document, as the previous subsection strongly suggests, what can explain these variations in coverage? We see two big classes of explanations here: the difference in coverage could be driven by supply factors (outlets attempting to persuade viewers) or demand factors (outlets responding to viewers' preferences). In this section, we put the supply-side theory to the test by examining what happens when a conservative media group, Sinclair, takes over local TV stations.

Over the 2013 to 2019 period, the Sinclair Broadcast Group (Sinclair) went from controlling 44 stations to almost 100 stations. Because Sinclair has a strong conservative leaning (Miho, 2024) and existing research has shown that Sinclair influences the content of the stations it acquires (Martin and McCrain, 2019), there are good reasons to anticipate that if coverage is meant to influence viewers, local TV stations acquired by Sinclair should change their publication strategies of weather events. In particular, weather events associated with climate change (i.e., temperature deviations above the historical mean) should receive less coverage after acquisition. At the same time, we would expect the opposite pattern for weather events possibly going against how climate change is generally understood (i.e., temperature deviations below the historical mean).

We test this hypothesis using a differences-in-differences design based on the staggered timing of Sinclair acquisitions. Identification rests on a parallel trends assumption: non-Sinclair stations provide the correct counterfactual for the editorial strategy that the stations that get acquired by Sinclair would have followed, had they had not been acquired. The main concern is that Sinclair acquisitions might be endogenous to station- or media market-level trends.¹⁴ We perform two sets of analysis to alleviate these concerns. First, we estimate event study specifications in which we allow editorial strategies to vary in time since/to the acquisition, to provide suggestive evidence that pre-trends are not too much of an issue. Second, we estimate a triple differences specification in which we include media market by date fixed effects. This ensures that we are only using within-media market variation, and allows us therefore to non-parametrically control for media market specific shocks.

We begin by estimating the following differences-in-differences specification:

$$Y_{st} = \gamma \mathbb{I}\{\operatorname{Sinclair}\}_{st} + \sum_{\rho} \sum_{k \in \{-1,0,1\}} \beta_k^{\rho} \mathbb{I}\{\rho^{th} \operatorname{bin}\}_{m(s),t+k}$$
(3)
+ $\sum_{\rho} \sum_{k \in \{-1,0,1\}} \lambda_k^{\rho} \mathbb{I}\{\rho^{th} \operatorname{bin}\}_{m(s),t+k} \times \mathbb{I}\{\operatorname{Sinclair}\}_{st}$
+ $\delta_{\eta(st)} + \delta_s + \delta_t + \epsilon_{st},$ (4)

where all variables are defined as before and $\mathbb{I}\{Sinclair\}_{st}$ is an indicator variable equal to 1 if the station is under Sinclair control. Our triple differences specification additionally includes $\delta_{m(s)t}$, that is, media market by date fixed effects. For the sake of the readability of the results, we only estimate the constrained version of our specification focusing on large and medium-sized weather events, above and below the mean. As before, we use a Poisson regression and we cluster standard errors at the media market level.

Table 2 presents the results with DMA fixed effect and day fixed effect (odd columns), with DMA-day fixed effect (even columns), and removing the always treated DMAs by restricting the sample to markets where Sinclair is not present in 2013 (columns (3) and (4)

¹⁴Importantly, Martin et al. (2024) and Mastrorocco and Ornaghi (Forthcoming) provide evidence that Sinclair's acquisition strategy is mostly an expansion strategy. Sinclair buys stations that come to the market rather than targets specific stations or areas.

			Ι	local Weath	ner Segment	s		
		Sun	nmer			Win	ter	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sinclair	0.090*	0.115**	0.141***	0.158***	0.075	0.124**	0.054	0.079*
	(0.053)	(0.053)	(0.043)	(0.044)	(0.052)	(0.054)	(0.043)	(0.045)
Bottom 10%	0.061***	0.066***			0.104***	0.102***		
	(0.008)	(0.009)			(0.009)	(0.011)		
Bottom $10\% \times \text{Sinclair}$	-0.012	-0.006	-0.002	0.007	-0.020	-0.025	-0.015	-0.013
	(0.015)	(0.018)	(0.013)	(0.016)	(0.016)	(0.023)	(0.014)	(0.024)
10%-40%	0.002	0.001			0.024***	0.021***		
	(0.003)	(0.003)			(0.005)	(0.006)		
10%-40% \times Sinclair	-0.001	0.014	-0.005	0.000	0.004	-0.010	0.003	-0.006
	(0.007)	(0.010)	(0.008)	(0.010)	(0.009)	(0.011)	(0.008)	(0.014)
60%-90%	0.018***	0.016***			-0.012***	-0.015***		
	(0.003)	(0.004)			(0.004)	(0.004)		
60%-90% \times Sinclair	0.004	0.012	0.006	0.016^{*}	0.016^{*}	0.004	0.006	-0.004
	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.012)	(0.008)	(0.011)
Top 10%	0.043***	0.046***	. ,	. ,	0.004	0.003	· /	
	(0.006)	(0.007)			(0.005)	(0.006)		
Top $10\% \times \text{Sinclair}$	0.013	0.015	0.014	0.002	0.030***	0.019	0.028^{***}	0.034^{**}
	(0.010)	(0.013)	(0.010)	(0.015)	(0.010)	(0.013)	(0.011)	(0.015)
Date FEs	\checkmark	\checkmark			\checkmark	\checkmark		
DMA-By-Date FEs			\checkmark	\checkmark			\checkmark	\checkmark
Drops Always Treated		\checkmark		\checkmark		\checkmark		\checkmark
Observations	297659	228724	289165	220499	288726	222094	280292	213730
Stations	698	537	683	522	699	537	684	522
DMAs (Clusters)	204	164	189	149	204	164	189	149
Mean Dep. Variable	27.905	27.241	28.489	27.948	27.915	27.261	28.526	28.028

Table 2: Sinclair Acquisitions and Weather Events Coverage

Notes: This table tests whether the relationship between news coverage of local weather and weather events changes after Sinclair acquires a local TV station. In columns (1) and (5), we regress the number of segments about local weather on an indicator for the station being under Sinclair control, indicator variables for the deviation from historical mean falling in a given bin of the within-media market deviation distribution, one lead and one lag of the same indicators, the interaction of the Sinclair and weather events indicators, one lead and one lag of these interactions, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 4). Columns (2) and (4) additionally include media market by date fixed effects. All even columns drop always treated media markets. The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (columns (1) to (4)) and for winter (columns (5) to (8)), using a Poisson model. Standard errors are clustered at the media market level.

for winter and (7) and (8) for summer). In general, we observe that after Sinclair acquires a station, coverage of weather events in days in which temperatures are in line with the historical mean increases, perhaps because this type of coverage might be relatively cheap to produce. However, this increase in coverage is not differential by weather event with the exception of days with large deviations above the historical mean in winter, that experience even higher coverage. In no case do we observe lower coverage of weather deviations above the historical mean. Event studies in which we allow the effect of Sinclair to vary by time since/to acquisition (Appendix Figure A.3 and A.4) show no evidence of pre-trends and confirm these findings.

6.3 Discussion

The empirical findings presented in the preceding section challenge the notion that supplyside factors predominantly drive publication bias in weather coverage. Instead, by process of elimination, the results lend credence to the hypothesis that demand-side considerations play a pivotal role in shaping editorial strategies. In Section 7, we propose a model where the publication bias is driven by individuals demanding coverage of uncommon weather events but also suffering from a form of confirmation bias: their utility depends on what they learn about climate change from weather news. Before moving on to the full exposition of the model, we mention here two pieces of evidence that support the basic assumptions of the approach we take.

First, the approach relies on individuals reacting to extreme weather events, that they hear about in the news, by changing their beliefs about climate change. A large body of work investigates how temperatures affect climate change beliefs (see Howe et al., 2019) for a review. In Online Appendix F we show using individual-level survey data from CCES and variation in interview dates, that, indeed, individuals do learn from weather events, and that this learning is heterogeneous depending on individuals' ideology.

Second, and in connection to this, it must be the case that the political leaning of media markets is proxying for attitudes towards climate change. Indeed, we can show using the same survey data that individuals who self-identify as liberal or belonging to the Democratic party are much more likely to believe that climate change requires immediate action than individuals who self-identify as conservative or belonging to the Republican party (see Appendix Figure A.5). In line with this, we show in Appendix Table B.2 patterns consistent with publication bias when we classify markets as climate change sceptic, non-sceptic, or neutral again using the CCES data.¹⁵

Taken together, these insights reinforce the view that editorial choices in local weather coverage are not merely the byproduct of journalistic discretion but are, to a considerable extent, shaped by audience demand and ideological predispositions. This interplay

¹⁵This raises the question of why not use climate change beliefs in the first place. The reason for this choice is data driven: CCES data, which to the best of our understanding are the most appropriate source of data for attitudes towards climate change in the early 2010s, are not representative at the media market level, which generates potential measurement issues.

between demand-driven coverage and confirmation bias has profound implications for public discourse, influencing how individuals interpret and internalize information about climate change. In the subsequent section, we formalize these dynamics within a theoretical framework, offering a structured analysis of the determinants of media coverage.

7 A Model of Coverage Decision

We now provide a stylized theoretical framework to rationalize the empirical patterns we have documented above. Our main contribution here is to study how much an outlet devotes to the event in its report rather than whether to cover this event.

7.1 Model Setup

We consider a game with one media outlet M and a mass of citizens of size one divided into two groups, $J \in \{D, R\}$. To study demand-driven and supply-driven coverage, we will consider in the analysis two possible types of outlet: a profit-maximizing outlet and a biased outlet who seeks to persuade citizens (we will look at a climate-sceptic and a climatebeliever outlet). The objective of a media outlet is known (ours is not a model of reputation building). The media outlet commits to a publication (or equivalently coverage) strategy, which consists in the amount of time devoted to weather news (denoted w) relative to other news (denoted n). When it comes to citizens, group D consists of Democratic citizens (which constitute a proportion α of the population) and group R consists of Republican citizens (a proportion $1 - \alpha$). Each citizen decides whether to watch the outlet based on the (anticipated) entertainment value of news and what they can learn from it. Given our interest in weather news, we suppose that only those are informative.

More precisely, we capture a weather event as a random variable \tilde{c} drawn from the interval [-1, 1]. We assume that the distribution from which an event is drawn depends on an underlying state of the world $\omega \in \{0, 1\}$. State $\omega = 0$ captures the absence of climate change (or, perhaps more accurately these days, the idea that climate change is not man-made), while state $\omega = 1$ indicates that there is climate change (or climate change is man-made). The underlying state is unknown to all actors and we assume that the common prior is that the

realisation of the state variable is 1 with probability π : $Pr(\omega = 1) = \pi \in (0, 1)$.¹⁶ A weather event is drawn from the Cumulative Distribution Function (CDF) $F_{\omega}(\cdot)$, with continuous probability density function (pdf) $f_{\omega}(\cdot)$, itself differentiable and $f_{\omega}(\cdot)$ single-peaked around zero. We also assume that large weather events c are relatively more frequent when the realisation of the state is $\omega = 1$. We impose that the pdfs $f_{\omega}(\cdot)$, $\omega \in \{0, 1\}$ satisfy the strict monotone likelihood ratio property: $\frac{f_1(c)}{f_0(c)} > \frac{f_1(c')}{f_0(c')}$ for all c > c'.

For each realization of weather event $c \in [-1, 1]$, a media outlet decides the amount of coverage w(c). As newscasts are time constrained, and without loss of generality, we assume that the total time available for local weather news and other news is one so that w(c) + n(c) = 1. If a citizen watches the newscast, she can update about the likelihood of (human-made) climate change. We denote her posterior belief as a function of the coverage of weather news by $\rho(w(c))$. This posterior consists either of what a citizen learns from learning c if w(c) > 0 ($\rho(w(c)) = Pr(\omega = 1|c) =: \mu(c)$) or of what a citizen infers from not observing any news about c given the outlet's strategy if w(c) = 0 ($\rho(0) = Pr(\omega = 1|\emptyset) =: \mu(\emptyset)$). If a citizen does not watch the newscast, we assume that she learns nothing (a simplification without loss of generality) and her posterior is her prior, equal to π .

The utility of consuming the newscast for potential viewers depends on two of its features. First, the amount of reporting on each type of news captured by the functions g(n) and h(w), which are strictly increasing in their argument. Second, the utility depends on the value of each news item, which acts as a scale-up. For non-weather news, the value for all citizens is assumed to be constant and equal to a finite value $\underline{u} < 1$. In turn, the value of weather news for a viewer from group $J \in \{D, R\}$ is: $v(c) + z_J(\rho(w(c)))$. The function v(c) captures the entertainment benefit of watching news about weather events. We assume v(c) is strictly decreasing in c for c < 0 and strictly increasing in c for c > 0 so that citizens prefer to watch news reports about extreme, rare weather events than common weather events. The second function $z_J(\rho(w(c)))$ captures the cost or benefit of learning. We assume that citizens suffer from a form of confirmation bias. We represent this by assuming that $z_D(\mu(c))$ is strictly increasing in its argument, whereas for Republican citizens $z_R(\mu(c))$ is strictly decreasing in

¹⁶Notice that this is the prior of the population, the relevant one for our purpose, which can differ from the prior in the scientific community. We could add different priors for different groups without affecting our results.

its argument, with $z_D(0) = z_R(0) = 0$. We assume that $v(1) + z_D(1) < 1$ and $v(0) + z_R(\pi) > 0$, a normalization.

The overall value of consuming the newscast for a citizen from group $J \in \{D, R\}$ is then: Value of time on weather news Value of time on other news

$$\underbrace{h(w)} \times \underbrace{\left(v(c) + z_J(\rho(w(c)))\right)}_{\text{Comsumption value of weather news}} + \underbrace{g(n)}_{\text{Consumption value of other news}} \times \underbrace{\underline{u}}_{\text{Consumption value of other news}} (5)$$

A citizen *i* can always decide not to watch the news in which case she receives her outside option payoff equal to an idiosyncratic event δ_i uniformly distributed (i.i.d.) over the interval $[0, \overline{\delta}]$, with $\overline{\delta} > 1$ (so that share of viewers is always less than the full population).

When it comes to media outlets, we first need to denote A as the proportion of citizens who watch the newscast. A profit-maximizing TV station only seeks to maximize its audience so its payoff is simply A (we assume that there is a monotonic relationship between audience size and revenues). In turn, a biased TV station seeks to persuade. A climate-believer outlet seeks to maximize the average belief in climate change. For each c, this is equivalent to maximizing $A\rho(w(\tilde{c})) + (1 - A)\pi$ (viewers update about climate change from the newscast, non-viewers keep their prior). Hence, we represent a climate-believer station's payoff as:

$$\int_{\widetilde{c}} V_b(A\rho(w(\widetilde{c})) + (1-A)\pi) d(\pi F_1(\widetilde{c}) + (1-\pi)F_0(\widetilde{c})),$$
(6)

with $V_b(\cdot)$ a strictly increasing, continuous, twice differentiable, and strictly concave function. The outlet considers all possible weather events $(\int_{\tilde{c}})$, since it commits to a strategy, as well as the expected distribution of weather events $(\pi F_1(\tilde{c}) + (1 - \pi)F_0(\tilde{c}))$ as it does not know ω when it chooses its coverage strategy.

In turn, a climate-sceptic outlet wants to minimize the average belief in climate change. As a result, we assume that its payoff assumes the following form

$$\int_{\widetilde{c}} V_s(A\rho(w(\widetilde{c}) + (1-A)\pi)d(\pi F_1(\widetilde{c}) + (1-\pi)F_0(\widetilde{c})),$$
(7)

with $V_s(\cdot)$ a strictly decreasing, continuous, twice differentiable, and strictly concave function.

The game, in turn, proceeds as follows:

- 0. Nature draws the state of the world $\omega \in \{0, 1\}$.
- 1. The outlet publicly commits to a publication strategy: $w : [0,1] \rightarrow [0,1]$.

- 2. Weather event c is drawn by Nature and coverage occurs according to the editorial strategy.
- 3. Citizens decide whether to watch the outlet. They observe what is reported if they watch the newscast and nothing if they don't.
- 4. Game ends and payoffs are realized.

The equilibrium concept is Perfect Bayesian Equilibrium. We focus on stationary pure strategies. A stationary pure strategy for the outlet is a mapping from the set of possible realizations of climate event to a coverage decision. (We are not looking for a coverage function, rather for a value of coverage for each c separately.) We also add a few assumptions to simplify the analysis. First, we impose that $\mu(0) = Pr(\omega = 1|c = 0) = \pi$. Second, we suppose that h(w) = w (i.e., weather news acts as a numeraire), whereas g(n) satisfies g'(0) > 1 and g'(1) = 0 and is C^{∞} and strictly concave. Finally, throughout, we assume that the value of entertainment is greater than the value of learning: $v'(c) > -\mu'(c)z_R(\mu'(c))$ for all c > 0 and $v'(c) < -\mu'(c)z_D(\mu'(c))$ for all c < 0.

Before proceeding to the analysis, a few remarks are in order. First, building on previous works (e.g., DellaVigna and La Ferrara, 2015; Durante et al., 2019), our model assumes that citizens consume the outlet, and even news, primarily for entertainment value. For weather events, this corresponds to citizens finding more entertainment in large, unexpected weather events than small, common events. This can correspond to the idea that citizens like surprise as in Ely et al. (2015), though we recognize we model the value of surprise very differently.

Yet, entertainment is not everything and we suppose that individuals learn from weather events. This assumption is crucial for our results below. Yet, we do not think it is unwarranted. In Appendix F, we use individual-level survey data from the CCES to show evidence of exactly the type of learning we assume in this model. While some individuals may observe the event directly, reducing the value of a newcast, media markets generally cover large area meaning that most possible watchers do not know about the weather in this relevant geographical area. On top of this, mentions of the weather event on the newscast could help a citizen interpret the event. A citizen can see that today is a hot day, but she may be unable to fully make sense of how hot it is relative to the historical mean if she doe not watch the newscast. In formal terms, her own experience of the weather can affect her belief about the distribution of \tilde{c} that day, but she can only learn the realisation c of the random variable by watching the outlet.

Our set-up further assumes that citizens differ in their demand for weather news depending on the group they belong to. We model this as a form of confirmation bias as in Mullainathan and Shleifer (2005) and Anand et al. (2007) (though, beyond the differences in payoffs, all citizens are fully rational). Democrats experience a utility gain if they see evidence confirming (man-made) climate change is occurring. In contrast, Republicans, who tend to oppose call for actions on climate change following weather events above the norms (Appendix Table F.1), suffer a loss when the evidence goes against their belief.¹⁷ This approach captures the idea that "[d]enialism is motivated by conviction rather than evidence" (Kemp et al., 2010) and the evidence that deniers simply reject evidence point to the existence of climate change (Washington, 2013).

Another payoff assumption worth commenting on is the complementarity between the amount of coverage received by a news item and the value of the news. More reporting on a news item provides higher utility, but the marginal value of increased coverage reduces with the amount of time spent on it. In turn, the value of an event acts as a scale-up. It increases the marginal value of an additional minute of coverage. These assumptions are meant to capture the choice of a media outlet of how to structure its newscast given the events that occurred that day. Fixing the value of other news to \underline{u} is without loss of generality.

The attentive reader would have noted that we allow an outlet to commit to an editorial strategy. This is a strong assumption as such strategy is not a contract with viewers and there would be no institution to enforce a hypothetical contractual agreement. Why this assumption then? We look at the best case scenario for a biased outlet. Absent commitment, the biased station's problem becomes one of information disclosure. As it is well known in the literature, an unravelling argument would apply and a biased outlet's coverage strategy would be independent of the weather event (a previous version of the paper formally proves

¹⁷Our approach to information is markedly different from Armona et al. (2024). They consider that viewers always want to learn about an underlying state of the world. In contrast, we assume an entertainment value of news and that the payoff from learning which depends on the event and individuals' ideological predisposition. As a result, we can dispense from the assumption that consumers do not learn if they observe nothing, which Armona et al. (2024) need for their results (otherwise, an unravelling argument would yield that outlets always cover an event no matter its informativeness in their model, contrary to what they seek to demonstrate).

this point). By imposing commitment, we leave open the possibility that supply-driven coverage varies with the weather event (indeed, we will show it may). In other words, we make it possible that a supply-driven coverage can match our empirical patterns (though, we will show it does not).

Finally, we briefly describe how our theoretical parameters and choices map into our empirical quantities above. The theoretical weather event c can be understood as the percentile in the distribution of all possible deviations from the mean. It is the theoretical equivalent to our dependent variable in the regression above. We see 0 as the seasonal norm, any positive (negative) value as weather events above (below) the norm with values further away from zero indicating greater deviation. In turn, the choice variable w(c) corresponds to the space devoted to the weather event in the newscast controlling for the number of segments in a broadcast (as per our normalization that total time available is equal to one).

7.2 Demand-driven Coverage

We start by analyzing demand-driven coverage in our model. In other words, we assume that the TV station is profit-maximizing. As the entertainment value of weather event is always valued more by possible viewers than learning (per assumptions), a TV station has never any interest in not covering weather event (under the assumption that g'(1) = 0 and h(w) = w). Hence, we can restrict attention to the case in which the outlet chooses w(c) > 0for all c.

To then determine the editorial strategy, we first need to study what a viewer can learn about the state $\omega \in \{0, 1\}$ upon observing c. The viewer forms a posterior:

$$\mu(c) = \frac{1}{1 + \frac{1 - \pi}{\pi} \frac{f_0(c)}{f_1(c)}}$$
(8)

Under the assumption of MLRP, the posterior is strictly increasing with c. Note that under our assumptions for all c < 0, $\mu(c) < \pi$, whereas $\mu(c) > \pi$ for all c > 0.

Given an editorial strategy $(w(c))_{\{c \in [-1,1]\}}$, citizens can compute their expected utility from consuming the outlet's news combining Equation 5 and Equation 8 for each weather event c. Citizens, however, do not know the value of the weather event that will be reported if they watch the outlet. They need to take into account the expected distribution of weather events, which we denote by $F^e(\tilde{c}) = \pi F_1(\tilde{c}) + (1 - \pi)F_0(\tilde{c})$ in what follows, to compute their expected utility from turning on the news. For a citizen from group $J \in \{D, R\}$, we obtain:

$$\int_0^1 w(\tilde{c}) \left(v(\tilde{c}) + z_J(\mu(\tilde{c})) \right) + g(1 - w(\tilde{c})) \underline{u} \ dF^e(\tilde{c})$$

Given the outside option of citizen i ($\delta_i \sim \mathcal{U}[0,\overline{\delta}]$) and the assumption that this event is i.i.d. and we have a mass of citizens in each group, the *proportion* of individuals from group $J \in \{D, R\}$ who watch the outlet given its editorial strategy is: $A_J = \frac{1}{\overline{\delta}} \int_0^1 w(\tilde{c}) (v(\tilde{c}) + z_J(\mu(\tilde{c}))) + g(1 - w(\tilde{c})) \underline{u} \, dF^e(\tilde{c}).$

From this, we can easily define the total audience as a function of the outlet's editorial strategy. It is simply:

$$A = \frac{1}{\overline{\delta}} \int_0^1 w(\tilde{c}) \left(v(\tilde{c}) + \alpha z_D(\mu(\tilde{c})) + (1 - \alpha) z_R(\mu(\tilde{c})) \right) + g(1 - w(\tilde{c})) \underline{u} \ dF^e(\tilde{c})$$

As the outlet seeks to maximize its audience size, it is immediate that its strategy corresponds to maximizing "point-by-point" the utility of the "average" citizen. We obtain that the equilibrium publication strategy satisfies (with superscript *dem* for demand-driven coverage):

Proposition 1. A TV stations's editorial strategy is a function defined for all $c \in [-1, 1]$ by:

$$g'(1 - w^{dem}(c; \alpha)) = \frac{v(c) + \alpha z_D(\mu(c)) + (1 - \alpha) z_R(\mu(c))}{\underline{u}}$$
(9)

Proof: The proof of Proposition 1 and all results can be found in Online Appendix H.

The next result provides some simple comparative statics on the coverage of weather event.

Corollary 1. The coverage of weather event $w^{dem}(c; \alpha)$:

- is strictly increasing with α ,
- is strictly decreasing with c for c < 0 and strictly increasing with c for c > 0.

This first comparative statics matches the basic descriptive for coverage collected in Appendix Figure A.2. With this, we now turn to studying how the leaning of the media market affects the coverage of extreme weather events relative to events consistent with the seasonal norm (c = 0 in our model). To do so, we define the theoretical equivalent of our empirical estimate as: $\Delta^{dem}(c; \alpha) = w^{dem}(c; \alpha) - w^{dem}(0; \alpha)$. We obtain:

Proposition 2. Suppose $\alpha^D > \alpha^R$. There exists $\overline{g} > 0$ such that if $g'''(c) \leq \overline{g}$ for all $c \in [-1, 1]$, then

• $\Delta^{dem}(c; \alpha)$ is strictly decreasing with c for c < 0 and strictly increasing in c for c > 0,

•
$$\Delta^{dem}(c; \alpha^D) > (<) \Delta^{dem}(c; \alpha^R)$$
 for all $c > (<)0$,
• $\frac{\partial \Delta^{dem}(c; \alpha^D) - \Delta^{dem}(c; \alpha^R)}{\partial c} > 0$ for all c .

Proposition 2 makes three points. The first states that the difference in coverage increases with the extremeness of weather events. The second highlights that the increase in coverage is greater for TV stations in Democratic-dominated media markets than in Republican markets for weather event above the seasonal norm, whereas the opposite holds true for events below the seasonal norm. Finally, the last result states that as we go from weather events below the norm to events below the norms, the difference-in-differences in coverage (i.e., the difference between stations in Democratic market versus Republican market on top of the difference between baseline events and other events) is increasing.

While the first result follows directly from Corollary 1, as the weather event becomes more extreme (away from zero), coverage increases relative to the baseline, the last two do not. Indeed, coverage increases in all types of markets, dominated by Republicans or Democrats. Hence, we need an additional condition so that the rate of increase is faster in Republicandominated markets for weather events below the norm (c < 0) and in Democrat-dominated markets for weather events above the norm (c > 0). This is what the condition on the third derivative of $g(\cdot)$ in the proposition guarantees. Notice that the learning part in the citizens' payoff matters. Absent this, to recover the same pattern, one would need to assume that Republican citizens have a higher (lower) entertainment value for news about cold (hot) weather than Democratic citizens and this difference is increasing as events become more unlikely. A utility function that includes benefits and losses from learning reproduces the same type of variations in a simple and (we hope) elegant way.

The theoretical results from Proposition 2 fits our empirical findings on presentation bias in summer (Figure 4 panel (a)). They also correspond to the patterns we observe for weather events below the mean in winter (Figure 4 panel (b)). The main difference between our theoretical and empirical results regard above the norms weather event in winter. While we do not have a robust theoretical explanation for this, our best guess, as already noted above, is that the entertainment value of warmer days than the norms in winter is low since those days are cold nonetheless. Despite the failure to parallel all of our empirical results, a demand-driven model with learning performs relatively well. Can a supply-driven model of coverage outperform it? We turn to this question in the next subsection.

7.3 Supply Driven Coverage

We now consider how coverage would look like if the media outlet's objective was to move individuals' beliefs in its preferred direction. In general, it proves very difficult to define the optimal strategy of a biased outlet as there an infinite number of possible combinations. We can, however, provide a basic idea of what coverage looks like. As Proposition 3 highlights, a biased TV station either fully omits weather events or only covers them. Denoting $w_{\tau}^{sup}(\cdot)$ the equilibrium editorial strategy for a biased outlet of type $\tau \in \{b, s\}$ (with the superscript sup standing for supply-driven coverage), we obtain:

Proposition 3. For all $c \in [-1, 1]$, the equilibrium coverage of weather event of a biased outlet of type $\tau \in \{b, s\}$ satisfies: $w_{\tau}^{sup}(c; \alpha) \in \{0, 1\}$ for all $\alpha \in [0, 1]$

To understand the result in Proposition 3, recall that a biased media outlet has two considerations in mind when it determines its editorial strategy. The first is whether to reveal the weather events to manipulate beliefs (i.e., to choose w(c) > 0 or w(c) = 0). The second is to design coverage so as to manipulate its audience size, who observe the weather news. Because the objective function of the TV station is strictly concave, the outlet has more to lose from citizens observing bad news than from citizens observing good news (e.g., for a climate-believer outlet, the gain from moving beliefs up by a certain amount is lower than the loss from moving beliefs down by the same amount). As such, the media outlet never seeks to maximize its audience. If it reveals the weather event (if w(c) > 0), it chooses a suboptimal coverage and the least optimal coverage (given our assumption on the citizens' utility) is w(c) = 1.¹⁸

¹⁸The result requires that outlets have concave payoff function, that they are risk avoiding. If their utility is convex (they are risk seeking), then they can choose some interior amount of coverage. Indeed, they will

Building on Proposition 3, we obtain that as weather events become more extreme, coverage either remain constant or increase abruptly. These variations are starker than those we theoretically obtain for profit-maximizing outlets and they are a far cry from the smooth increase we empirically document. Denoting $\Delta_{\tau}^{sup}(c;\alpha) = w_{\tau}^{sup}(c;\alpha) - w_{\tau}^{sup}(0;\alpha)$, we get:

Corollary 2. For all $c \in [-1, 1]$, all $\alpha \in [0, 1]$, and $\tau \in \{b, s\}$, $\Delta_{\tau}^{sup}(c; \alpha) \in \{-1, 0, 1\}$.

Corollary 2 indicates that fixing all elements of our model, but the objective of the media outlet, supply-driven coverage fails to match our empirical patterns whereas demand-driven coverage works relatively well. A further implication of Corollary 2 is that if coverage is supply-driven (by TV stations who are biased), we should observe large swings in coverage when the ideology of the outlet changes (note that this is a reasonable conjecture, but we cannot prove this result as we cannot fully define an outlet's strategy). In turn, by definition, if the coverage is demand-driven, we should observe relatively little change in they weather events are covered. This last theoretical prediction is again relatively conform to our findings in Table 2 when we look at the effect of TV station acquisitions by Sinclair. Overall, our parsimonious set-up provides a way to rationalize (most of) our empirical findings and to justify our claim that those results come from demand-side forces rather than supply-side ones.

8 Conclusion

Our paper explores the daily decision of what to cover in the news by local TV stations in the United States. To do so, we look at weather events, which we define as temperature deviations from the historical mean. We document a clear "man bites dog" effect: Outlets cover significantly more severe (uncommon) weather events than typical ones. Interestingly, even moderate deviations can sometimes be deemed newsworthy, offering deeper insight into how news is produced. Beyond this, we document striking publication bias in the coverage of even seemingly mundane events like the weather. In summer, Republican-leaning markets

choose the demand-driven level of coverage $w^{dem}(c; \alpha)$. This would imply that demand forces also shape the coverage of biased TV stations.

downplay above-average temperatures, while Democratic-leaning markets do the opposite, amplifying hot weather and minimizing cold spells. Crucially, our evidence suggests this bias is not driven by supply-side persuasion efforts but rather by audience demand. Using a stylized theoretical model, we demonstrate how media outlets tailor coverage to viewers' preferences. Additionally, we show that the salience of weather news follows the same pattern as publication bias. However, we find little evidence of systematic differences in how the these news are framed.

How are we to understand this last result? One possibility is that temperature deviations are easy to interpret in the context of the climate crisis. After all, climate change has been understood as global warming and unseasonably hot and cold days can have clear meaning in this context. Others, studying different media outlets, have robustly shown presentation bias in the coverage of disasters (Djourelova et al. (2024)). If we combine the easiness of interpretation of temperature deviations and the complementarity with the coverage of disasters, one can maybe see why narratives supplied by the media (a la Eliaz and Spiegler (2024)) may well be unnecessary for the weather events we study. While our focus on the mundane choices of what to cover every day make it impossible for us to test the consequences of the publication bias we uncover, we believe that our findings still pain a striking picture. Our paper suggests that little by little, day by day, without the need for sensational events like disasters, the media may shape divergent views on the existence and the cause of climate changes.

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Appendix

(For online publication only)

A Appendix Figures



Figure A.1: Coverage of Local Weather

Notes: This figure shows coverage of local weather in different weather events. In particular, we show the average number of segments about local weather in each bin of the within-media market deviation distribution, separately for summer (panel (a)) and for winter (panel (b)).



Figure A.2: Coverage of Local Weather by DMA Political Leaning

Notes: This figure shows coverage of local weather in different weather events, by the political leaning of the media market. In particular, we show the average number of segments about local weather in each bin of the within-media market deviation distribution for media markets that are Democratic-leaning, swing, and Republican-leaning, separately for summer (panel (a)) and for winter (panel (b)).

Figure A.3: Effect of Sinclair Acquisitions on Coverage of Weather Events, Event Studies for Differences-in-Differences Specification



Notes: This figure shows the dynamic effect of Sinclair acquisitions on the reporting of different weather events. We regress the number of segments about local weather on an indicators for years to/since the acquisition, indicator variables for the deviation from historical mean falling in a given bin of the within-media market deviation distribution, one lead and one lag of the same indicators, the interaction of the Sinclair and weather events indicators, one lead and one lag of these interactions, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 4). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (panel (a)) and for winter (panel (b)), using a Poisson model. Standard errors are clustered at the media market level.





Notes: This figure shows the dynamic effect of Sinclair acquisitions on the reporting of different weather events. We regress the number of segments about local weather on an indicators for years to/since the acquisition, indicator variables for the deviation from historical mean falling in a given bin of the within-media market deviation distribution, one lead and one lag of the same indicators, the interaction of the Sinclair and weather events indicators, one lead and one lag of these interactions, station fixed effects, media market by day fixed effects, and number of segments decile fixed effects (see Equation 4). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (panel (a)) and for winter (panel (b)), using a Poisson model. Standard errors are clustered at the media market level.

Figure A.5: CCES Descriptive



Notes: This figure shows the mean share of respondents in CCES stating that climate change requires action by ideology (panel (a)) and by party identity (panel (b)).

B Appendix Tables

	Local Weather Segments, Rank							
		Summer			Winter			
	(1)	(2)	(3)	(4)	(5)	(6)		
Bottom 10%	-0.043***	-0.042***	-0.022***	-0.104***	-0.096***	-0.058***		
	(0.007)	(0.009)	(0.008)	(0.009)	(0.012)	(0.010)		
Bottom $10\% \times$ D-Leaning		0.012	0.008		-0.007	-0.017		
		(0.015)	(0.013)		(0.019)	(0.017)		
Bottom $10\% \times \text{R-Leaning}$		-0.028	-0.016		-0.032	-0.018		
		(0.017)	(0.016)		(0.019)	(0.017)		
10%-40%	0.001	0.002	0.001	-0.025***	-0.020***	-0.013**		
	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.005)		
$10\%-40\% \times D$ -Leaning		0.007	0.005		-0.002	-0.005		
		(0.009)	(0.008)		(0.011)	(0.009)		
$10\%-40\% \times \text{R-Leaning}$		-0.014	-0.014		-0.017	-0.018		
		(0.013)	(0.012)		(0.013)	(0.011)		
60%-90%	-0.018***	-0.009*	-0.004	0.009**	0.010	0.006		
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)		
60%-90% × D-Leaning	. ,	-0.022**	-0.018**	. ,	0.012	0.013		
-		(0.009)	(0.008)		(0.010)	(0.009)		
60%-90% × R-Leaning		-0.010	-0.013		-0.024**	-0.017		
-		(0.010)	(0.009)		(0.011)	(0.011)		
Top 10%	-0.045***	-0.034***	-0.017**	-0.006	0.003	0.005		
•	(0.007)	(0.009)	(0.008)	(0.007)	(0.010)	(0.008)		
Top $10\% \times D$ -Leaning	· /	-0.049***	-0.040***	· /	-0.017	-0.012		
		(0.015)	(0.014)		(0.014)	(0.013)		
Top $10\% \times \text{R-Leaning}$		0.018	0.008		-0.020	-0.018		
		(0.017)	(0.015)		(0.015)	(0.015)		
Observations	284444	284444	284444	274000	274000	274000		
Stations	697	697	697	699	699	699		
DMAs (Clusters)	204	204	204	204	204	204		
Mean Dep. Variable	1.966	1.966	1.966	1.896	1.896	1.896		
Bottom $10\% \times D = Bottom 10\% \times R$		0.035	0.175		0.248	0.950		
$10\%-40\% \times D = 10\%-40\% \times R$		0.132	0.121		0.284	0.296		
60%-90% × D = $60%$ -90% × R		0.275	0.618		0.005	0.015		
Top 10% × D = Top 10% × R		0.001	0.006		0.864	0.677		

Table B.1: Salience Bias

Notes: This table shows the relationship between the salience of news coverage of local weather and weather events, on average and by media market political leaning. In columns (1) and (4), we regress the log minimum rank of segments about local weather (averaged across the different newscasts) on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, one lead and one lag of the same indicators, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 1). Columns (2) and (5) additionally include the weather events indicators interacted with interacted with dummies for the market being either Democratic- or Republicanleaning, with one lead and one lag of the same variables (see Equation 2). Columns (3) and (6), additionally control for number of local weather segments deciles. The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (columns (1) to (3)) and for winter (columns (4) to (6)), using OLS. Standard errors are clustered at the media market level.

	Local Weather Segmen			
	Summer	Winter		
	(1)	(2)		
Bottom 10%	0.070***	0.109***		
	(0.012)	(0.011)		
Bottom $10\% \times \text{Non-Sceptic}$	-0.031**	-0.040**		
	(0.015)	(0.019)		
Bottom $10\% \times \text{Sceptic}$	-0.011	0.035		
	(0.017)	(0.024)		
10%-40%	0.005	0.022***		
	(0.004)	(0.006)		
10%-40% × Non-Sceptic	-0.006	0.000		
	(0.007)	(0.011)		
$10\%-40\% \times \text{Sceptic}$	-0.009	0.016		
	(0.009)	(0.011)		
60%-90%	0.014^{***}	-0.015***		
	(0.004)	(0.005)		
60%-90% × Non-Sceptic	0.013^{**}	-0.003		
	(0.006)	(0.009)		
60%-90% × Sceptic	-0.002	0.030^{***}		
	(0.008)	(0.008)		
Top 10%	0.028^{***}	0.001		
	(0.008)	(0.007)		
Top $10\% \times \text{Non-Sceptic}$	0.045^{***}	-0.001		
	(0.011)	(0.012)		
Top $10\% \times \text{Sceptic}$	0.007	0.033^{***}		
	(0.013)	(0.012)		
Observations	297659	288726		
Stations	698	699		
DMAs (Clusters)	204	204		
Mean Dep. Variable	27.905	27.915		
Bottom $10\% \times D = Bottom 10\% \times R$	0.205	0.005		
$10\%-40\% \times D = 10\%-40\% \times R$	0.756	0.269		
60%-90% × D = $60%$ -90% × R	0.109	0.001		
Top 10% × D = Top 10% × R	0.005	0.019		

Table B.2: Publication Bias, CCES

Notes: This table shows the relationship between news coverage of local weather and weather events by media market climate change scepticism. We regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with dummies for the market being either Democratic- or Republican-leaning, one lead and one lag of the same indicators, station fixed effects, day fixed effects, and number of segments decile fixed effects (similar to Equation 1). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (column (1)) and for winter (column (2)), using a Poisson model. Standard errors are clustered at the media market level.

C Classification

We use a simple, but effective, dictionary method to identify whether a segment is about the weather. In particular, as we explain in the data section, we define a segment to be about weather if it contains at least *two* words from a dictionary of weather-related terms. We then define a segment to about local weather, if it additionally mentions at least one county or one municipality located in the media market the station operates in.

The dictionary we follow is from Baylis et al. (2019), who use to identify Tweets that are about weather, and contains the following terms:

aerovane air airstream altocumulus altostratus anemometer anemometers anticyclone anticyclones arctic arid aridity atmosphere atmospheric autumn autumnal balmy baroclinic barometers barometers bizzard blizzards blustering blustery blustery breeze breezes breezy brisk calm celsius chill chilled chillier chilliest chilly chinook cirrocumulus cirrostratus cirrus climate climates cloud cloudburst cloudbursts cloudier cloudiest clouds cloudy cold colder coldest condensation contrail contrails cool cooled cooling cools cumulonimbus cumulus cyclone cyclones damp damper damper dampest dampest degree degrees deluge dew dews dewy doppler downburst downbursts downdraft downdrafts downpour downpours dried drier dries driest drizzle drizzled drizzles drizzly drought droughts dry dryline fall farenheit flood flooded flooding floods flurries flurry fog fogbow fogbows fogged fogging foggy fogs forecast forecasted forecasting forecasts freeze freezes freezing frigid frost frostier frostiest frosts frosty froze frozen gale gales galoshes gust gusting gusts gusty haboob haboobs hail hailed hailing hails haze hazes hazy heat heated heating heats hoarfrost hot hotter hottest humid humidity hurricane hurricanes ice iced ices icing icy inclement landspout landspouts lightning lightnings macroburst macrobursts maelstrom mercury meteorologic meteorologist meteorology microburst microbursts microclimate microclimates millibar millibars mist misted mists misty moist moisture monsoon monsoons mugginess muggy nexrad nippy NOAA nor'easter nor'easters noreaster noreasters overcast ozone parched parching pollen precipitate precipitated precipitates precipitating precipitation psychrometer radar rain rainboots rainbow rainbows raincoat raincoats rained rainfall rainier rainiest raining rains rainy sandstorm sandstorms scorcher scorching searing shower showering showers skiff sleet slicker slickers slush slushy smog smoggier smoggiest smoggy snow snowed snowier snowiest snowing snowmageddon snowpocalypse snows snowy spring sprinkle sprinkles sprinkling squall squalls squally storm stormed stormiest storming storms stormy stratocumulus stratus subtropical summer summery sun sunnier sunniest sunny temperate temperature tempest thaw storm thunderstorms tornadic tornado tornadoes tropical troposphere tsunami turbulent twister twisters typhoon typhoons umbrella umbrellas vane warm warmed warming warms warmth waterspout waterspouts weather wet wetter wettest wind windchill windchills windier windiest windspeed windy winter wintery wintry

	One weather-related term	Two weather-related terms
	(1)	(2)
False positive rate	0.265	0.056
False negatives rate	0.007	0.044
Precision	0.523	0.833
Recall	0.993	0.956
F-score	0.685	0.890
Accuracy	0.793	0.947

Table C.1: Weather classification performance measures

We explore whether our simple classification method is effective at identifying weather stories by implementing the following validation exercise. First, we randomly select 600 segments stratifying by political leaning of the DMA (in other words, we randomly 200 segments from Democratic-leaning DMAs, 200 segments from swing DMAs, and 200 segments from Republican-leaning DMAs). Second, we hand-classify these segments as being about weather or not through close reading. Third, we use our hand-classification as the "ground truth" and test the performance of our dictionary method against it.

Appendix Table C.1 reports different measures of predictive performance using either one or two weather-related terms to identify weather segments. This exercise makes clear that using one weather-related term only captures virtually all weather-related segments, but yields a relatively high number of false positives. To the extent that several of the weather-related terms are polysemic, this is not surprising: think of "hot" or even "ice." Instead, requiring *two* weather words (rather than just one) to appear in a segment for it to be classified as weather-related greatly minimize this type of error, at the cost of a negligible increase in false negatives. Overall, the dictionary-based method we appears to have a good performance in this setting.

Our method to classify stories as local, instead, might yield both false positives (for example, if a county/municipality has a polysemic or common name) and false negatives (for example, if neighborhoods are mentioned instead of municipalities). However, this is

Notes: This table shows classification performance metrics for identifying weather-related segments using a keyword-based approach. Column (1) shows results when classifying segments containing at least one weather-related term, while column (2) restricts to segments containing at least two such terms. We report the false positive rate, false negative rate, precision, recall, F-score, and overall accuracy.

only problematic to the extent that this type of measurement error varies depending on the size of weather events, which is not likely to be the case.

Finally, we might also be concerned that requiring both two weather terms and a county or municipality name to appear in the same 150-word segment might lead to further underestimating coverage of local weather. The fact that our results are robust to using longer segments assuages this concern.

D Additional Data Sources

Climate Regions. We follow the definition of climate regions from the National Centers for Environmental Information. We assign each DMA to the climate region that covers the majority of its area.

Additional DMA characteristics. Media market characteristics (population, population in urban versus rural areas, and population employed in different industries) are from NHGIS. In all cases, we start from county level data and aggregate them to the media market level. The area of each media market is from our own calculations, based on a shapefile of media markets.

Wildfires. Wildfire data is from the National Interagency Fire Center. The data reports the date of discovery and geographic coordinates for each wildfire event identified by the agency. We match each wildfire event to the relevant DMA using these geographic coordinates.

Natural Disasters. Information on natural disasters is from Federal Emergency Management Agency's (FEMA) Disaster Declarations Summaries dataset. We exclude incidents categorized as "fire" to avoid duplicates with wildfires. Natural disasters geographic information at the county level is then aggregated to the media market level.

E Additional Analyses

In this Appendix we show that our results are robust to a number of concerns.

Heterogeneity in Shocks. A first concern is that the different responsiveness to weather events of stations that operate in Republican- and Democratic-leaning media markets might be explained by these markets experiencing substantively different events. This is possible in this case because we define weather events based on where a given day falls in the within-media market deviation distribution. If this distribution is systematically different in Republican- and Democratic-leaning media markets, then we might be treating as equivalent events that correspond to very different deviations.

However, this is unlikely to be the case in our setting. To start with, Figure 2 shows that the distribution of deviations within each weather event in the three types of media market is substantially overlapping, both in summer (panel (a)) and in winter (panel (b)). Nonetheless, it is also possible to see that the median deviation is at times slightly different across the different types of media markets.

In Appendix Table E.1, we show that, even if we were to take these differences at face value, they would be too small to explain the effects we estimate through a simple back of the envelope calculation. We begin by computing the median deviation that correspond to each of the weather events we consider in the analysis. We report this in columns (1) for summer and column (4) for winter. From our usual specification, we can recover the percentage increase in coverage of local weather corresponding to each of these weather events. We use swing-DMAs as our benchmark. These are the estimates in columns (2) and (4). Finally, under a linearity assumption, we can estimate the predicted differential change in coverage that one would expect given the difference in median deviation in D-leaning and R-leaning markets for each event. The estimates reported in columns (3) and (6) are of one order of magnitude smaller than the ones we estimate in Table 1. This suggests that any differences in

deviations across DMAs with different political leanings are unlikely to explain the patterns we estimate.

Finally, in line with these results, we can also show that the patterns we estimate are robust to using within-climate region variation only. Appendix Table E.2 shows that our results are fully robust to estimating specifications that include climate region-by-year fixed effects (columns (1) and (2)).

DMA Characteristics. A second concern is that our publication bias estimates are measuring the effect of media market's characteristics that are different than ideology, and just happen to correlate with it. We explore this concern in Appendix Table E.3, where we re-estimate our baseline specification but include different media market characteristics also interacted with the indicators for the weather events. The table clearly shows that our results are robust to controlling for media market population, area, level of urbanization, and industry composition. It is particularly interesting that most of our heterogeneity survives even a very stringent specification that includes all controls at the same time.

Wildfires and Natural Disasters. Third, one might be concerned that our extreme weather events (those in the top and bottom 10% of the deviation distribution, that imply the largest increases in coverage of local weather) are simply proxies for wildfires or other natural disasters. To test whether this is the case, we once again re-estimate our specification, but including interactions between whether the DMA is experiencing a wildfires or a natural disaster and DMA ideology. Appendix Table E.4 shows that our results are virtually unchanged when including these controls, separately or together.

Robustness Checks. Finally, we also show that our results are robust to several perturbations to our measurement and modeling choices. In particuar, in Appendix Table E.5 we show that our findings for the summer are fully robust to using 300 word long segments (column (1)), estimating OLS specifications with the outcome expressed in logs (column (2)) or shares (column (3)), and splitting markets by ideology using 20th and 80th percentiles (column (4)) and the 30th and 70th percentiles (column (5)) as cutoffs. The heterogeneity in reporting in days in the bottom 10% of the deviation distribution in winter is instead not robust to defining the outcome as a share (while all other alternative specifications yield the same results).

			Winter			Summer	
		Median Deviation	% Change in Swing DMA	Predicted % Change	Median Deviation	% Change in Swing DMA	Predicted % Change
		(1)	(2)	(3)	(4)	(5)	(6)
Bottom 10%	D-Leaning	-5.359		-0.004	-10.955		-0.004
	Swing	-5.707	0.061		-11.423	0.096	
	R-Leaning	-5.849		0.002	-11.893		0.004
10%- $40%$	D-Leaning	-1.947		0.000	-4.052		-0.002
	Swing	-2.059	-0.001		-4.443	0.018	
	R-Leaning	-2.021		0.000	-4.450		0.000
60%- $90%$	D-Leaning	2.218		0.002	3.942		0.002
	Swing	1.944	0.012		4.622	-0.015	
	R-Leaning	1.764		-0.001	4.927		-0.001
Top 10%	D-Leaning	5.336		0.004	10.023		
	Swing	4.789	0.032		10.271	0.003	
	R-Leaning	4.525		-0.002	10.440		0.000

Table E.1: Back-of-the-Envelope Calculation

Notes: This table performs a back-of-the-envelope calculation to understand whether the effects we estimate can be explained by differences in the median temperature deviation from the historical mean across media markets with different political leanings. Column (1) shows the median temperature deviation corresponding to different weather events by media market political leaning. Column (2) reports the increase in media coverage of local weather corresponding to a given weather event in swing media markets, that we estimate using Equation 2. Column (3) reports the predicted difference in reporting that we should expect in media markets with different political leanings based on (1) and (2).

	Local Weat	ther Segments
	Summer	Winter
	(1)	(2)
Bottom 10%	0.060***	0.096***
	(0.012)	(0.012)
Bottom $10\% \times D$ -Leaning	-0.015	-0.014
0	(0.016)	(0.019)
Bottom $10\% \times \text{R-Leaning}$	0.016	0.068^{***}
0	(0.017)	(0.020)
10%-40%	-0.001	0.016***
	(0.004)	(0.006)
$10\%-40\% \times D$ -Leaning	0.004	0.009
0	(0.007)	(0.010)
$10\%-40\% \times \text{R-Leaning}$	0.007	0.022**
0	(0.008)	(0.010)
60%-90%	0.012***	-0.013**
	(0.004)	(0.005)
60%-90% × D-Leaning	0.017**	-0.002
0	(0.007)	(0.009)
60%-90% × R-Leaning	-0.002	0.030***
0	(0.006)	(0.008)
Тор 10%	0.030***	0.005
1	(0.008)	(0.007)
Top $10\% \times D$ -Leaning	0.034***	-0.003
1 0	(0.012)	(0.011)
Top $10\% \times \text{R-Leaning}$	-0.004	0.022
	(0.011)	(0.013)
Observations	297659	288726
Stations	698	699
DMAs (Clusters)	204	204
Mean Dep. Variable	27.905	27.915
Bottom $10\% \times D = Bottom 10\% \times R$	0.048	0.000
$10\%-40\% \times D = 10\%-40\% \times R$	0.711	0.291
$60\%-90\% \times D = 60\%-90\% \times R$	0.011	0.001
Top $10\% \times D = Top 10\% \times R$	0.003	0.111

Table E.2: Publication Bias, Controls for Climate Region-Specific Shocks

Notes: This table shows the relationship between news coverage of local weather and weather events by media market political leaning, using only within climate region and year variation. We regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with indicators for the market being either Democratic- or Republican-leaning, one lead and one lag of the same variables, climate region by year fixed effects, station fixed effects, day fixed effects, and number of segments decile fixed effects (similar to Equation 2). The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (column (1)) and for winter (column (2)), using a Poisson model. Standard errors are clustered at the media market level.

					Local Wea	ther Segme	nts			
			Summer					Winter		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bottom 10%	0.058***	0.058***	0.057***	0.051***	0.049***	0.095***	0.097***	0.097***	0.089***	0.087***
	(0.011)	(0.011)	(0.010)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
Bottom $10\% \times \text{D-Leaning}$	-0.011	-0.037*	-0.033*	-0.001	-0.008	-0.008	-0.014	-0.013	0.005	0.012
	(0.015)	(0.020)	(0.017)	(0.013)	(0.013)	(0.019)	(0.020)	(0.019)	(0.018)	(0.017)
Bottom $10\% \times \text{R-Leaning}$	0.013	0.034**	0.026	0.021	0.023	0.063***	0.071***	0.070***	0.075***	0.073***
	(0.019)	(0.016)	(0.018)	(0.015)	(0.015)	(0.021)	(0.021)	(0.020)	(0.022)	(0.022)
10%-40%	-0.003	-0.001	-0.001	-0.002	-0.005	0.019^{***}	0.018^{***}	0.018^{***}	0.018^{***}	0.019^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
10%-40% × D-Leaning	0.007	0.006	0.003	0.008	0.011	0.009	0.008	0.009	-0.005	-0.001
	(0.006)	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
10%-40% × R-Leaning	0.003	0.006	0.008	0.005	0.003	0.021^{*}	0.022^{**}	0.021*	0.031^{***}	0.031^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
60%-90%	0.011**	0.012^{***}	0.012^{***}	0.013^{***}	0.011^{**}	-0.017^{***}	-0.014^{***}	-0.014***	-0.016***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
60%-90% × D-Leaning	0.019^{***}	0.023^{***}	0.021^{***}	0.012^{*}	0.018^{**}	0.000	0.008	0.007	0.004	0.011
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
60%-90% × R-Leaning	-0.001	-0.003	-0.001	0.001	-0.001	0.028^{***}	0.025^{***}	0.027^{***}	0.028^{***}	0.026^{***}
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Top 10%	0.032^{***}	0.031^{***}	0.032^{***}	0.034^{***}	0.034^{***}	0.001	0.003	0.003	0.000	-0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Top $10\% \times \text{D-Leaning}$	0.035^{***}	0.027^{**}	0.035^{***}	0.035^{***}	0.029^{**}	0.002	-0.002	0.000	0.001	0.002
	(0.012)	(0.013)	(0.012)	(0.014)	(0.013)	(0.011)	(0.013)	(0.012)	(0.012)	(0.012)
Top $10\% \times \text{R-Leaning}$	-0.005	-0.001	-0.005	-0.009	-0.004	0.024^{*}	0.024^{*}	0.022^{*}	0.024	0.024^{*}
	(0.012)	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.014)	(0.013)	(0.015)	(0.015)
Log Area	\checkmark				√	√				√
Log Population		\checkmark			\checkmark		\checkmark			\checkmark
Urban Share			\checkmark		\checkmark			\checkmark		\checkmark
Industry Shares				\checkmark	\checkmark				\checkmark	\checkmark
Observations	297659	297659	297659	297659	297659	288726	288726	288726	288726	288726
Stations	698	698	698	698	698	699	699	699	699	699
DMAs (Clusters)	204	204	204	204	204	204	204	204	204	204
Mean Dep. Variable	27.905	27.905	27.905	27.905	27.905	27.915	27.915	27.915	27.915	27.915
Bottom $10\% \times D = Bottom 10\% \times R$	0.170	0.002	0.002	0.223	0.101	0.003	0.001	0.000	0.009	0.022
$10\%-40\% \times D = 10\%-40\% \times R$	0.728	0.995	0.639	0.808	0.409	0.329	0.276	0.373	0.012	0.028
$60\%-90\% \times D = 60\%-90\% \times R$	0.016	0.007	0.008	0.218	0.081	0.005	0.122	0.033	0.035	0.208
Top 10% \times D = Top 10% \times R	0.003	0.074	0.002	0.007	0.049	0.167	0.126	0.147	0.208	0.219

Table E.3: Publication Bias, Controls for Media Market Characteristics

Notes: This table shows the relationship between news coverage of local weather and weather events by media market political leaning, controlling for additional media market characteristics. We regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with indicators for the market being either Democratic- or Republican-leaning, one lead and one lag of the same variables, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 2). The regression further includes the interaction between indicator variables for the deviation from the historical market deviation distribution and the control variable(s) noted in the respective column. The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (columns (1) to (5)) and for winter (columns (6) to (10)), using a Poisson model. Standard errors are clustered at the media market level.

Table E.4: Publication Bias, Controls for Wildfires and Natural Disasters

	Local Weather Segments								
		Summer			Winter	<u> </u>			
	(1)	(2)	(3)	(4)	(5)	(6)			
Bottom 10%	0.061***	0.058***	0.058***	0.096***	0.095***	0.095***			
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)			
Bottom $10\% \times D$ -Leaning	-0.015	-0.012	-0.012	-0.012	-0.010	-0.010			
	(0.016)	(0.015)	(0.015)	(0.019)	(0.019)	(0.019)			
Bottom $10\% \times \text{R-Leaning}$	0.018	0.017	0.017	0.069^{***}	0.068***	0.068^{***}			
	(0.018)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)			
10%-40%	-0.001	-0.001	-0.001	0.018***	0.018***	0.018***			
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)			
10%-40% × D-Leaning	0.003	0.006	0.005	0.009	0.008	0.008			
	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)			
10% - $40\% \times \text{R-Leaning}$	0.008	0.010	0.010	0.021^{**}	0.018^{*}	0.018^{*}			
	(0.008)	(0.008)	(0.008)	(0.011)	(0.010)	(0.011)			
60%- $90%$	0.012^{***}	0.011^{**}	0.011^{**}	-0.015***	-0.014***	-0.014^{***}			
	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)			
60%-90% × D-Leaning	0.017^{**}	0.019^{***}	0.018^{***}	-0.001	-0.001	-0.001			
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)			
60%-90% × R-Leaning	0.000	0.001	0.001	0.031^{***}	0.029^{***}	0.029^{***}			
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)			
Top 10%	0.032^{***}	0.032^{***}	0.032^{***}	0.003	0.004	0.004			
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)			
Top $10\% \times \text{D-Leaning}$	0.035^{***}	0.037^{***}	0.038^{***}	0.002	-0.000	0.000			
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)			
Top $10\% \times \text{R-Leaning}$	-0.005	-0.003	-0.003	0.023^{*}	0.021	0.020			
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)			
Wildfires	\checkmark		\checkmark	\checkmark		\checkmark			
Disasters		\checkmark	\checkmark		\checkmark	\checkmark			
Observations	297659	297659	297659	288726	288726	288726			
Stations	698	698	698	699	699	699			
DMAs (Clusters)	204	204	204	204	204	204			
Mean Dep. Variable	27.905	27.905	27.905	27.915	27.915	27.915			
Bottom $10\% \times D = Bottom 10\% \times R$	0.047	0.070	0.066	0.000	0.001	0.001			
10%-40% \times D = 10%-40% \times R	0.590	0.657	0.614	0.335	0.391	0.392			
60%-90% × D = 60%-90% × R	0.027	0.018	0.021	0.001	0.001	0.001			
Top 10% × D = Top 10% × R	0.001	0.001	0.001	0.157	0.158	0.172			

Notes: This table shows the relationship between news coverage of local weather and weather events by media market political leaning, controlling for wildfires and natural disasters. We regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with indicators for the market being either Democratic- or Republican-leaning, one lead and one lag of the same variables, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 2). Columns (1) and (4) additionally control for presence of an active wildfire in the media market, columns (2) and (5) for presence of a declared natural disaster in the media market, and columns (3) and (6) for both. The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (columns (1) to (3)) and for winter (columns (4) to (6)), using a Poisson model. Standard errors are clustered at the media market level.

					Local Weat	her Segmer	nts			
	C	Outcome De	ef.	DMA	s Split	C	Outcome De	ef.	DMA	s Split
	300	Log	Share	20-80	30-70	300	Log	Share	20-80	30-70
			Summer					Winter		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bottom 10%	0.038***	0.049***	0.005***	0.059***	0.071***	0.067***	0.087***	0.011***	0.105***	0.101***
	(0.008)	(0.009)	(0.001)	(0.011)	(0.015)	(0.008)	(0.011)	(0.001)	(0.011)	(0.012)
Bottom $10\% \times \text{D-Leaning}$	-0.007	-0.010	-0.001	-0.009	-0.029*	-0.008	-0.012	0.000	-0.033*	-0.023
	(0.011)	(0.013)	(0.002)	(0.016)	(0.017)	(0.013)	(0.018)	(0.003)	(0.020)	(0.018)
Bottom $10\% \times \text{R-Leaning}$	0.014	0.025^{*}	0.001	0.016	0.002	0.041^{***}	0.050^{***}	0.003	0.057^{**}	0.056^{***}
	(0.011)	(0.013)	(0.001)	(0.018)	(0.018)	(0.013)	(0.018)	(0.003)	(0.023)	(0.021)
10%-40%	-0.002	-0.002	-0.000	-0.000	0.000	0.013^{***}	0.016^{**}	0.002^{***}	0.018^{***}	0.019^{***}
	(0.003)	(0.004)	(0.000)	(0.004)	(0.004)	(0.004)	(0.006)	(0.000)	(0.006)	(0.006)
$10\%-40\% \times D$ -Leaning	0.003	0.002	0.000	0.005	0.000	0.005	-0.005	0.001	0.011	0.004
	(0.005)	(0.008)	(0.001)	(0.007)	(0.007)	(0.007)	(0.009)	(0.001)	(0.011)	(0.010)
10% - $40\% \times \text{R-Leaning}$	0.004	-0.001	0.001	0.002	0.006	0.009	0.006	0.001	0.022^{*}	0.020^{**}
	(0.006)	(0.009)	(0.001)	(0.009)	(0.008)	(0.007)	(0.011)	(0.001)	(0.011)	(0.010)
60%-90%	0.007**	0.011**	0.001**	0.014***	0.011**	-0.007*	-0.012**	-0.001**	-0.013***	-0.017***
	(0.003)	(0.005)	(0.000)	(0.004)	(0.005)	(0.004)	(0.006)	(0.001)	(0.005)	(0.006)
60%-90% × D-Leaning	0.011**	0.014*	0.002**	0.015**	0.017***	-0.002	0.001	0.000	-0.004	-0.001
_	(0.005)	(0.008)	(0.001)	(0.007)	(0.007)	(0.006)	(0.008)	(0.001)	(0.009)	(0.008)
60%-90% × R-Leaning	-0.001	-0.005	0.000	-0.003	-0.000	0.017***	0.018*	0.002***	0.029***	0.034***
5	(0.005)	(0.008)	(0.001)	(0.007)	(0.008)	(0.006)	(0.009)	(0.001)	(0.008)	(0.008)
Top 10%	0.022***	0.039***	0.003***	0.036***	0.031***	0.005	-0.004	0.000	0.004	0.004
*	(0.005)	(0.007)	(0.001)	(0.007)	(0.009)	(0.005)	(0.009)	(0.001)	(0.006)	(0.008)
Top $10\% \times D$ -Leaning	0.022***	0.023**	0.003***	0.033***	0.033***	-0.001	0.014	0.001	-0.000	-0.002
	(0.008)	(0.011)	(0.001)	(0.012)	(0.012)	(0.008)	(0.012)	(0.001)	(0.012)	(0.011)
Top $10\% \times \text{R-Leaning}$	-0.011	-0.021	-0.001	-0.011	-0.005	0.010	0.010	0.001	0.021	0.019
	(0.007)	(0.013)	(0.001)	(0.012)	(0.012)	(0.009)	(0.014)	(0.001)	(0.014)	(0.012)
Observations	297659	284444	297714	297659	297659	288726	274000	288731	288726	288726
Stations	698	697	698	698	698	699	699	699	699	699
DMAs (Clusters)	204	204	204	204	204	204	204	204	204	204
Mean Dep. Variable	30.406	2.957	0.092	27.905	27.905	29.375	2.909	0.096	27.915	27.915
Bottom $10\% \times D = Bottom 10\% \times R$	0.058	0.014	0.134	0.185	0.027	0.002	0.002	0.499	0.001	0.001
$10\%-40\% \times D = 10\%-40\% \times R$	0.951	0.821	0.670	0.774	0.471	0.609	0.309	0.920	0.432	0.173
60%-90% × D = 60%-90% × R	0.021	0.043	0.031	0.026	0.024	0.005	0.095	0.055	0.002	0.000
Top 10% \times D = Top 10% \times R	0.000	0.002	0.001	0.001	0.002	0.275	0.796	0.886	0.198	0.111

Table E.5: Publication Bias, Robustness

Notes: This table shows robustness of the relationship between news coverage of local weather and weather events by media market political leaning. Unless otherwise specified, we regress the number of segments about local weather on indicator variables for the deviation from the historical mean falling in a given bin of the within-media market deviation distribution, the same indicators interacted with indicators for the market being either Democratic- or Republican-leaning, one lead and one lag of the same variables, station fixed effects, day fixed effects, and number of segments decile fixed effects (see Equation 2). Columns (1) and (6) use variables defined based on 300-word long segments. Columns (2) and (7) report estimates from an OLS regression using the log number of local weather segments as the outcome, and columns (3) and (8) using the share of segments that are about local weather. Columns (4) and (9) define as Democratic-leaning (Republican-leaning) media markets in the bottom (top) 20% of the Republican vote share in the 2008 Presidential election and columns (5) and (10) media markets in the bottom (top) 30% of the same variable. The omitted category is the 40%-60% bin, which approximately corresponds to days in which temperatures are in line with the historical mean. We estimate the regression separately for summer (columns (1) to (5)) and for winter (columns (6) to (10)), again using a Poisson model unless otherwise specified. Standard errors are clustered at the media market level.

F Weather Events and Climate Change Beliefs

A large body of works investigate how temperatures affect climate change beliefs. This is usually done using individual-level survey data and correlating respondents' perspective on climate change with the temperatures they experience (objectively and subjectively). In an excellent review, Howe et al. (2019) summarize a few patterns emerging from the literature. First, individuals seem to be much more sensitive to short-term variations than long-term trends: temperature anomalies on the day or in the temporal vicinity of an individual's interview tends to affect the respondent's belief on climate change. Second, individuals tend to believe more in climate change or become more supportive of actions to mitigate climate change following hotter than usual days, whereas the effect of days colder than usual is more ambiguous (e.g., Joireman et al. (2010); Hamilton and Stampone (2013); Brooks et al. (2014); Di Leo and Midões (2023)).

While several studies have addressed the question of how temperatures influence individuals' states positions over climate change, there is no agreement on how to measure temperature anomalies or over which geography (Howe et al. (2019)). This makes it important for us to show that indeed weather events, as we define them, also induce the same shifts in beliefs. To do so, we use questions about individuals' stated position on whether action against climate change is required, which were included in the CCES 2009 to 2013 waves.

To get identification, we exploit the fact that CCES is a large scale survey that is fielded over several days, even within the same media market. This gives us quasi-random withinmarket variation in exposure to weather events on the data individuals responded to the interview. We focus in particular on exposure to weather events in the top or bottom 10% of the within-market deviation distribution. To allow short-term effects of exposure, we consider a respondent exposed if they experienced such weather events in the seven days prior to the interview. Because we are interested in the political dimension of the relationship between weather events and beliefs, we always estimating heterogeneous effects based on individuals' stated ideology.¹⁹ One important caveat is that the survey is fielded in autumn, when the weather tends to be slightly less predictable. However, by making it harder for individuals to benchmark the temperatures they experience against the seasonal norms, this higher variability should, if anything, bias our estimates downwards.

More precisely, we estimate the following specification:

$$Y_{j} = \sum_{i \in \{L,M,C\}} \beta_{i}^{top10\%} \{ \# \text{ days in top } 10\%_{m(j)d(j)} \} \times \mathbb{I} \{ ideology_{j} = i \}$$

$$+ \sum_{i \in \{L,M,C\}} \beta_{i}^{bottom10\%} \{ \# \text{ days in bottom } 10\%_{m(j)d(j)} \} \times \mathbb{I} \{ ideology_{j} = i \}$$

$$+ \sum_{i \in \{L,C\}} \lambda_{i} \mathbb{I} \{ ideology_{j} = i \} + X_{j}^{'} \gamma + \delta_{m(j)t(j)} + \epsilon_{i}, \qquad (F.1)$$

where Y_j is an indicator variable equal to 1 if individual j reports that climate change requires action; # days in top $10\%_{m(j)}$ measures the number of days in the top 10% of the withinmarket deviation distribution that individual j in media market m(j) was exposed to in the week prior to the interview;²⁰ I{ $ideology_j = i$ } are indicator variables for the self-reported ideology of individual j (which can be liberal, moderate, or conservative); X_j is a matrix of individual-level controls (namely, age, gender, race, employment status, education, marital status, homeowner status); $\delta_{m(j)t(j)}$ are media market by year fixed effects. Standard error are clustered at the media market level.

Table F.1 reports the estimates from regressions that progressively build to our preferred specification. In particular, column (1) reports estimates from a regression that only includes media market and year fixed effects (separately); column (2) includes media market by year fixed effects; column (3) further includes individual-level controls (equation F.1). In line with the existing evidence, we document a small effect of short-term temperature anomalies on climate change beliefs. Moderates, in particular, tend to be more (less) supportive of

 $^{^{19}}$ A potential concern with this approach is that ideology could also be post-treatment. However, we believe this concern to be unwarranted. We are, after all, looking at relatively small events: the weather.

 $^{^{20}}$ Since the survey waves we use correspond to the period 2009-2013, we define the historical mean on the period 2000-2008.

actions against climate change after experiencing temperatures above (below) the historical mean. The same is true to a lesser extent for liberals, who already believe more in climate change (see Appendix Figure A.5). Conservatives, in contrast, always react negatively: they become less supportive of climate change action following any type of weather events.

This pattern should be interpreted with caution. It could indicate that conservatives engage in motivated reasoning discarding evidence going against their beliefs. Alternatively, it could be that weather events increase the salience of climate change issue and motivate conservatives to respond more negatively to a (somewhat) politically charged question. As we do not have data to adjudicate between these possible rationales (they survey, after all, is not incentivized), we leave a further exploration of these findings to future research. Nonetheless, we believe that there are several lessons we can learn from this exercise. In particular, the evidence points to: i) individuals having a (small) propensity to react to weather events; and ii) those reactions being different according to the baseline ideology of the individual. As such, individuals' interpretation of weather events may provide one rationale for why TV stations cover the same event differently depending on the media market they operate in.²¹

²¹One limitation of our approach here is that the lack of available data (questions about local TV viewership are asked inconsistently) do not allow us to test for the impact of local TV newscasts on individuals' interpretation of weather events. Yet, others have documented an effect of cable news (Ash et al. 2023) and local media outlets (Andrews et al., 2023) on how citizens interpret weather events or natural disasters, which would be in line with the mechanisms we will develop later in the paper.

	Climate C	hange Requ	ires Action
	(1)	(2)	(3)
Liberal	0.204***	0.204***	0.193***
	(0.005)	(0.005)	(0.005)
Conservative	-0.470***	-0.469***	-0.447***
	(0.006)	(0.006)	(0.007)
$\#$ Top 10% Days \times Liberal	0.003	0.003^{**}	0.003^{*}
	(0.002)	(0.002)	(0.002)
$\#$ Top 10% Days \times Moderate	0.004^{*}	0.005^{**}	0.004^{*}
	(0.002)	(0.002)	(0.002)
$\#$ Top 10% Days \times Conservative	-0.007***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)
$\#$ Bottom 10% Days \times Liberal	-0.002	-0.003	-0.002
	(0.003)	(0.003)	(0.003)
$\#$ Bottom 10% Days \times Moderate	-0.004**	-0.005**	-0.004*
	(0.002)	(0.002)	(0.002)
$\#$ Bottom 10% Days \times Conservative	-0.006**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)
DMA FEs	\checkmark		
Year FEs	\checkmark		
DMA-By-Year FEs		\checkmark	\checkmark
Additional Controls			\checkmark
Observations	146375	146374	144463
DMAs (Clusters)	204	204	204
Mean Dep. Variable if Moderate	0.694	0.694	0.694

Table F.1: Weather Events and Support for Climate Change Action

Notes: This table shows the relationship between climate change beliefs and weather events, by individual ideology. In columns (1), we regress an indicator variable equal to one if the respondent reports that climate change requires action on indicator variables for whether the individual is liberal or conservative, the same indicator variables interacted with the number of days in the top 10% of the within-media market deviation distribution that the respondent was exposed to in the week prior to the interview, media market fixed effects and year fixed effects. Column (2) includes media market by year fixed effects. Column (3) reports estimates from our preferred specification (see F.1), that further includes individual level controls (namely: age, gender, race, employment status, education, marital status, and homeownership status). Standard errors are clustered at the media market level.

G Topic Modelling

Our topic modelling approach leverages BERTopic, a framework designed to extract meaningful themes from large collections of text by combining transformer-based embeddings, dimensionality reduction, clustering, and topic representation techniques. The main challenge in topic modelling lies in effectively capturing the semantic meaning of text and grouping similar documents into coherent topics without predefined labels. Traditional methods often rely on simple word frequency counts, which fail to account for the complex relationships between words and their contextual meanings. To overcome this limitation, we use a BERT-based sentence embedding model, which transforms text into high-dimensional numerical representations that encode rich contextual and semantic information. Unlike earlier approaches based on word co-occurrence (e.g., LDA), transformer models like BERT allow us to understand how words are used in different contexts, leading to more accurate topic clustering.

Since these embeddings exist in a high-dimensional space, we apply UMAP (Uniform Manifold Approximation and Projection for Dimension Reduction) for dimensionality reduction. UMAP preserves the structure of the data while projecting it into a lower-dimensional space, where similar documents remain close together. We then apply HDBSCAN, a hierarchical density-based clustering algorithm, to identify groups of documents that share similar topics. Unlike traditional clustering methods that require specifying the number of clusters (topics) in advance, HDBSCAN dynamically determines the number of topics based on the density of the data, making it more flexible for tasks where the number of topics is not known beforehand.

Clustering alone does not produce interpretable topics. To address this, we apply different representation techniques to refine topic descriptions. Specifically, we use KeyBERT inspired keyword extraction, a method that builds on BERT embeddings to generate keywords and key phrases with minimal computational overhead. Although many existing methods for keyword extraction are available (e.g., RAKE, YAKE!, TF-IDF), KeyBERT offers a simple yet effective approach using pre-trained BERT embeddings and cosine similarity. The process begins by extracting document embeddings with BERT to obtain a document-level representation. Then, word embeddings are generated for N-gram words and phrases. Finally, cosine similarity is used to determine which words and phrases are most similar to the document as a whole. The highest-ranked words are identified as the most representative of the document's content. To further enhance topic interpretability, we integrate Maximal Marginal Relevance (MMR), which balances relevance and diversity when selecting topic keywords. This ensures that extracted terms are not only representative but also varied, preventing redundancy in topic descriptions.

One limitation of clustering-based topic modelling is that some documents may not fit neatly into a single topic. To improve accuracy, we apply an outlier reduction strategy, reassigning ambiguous documents based on their similarity to existing topic embeddings. This ensures that documents are categorised into the most appropriate topics, improving the overall coherence of the model.

In the final step, we update the topic model with these refined assignments and generate a structured dataset containing document-topic distributions and keyword representations. By leveraging BERT-based embeddings, dimensionality reduction, density-based clustering, and topic representation techniques, our approach provides a robust and scalable method for discovering latent topics in large text corpora.

We apply the topic model to segments about local weather. Because the number of segments about local weather is large, running the topic model on the entire set would be computationally expensive. To address this, we focus on segments about local weather in five randomly selected days per year per season (summer and winter). Even after this initial sampling, we are left with over one million stories, so we further reduce the data by selecting a random subsample of 250,000 observations per season.

Table	G.1:	Topics	of Segmer	nts about	Local	Weather,	Winter
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	Top Words	Segments Count
Topic 1	morning, snow, today, rain, weather, temperatures, day, right, cold, look	248053
Topic 2	pope, vatican, morning, cardinals, new, today, church, day, conclave, new pope	1947

Notes: This table shows the top words generated by a BERTopic model trained on text segments about local weather in winter. We construct the dataset by randomly selecting five winter days per year and sampling 250,000 observations. Text embeddings are generated using the pre-trained sentence transformer model all-MiniLM-L6-v2. To group similar texts, we reduce the dimensionality of the embeddings using UMAP and then apply HDBSCAN clustering with a minimum cluster size of 1,000. Texts are represented using a bag-of-words approach via CountVectorizer, which removes English stopwords, includes bigrams, and filters out rare terms. Topic representations are based on a combination of KeyBERT-inspired keywords and Maximal Marginal Relevance (MMR). Outliers are reassigned using an embedding-based similarity strategy.

Table G.2: Topics of Segments about Local Weather, Summer

	Top Words	Segment Count
Topic 1	rain, showers, temperatures, afternoon, degrees, tomorrow, day, today, going, morning	46407
Topic 2	police, morning, man, say, old, year old, year, county, news, today	32770
Topic 3	new, good, today, morning, day, like, summer, just, right, time	23288
Topic 4	water, flooding, people, flood, help, harvey, hurricane, storm, florence, county	17260
Topic 5	traffic, road, morning, right, delays, look, lane, good, southbound, accident	15451
Topic 6	game, team, sports, season, football, today, day, tonight, high, just	14582
Topic 7	trump, president, clinton, morning, today, donald, new, donald trump, news, hillary	12370
Topic 8	firefighters, acres, fires, crews, burning, flames, homes, burned, contained, morning	11552
Topic 9	rain, showers, storms, beach, coast, florida, west, county, right, miami	10717
Topic 10	san, degrees, temperatures, bay, inland, low, today, high, going, valley	10495
Topic 11	school, students, kids, schools, summer, year, district, new, day, today	10157
Topic 12	power, tornado, damage, trees, tree, storm, county, people, just, weather	7906
Topic 13	rain, texas, temperatures, heat, showers, today, degrees, going, afternoon, dallas	5785
Topic 14	dog, dogs, animal, animals, pet, pets, zoo, shelter, just, today	5359
Topic 15	iowa, storms, dakota, weather, morning, low, highs, showers, south, today	5162
Topic 16	oklahoma, kansas, storms, rain, tulsa, heat, morning, chance, showers, hot	5094
Topic 17	seattle, clouds, degrees, temperatures, coast, tomorrow, low, mid, cascades, morning	4300
Topic 18	denver, colorado, storms, tomorrow, today, rain, afternoon, plains, pueblo, 80s	3963
Topic 19	virus, mosquito, zika, mosquitoes, nile, west nile, health, nile virus, mosquitos, west	2635
Topic 20	fireworks, july, fourth, fourth july, 4th, weekend, day, 4th july, city, weather	2507
Topic 21	utah, salt lake, salt, wasatch, st george, northern utah, george, lake, northern, southern utah	2240

Notes: This table shows the top words generated by a BERTopic model trained on text segments about local weather in summer. We construct the dataset by randomly selecting five summer days per year and sampling 250,000 observations. Text embeddings are generated using the pre-trained sentence transformer model all-MiniLM-L6-v2. To group similar texts, we reduce the dimensionality of the embeddings using UMAP and then apply HDBSCAN clustering with a minimum cluster size of 1,000. Texts are represented using a bag-of-words approach via CountVectorizer, which removes English stopwords, includes bigrams, and filters out rare terms. Topic representations are based on a combination of KeyBERT-inspired keywords and Maximal Marginal Relevance (MMR). Outliers are reassigned using an embedding-based similarity strategy.

H Proofs of the Formal Model

Proof of Proposition 1

As we noted in the text, the outlet maximizes pointwise $\frac{1}{\delta} \int_0^1 w(\tilde{c}) \left(v(\tilde{c}) + \alpha z_D(\rho(w(\tilde{c}))) + (1-\alpha) z_R(\rho(w(\tilde{c}))) \right) + g(1-w(\tilde{c})) \underline{u} \, dF^e(\tilde{c}).$

Notice that if for a given c, the outlet chooses w(c) = 0, then the utility of the "average" citizen of watching the newscast conditional on the realization of this event is $g(1)\underline{u}$. Hence, we can define an alternative objective function for the outlet: $w(c)(v(c) + \alpha z_D(\mu(c))) + (1 - \alpha)z_R(\mu(c))) + g(1 - w(c))\underline{u}$ for any realization c. This function removes the discontinuity in posterior at w(c) = 0 compared to the original objective function. Yet, point by point (relative to w(c)), it equals $w(c)(v(c) + \alpha z_D(\rho(w(c))) + (1 - \alpha)z_R(\rho(w(c)))) + g(1 - w(c))\underline{u}$. Hence, any maximum of our alternative function is a maximum of the function we study. Under the assumption of the model (especially g'(1) = 0 and $g(\cdot)$ strictly concave), the maximum is unique and interior and satisfies:

$$g'(1 - w^{dem}(c; \alpha)) = \frac{v(c) + \alpha z_D(\mu(c)) + (1 - \alpha) z_R(\mu(c))}{\underline{u}}$$
(H.1)

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Proof of Corollary 1

As all functions are differentiable, we obtain (with subscript denoting the partial derivative with respect to the variable):

$$w_c^{dem}(c;\alpha)(-g''(1-w^{dem}(c;\alpha))) = \frac{v'(c) + \mu'(c) \left(\alpha z'_D(\mu(c)) + (1-\alpha) z'_R(\mu(c))\right)}{u}$$
(H.2)

$$w_{\alpha}^{dem}(c;\alpha)(-g''(1-w^{dem}(c;\alpha))) = \frac{z_D(\mu(c)) - z_R(\mu(c))}{\underline{u}}$$
(H.3)

Given that g'' < 0, $z_D(\mu(c)) \ge 0 \ge Z_R(\mu(c))$ and our assumptions $v'(c) > -\mu'(c)z_R(\mu'(c))$ for all c > 0 and $v'(c) < -\mu'(c)z_D(\mu'(c))$ for all c < 0, the result follows.

Proof of Proposition 2

Define $\overline{g} = \min_{c \in [-1,1], \alpha \in [0,1]} \frac{1}{\underline{u}} \frac{\mu'(c) \left(z'_D(\mu(c)) - z'_R(\mu(c)) \right)}{w_c^{dem}(c; \alpha) w_\alpha^{dem}(c; \alpha)}$. Notice that since all functions are continuous, the minimum is well defined. Further, observe that $\overline{g} > 0$. We will first show that if $g'''(c) \leq \overline{g}$ for all c, then $w_{\alpha c}^{dem}(c; \alpha) > 0$ for almost all c and all α .

Using Equation H.3 (noting that all functions are again differentiable by assumption), we obtain:

$$w_{c\alpha}^{dem}(c;\alpha)(-g''(1-w^{dem}(c;\alpha))) + w_{c}^{dem}(c;\alpha)w_{\alpha}^{dem}(c;\alpha)g'''(1-w^{dem}(c;\alpha)) = \frac{\mu'(c)(z'_{D}(\mu(c)) - z'_{R}(\mu(c)))}{\frac{u}{(\mathrm{H.4})}}$$

Quite directly, if $g'''(c) \leq \overline{g}$, then $w_{\alpha c}^{dem}(c; \alpha) > 0$ for almost all c.

With this, we can prove the proposition. As noted in the text, the first point of the proposition follows from Corollary 1. We then prove the third point. Notice that $\frac{\partial \Delta^{dem}(c; \alpha^D) - \Delta^{dem}(c; \alpha^R)}{\partial c} = w_c^{dem}(c; \alpha^D) - w^{dem}(c; \alpha^R) = \int_{\alpha^R}^{\alpha^D} w_{c\alpha}^{dem}(c; \tilde{\alpha}) d\tilde{\alpha} > 0$ since $w_{c\alpha}^{dem}(c; \alpha) > 0$ for almost all c and all α . The second point of the proposition follows from the previous result by noting that $\Delta^{dem}(0; \alpha) = 0$ for all α by construction.

Proof of Proposition 3

Consider the following three sets:

$$H_{\tau} := \left\{ c \in [-1, 1] : w_{\tau}^{sup}(c; \alpha) = 0 \right\}$$
$$F_{\tau} := \left\{ c \in [-1, 1] : w_{\tau}^{sup}(c; \alpha) = 1 \right\}$$
$$I_{\tau} := \left\{ c \in [-1, 1] : w_{\tau}^{sup}(c; \alpha) \in (0, 1) \right\}$$

The first is the set of events that a biased outlet $\tau \in \{b, s\}$ hides. F is the set of events that take up the whole programme. I is the set of events that have interior coverage. We suppose that none of these sets is empty (and not singleton). We will show then that the outlet is better off by deviating for each $c \in [-1, 1]$. Recall that A is the audience of the outlet, when all sets are non-empty, the expected utility of the outlet τ is:

$$F^{e}(H_{\tau})V_{\tau}(A\mu(\emptyset) + (1-A)\pi) + \int_{\widetilde{c}\in F_{\tau}\cup I_{\tau}} V_{\tau}(A\mu(\widetilde{c}) + (1-A)\pi)dF^{e}(\widetilde{c})$$

For any $c \in I_{\tau}$, the first derivative satisfies:

$$\frac{\partial A}{\partial w(c)} \Big[F^e(H_\tau) V'_\tau(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] + \int_{\widetilde{c} \in F_\tau} V'_\tau(A\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big]$$

Define $c_{\tau}^* = \arg \max_{c \in F_{\tau} \cup I_{\tau}} \mu(c) \ s.t. \ \mu(c) \le \pi$ and

$$\underline{V}'_{\tau} = \begin{cases} V'_{\tau}(A\mu(\emptyset) + (1 - A)\pi) & \text{if } \pi \ge \mu(\emptyset) \ge \mu(c^*_{\tau}) \\ V'_{\tau}(A\mu(c^*_{\tau}) + (1 - A)\pi) & \text{otherwise} \end{cases}$$

We now show that $V'_{\tau}(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) \leq \underline{V}'_{\tau}(\mu(\emptyset) - \pi)$. In the first case $(\pi \geq \mu(\emptyset) \geq \mu(c^*_{\tau}))$, it is immediate as the two are equal. Suppose $\mu(\emptyset) \geq \pi$ (recall that $\mu(\pi) \geq \mu(c^*_{\tau})$ by definition). Then, given the concavity of $V_{\tau}(\cdot)$, $V'_{\tau}(A\mu(\emptyset) + (1-A)\pi) \leq V'_{\tau}(A\mu(c^*_{\tau}) + (1-A)\pi)$. Since $\mu(\emptyset) - \pi > 0$, we get $V'_{\tau}(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) < \underline{V}'_{\tau}(\mu(\emptyset) - \pi)$. Suppose $\mu(\emptyset) < \mu(c^*_{\tau})$ (which implies $\mu(\emptyset) < \pi$ since $\mu(\pi) \geq \mu(c^*_{\tau})$ by definition). Then, given the concavity of $V_{\tau}(\cdot)$, $V'_{\tau}(A\mu(\emptyset) + (1-A)\pi) \geq \nu'_{\tau}(A\mu(c^*_{\tau}) + (1-A)\pi)$. Since $\mu(\emptyset) < \mu(c^*_{\tau})$ (which implies $\mu(\emptyset) < \pi$ since $\mu(\pi) \geq \mu(c^*_{\tau}) + (1-A)\pi$). Since $\mu(\emptyset) - \pi < 0$, we get $V'_{\tau}(A\mu(\emptyset) + (1-A)\pi) \geq V'_{\tau}(A\mu(c^*_{\tau}) + (1-A)\pi)$.

We now show that $V'_{\tau}(A\mu(c)+(1-A)\pi)(\mu(c)-\pi) \leq \underline{V}'_{\tau}(\mu(c)-\pi)$ for all $c \in F_{\tau} \cup I_{\tau}$ with strict inequality for a non-empty, non-singleton subset. To do so, we divide the set $F_{\tau} \cup I_{\tau}$ into two subsets: $(F_{\tau} \cup I_{\tau})^+ = \{c \in F_{\tau} \cup I_{\tau} : \mu(c) > \pi\}$ and $(F_{\tau} \cup I_{\tau})^- = \{c \in F_{\tau} \cup I_{\tau} : \mu(c) \leq \pi\}$. Note that by definition $c^*_{\tau} \in (F_{\tau} \cup I_{\tau})^-$.

Take any $c \in (F_{\tau} \cup I_{\tau})^+$, by concavity of $V_{\tau}(\cdot)$, $V'_{\tau}(A\mu(c) + (1-A)\pi) < V'_{\tau}(A\mu(\emptyset) + (1-A)\pi)$ if $\pi \ge \mu(\emptyset) \ge \mu(c^*_{\tau})$ (as $\mu(c) > \pi$) and $V'_{\tau}(A\mu(c) + (1-A)\pi) < V'_{\tau}(A\mu(c^*_1) + (1-A)\pi)$ (as $\mu(c) > \pi \ge \mu(c^*_{\tau})$ by definition of c^*_{τ}). Hence, $V'_{\tau}(A\mu(c) + (1-A)\pi) < \underline{V}'_{\tau}$ and since $\mu(c) > \pi$, $V'_{\tau}(A\mu(c) + (1-A)\pi)(\mu(c) - \pi) < \underline{V}'_{\tau}(\mu(c) - \pi)$. Take any $c \in (F_{\tau} \cup I_{\tau})^{-}$, by concavity of $V_{\tau}(\cdot)$, $V'_{\tau}(A\mu(c) + (1-A)\pi) \ge V'_{\tau}(A\mu(\emptyset) + (1-A)\pi)$ if $\pi \ge \mu(\emptyset) \ge \mu(c^*_{\tau})$ (as $\mu(c) > \pi$) and $V'_{\tau}(A\mu(c) + (1-A)\pi) \ge V'_{\tau}(A\mu(c^*_1) + (1-A)\pi)$ (by definition of c^*_{τ}). Hence, $V'_{\tau}(A\mu(c) + (1-A)\pi) \ge \underline{V}'_{\tau}$ and since $\mu(c) \le \pi$, $V'_{\tau}(A\mu(c) + (1-A)\pi)$ $A(\pi)(\mu(c) - \pi) \le \underline{V}'_{\tau}(\mu(c) - \pi)$. Using all these results, we obtain that

$$F^{e}(H_{\tau})V_{\tau}'(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) + \int_{\widetilde{c}\in F_{\tau}\cup I_{\tau}} V_{\tau}'(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi)dF^{e}(\widetilde{c})$$
$$< \underline{V}_{\tau}'\Big(F^{e}(H_{\tau})(\mu(\emptyset) - \pi) + \int_{\widetilde{c}\in F_{\tau}\cup I_{\tau}} (\mu(\widetilde{c}) - \pi)dF^{e}(\widetilde{c})\Big)$$

Since citizens are Bayesian:

$$\mu(\emptyset) = \frac{\pi F_1(H_\tau)}{F^e(H_\tau)}$$
$$\mu(c) = \frac{\pi f_1(c)}{f^e(c)}$$

Then,

$$F^{e}(H_{\tau})(\mu(\emptyset) - \pi) + \int_{\widetilde{c} \in F_{\tau} \cup I_{\tau}} (\mu(\widetilde{c}) - \pi) dF^{e}(\widetilde{c})$$

= $\pi F_{1}(H_{\tau}) + \int_{\widetilde{c} \in F_{\tau} \cup I_{\tau}} \pi f_{1}(\widetilde{c}) d\widetilde{c} - \pi (F^{e}(H_{\tau}) + F^{e}(H_{\tau} \cup I_{\tau}) = 0$

This implies that

$$F^{e}(H_{\tau})V_{\tau}'(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) + \int_{\widetilde{c}\in F_{\tau}\cup I_{\tau}} V_{\tau}'(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi)dF^{e}(\widetilde{c}) < 0$$

By Proposition 1, we know that $\frac{\partial A}{\partial w(c)} > 0$ for all $w(c) < w^{dem}(c)$ and $\frac{\partial A}{\partial w(c)} < 0$ for all $w(c) > w^{dem}(c)$. Hence, the first derivative

$$\frac{\partial A}{\partial w(c)} \Big[F^e(H_\tau) V'_\tau(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] \Big] \Big] = \frac{\partial A}{\partial w(c)} \Big[F^e(H_\tau) V'_\tau(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] \Big] = \frac{\partial A}{\partial w(c)} \Big[F^e(H_\tau) V'_\tau(A\mu(\emptyset) + (1-A)\pi)(\mu(\emptyset) - \pi) + \int_{\widetilde{c} \in F_\tau \cup I_\tau} V'_\tau(A\mu(\widetilde{c}) + (1-A)\pi)(\mu(\widetilde{c}) - \pi) dF^e(\widetilde{c}) \Big] \Big]$$

is strictly negative for all $w(c) < w^{dem}(c)$ and strictly positive for $w(c) > w^{dem}(c)$. This means that for any $w(c) \in (0, 1)$, the outlet has a profitable deviation by either increasing the coverage of weather event or decreasing it. Hence, it cannot be that there is an equilibrium in which all three sets $(H_{\tau}, F_{\tau}, I_{\tau})$ are non-empty and non-singleton. We can then perform the same analysis with two of the sets including I_{τ} being non-empty, non-singleton or I_{τ} to encompass all events (indeed, the proof above does not require all sets to be non-empty, nonsingleton, just I_{τ}) and obtain the same profitable deviation. Hence, there is no equilibrium in which I_{τ} is non-empty, non-singleton. We can then exclude that it is a singleton using the same as above. As a result, I_{τ} must be empty, which completes the proof.

Proof of Corollary 2

Immediate from Proposition 3.