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 and what is not. We unpack the process of news production by looking at the share of newscasts devoted to weather events by local TV stations in the United States. We document that coverage increases with the severity of the weather event that day. We also uncover that stations operating in Democratic-leaning markets devote more time to extreme weather events and mention climate change more than outlets in Republican-leaning markets. We make sense of these publication and presentation biases with a stylised model of news production and consumption.

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

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Every day, editors of news outlets decide what events to cover and how much space to devote to each of them. Doing so, they define what is newsworthy and what is not. They determine "[a]ll the news that's fit to print," as the front page of the New York Times promises. All the news according to the editorial team of the newspaper that is. But what are these news that are fit to print or to broadcast? A well-know 19th-century aphorism, which inspires the title to this paper, gives a clue: "When a dog bites a man, that is not news, because it happens so often. But if a man bites a dog, that is news."

In this paper, we study the daily choice of what makes the news and what does not. We do so focusing on local TV channels in the United States, one of the main sources of news for many Americans (86% watch local TV news at least from time to time according to the Pew Research Center, 2019). We focus on the coverage of the local weather. Each day, the weather can be more or less in line with seasonal norms. Large deviations are likely to attract attention, small ones are unlikely to be interesting, intermediate differences become news only when TV editors choose to include them in the newscast that day. Weather events are thus especially appropriate to study the editorial strategy of TV editors and what influences them.

We document that not all weather events get the same attention. Consistent with the idea that "man bites dog" is news, extreme deviations from the seasonal norms receive substantially more coverage than average weather events. The differences are substantial. An uncommon event can receive up to 17% more coverage relative to the usual time devoted to the weather in local TV newscasts. We also show that local TV news also cover more moderate deviations than weather in line with the seasonal averages, up to 4% more. Hence, "big dog's bites" are also sometimes news.

We go further and study whether TV stations' editorial strategies vary with the ideology of the audience of the media market they operate in.[1] In itself, there is no reason for it. Weather news only describe factual events, with no political content. Further, TV local channels are rarely seen as political.[2] Yet, we find significant differences in the coverage of weather events in Democratic- and Republican-leaning media markets. This difference is especially marked when it comes to the most uncommon events in summer, which are particularly newsworthy as per our previous analysis. Relative to the coverage of the weather close to seasonal norms, we observe a much more pronounced increase in the reporting of extreme deviations in media markets with a large

[1]Media markets, also known as Designated Market Areas (DMAs), are regions in which households have access to the same local TV station offering.

[2]They are trusted by up to 83% of Americans (Advanced Television, 2022, who see them as mostly invested into the community (Pew Research Center, 2019).

Democratic audience than in media markets with a large Republican audience. We also show how these variations in the extent of coverage (publication bias) go in hand-in-hand with differences in how the events are covered (presentation bias). TV channels in Democratic-leaning media markets are more likely to evoke climate change when reporting very large deviations from the summer norms than outlets in Republican-dominated markets.

To quantify daily weather events, we use data from the PRISM Climate Group on minimum temperatures in winter and maximum temperatures in summer. We proceed in several steps. We first compute the mean temperature in a media market for each calendar day in the period 2000-2009. We then compute the deviation from this historical mean for each day in the period 2010-2018. We define a weather event as a deviation in the tail of the distribution of deviations during the relevant season. We are interested in the coverage in local TV channels' newscasts of intermediate deviations (falling in the 5% to 10%, 10% to 20% or 80% to 90%, 90% to 95% of the distribution) and of severe weather events (falling in the bottom 1%, 1% to 5% or 95% to 99%, top 1% of the distribution) relative to small deviations (in between the bottom 20% and the top 20%).

To measure coverage of weather in the news we use a dataset that includes daily newscasts transcripts for 178 local TV stations across 66 media markets (out of 205) in the United States over the period 2010-2018. We define a 150-word newscast segment to be about local weather if (i) it contains a weather-related word from a dictionary compiled by Baylis et al. (2019) and (ii) it mentions one municipality or county located in the media market. Our main dependent variable is the share of segments in a newscast which cover local weather.

We first look at how the share of a newscast devoted to local weather varies with the size of the weather events, as defined above. We show that the more uncommon the event, the greater the extent of reporting for below the mean deviations in winter and above the mean deviations in summer. The increase in coverage is quite significant for severe weather events that fall in the bottom 5% in winter or top 5% in summer of the distribution of deviations (this corresponds to temperatures around 9^{o}C and 6^{o}C away from the historical mean in winter and summer, respectively). For events in the bottom 1% to 5% (bottom 1%) in winter, coverage is 2.5 (3.3) percentage points higher than for deviations in line with seasonal norms. These effects are large in magnitude, corresponding to a 12% (16%) increase relative to the baseline mean or up to 1/3 of the within media market standard deviation. In summer, events in the top 5% to 1% (top 1%) of deviations see a rise in the time devoted to local weather news by 2.1 (3.7) percentage points, corresponding to a 10% (18%) increase relative to the baseline mean or, again, up to 1/3 of the within media market standard deviation. We also show that intermediate deviations (between 5^{o}C and 9^{o}C degrees away from the average in winter and 3^{o}C and 6^{o}C in summer) are often defined as newsworthy by TV newscast editors. These events see an increase in reporting by 3 to 4% relative to our baseline category of small deviations.

Dividing media markets as Republican-leaning if they belong to the top quartile in terms of Republican vote share in the 2008 presidential election, Democratic-leaning if they belong to the bottom quartile for the same quantity, and swing otherwise, we study how TV stations' editorial strategies vary with the ideology of their potential viewers. We document two distinct patterns. In terms of the amount of coverage, we show that TV channels in Republican-leaning media markets report more on local weather than their counterparts in Democratic-leaning markets for low deviations from the historical mean, whereas the reverse is true for large deviations. Consistently, we also observe a greater increase in coverage within media market as the weather events become more uncommon when the audience consists of mostly Democratic voters compared to when the audience is mostly made of Republican voters. In other words, we find clear evidence of publication bias: local TV stations react differently to similar weather events depending on the audience they face.

We complement our analysis of publication bias by also looking at presentation bias, that is, how weather news are presented (sometimes also referred to as slant). We employ a dictionary of terms associated with climate change collected from ChatGPT and look at the probability that a local weather segment also mentions climate change-related terms. We show how publication bias and presentation bias can be complement in some circumstances. For extremely high deviations in summer (top 5%), we observe more coverage of climate change in Democratic-leaning media markets, whereas we document less coverage of the same topic in Republican-leaning media market (albeit, only significant at the 10% level). Yet, for almost all other deviations from normal temperatures, there is little change in climate change reporting compared to the baseline. The decision of what to cover exhibits much more variation than the choice of how to report an event.

In the final part of the paper, we provide a rationale for the empirical patterns we uncover in the form of a stylised formal model of news production and consumption. 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: they receive a utility loss if the news they observe leads them to update against their preferred belief. They are in some sense ideological. While for Democrats, the preferred belief is that climate change is real (or due to human activity), for Republicans, the preferred belief is that climate change is not occurring (or due to nature). The 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 channel 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 they are also indicating that climate change is happening.

We show that bigger events receive more attention due to the value of watching news about uncommon events. Yet, there are important differences depending on the audience the outlet faces. In Republican-leaning markets, outlets cover quite a bit moderate deviations and only slightly more large deviations from normal temperatures. In Democratic-leaning markets, channels cover little moderate deviations and significantly more large deviations. This is due to the learning effect of moderate and large events, which indicate that climate change is not real (Republicans' preferred belief) and is occurring (Democrats' preferred belief), respectively. As such, we recover both the difference in levels between Republican-dominated and Democratic-dominated markets as well as the steeper increase in coverage in markets with a large number of Democrats as the weather deviation increases. We also show that channels in Republican-leaning markets tend to mention climate change in their reporting when weather deviations are intermediary, whereas outlets in Democratic-leaning markets do so when weather deviations are large. All these patterns combined cannot be rationalised by a set-up in which Democrats value weather news more. In this case, we would observe more coverage in Democratic-leaning markets for all weather shocks. They also cannot be explained by supply-side factors only since we would then observe very little variation in coverage if channels try to convince citizens rather than to adapt to their demands. As such, our paper documents a new form of demand-driven media bias, this time in the coverage of daily events such as weather events.

Related Literature

To conclude this introduction, we relate our work to the most closely related literature. Our paper speaks to a large empirical literature trying to better understand the production of news. Two types of non mutually exclusive editorial choices have received much attention: presentation bias (or slant) and publication bias. Presentation bias occurs when outlets differ in the way they report a news item, conditional on coverage. Following the pioneering works of Groseclose and Milyo (2005) and Gentzkow and Shapiro (2010), this has mostly been done by analysing the sources and language used by media outlets (e.g., Martin and Yurukoglu, 2017; Djourelova, 2023). Recent papers have also developed new methods to study presentation bias. When it comes to newspapers or online news sites, scholars have documented a bias not only in the text of newspaper articles, but the images that accompany them (Ash et al., 2023; Caprini, 2023). When it comes to TV programmes, there has been a recent interest in the political leaning of the guests on important TV shows in the United States (Kim et al., 2022) and in France (Cagé et al., 2022), with both papers uncovering a strong bias in who gets to talk on TV. This last approach combines both how events are commented on and, indirectly, what receive media attention. As such, it builds a gap between presentation bias and publication bias, between how a news item is covered and how much coverage news items receive.

Presentation bias is generally associated with the amount of space (or time) devoted to different issues. Puglisi and Snyder (2011) look at municipal scandals in U.S. cities and show that newspapers are less likely to cover misbehaviours from ideologically aligned politicians (in a similar vein, Beattie et al., 2021, explore how coverage of the dieselgate in Germany varied with newspapers' reliance on Volkswagen's advertising revenues). Larcinese, Puglisi, and Snyder (2011) use the same approach to look at the reporting of economic news and find that printed media outlets emphasize (hide) good economic news and hide (cover extensively) bad economic news when a politician they support (oppose) holds the presidency. Our paper, however, is not concerned with newspapers, but with local TV news like Martin and McCrain (2019) and Mastrorocco and Ornaghi (2022). Yet, while the latter explore how change in ownerships (the purchase of a local station by the Sinclair group) affect the coverage of different issues, we study the daily decisions of what to include in the news.

Our paper covers both publication bias and presentation bias. In line with the literature on publication bias, we look at the amount of time (the share of a newscast) devoted to a particular type of news, news about the weather. In line with presentation bias analyses, we also study how weather news are reported on with a special attention to mentions of climate change. Our work is in close conversation with Djourelova et al. (2023), but with noticeable differences. Rather than looking at disasters, as Djoureleva et al. (2023) do, we look at weather events (i.e., temperatures in a given day) and how they deviate from seasonal norms. Like Djoureleva et al. (2023), we document presentation bias in the way uncommon events are discussed. Unlike them, we also uncover a substantial publication bias when it comes to severe weather events. As such, our paper shows that while editors cannot avoid covering disasters, they still have some leeway when it comes to significant, yet less sensational weather phenomena. Further, while they focus on the downstream effect of slanted coverage on beliefs about climate change (complementing the work of Ash et al. 2023, on the influence of Fox News on beliefs about and policies to remedy climate change), we instead provide a formal model to explain the empirical patterns we uncover.

Two sorts of theoretical explanations have been proposed to explain media bias: supply-side factors and demand-side factors. Among the first type, we find different economic forces that can lead to biased coverage: news outlets tailor their coverage to maximize advertising revenues (Strömberg, 2004), owners accept some biases from their journalists in exchange for lower wages (Baron, 2006), or media competition can yield over-specialisation (Perego and Yuksel, 2022). Sometimes, biased coverage can result from political pressures, such as politicians bribing news outlets (Besley and Prat, 2006; Castaneda and Martinelli, 2018). Demand-side explanations, in turn, suppose that the media adjust coverage to their target audience. Newspapers try to convince readers of their high quality by pandering to their (possibly biased) prior (Gentzkow and Shapiro, 2006; Anand, di Tella, and Galetovic, 2007). Alternatively, readers may have confirmation bias and only consume an outlet if the outlet's slant is conform with their underlying ideological bias (Mullainathan and Shleifer, 2005). In our proposed theory, potential viewers care about the entertainment value of news and about what they can learn from it. As in Mullainathan and Shleifer (2005), we assume a form of confirmation bias. As in Anand et al. (2007), the confirmation bias we model is related to the information viewers obtain from the outlet. We suppose that viewers receive a benefit (loss) when the information they observe in the media confirms (contradicts) their preferred belief (as in Herrera and Sethi, 2023, and in Hu, Li, and Tan, 2022, in the context of social media). Unlike previous works, we develop a model to study how much coverage different issues receive rather than the slant in reporting. We also highlight how a model of differentiated demands for weather news or of persuasion by local TV owners are unlikely to explain the empirical patterns we find. Our work, by combining empirical and theoretical results, presents additional evidence in favour of demand-side explanations driving media bias following Gentzkow and Shapiro (2010).

Overall, our paper unpacks, a bit, the day-to-day business operations of news production. We do not look at sensational events, such as scandals as in Puglisi and Snyder (2011) or natural disasters as in Djourelova et al. (2023). We do not even study events that are necessarily newsworthy per se, such as the release of economic statistics as in Larcinese, Puglisi, and Snyder (2011). Our focus is on something generally very mundane, what the temperatures are that day. Then, media outlets, in our case TV local channels, must decide how much to cover those events. We document a clear "man bites dog" effect as extreme deviations from normal temperatures receive significantly more coverage and a "big dog's bite" effect as moderately atypical weather also receives more attention than seasonal temperatures. We also uncover the politicisation of weather news. While weather events are in themselves just factual, they become political due to the editorial decision of media outlets. Coverage of uncommon weather events is different in Democratic-leaning markets than in Republican-leaning markets both in terms of how much space is devoted to weather news and how weather news are reported on. This politicisation of weather news is more likely to be due to demand-side pressure than supply-side factors. While many hope local meteorologists can shape beliefs about climate changes in the United States (The Atlantic, February 22, 2022), our paper highlights that they may do so inadvertently by focusing on daily weather events that confirm their audience belief.

1 Data & Measurement

For the empirical part of the paper, we combine two main sources of data, that we use to measure weather events and the content of news reporting.

1.1 Weather Events

The information on weather events comes from the the AN81d dataset of the PRISM Climate Group. The data contain the minimum and maximum temperatures measured in degree Celsius for 4km by 4km cells in the United States at the daily level for the period 2000 to 2018 (in addition to information on other weather elements such as precipitations, that we do not use in this paper). We take the population-weighted average across cells to aggregate the cell data to the media market level.[3] We use the first ten years of the data (2000-2009) to calculate the historical average minimum and maximum temperature for each calendar day d in each media market m in winter and summer. We focus on these two seasons because they tend to be associated with clear weather patterns (cold and warm), whereas spring and fall tend to be more volatile. We use the remaining years to define what constitutes our weather events.

We proceed as follows. For each media market m, for each date t of season $\sigma \in \{winter, summer\}$ in 2010-2018, we compute the difference between the temperature on that date and the 2000-2009 mean for the same calendar day. This gives us the deviation from the historical mean for date t in media market m.[4] We then look at how this deviation from the mean compares with the national distribution of deviations in season σ over the 2010-2018 period. In particular, for each observed deviation from the mean, we record its percentile in the overall distribution of season-specific deviations.

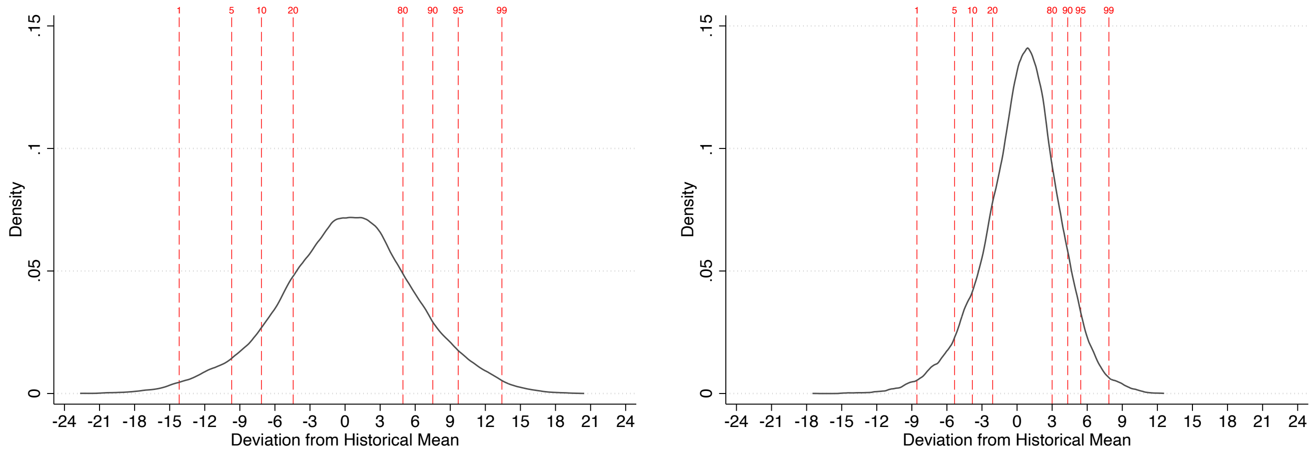
Figure 1 shows the distribution of deviations from the historical mean for the two quantities we use in our analysis: the minimum temperature in winter and the maximum temperature in summer. The two distributions have a bell shape. The distribution of deviations from the mean is flatter in winter than in summer, suggesting that winter minimum temperatures are more dispersed. The two figures also include vertical lines which demarcate the cutoffs in the distribution of events that we use in our empirical analysis. The first line on the left separates the deviations in the 1st percentile from deviations falling between the 1st and 5th percentile, the second line divide the latter category from deviations falling between the 5th and 10th percentile, the third splits the 5-10th percentiles and the 10-20th percentiles, the next is our baseline category between the 20th and 80th percentile, the lines to the right of the baseline proceeds along the same as above for the deviations at the top of the distribution.

Our definition of weather event consists of a double comparison. We first compare the temperature in a given date in a media market relative to its recent mean. We then look at whether the difference in temperature corresponds to a large deviation relative to all possible deviations from the mean during the same season across all media markets. As a result, a weather event is large, not only if the distance between the experienced temperature and its recent mean is big, but also

[3]To 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).

[4]Figure B.1 in Appendix B shows the average deviation in winter minimum temperatures and summer maximum temperatures from the respective historical mean for the in-sample DMAs over 2010-2018 time period.

Figure 1: Distribution of Deviations



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the distribution of daily deviations from the historical mean in the 2000-2009 period, separately for minimum temperatures in winter (Panel (a)) and maximum temperatures in summer (Panel (b)). The vertical lines indicate values used as cutoffs to define the weather events (namely, 1st, 5th, 10th, 20th, 80th, 90th, 95th, and 99th percentile). The values from left to right are (all in degree Celsius): -14.85, -9.694, -7.153, -4.438, 4.950, 7.507, 9.680, 13.416 for minimum temperatures in winter and -8.565, -5.345, -3.824, -2.089, 2.999, 4.331, 5.445, 7.855 for maximum temperatures in summer.

if this difference is substantial relative to the expected variations experienced during the season across the United States in the 2010s.

In our definition of weather events, we make three choices that each deserves a brief comment. The first choice is that we look at deviations in a given day in a given media market relative to the *national* distribution of deviations, rather than the *DMA-specific* distribution. This choice would be inconsequential if all media markets exhibited the same volatility, yet this is not exactly the case as Figure B.1 suggests. We believe that looking at the national distributions of deviations is warranted for comparability. Using DMA-specific distributions would imply attributing the same event to very different deviations from the historical mean: a top 5% weather event in a low-variability DMA could correspond to a deviation of (say) less than 3^oC against more than (say) 7^oC in a high variability market. Instead, we believe that the difference in temperatures relative to seasonal norms is the primary concern of citizens—after all, this is what citizens directly experience—and we seek a common measure for this sort of deviations (see Moore et al., 2019, for an approach consistent with ours, albeit to study a different question).

The second choice we make is to look at the distribution of deviations over the whole season. This is to facilitate the exposition of our findings. In Online Appendix D, we look at deviations in a given day t in a month η relative to the national distribution of deviations in the same month. Results are very consistent.

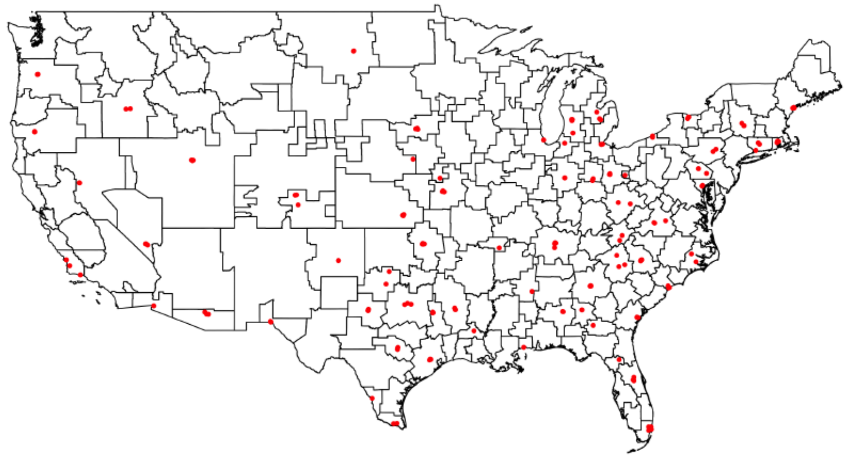
Finally, we define our baseline category as deviations falling in the 20-80 percentiles. We expect that "small" deviations from the historical mean are barely perceivable and likely to fall within a margin of error. For the winter season, this corresponds to temperatures falling between -4.44^{o}C (for bottom 20) and +4.95^{o}C relative to the historical mean (remember that there is significant variability in winter as per Figure 1). For summer, all deviations that fall in between -2.1^{o}C and +3^{o}C of the historical mean belongs to our baseline category.

The types of events we are interested in in our analysis of news coverage of weather can then be combined into two broad categories. First, we have severe weather events: deviations in the bottom or top 5% of the distribution. These are deviations 9.7^{o}C (5.3^{o}C) below the mean and deviations 9.7^{o}C (5.4^{o}C) above the mean in winter (summer). To better understand why we classify these events as extreme weather events, take the summer 2023 heatwave in the South of the United States. The temperature recorded in Albuquerque, New Mexico on July, 17th 2023 was 104^{o}F or 40^{o}C. The mean temperature for the period 2000-2009 for July, 17th in this city equals 93.6^{o}F (according to the National Weather Service) or 34.2^{o}C. As such, Albuquerque experienced a deviation of +5.8^{o}C, which enters the top 5% of national deviations in summer over the period 2010-2018. The second category consists of intermediate deviations from the historical mean that belong to the 5-20% or 80-95% of the distribution. These deviations are relatively large, especially in winter—4.5 to 9.7^{o}C from the norm in winter and between approximately 3 to 5.4^{o}C in summer. Yet, they are not so massive as to be necessarily newsworthy. Indeed, continuing with the example of Albuquerque, on July, 17th over the period 2010-2018, the city experienced three times deviations that fall in this range of the distribution (in 2010, 2013, and 2015).

1.2 Weather News

To measure coverage of weather, we rely on transcripts of local TV newscasts from ShadowTV, a media monitoring company. This dataset contains the (approximately) complete daily transcripts of newscast of 178 local TV stations across 66 media markets. Media markets, also known as Designated Market Areas (DMAs), are the relevant geography to capture the reach of local TV stations. More precisely, media markets are regions in which households have access to the same local TV station offering. Multiple local TV stations can serve the same media market. Here, we

Figure 2: Map of In-Sample Local TV Stations



Notes: This figure shows the location of the studio of the 178 local TV stations included in our sample (represented by red dots), against a map of media markets' boundaries.

focus on stations that are affiliated with one of the big-four networks (ABC, NBC, CBS, FOX) as they tend to have the highest viewers' shares. Networks provide much of the content that is transmitted by the local TV stations, but newscasts are locally produced. Figure 2 displays the stations (and media markets) that are part of our sample (the red dots on the map). We have good geographical coverage, though we are missing media markets in the North West and have slightly more observations in the Eastern part of the United States.

The transcripts do not contain indications about when a news story starts and when it ends. They also do not provide information about the content of the newscast other than the words used. To identify how much of a newscast is devoted to weather, we proceed in three steps. We first break the transcript into segments of 150 words. We chose 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). We define a segment as a *weather* segment if it contains at least one term associated with the weather according to a dictionary compiled by Baylis et al. (2019) (see Appendix A for a list of the words included). Finally, we treat a weather segment as *local* if it also mentions at least one county or municipality located in the media market.

Our approach is likely to both over-estimate and under-estimate the space devoted to local weather in a newscast. As we treat any mention of weather as a weather-related segment, even if the topic of the associated news story has nothing to do with weather, we are likely to over-count the coverage of weather news in a newscast. At the same time, however, we tend to under-count the amount of time devoted to local weather since a 150-word segment must contain both at least one weather term and at least one locality to be considered in our classification. We are not especially worried by the noise associated by our measure for three reasons. First, we believe that raising the salience of weather conditions ("it was chilly today," "it was a hot day," etc.) can still provide information to viewers about weather patterns in their locality. Second, most of our analyses compare the amount of reporting on "local weather" for different levels of weather events as defined above. As such, the relationships we uncover are robust to the presence of noise as long as the noise introduced by our measure is unaffected by the size of the weather event. Finally, we perform many of our analyses using station fixed effects, meaning that the way weather is covered in a TV newscast by a given TV station must significantly differ for low deviations compared to big deviations for our results to be fundamentally biased.

In the main text, our outcome variable is the number of segments devoted to local weather over the total number of segments in a given day. This approximates the coverage of weather in a day, the share of newscast devoted to local weather news, with all the caveats mentioned above. In the Appendix D, we show that our main results are broadly consistent when we use the log plus one of the number of segments about local weather as an alternative measure. We prefer the share of segments as outcome because it takes into account that the number of segments may vary with the speed of speech of the anchor or the number of images without commentaries in the broadcast, or any other differences in coverage of newscast in our dataset.

Two last points are worth noting. First, we restrict the analysis to weekdays, as weekend programming of local TV stations tends to be different. Second, while our dataset has excellent coverage for the stations we consider, it is still unbalanced, as there are days for which no transcripts are recorded in our source data. Similarly to measurement error, we believe it is unlikely that this issue biases our results. First, the share of observations missing in the data is small (6%). Second, given our empirical strategy described below, the presence (or lack thereof) of transcripts need to depend on the weather events that day to fundamentally affect our findings.

1.3 Descriptive Statistics

The descriptive statistics for local weather news can be found in Table B.1 in the Appendix B. The attentive reader will notice that slightly more than 20% of a newscast on average is devoted to weather news. This is not surprising. The transcripts we obtained do not allow us to separate the part of a newscast devoted to the weather forecast from the part devoted to other news. Since we look at local TV stations, quite logically, a large part of the newscast will consist of weather forecasts, that will be identified as local weather news according to our definition. Importantly, this means that any change in coverage we document comes on top of the space devoted to the forecast. It is very likely to come from news stories broadcast during the newscast.

2 Empirical Approach

In this section, we detail our empirical approach. We proceed in two ways. First, we study how TV local stations cover different weather events. Second, we show how reporting varies with the ideological leaning of the media market: that is, we estimate publication bias.

2.1 Estimating Editorial Strategies

To estimate the average editorial strategy of weather events across stations, we estimate the following regression:

$$Y_{st} = \sum_{\rho} \beta^{\rho} \mathbb{I}\{\rho^{th} bin\}_{m(s)t} + \delta_s + \delta_t + \epsilon_{st}. \tag{1}$$

Our main dependent variable Y_{st} is the share of segments about local weather over the total number of segments in the newscasts of station s on date t. Our main variables of interest are indicator variables capturing how severe a weather event (defined as the deviation from the historical mean) is. The dummies capture where the deviation falls in the national distribution of deviations for the season. Our reference category consists of weather events falling between the 20th percentile and the 80th percentile of the distribution of deviations. We split the remaining events into eight bins as follows: bottom 1%, 1-5%, 5-10%, 10-20%, 80-90%, 90-95%, 95-99% and top 1%. The first four categories correspond to weather events below the seasonal norm with decreasing degree of severity. The last four bins capture events higher than normal with increasing degree of severity. Positive (and statistically significant) β^{ρ} coefficients indicate that large and uncommon weather deviations receive more attention by local TV channels relative to smaller and more likely deviations. The day fixed effects (δ_t) control for differences in deviations or reporting that affect all media markets/stations equally (for example, because of other events happening on the same date). The station fixed effects (δ_s) imply that we are only exploiting within station variation. Finally, we cluster standard errors at the media market level.

2.2 Estimating Publication Bias

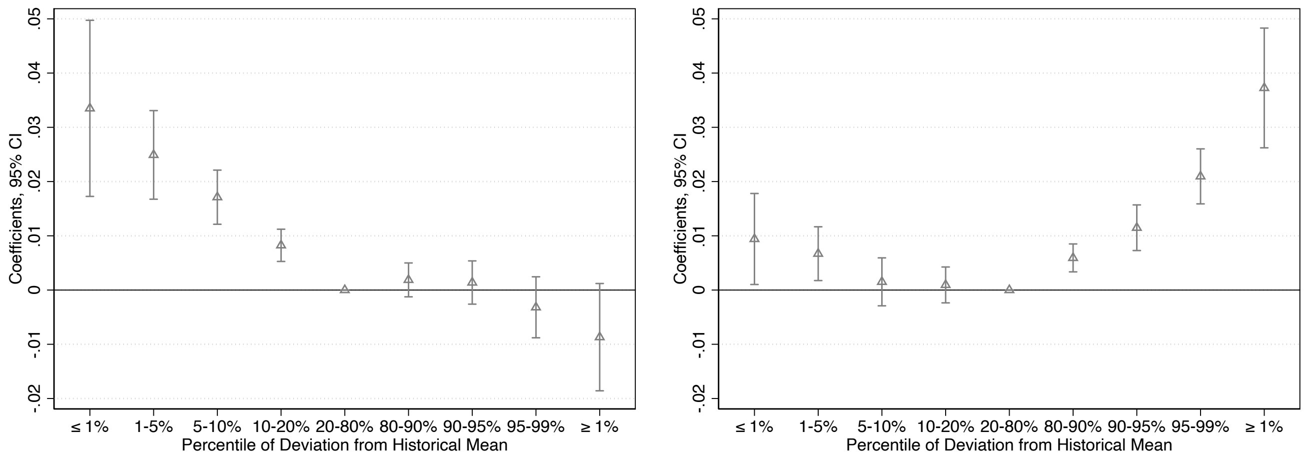
We are also interested in the possibility of publication bias in the reporting of weather news. That is, whether editorial strategies varies with the ideological leaning of the media market. To determine ideology, we use the Republican vote share. In particular, we focus on the 2008 presidential election and use county-level data from the MIT Election Lab, that we aggregate at the media market level. We denote a media market as Republican-leaning if it belongs to the top quartile in terms of Republican vote share (average Republican vote share is 65% in these media markets). In turn, a media market is Democratic-leaning if it belongs to the bottom quartile in term of Republican vote share (average Republican vote share is 38% in these markets). Finally, our last category consists of "swing" media markets that fall in-between the other two (average Republican vote share is 52%). In Online Appendix C, we also reproduce all our analyses separating media markets according to the approximated proportion of climate sceptics recovered from the Cooperative Election Study (CCES). Our findings are broadly consistent, though noisier due to the fact that the CCES is representative at the state level, not at the media market level (see Online Appendix C). The similarity between the approaches should not come as a surprise, given the strong relationship between climate belief and ideology that we show in Appendix Figure C.1.

Our analysis of publication bias first looks at the average amount of reporting as a function of the weather event in the three types of media markets described above. We then reproduce the same analysis within TV station to study whether a TV channel's strategy depends on the environment it operates in. That is, we expand Equation 1 to include interactions for each ideology of the market (Republican, denoted by R, Democratic by D, and Swing by S). Specifically, we estimate:

$$Y_{st} = \sum_{\rho} \sum_{ideol \in \{D,R,S\}} \beta^{\rho}_{ideol} \mathbb{I}\{\rho^{th} bin\}_{m(s)t} \times \mathbb{I}\{Ideol\}_{m(s)} + \delta_s + \delta_t + \epsilon_{st}, \tag{2}$$

where all variables are defined as above. Notice that because of the TV station fixed effect, for each ideological category, the reference category is the weather shock falling between the first quintile and last quintile of deviation nationally, as in our main analysis.

Figure 3: Editorial Strategies



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution, station fixed effects, and day fixed effects. We consider the following bins: $\leq$1%, 1%-5%, 5%-10%, 10%-20%, 20%-80%, 80%-90%, 90%-95%, 95%-99%, $\geq$99%. The omitted category is the 20%-80% bin. Standard errors are clustered at the media market level.

3 Empirical Results

In this section, we first look at the editorial strategy of TV stations. We then show how this editorial strategy varies with the ideology of the media market: that is, we show publication bias. Finally, we complement our analysis by looking at presentation bias, or how local TV channels operating in different markets talk about weather news.

3.1 Editorial Strategies

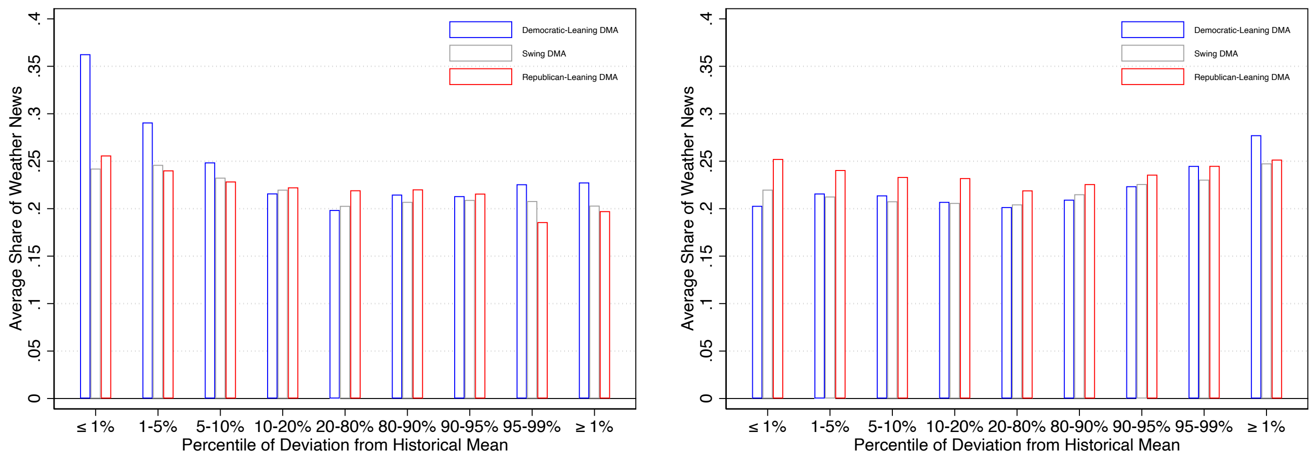
Figure 3 displays estimates from Equation 1 for minimum temperatures in winter (panel (a)) and maximum temperatures in summer (panel (b)). In winter, extreme low temperatures (that is, large negative deviations from the historical mean) receive much more attention than normal temperatures (i.e., small deviation from the mean, between the first and last quintile of the distribution). Similarly, temperatures much higher than usual in summer come along with a large increase in coverage relative to "normal" temperatures. Further, in both cases, the most uncommon events receive more attention: the coefficients are increasing with the relative size of the event.

The effects we document are substantial in magnitude. Severe weather events, in particular, see a large increase in coverage. The effect of a weather events in the 1%-5% percentile of the deviations distribution in winter corresponds to an increase in coverage of 2.5 percentage points relative to the omitted category (20th-80th percentile deviations), which is approximately 12.3% of the omitted category mean (0.204). For summer events, deviations in the 95%-99% of the distribution are associated with an increase in coverage of 2.1 percentage points relative to the omitted category, which is 10.2% of the omitted category mean (0.206). The same estimates also represent around 23% of the within stations standard deviation in winter (within standard deviation equal to 0.107) and 17% in summer (within standard deviation equal to 0.099). If we look at the extremes of our distributions—the bottom 1% in winter and top 1% in summer—, the increases in coverage are even more important, corresponding respectively to increases of 16.2% and 18% relative to the mean of the omitted category, or around 1/3 of a standard deviation in both cases.

We also observe that intermediate deviations below the mean in winter and above the mean in summer are also sometimes deemed newsworthy by editors. They receive less coverage than severe weather events, but more than small deviations. The effects are pretty similar for deviations falling in the 10-20% of the national distribution in winter and deviations falling in the 80-90% of the national distribution in summer. In winter, the share of broadcast increases by 0.8% or 3.9% relative to the baseline mean and in summer, coverage rises by 0.6% or 2.9% relative to the omitted category mean (for events in the 5%-10% bin in winter and 90-95% bin in summer, the increase is of 8.3% and 5.3% relative to their respective omitted category mean). Overall, severe weather events are treated as fundamentally newsworthy—that is, "man bites dog" is indeed news—, but intermediate temperature deviations sometimes also become news—"big dog's bites" can also be news.

Two additional empirical patterns deserve mention. In winter, we observe that large positive deviations from the norm do not lead to more coverage of weather. Indeed, if anything, the amount of time devoted to weather news reduces for temperatures largely above the seasonal mean (in the top 1% bin). In summer, we see a slight increase for deviations below the mean, though this increase is much smaller in magnitude relative to deviations above the historical mean. The asymmetry in these patterns might be surprising at first glance. These weather events, however, may be less 'remarkable,' explaining these patterns. Using social media data for the United States, Moore et al. (2019) 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. In contrast, in warm periods, temperatures below the

Figure 4: Mean Coverage of Local Weather



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the mean coverage of local weather, by weather event and media market ideology. We define coverage of local weather as the share of segments about local weather in a given day. Weather events are deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) that fall in a given bin of the national deviation distribution. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two.

historical mean do not induce reactions on social media, whereas temperatures above the historical mean induce a large increase in the amount (and negative sentiment) of weather tweets.

The results above, if we give credence to the findings in Moore et al. (2009) in our context, tentatively suggests that TV local newscasts may be responding to demand from the public. We provide additional evidence for this in what follows. We first show how TV channels differ in their reporting of weather events as a function of the ideology of the market they operate in. We then use a formal model to differentiate demand-side and supply-side explanations.

3.2 Publication Bias

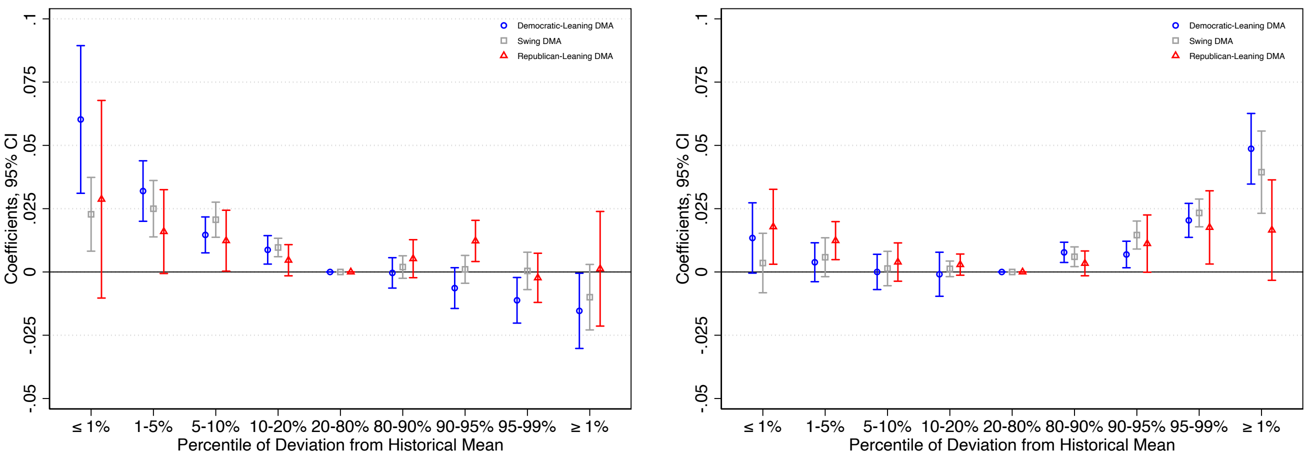
We begin by showing in Figure 4 the average share of news devoted to the local weather as a function of the strength of the weather event in each of the three types of media markets we consider: Republican-leaning (Republican vote share in the 2008 presidential election in the top 25%), Democratic-leaning (bottom 25%) and swing (in-between).

We observe that for "normal temperatures" (deviations that fall in our baseline category), TV channels in media markets with a large proportion of Republican voters cover the weather more than stations in Democratic-leaning markets. Second, the reverse is true for severe events consistent with the season: large deviations below the mean in winter and large deviations above the mean in summer. Third, TV stations in media markets dominated by the Republican party see a net increase in coverage of weather in summer when the deviation is far below the normal. The same does not appear true for stations in Democratic-leaning markets, or for minimum temperatures in winter.

Of course, some of these differences may be due to media market specificities, including being exposed to different weather shocks. To deal with this, we display the estimates from Equation 2 in Figure 5. These specifications include both station fixed effects, which effectively control for any fixed differences across stations' locations and average reporting practices, and day fixed effects, which control for other events that day. The regression results are generally consistent with the visual impression from Figure 4. TV channels in Democratic-leaning media markets tend to be more reactive to weather events than stations in Republican-leaning market, with swing media markets somewhat in between. This is especially telling for severe weather events in summer. While the within station change in coverage between deviations in the 95%-99% bin and the top 1% is almost null in media markets dominated by Republicans, and if anything negative, we observe a large increase in coverage in media markets dominated by Democrats. That is, the most extreme weather events, which are also the most newsworthy according to our analysis above, receive much more attention than intermediate weather events only in Democratic-dominated markets. In Republican-leaning media markets, the difference is not statistically significant (the difference between the two types of markets is statistically significant at 1% with a p-value of 0.008).

There is, however, one noticeable difference between Figure 4a and Figure 5a. Figure 5a documents a decrease in the coverage of weather events for temperature above the mean in winter within Democratic-leaning markets, rather than an increase as Figure 4a. This difference is due to sample composition. Not all markets experience large deviations above the historical mean in winter. Those that do tend to generally report more on weather than those that do not see such large positive deviation. Hence, once we include a station specific DMA, the ranking between Democratic-leaning and Republican-leaning media markets gets inverted between the across (Figure 4a) and the within analysis (Figure 5a). Since this is the only case for which we have this issue, we are not too worried about it. Further, in Appendix D, Figure D.5 shows that our findings remain substantially unchanged when we restrict our analysis to the sample of media markets that span the full support of shocks.

Figure 5: Publication Bias



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

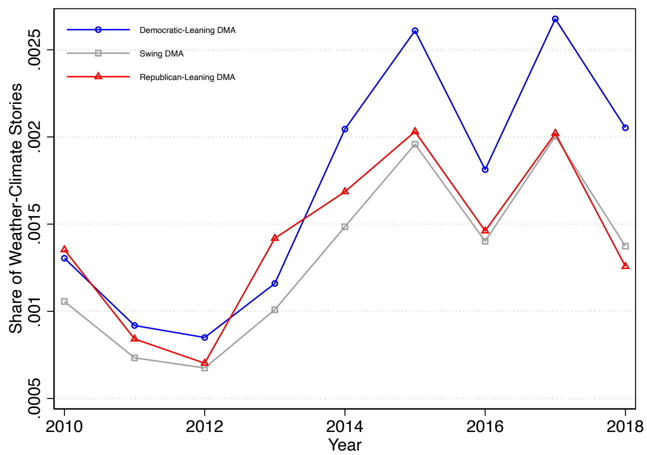
Notes: This figure shows the relationship between news coverage of local weather and weather events, by media market ideology. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

The analysis in this section reveals some important differences in editorial strategies between local TV stations operating in Republican-leaning and Democratic-leaning media markets. That is, we uncover a substantial publication bias in the reporting of weather events. When potential viewers are mostly Republicans, temperatures that are in line with the seasonal norm receive only slightly less attention than large deviation from normal. In turn, when potential viewers tend to be Democrats, temperatures far away from the norm receive way more coverage than those who fall within the normal ranges. As such, if one associates severe events with climate change stories, our results imply that Republicans tend to receive less information on the topic from their local TV stations than Democrats do. To show evidence consistent with this interpretation, we complement the analysis above by looking at the slant of newscast as a function of the weather events that day.

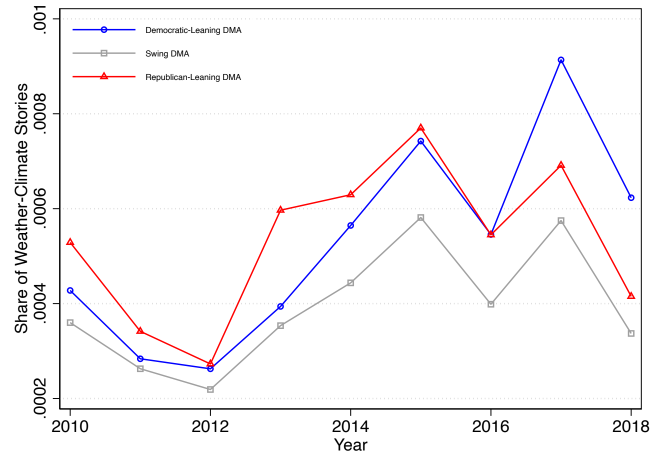
3.3 Presentation Bias

In this section we study how local newscasts present weather news, by looking specifically at the mention of terms related to climate change. To identify climate change-related phrases in our transcripts, we use a dictionary of terms suggested by Chat GPT. The terms we employ are "global warming, greenhouse gases, carbon emissions, climate crisis, climate mitigation, climate variability,

Figure 6: Coverage of Climate Change Over Time



(a) Climate Change Coverage in Weather News



(b) Climate Change Coverage in Local Weather News

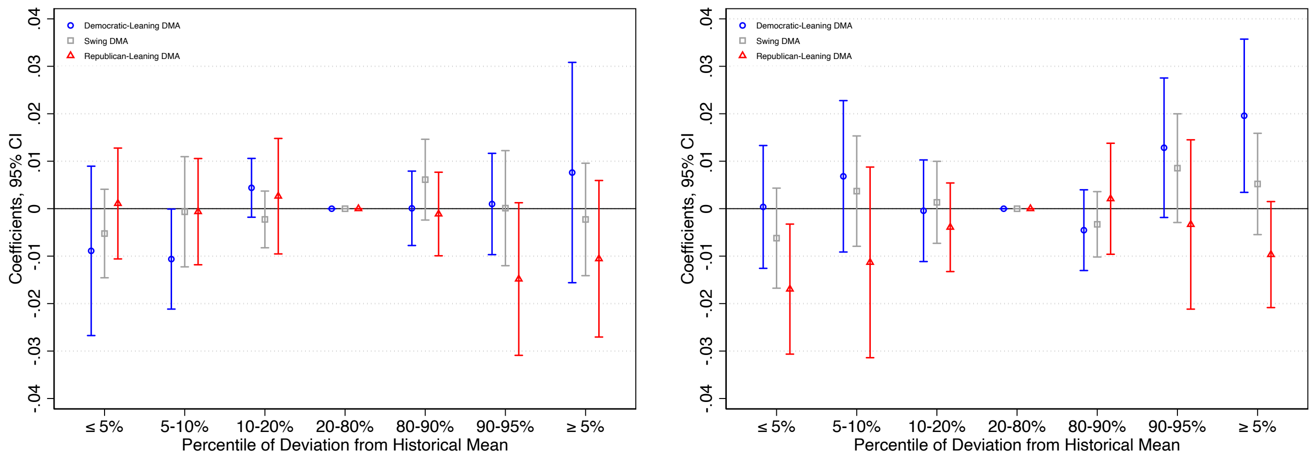
Notes: This figure shows the evolution over time in the share of segments mentioning climate change and weather terms (panel (a)) and in the share of segments mentioning climate change and local weather (panel (b)). Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two.

climate extremes, climate denial, climate action, sustainability, renewable energy, deforestation, climate refugees, sea level rise, ocean acidification, weather patterns, climate engineering, climate justice, climate policy, climate change." We define a 150-word segment as connecting local weather and climate change if it contains (i) a weather term, (ii) a locality in the media market, and (iii) a term or phrase from our climate change dictionary.[5]

In Figure 6, we display the amount of climate change coverage over time, looking at any segment mentioning climate change (panel (a)) and segments that also mention local weather event (panel (b)). We observe similar trends between all types of markets until 2014 for the coverage of climate change coupled with all weather news and until 2016 for the coverage of climate change in local weather news. At that time, local TV stations in Democratic-leaning markets tend to diverge and report more about climate change than their counterparts in other markets. Of course, the very low share of segments about climate change and weather means that these results should be interpreted with caution. Yet, they provide suggestive evidence that news channels make different choices when it comes not just how much coverage they give to weather news, but also how they cover weather news.

[5]Our findings are substantially unchanged if we only look at segments containing weather and climate change terms (i.e., dropping the local requirement) or just climate change terms. Results are available upon request.

Figure 7: Presentation Bias



(a) Minimum Temperatures in Winter (b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between weather events and coverage of climate change in news about weather, by media market ideology. In particular, we regress an indicator variable equal to one if there is at least one segment about local weather that mentions climate change on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, ≥95. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

We complement these descriptive patterns by running the same regression as for coverage by media market ideology (Equation 2), but replacing the share of local weather news with an indicator variable equal to one if there is at least one segment about local weather that mentions climate change as our dependent variable. Our choice of an indicator variable over the share of segments is due to the low frequency of newscasts covering climate change in our sample, but we show that our results remain unchanged when we use share of segments as our dependent variable in Online Appendix D. For the same reason, we combine extreme weather events into a single category (i.e., we group the bottom—1% and 1-5% bins—and top—top 1% and 95%-99% bins). The results are displayed in Figure 7.

In winter, stations in Democratic-leaning media markets are slightly less likely to mention climate change when temperatures are below the norm than when they fall into our baseline category, although the estimates are not significant when we look at share of segments. There is limited variation in reporting as far as Republican-leaning markets are concerned. The patterns are very different when we look at maximum temperature in summer. There, we observe significantly more coverage of climate change in local weather news during large positive deviations from the norm in Democratic-leaning media markets than in Republican-leaning media markets. Indeed, TV stations with a Democratic audience increase their mentions of climate change when temperatures are much hotter than normal. While the coefficient is small (0.02), the effect is very large relative to the mean of climate change segments in local TV news in these markets: +31.25%. In contrast, TV stations with Republican audience appear to decrease their use of climate change-related terms (by 18.2% relative to the mean, though the estimates are only significant at 10% level, p-value is 0.089). While these findings need to be taken with caution given the low frequency of climate change segments, they are at least indicative that publication bias and presentation bias seem to go in the same direction when it comes to weather news.

Overall, our empirical analysis reveals several important findings. The reporting of TV local news exhibit a man bites dog pattern: severe events receive more attention than any other type of events. Yet, even moderately atypical temperatures may receive substantially more coverage than normal weather patterns (Figure 3). We also document the existence of a publication bias in the coverage of weather news, which are a priori non political. Local TV stations' editorial strategy differ with the ideology of the audience. Democratic audiences tend to see more news about temperatures deviating from the seasonal norms than Republican ones, whereas Republican audiences are more exposed than Democratic ones to weather news when climate events fall within a normal range (Figure 4). This means that TV stations operating in Democratic-dominated markets increase their coverage of weather news more following below the mean deviations in winter and above the mean deviations in summer than TV stations in Republican-dominated markets (Figure 5). This publication bias goes hand-in-hand with presentation bias, at least in summer. Then, Democratic viewers see more mentions of climate change when temperatures are abnormally high, whereas Republican viewers tend to see less of it (Figure 7). How can we make sense of all these results? In the next section, we show that a formal model of demand-driven news production is able to match many of the empirical patterns we have uncovered.

4 A Demand-driven Model of Publication Bias

4.1 Model Setup

In our baseline model, we consider a game with one media outlet M and a mass of citizens of size one divided into two groups, $J \in \{D, R\}$. Group D consists of Democratic voters (which constitute a proportion α of the population), Group R consists of Republican voters (a proportion $1 - \alpha$).

Each citizen decides whether to watch the outlet. The outlet is profit-motivated and decides an editorial strategy so as to maximize viewership (we suppose there is a positive relationship between profits and audience size). An editorial strategy consists in deciding the amount of time devoted to local weather news, denoted w, over other news, denoted n. We normalise the time available in the newscast to one so that $n + w = 1$.

The utility of consuming the newscast for potential viewers depends on two components. First, the amount of reporting on each type of news captured by the functions $g(n)$ and $h(w)$, which are strictly increasing and strictly concave 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 $\underline{u}$. For weather news, the value of the news depends on the weather event that day in two ways: (a) the consumption value of the event and (ii) what viewers can learn from it.

More precisely, we capture a weather event as a random variable c drawn from the interval $[0, 1]$. 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), 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: $Pr(\omega = 1) = \pi \in (0, 1)$.[6] As such, we believe that 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 satisfying $f'_\omega(\cdot) < 0$ so that events furthest away from zero are rare events. We also assume that large weather events c are relatively more frequent when the realisation of the state is $\omega = 1$. More specifically, 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 $c > c'$. This means that citizens can learn from a news report on weather events and we denote $\mu(c)$ the posterior that climate change is real following weather event c: $\mu(c) = Pr(\omega = 1|c)$.

We assume that the value of weather news for a viewer from group $J \in \{D, R\}$ is: $v(c) + z_J(\mu(c))$. The function $v(c)$ captures the entertainment benefit of watching news about weather events. We assume $v(c)$ is strictly increasing in c so that citizens prefer to watch news reports about extreme, rare weather events than common weather events. This can correspond to the

[6]Notice that this is the prior of the population, the relevant one for our purpose, which can differ from the prior in the scientific community.

idea that citizens like surprise as in Ely et al. (2015), though we recognize we model the value of surprise very differently. The second function $z_J(\mu(c))$ captures the cost or benefit of learning. We assume that citizens suffer from a form of confirmation bias. We represent this by assuming that $z_J(\pi) = 0$ for $J \in \{D, R\}$ (a normalisation) and for Democratic citizens, $z_D(\mu(c))$ is strictly increasing with its argument, whereas for Republican citizens $z_R(\mu(c))$ is strictly decreasing with its argument.

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

$$\overbrace{h(w)}^{\text{Value of time on weather news}} \times \underbrace{\big(v(c) + z_J(\mu(c))\big)}_{\text{Comsumption value of weather news}} + \overbrace{g(n)}^{\text{Value of time on other news}} \times \underbrace{\underline{u}}_{\text{Consumption value of other news}} \tag{3}$$

In the main text, we assume that $h(w) = w^\rho$ with $0 < \rho < 1$ and $g(n) = n$ so that other news play the same role as a numeraire good in utility maximisation problems. In Online Appendix F, we show that all our results hold with more general functional forms (one result requires $g'(1 - w)/h'(w)$ to be not too concave, a condition we formalise in the appendix). We also assume that $\max\{v(0) + z_R(\mu(0)), v(1) + z_D(\mu(1))\} < \underline{u} \leq 1$, a condition that guarantees interior solutions and avoids dealing with too many (substantively uninteresting) cases.

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).

With this in mind, we can define outlet M's editorial strategy. An editorial strategy is a mapping from $c \in [0, 1]$ to time spent on weather news $w \in [0, 1]$: $w : [0, 1] \to [0, 1]$ (with $n(c) = 1 - w(c)$).

The game, in turn, proceeds as follows:

0. Nature draws the state of the world $\omega \in \{0, 1\}$.
1. The outlet announces an editorial strategy: $w : [0, 1] \to [0, 1]$.
2. Weather event c is drawn by Nature and observed by M.
3. The outlet allocates time $w(c)$ to weather news (covering c) and time $n(c)$ to other news, with $w(c) + n(c) = 1$. 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 Subgame Perfect Equilibrium.

Before proceeding to the analysis, a few remarks are in order. The model assumes that large, unexpected events are more newsworthy than small events. Citizens are more interested in large terrorist attacks than in small ones, the audience care more about big games (e.g., Superbowl, World Cup finals) than the weekend routine ones. We believe the same holds true for weather news. Citizens are more interested in severe weather events. As such, building on previous works (e.g., DellaVigna and La Ferrara, 2015; Durante, Pinotti, and Tesei, 2019), our model assumes that citizens consume the outlet, and even news, primarily for entertainment value.

Further, our set-up also 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 (though, beyond the differences in payoffs, all citizens are fully rational). Republicans, who tend to deny climate changes as we show in Online Appendix C, suffer a loss when the evidence goes against their belief. This approach captures the idea that "[d]enialism is motivated by conviction rather than evidence" (Kemp, Milne, and Reay, 2010) and the evidence that deniers simply reject arguments in favour of climate change (Washington, 2011). Our model is, thus, not unique in creating variation in demands for weather-related news, but it takes seriously the notion that climate change denial as well as faith in climate change is a form of ideology.

Another payoff assumption worth commenting 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 assumption that a citizen observes nothing if she does not consume the news is only to simplify the exposition. The important assumption is that there are an entertainment value and a learning value of watching weather news relative to not watching a local TV newscast. A citizen can see that today is a hot day, but she is unable to fully make sense of how hot it is relative to the norms 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.

We also assume that an outlet cannot commit to an editorial strategy. An editorial strategy is not a contract between citizens and the outlet (who could enforce it?). Rather, an editorial strategy is a form of advertising or corresponds to the identity of the media outlet. The impossibility to commit does not play any role for the baseline, demand-driven model, but is important when we look at an alternative supply-driven model of publication bias in one of the extensions below.

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. In this baseline model, we see 0 as no deviation and any positive number as deviations below the mean in winter and above the mean in summer. In an extension, we also consider that $\tilde{c}$ can take both positive and negative values. In turn, the choice variable $w(c)$ corresponds to the space devoted to the weather event in the newscast. It is a close theoretical correspondent to the share of segments mentioning local weather event, our dependent variable in the empirical analyses.

4.2 Formal Results

We start with the demand for weather news from citizens. To compute it, 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:

$$\mu(c) = \frac{1}{1 + \frac{1-\pi}{\pi}\frac{f_0(c)}{f_1(c)}} \tag{4}$$

Under the assumption of MLRP, the posterior is strictly increasing with c. It will prove useful in what follows to define the following quantity. Denote $c^0 \in [0,1]$ as the unique solution to $f_0(c) = f_1(c)$. Note that for all $c < c^0$, $\mu(c) < \pi$, whereas $\mu(c) > \pi$ for all $c > c^0$.

Given an editorial strategy $(w(c))_{\{c\in[0,1]\}}$, citizens can compute their expected utility from consuming the outlet's news combining Equation 3 and Equation 4 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, denoted $F^e(\tilde{c}) = \pi F_1(\tilde{c}) + (1-\pi)F_0(\tilde{c})$ to compute their expected utility from turning on the news. For a citizen from group $J \in \{D, R\}$, we obtain:

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

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: $P_J = \frac{1}{\overline{\delta}} \int_0^1 h(w(\tilde{c}))\big(v(\tilde{c}) + z_J(\mu(\tilde{c}))\big) + g(1 - w(\tilde{c}))\underline{u}\; dF^e(\tilde{c})$.

From this, we can easily define the total demand for M's newscast as a function of its editorial strategy. It is simply:

$$\frac{1}{\overline{\delta}} \int_0^1 h(w(\tilde{c}))\big(v(\tilde{c}) + \alpha z_D(\mu(\tilde{c})) + (1-\alpha) z_R(\mu(\tilde{c}))\big) + g(1 - w(\tilde{c}))\underline{u}\; dF^e(\tilde{c})$$

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.

Proposition 1. *Media outlet M's editorial strategy is a function defined for all* $c \in [0, 1]$ *by:*

$$w^*(c; \alpha) = \left(\rho \frac{v(c) + \alpha z_D(\mu(c)) + (1-\alpha) z_R(\mu(c))}{\underline{u}}\right)^{\frac{1}{1-\rho}} \tag{5}$$

With this result in hand, we can study both across media markets (varying the α) and within media market (varying the weather event c) dynamics. Recall that c^0 satisfies $f_1(c^0) = f_0(c^0)$. The next proposition describes how reporting differs in Democratic-leaning media market versus Republican-leading media market.

Proposition 2. *Suppose* $\alpha^d > \alpha^r$*, then:*

- *For all* $c < c^0$*,* $w^*(c; \alpha^d) < w^*(c; \alpha^r)$*;*
- *For* $c = c^0$*,* $w^*(c; \alpha^d) = w^*(c; \alpha^r)$*;*
- *For all* $c > c^0$*,* $w^*(c; \alpha^d) > w^*(c; \alpha^r)$*;*

Proposition 2 states that for relatively low weather events ($c < c^0$) a media outlet allocates more time of its newscast to weather news when the share of Republicans among potential viewers is high ($\alpha = \alpha^r$) than when it is low ($\alpha = \alpha^d$). The reverse is true for relatively extreme weather events ($c > c^0$). This result follows from the combinations of three assumptions. First, we have assumed that the distribution of weather events satisfy MLRP so that the posterior is strictly increasing in c. Second, we have assumed that citizens suffer from confirmation bias (our $z_J(\cdot)$ functions). Lastly, the learning (dis)utility for citizen from the Republican and Democratic groups cross at some posterior, which (for simplicity, but without loss of generality) we have assumed to be equal to the prior. As a result, for every $c > c^0$, $z_D(\mu(c)) > z_R(\mu(c))$, and Democratic citizens have a greater demand for weather news than Republicans. The media outlet then covers more weather news in media markets with larger share of Democratic potential viewers. In contrast, every $c < c^0$ comes along with greater demand from Republican citizens for weather news compared to Democratic citizens, and we observe more reporting in Republican-dominated media markets.

The patterns described in Proposition 2 are consistent with the empirical across market variations displayed in Figure 4. Both in Figure 4a and Figure 4b, we document that for intermediate weather events (in the 20%-80% bin), media outlets in Republican-leaning markets tend to report more about the weather than outlets in Democratic-leaning markets. For large events, in the bottom 10% for winter and in the top 5% for summer, the reverse holds true. We observe more weather reporting in media markets with a large share of Democrats than in media markets with a low share of Democrats.

Proposition 2 is also useful to contrast our results with an alternative model of demand-driven reporting. One could have assumed instead that Democrats have a greater demand for weather-related news. For example, the demand for news is $v(c)$ for Democratic citizens and $\gamma v(c)$ for Republicans with $0 < \gamma < 1$ (other formulations are obviously possible). In this alternative set-up, a media outlet in a Democratic-leaning media market would always (i.e., for all c) cover weather events more than an outlet located in a Republican-leaning media market. As mentioned above, this is not what we observe in the data.

We now consider within media market variations and how they differ between Democratic-dominated and Republican-dominated media markets. To match our empirical result, we compare the average reporting for weather event close to the seasonal norms—denoted by $c \leq c^{ref}$—with the reporting of more uncommon events—denoted by $c \geq \bar{c}$. The difference in the average amount of time on weather news in the newscast takes value: $\Delta(c^{ref}, \bar{c}; \alpha) = E\big(w^*(c;\alpha)|c \geq \bar{c}\big) - E\big(w^*(c;\alpha)|c \leq c^{ref}\big)$. We focus on the case when $\bar{c} \geq c^0$. This is consistent with Proposition 2 and our finding that outlets in Democratic-leaning market generally cover weather events more than outlets in Republican-leaning markets for the events we consider. We obtain:

Proposition 3. *Suppose* $\bar{c} \geq c^0$ *and* $\alpha^d > \alpha^r$ *with* $v'(c) + \mu'(c)(\alpha^d z'_D(\mu(c)) + (1-\alpha^d) z'_R(\mu(c))) > 0$ *for all* $c \in [c^0, 1]$, *then*

- $\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) > 0$
- $\dfrac{\partial\big(\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r)\big)}{\partial \bar{c}} > 0$

The proposition makes two points. First, it states that the within market differences in reporting of typical versus atypical weather events are greater for Democratic-leaning media markets than for Republican-leaning ones. We already know from Proposition 2 that $E\big(w^*(c;\alpha^d)|c \geq \bar{c}\big) > E\big(w^*(c;\alpha^r)|c \geq \bar{c}\big)$. If $c^{ref} \leq c^0$, Proposition 2 also indicates that $E\big(w^*(c;\alpha^d)|c \leq c^{ref}\big) < E\big(w^*(c;\alpha^r)|c \leq c^{ref}\big)$. Hence, the result is immediate when $c^{ref} \leq c^0$. One issue we face is that we cannot guarantee that this condition holds. When $c^{ref} > c^0$, the condition $E\big(w^*(c;\alpha^d)|c \leq c^{ref}\big) < E\big(w^*(c;\alpha^r)|c \leq c^{ref}\big)$ does not necessarily hold and proving the first point of Proposition 3 requires some additional work. A sufficient condition is that the amount of weather reporting increases faster with the severity of the event in places with large fraction of Democrats than in markets with high proportion of Republicans (in formal terms, $\frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} > 0$ for $c > c^0$). In this case, even if $E\big(w^*(c;\alpha^d)|c \leq c^{ref}\big) - E\big(w^*(c;\alpha^r)|c \leq c^{ref}\big) > 0$, we also get $E\big(w^*(c;\alpha^d)|c \geq \bar{c}\big) - E\big(w^*(c;\alpha^r)|c \geq \bar{c}\big) > E\big(w^*(c;\alpha^d)|c \leq c^{ref}\big) - E\big(w^*(c;\alpha^r)|c \leq c^{ref}\big)$ and, therefore, $\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) > 0$. This sufficient condition is met thanks to our functional form assumptions for $h(\cdot)$ and $g(\cdot)$ (we also establish a more general condition in Online Appendix F). This same sufficient condition directly implies the second point of Proposition 3. Fixing the reference category, we obtain bigger changes in reporting in Democratic-leaning markets since outlets there expand the time devoted to weather news at a faster rate than outlets in Republican-leaning markets, as c increases.

Proposition 3 provides a rationale for the greater increase in coverage (relative to the baseline) we observe in Democratic-dominated markets compared to Republican-leaning markets when the weather event is large (Figure 5). This differential effect is driven by the learning component in our model. Republican citizens are less interested in weather stories about severe events because those events force them to change their views in ways that run counter to their ideology. The same logic can also explain why temperature deviations that fall in the top 1% of the distribution, and so should be very newsworthy, can receive less (or at least not more) coverage than smaller events (see Figure 5b).

Corollary 1 documents conditions such that an increase in the severity of an event can lead to a drop in the coverage of weather news. These conditions are quite intuitive. For Republicans, the loss from learning must be sufficiently high to compensate for the gain from surprise. Further, the proportion of Republican citizens in the media market needs to be large enough.

Corollary 1. *Suppose that there exists $c^R_- \in (0,1)$ such that $v'(c) + \mu'(c) z'_R(\mu(c)) \in (-\infty, 0)$ if and only if $c > c^R_-$.*

- *There exists $\alpha^a_- \in (0,1)$ such that for all $\alpha > \alpha^a_-$ and all $\bar{c} \geq c^0$, $\frac{\partial \Delta(c^{ref}, \bar{c}; \alpha)}{\partial \bar{c}} > 0$.*

- *For all $\bar{c}_- \in (c_-^R, 1)$, there exists $\alpha_-^b(\bar{c}_-) \in (0,1)$ such that for all $\alpha < \alpha_-^b(\bar{c}_-)$ and $\bar{c} > \bar{c}_-$, $\frac{\partial \Delta(c^{ref}, \bar{c}; \alpha)}{\partial \bar{c}} < 0$.*

The main interest of Corollary 1 may actually be to illustrate once more the differences between a model with confirmation bias and a model with differential demands for weather news. In the latter, there is always more reporting of larger weather events (under our assumption that citizens like to learn about unexpected events) so that the difference $\Delta(c^{ref}, \bar{c}; \alpha)$ is strictly increasing for all α. In a model with confirmation bias, this is not always guaranteed. As such, a model with differential demands fails to explain some of the patterns in Figure 4 (i.e., the higher coverage of weather news for low shocks in Republican-dominated markets than in Democratic-dominated markets with the reverse being true for low shocks) and in Figure 5b (the lack of increase in coverage within Republican-dominated markets for extreme shocks). In what follows, we extend our baseline model with confirmation bias to offer a possible theoretical explanation for some of the other empirical patterns we have documented above.

4.3 Model Extensions

In this section, we present three extensions. We first look at the case when some shocks are more informative than others. We then consider the possibility of slanting news by increasing the salience of the learning component of viewers' weather news utility. We finally compare the results arising from a demand-driven model with those obtained using a *pure* supply-driven approach.

Different Shocks

We extend the model to assume that the distribution of events is now $\tilde{c} \in [-1, 1]$. We further impose that $f_\omega(c)$ is continuously differentiable on $[-1, 1]$, strictly increasing in $[-1, 0)$ and remains strictly decreasing in $(0, 1]$. That is, weather events close to the (lower and upper) bounds of the distribution are rare events. As a result, we naturally suppose that the consumption value of weather event c is $v(|c|)$ strictly increasing in its argument (i.e., viewers still like surprises). We let the distribution satisfies the MLRP on both sides of 0: $\frac{f_1(c)}{f_0(c)} > \frac{f_1(c')}{f_0(c')}$ for all $c > c' \geq 0$ and for all $c < c' \leq 0$. We, however, assume that negative shocks are less informative than positive ones. That is, we suppose that for all $c \in (0, 1)$, $\frac{\partial \frac{f_1(c)}{f_0(c)}}{\partial c} > \frac{\partial \frac{f_1(-c)}{f_0(-c)}}{\partial (-c)}$. This assumption is somewhat adapted to temperatures lower than the mean in summer. Indeed, climate change is often associated with global *warming* in the media and popular culture (e.g., recent talks about the era of "global boiling", Guardian, 27 July 2023), rather than with greater volatility in climate as it appears to be the consensus now.

We slightly adjust our definitions of within market effect to take into account the fact that shocks can now take negative values. We denote $\Delta^+(c^{ref}, \bar{c}; \alpha) = E\big(w^*(c;\alpha)|c \geq \bar{c}\big) - E\big(w^*(c;\alpha)| - c^{ref} \leq c \leq c^{ref}\big)$ and $\Delta^-(c^{ref}, \bar{c}; \alpha) = E\big(w^*(c;\alpha)|c \leq \bar{c}\big) - E\big(w^*(c;\alpha)| - c^{ref} \leq c \leq c^{ref}\big)$. Using these new definitions and the assumptions above, we obtain the following results:

Proposition 4. *There exist* $0 < \underline{\alpha} < \overline{\alpha} < 1$ *and a unique* $c^1 \in (-1, 0)$ *such that for all* $\alpha^r < \underline{\alpha}$ *and* $\overline{\alpha} < \alpha^d$*,*

- *For all* $c \in (0, 1)$*,* $w^*(c; \alpha^d) > w^*(-c; \alpha^d)$ *and* $w^*(c; \alpha^r) < w^*(-c : \alpha^r)$*;*
- *For all* $\bar{c} \geq -c^1$ *and* $c^{ref} \in (0, \bar{c})$*,* $\Delta^+(c^{ref}, \bar{c}; \alpha^d) > \Delta^-(c^{ref}, -\bar{c}; \alpha^d)$ *and* $\Delta^+(c^{ref}, \bar{c}; \alpha^r) < \Delta^-(c^{ref}, -\bar{c}; \alpha^r)$*.*

The proposition uses a few additional conditions. First, we focus on dominant Republican media markets so that $\alpha^r v_R(\mu(c)) + (1-\alpha^r)v_D(\mu(c))$ is decreasing (increasing) for all $c \in [0, 1]$ ($c \in [-1, 0]$)—guaranteed by $\alpha^r < \underline{\alpha}$—and dominant Democratic media markets so that $\alpha^d v_R(\mu(c)) + (1 - \alpha^d)v_D(\mu(c))$ is increasing (decreasing) for all $c \in [0, 1]$ ($c \in [-1, 0]$)—guaranteed by $\alpha^d > \overline{\alpha}$. Second, we look at cases when even a negative shock increases learning about climate change. This is guaranteed by assuming that $\bar{c} > c^1$ in the second point of the proposition, with c^1 defined as the unique solution to $f_0(c) = f_1(c)$ in the interval $[-1, 0]$. It can be verified that $|c^1| > c^0$.

If one assumes that temperatures below the mean are less informative than temperatures above the mean in summer (an assumption we cannot test directly), then Proposition 4 helps to rationalise some of our additional empirical results. It explains why in Democratic-leaning media markets, outlets expand their coverage of weather news more for above the mean deviations than for below the mean deviations, whereas we observe a more similar pattern in Republican-dominated media markets (Figure 4b). It also provides an explanation for why the amount of coverage of summer weather events is asymmetric between above and below mean deviations in Democratic-leaning media markets, whereas it appears much more symmetric in Republican-dominated regions (Figure 5b).[7]

[7] The attentive reader will note that we document the same level of within market changes below and above the mean in Republican-leaning market, rather than greater coverage for below the mean deviations. Of course, this pattern can also be explained by assuming that below-the-mean deviations are less newsworthy. In some sense, our model has too many degrees of freedom. This is why we focus on differences between Republican and Democratic media markets and we do not attempt to match every moment in the data.

For transparency, we note that the extension developed in this subsection fails to explain the patterns for deviations above the historical mean in winter (see Figure 5a). Indeed, one could argue that temperatures way above the norm are very much indicative of global warming as climate change is often understood and we should see a rise in reporting in Democratic-leaning markets as the severity of the shock increases according to the model. We document the contrary. As our model fails in that particular case, we make two conjectures. First, as the temperature is never that hot in winter, large positive deviations may not contain much information (this is consistent with the lack of increased in the mentions of climate change, see Figure 7a). Second, citizens may not care about this sort of deviations (this is consistent with the findings in Moore et al., 2019, discussed above).

Increasing the Salience of Learning

In this extension, we now return to weather events ranging from $[0,1]$ (for simplicity) and we assume instead that the media outlet can better connect weather events with climate change by slanting its reporting of weather news. We take a very reduced form approach to slant and assume that a media outlet can choose for each weather shock $\tilde{c}$ whether to emphasize the learning component in the viewers' utility functions. That is, we assume that the consumption value of a shock c is now $(1-\lambda(c))v(c) + (1+\lambda(c))z_J(\mu(c))$ with $\lambda(c) \in \{0, \underline{\lambda}\}$ a choice of the outlet itself. We obviously impose $\underline{\lambda} < 1$ so that the two components of utility always receive positive weight.

We obtain not surprisingly that outlets insist differently on climate change in media markets with a strong Republican dominance ($\alpha^r < \underline{\alpha}$) or a strong Democratic dominance ($\alpha^d > \overline{\alpha}$). In the first, an outlet would stress learning only if the weather event is low. In the second, an outlet would stress learning only if the weather event is high (assuming the marginal benefit from entertainment is low enough for high weather shocks, a condition formalised in the text of the proposition below).

Proposition 5. *Suppose $\mu'(c)z'_D(\mu(c)) > v'(c)$ if and only if $c \geq c^0$. Then there exist $0 < \underline{\alpha} < \overline{\alpha} < 1$ such that*

- *For all $\alpha^r < \underline{\alpha}$, there exists a unique $c^r \in [0, c^0)$ (possibly a corner solution), such that the slanting strategy of the media outlet satisfies $\lambda^*(c;\alpha^r) = \underline{\lambda}$ if and only if $c < c^r$;*
- *For all $\alpha^d > \overline{\alpha}$, there exists a unique $c^d \in (c^0, 1]$ (possibly a corner solution), such that the slanting strategy of the media outlet satisfies $\lambda^*(c;\alpha^d) = \underline{\lambda}$ if and only if $c > c^d$.*

In terms of within market predictions, this means that we should observe greater insistence on climate change (in negative terms) when the event is low compare to high in Republican media market, whereas the reverse is true (including the tone) in Democratic-leaning ones. Our empirical observations partially meet these theoretical implications. In summer, outlets operating in Democratic-dominated media markets tend to highlight the importance of climate change for deviations way above the mean (top 5%). In contrast, outlets in Republican-dominated markets de-emphasize it for large deviations both below and above the mean, though for the latter the coefficients are only significant at 10% (Figure 7b). We do not observe similar patterns in Winter (Figure 7a, which may be do in part to the words used to identify climate change segments, see Section 3.3 for more details).

A Pure Supply Driven Model of News

In this last "extension," we change perspective and consider how reporting would look like if the media outlet's objective was to move individuals' beliefs in its preferred direction. We consider two types of outlets: sceptical outlets (type $\tau = s$) and believer outlets (type $\tau = b$). Sceptical outlets want to minimize the belief in climate change in the population in their media market, believer outlets want to maximize the same belief.

Recall that the *proportion* of individuals from group $J \in \{D, R\}$ who watch the outlet given its editorial strategy is: $P_J = \frac{1}{\delta} \int_0^1 h(w(\tilde{c}))\big(v(\tilde{c}) + z_J(\mu(\tilde{c}))\big) + g(1 - w(\tilde{c}))\underline{u}\ dF^e(\tilde{c})$. Non-viewers get no information so they do not get to update their belief relative to the prior. Viewers can change their opinion about climate change based on the reporting of the shock $r = c$ or the absence of reporting $r = \emptyset$ (i.e., when the editorial strategy implies $w(c) = 0$). The average population belief for each shock c is then:

$$\alpha(P_D\mu(r) + (1 - P_D)\pi) + (1 - \alpha)(P_R\mu(r) + (1 - P_R)\pi)$$

A sceptical outlet seeks to maximize $v^s(\alpha(P_D\mu(r) + (1 - P_D)\pi) + (1 - \alpha)(P_R\mu(r) + (1 - P_R)\pi))$ with $v^s(\cdot)$ strictly decreasing and concave. A believer media outlet seeks to maximize $v^b(\alpha(P_D\mu(r) + (1 - P_D)\pi) + (1 - \alpha)(P_R\mu(r) + (1 - P_R)\pi))$ with $v^b(\cdot)$ strictly increasing and concave. We suppose the two functions are $\mathcal{C}^\infty$. The outlet chooses how much to report weather event c in order to maximize its objective function. To make the maximization problem well-behaved, we assume that if the outlet decides to cover a weather event c ($w(c) > 0$), then there is a minimal amount of coverage required (i.e., $w(c) \geq \underline{w}$ with $\underline{w} > 0$ if $w(c) > 0$).

We focus on a sceptical outlet, with the reasoning for a believer outlet following along the same lines. We can think of this outlet's reporting choice and editorial strategy as a two-step problem. First, the outlet chooses whether to report weather news as a function of the realisation of the event c. Second, the outlet chooses how much to report conditional on having chosen to cover the weather event c.

Regarding the first step, it is clear that when $c \leq c^0$ (with c^0 the solution to $f_0(c) = f_1(c)$, you will recall), a sceptical outlet always reports the weather event since it reduces viewers' posteriors. What about when $c > c^0$? Is the outlet always avoiding weather news then ($w(c) = 0$ for all $c > c^0$)? The answer is no. Suppose no reporting was indeed the strategy of a sceptical outlet for $c > c^0$. Viewers would then form expectations $E(\mu(c)|c > c^0)$ after no news. By the properties of conditional expectations, $E(\mu(c)|c > c^0) > \mu(c_0)$. This means that for a weather shock close enough to c_0, for a fixed viewership, a sceptical media outlet would like to deviate and report the weather news. The same reasoning applies for any possible threshold strategy of the form 'the outlet does not report if $c > c^s$, with $c^s > c^0$.' Then again, when the realized weather event is close enough to c^s, the outlet would rather report it than hide it. This unravelling argument yields a unique outcome. The outlet always covers the weather event: $w(c) > 0$ for all $c \in [0, 1]$.

This leaves the amount of reporting as the unique possible margin of choice. The media outlet can either choose to maximize its audience or to minimize it. In our model, the concave shape of the sceptical outlet's objective function implies that it is always optimal to minimize viewership. Hence, when it reports, the sceptical outlet picks citizens' least preferred strategy. Under our assumption that weather news are worth less than other news for citizens, a sceptical outlet always devotes all its newscast to weather news. The actual result is less important than the observation that citizens decide whether to watch the outlet before knowing the value of the weather shock. In practice, it is as if this decision *pre-dates* the realisation of the event. Hence, the media outlet's decision of how much to report is not conditional on the value of c. We obtain the following results.

Proposition 6. *For all $\bar{c} \geq c^0$, within market changes satisfy $\Delta(c^{ref}, \bar{c}; \alpha) = 0$ for a sceptical outlet and $\Delta(c^{ref}, \bar{c}; \alpha) = 0$ for a believer outlet.*

A supply-driven approach in the context of our set-up fails to match any of the empirical patterns we document. Of course, the null effect from Proposition 6 is specific to some of our assumptions, especially the lack of commitment capacities by media outlets. However, even assuming media outlets can commit to threshold strategies (report weather news only if $c < c^s$ for a sceptical or only if $c > c^b$ for a believer outlet for some thresholds c^s and c^b) would not change our main conclusions. The amount of coverage would still be decided without conditioning on the realisation of the weather event. We would observe too little variation compared to what the data indicate and a decrease in coverage with the size of the weather shock within Republican-leaning media markets contrary to what we document (see Figures 4 and 5). This is not to say that supply forces do not matter. However, our theoretical results suggest that on their own, supply forces are unlikely to explain the patterns we have uncovered, whereas a demand-driven model can. As such, we believe that our empirical findings coupled with our theoretical results highlight the importance to look at demand-side factors to understand outlets' editorial strategies.

5 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, deviations in temperatures from historical means in summer and winter and how they compare to all experienced deviations. We document a clear "man bites dog" effect. Outlets cover significantly more severe weather events than typical ones. We also document that intermediary deviations are sometimes deemed newsworthy, hence providing a better understanding of the daily production of news. We also show presence of publication bias: the extent of the increase in reporting depends on the ideology of the markets outlets operate in. While weather news are not political, they are politicized by the local TV channels. Outlets located in Republican-leaning markets tend to cover severe weather events less than outlets facing many Democrats as potential viewers. Using a stylised set-up of news production and consumption, we show that a demand-driven model of media bias with confirmation bias is well adapted to explain the empirical patterns we uncover.

Our result have implications, we believe, for the way citizens perceive climate change. 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 do not have exogenous variation to exploit.

Yet, others have shown how biased reporting can affect beliefs, both theoretically (Anderson and McLaren, 2008; Wolton, 2019) and empirically (DellaVigna and Kaplan, 2007; Djourelova, 2023; Lajevardi, 2021, with special mentions for Djourelova et al., 2023 and Ash et al., 2023, who look at beliefs in climate change). Building on these works, our paper also 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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Online Appendix

(For online publication)

A Weather Dictionary (Baylis et al. (2019))

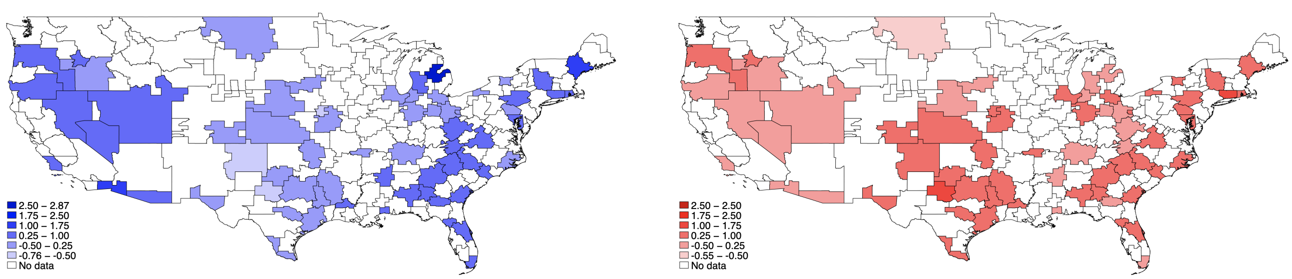
The dictionary we use to identify segments about weather includes to following words:

“aerovane air airstream altocumulus altostratus anemometer anemometers anticyclone anticyclones arctic arid aridity atmosphere atmospheric autumn autumnal balmy baroclinic barometer barometers barometric blizzard 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 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 meteorologists 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 stormier stormiest storming storms stormy stratocumulus stratus subtropical summer summery sun sunnier sunniest sunny temperate temperature tempest thaw thawed thawing thaws thermometer thunder thundered thundering thunders thunderstorm 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."

B Descriptive Statistics

Figure B.1 shows the average deviation for minimum temperatures in winter (panel (a)) and maximum temperature in summer (panel (b)) from the respective historical mean for the media markets included in our sample. Table B.1 shows descriptive statistics for coverage of weather news. Figure B.2 presents within station variation in coverage of local weather.

Figure B.1: Average Deviations by Media Market



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

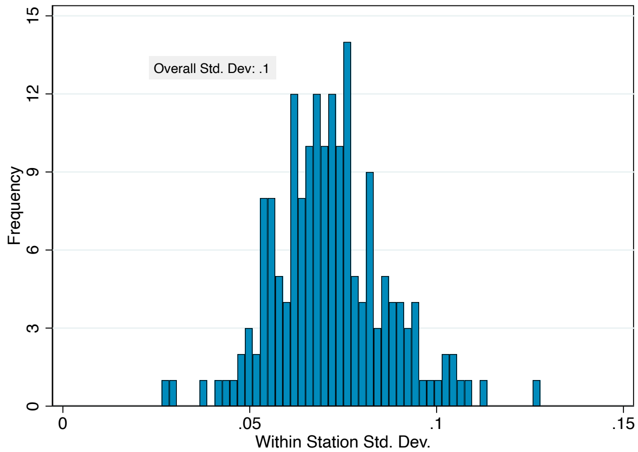
Notes: This figure shows the average deviation from the historical mean for minimum temperatures in winter (panel (a)) and for maximum temperatures in summer (panel (b)) for the 66 media markets included in our sample.

Table B.1: Descriptive Statistics

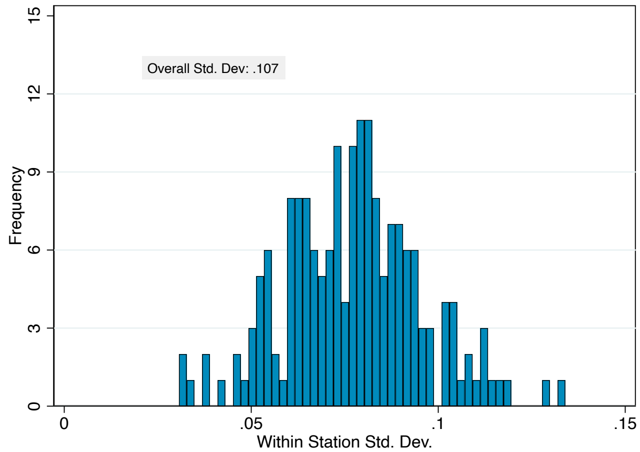
	Overall	Winter	Summer
All media markets			
# of local weather segments	39.668	40.175	40.623
Share of local weather segments	0.207	0.211	0.212
Share of local weather segments (20% - 80% temp. deviations)	-	0.204	0.206
Presence of local weather segment	0.987	0.986	0.987
# of local climate change segments	0.094	0.079	0.082
Share of local climate change segments	0.00048	0.00043	0.00042
Presence of local climate change segment	0.0615	0.0549	0.0571
Democratic-leaning media markets			
# of local weather segments	41.711	42.819	42.476
Share of local weather segments	0.203	0.210	0.208
Share of local weather segments (20% - 80% temp. deviations)	-	0.198	0.201
Presence of local weather segment	0.991	0.990	0.991
# of local climate change segments	0.115	0.091	0.096
Share of local climate change segments	0.00055	0.00043	0.00046
Presence of local climate change segment	0.071	0.062	0.064
Republican-leaning media markets			
# of local weather segments	35.930	35.500	37.096
Share of local weather segments	0.219	0.219	0.226
Share of local weather segments (20% - 80% temp. deviations)	-	0.219	0.221
Presence of local weather segment	0.989	0.987	0.990
# of local climate change segments	0.097	0.092	0.081
Share of local climate change segments	0.00057	0.00058	0.00048
Presence of local climate change segment	0.061	0.059	0.055

Notes: This table shows descriptive statistics for coverage of weather news. In particular, we report the mean of different measures of coverage of weather by period (overall, winter, and summer) and by media market type (all, Democratic-leaning, and Republican-leaning). The number of local weather segments is the number of 150-word segments that mention a weather word and the name of a county of municipality in the media market. Local climate change segments are segments that mention a climate-change related word and the name of county of municipality in the media market.

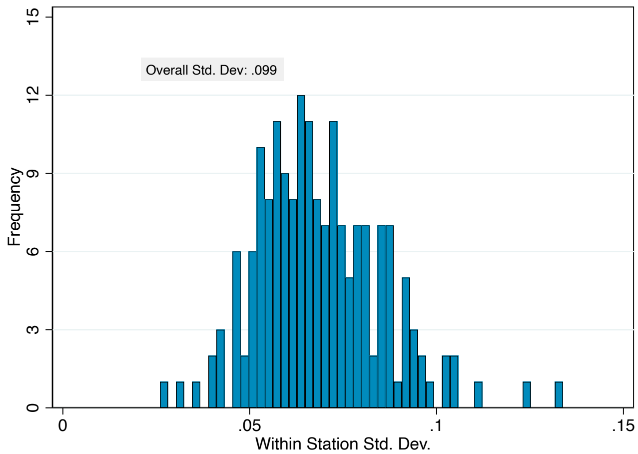
Figure B.2: Within Station Variation in Coverage of Local Weather



(a) All seasons



(b) Winter



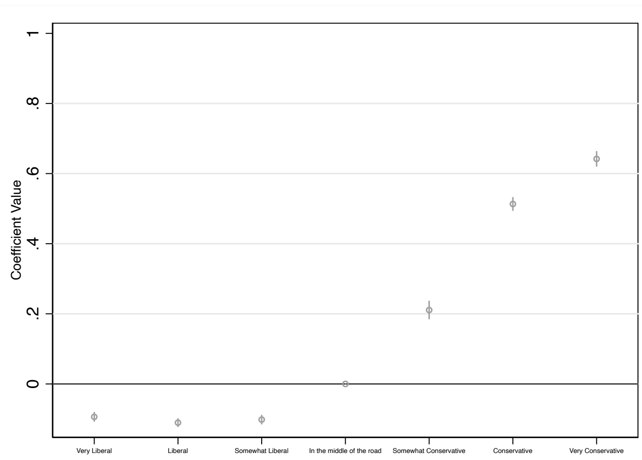
(c) Summer

Notes: These figures show the distribution of the within station standard deviation of coverage of local weather (namely, of the share of segments about local weather) for all seasons (panel (a)), winter (panel (b)), and summer (panel (c)).

C Ideological Leaning and Climate Denial

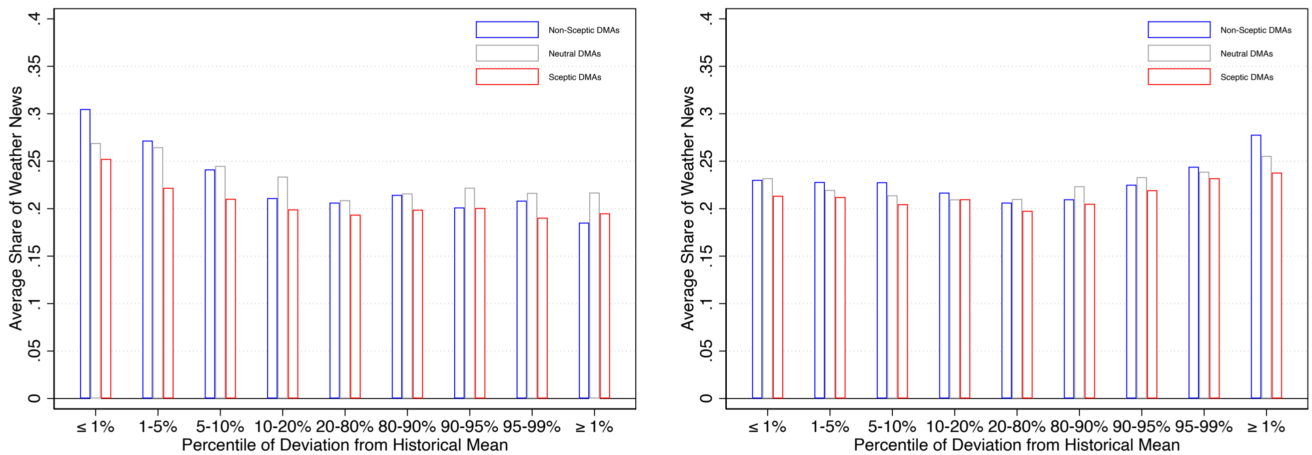
In this section, we show results from Equation 2 separating media markets according to the share of respondents sceptical of climate change in CCES. Sceptic media markets are media markets with share sceptical of climate change in the top 25% of the media market distribution, non-sceptical media markets in the bottom 25%, and neutral media markets in-between the two. We construct the share of respondents sceptical of climate change using the question “From what you know about global climate change, which one of the following statements comes closest to your opinion?” which was asked in 2006, 2007 and 2008 (before our analysis starts). We define a respondent as being sceptical of climate change if they answer “Concern about global climate change is exaggerated. No action is necessary” or “Global climate change is not occurring; this is not a real issue.” Everyone else is coded as non-sceptical. Additionally, Figure C.1 illustrates the relationship between climate change scepticism, discussed as the aforementioned question, and individual ideological leanings, using CCES waves from 2010 to 2013. As it is possible to see, there is a clear positive relationship between individuals identifying as climate change sceptics and those aligning with conservative ideologies.

Figure C.1: Ideology and Climate Change Scepticism



Notes: This figure shows the the relationship between climate scepticism and self-reported ideology. We regress an indicator variable equal to one if the respondent is sceptical of climate on indicator variables for different self-reported ideology, individual-level controls (age, education, income, race, and marital status), county fixed effects, and and time fixed effects. A responded is considered sceptical of climate change if they answered “Concern about global climate change is exaggerated. No action is necessary” or “Global climate change is not occurring; this is not a real issue,” to the question “From what you know about global climate change, which one of the following statements comes closest to your opinion?” in the 2010 to 2013 waves of CCES. Standard errors are clustered at the county level.

Figure C.2: Mean Coverage of Local Weather [Climate Change Scepticism]

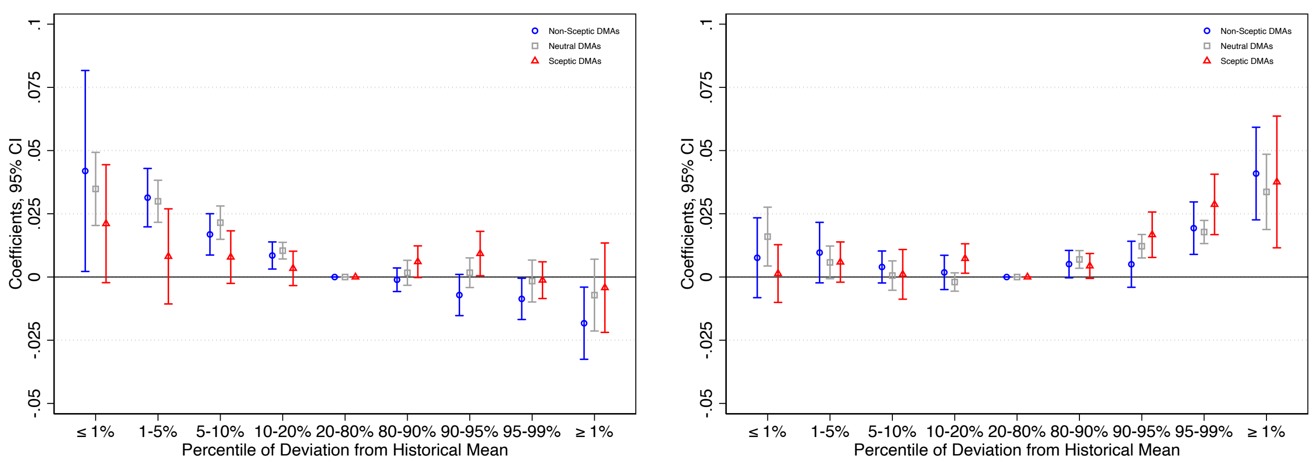


(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows mean coverage of local weather, by weather event and media market scepticism to climate change. We define coverage of local weather as the share of segments about local weather in a given day. Weather events are deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) that fall in a given bin of the national deviation distribution. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. Sceptic media markets are media markets with share of respondents sceptical of climate change in the top 25% of the distribution, non-sceptical media markets in the bottom 25%, and neutral media markets in-between in the two.

Figure C.3: Publication Bias [Climate Change Scepticism]

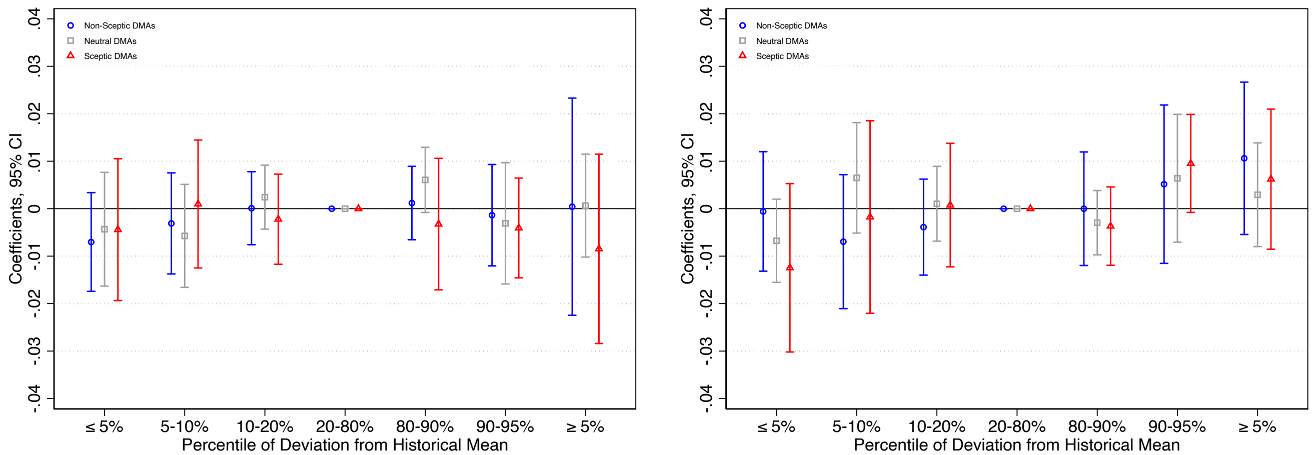


(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events, by media market climate change scepticism. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the level of climate change scepticism of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. The omitted category is the 20-80% bin. Sceptic media markets are media markets with share of respondents sceptical of climate change in the top 25% of the distribution, non-sceptical media markets in the bottom 25%, and neutral media markets in-between in the two. Standard errors are clustered at the media market level.

Figure C.4: Presentation Bias [Climate Change Scepticism]



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

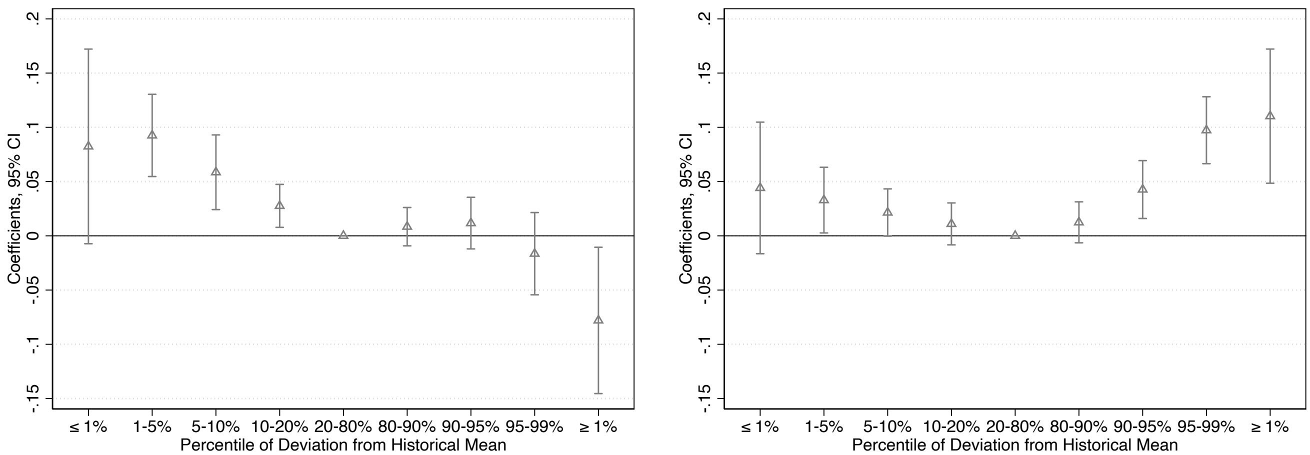
Notes: This figure shows the relationship between weather events and coverage of climate change in news about local weather, by media market climate change scepticism. In particular, we regress an indicator variable equal to one if there is at least one weather segment that mentions climate change on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the level of climate change scepticism of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. The omitted category is the 20-80% bin. Sceptic media markets are media markets with share of respondents sceptical of climate change in the top 25% of the distribution, non-sceptical media markets in the bottom 25%, and neutral media markets in-between in the two. Standard errors are clustered at the media market level.

D Robustness

Log+1 Segments about Local Weather

In this subsection, we reproduce Figures 3–5 using the log+1 of the number of segments about local weather (rather than the share of share of segments about local weather) as dependent variable.

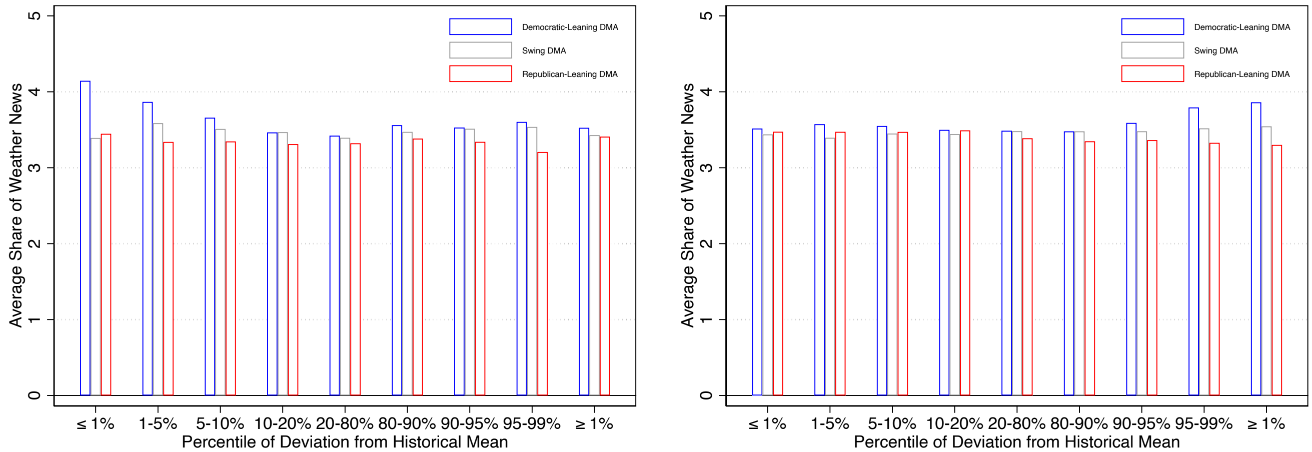
Figure D.1: Editorial Strategies [Log+1 Segments about Local Weather]



(a) Minimum Temperatures in Winter (b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events. In particular, we regress the log+1 of the number of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution, station fixed effects, and day fixed effects. We consider the following bins: ≤1%, 1%-5%, 5%-10%, 10%-20%, 20%-80%, 80%-90%, 90%-95%, 95%-99%, ≥99%. The omitted category is the 20%-80% bin. Standard errors are clustered at the media market level.

Figure D.2: Mean Coverage of Local Weather [Log+1 Segments about Local Weather]

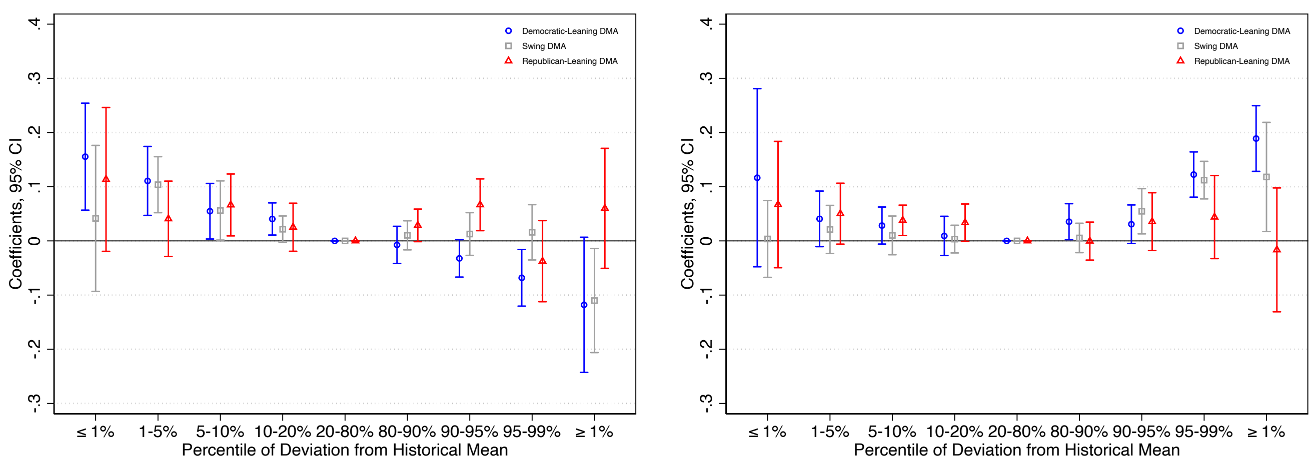


(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the mean coverage of local weather, by weather event and media market ideology. We define coverage of local weather as the log+1 of the number of segments about local weather in a given day. Weather events are deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) that fall in a given bin of the national deviation distribution. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two.

Figure D.3: Publication Bias [Log+1 Segments about Local Weather]



(a) Minimum Temperatures in Winter

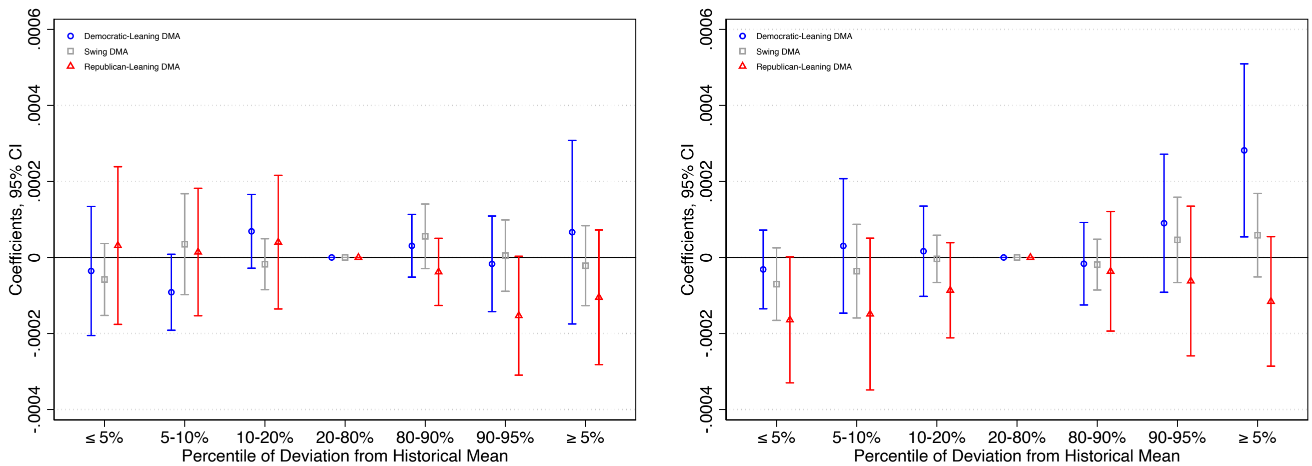
(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events, by media market ideology. In particular, we regress the log+1 of the number of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤ 1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥ 99. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

Share of Segments about Local Weather and Climate Change

We present the result from Figure 7 but this time using the share of segments about local weather that mention climate change as our main outcome variable.

Figure D.4: Presentation Bias [Share of Segments about Local Weather and Climate Change]



(a) Minimum Temperatures in Winter

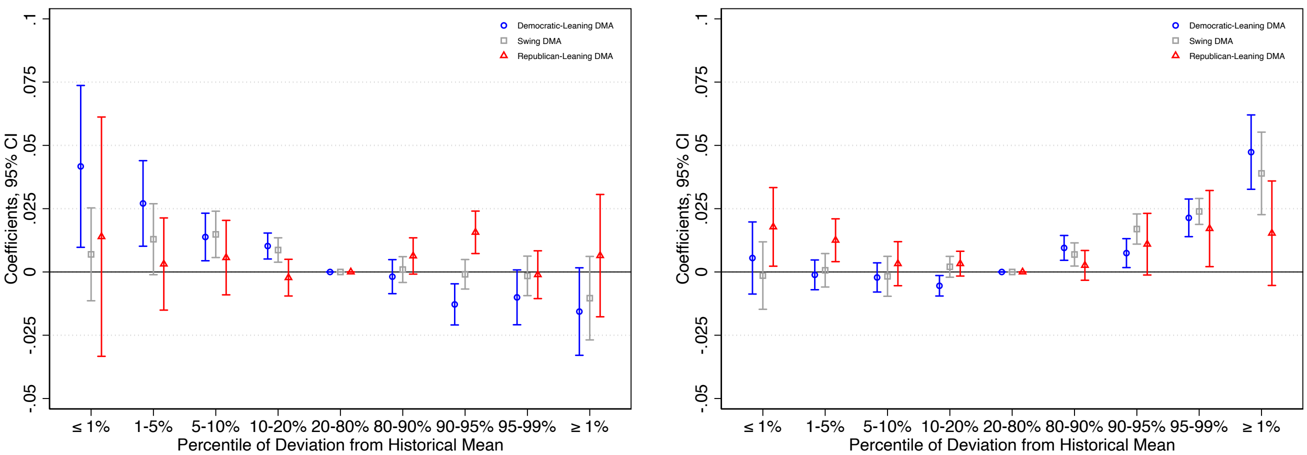
(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between weather events and coverage of climate change in news about local weather, by media market ideology. In particular, we regress the share of segments about local weather that mention climate change on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, ≥95. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

Media Markets Spanning the Full Support of Weather Events

In Figure D.5 we estimate equation 2 restricting our analysis to the sample of media markets that span the full support of weather events. Out of 66 media markets in our sample, we have 41 media markets in winter and 43 media markets in summer that experience deviations from the historical means that fall in all the bins of the deviation distribution that we consider.

Figure D.5: Publication Bias [Media Markets Spanning the Full Support of Weather Events]



(a) Minimum Temperatures in Winter

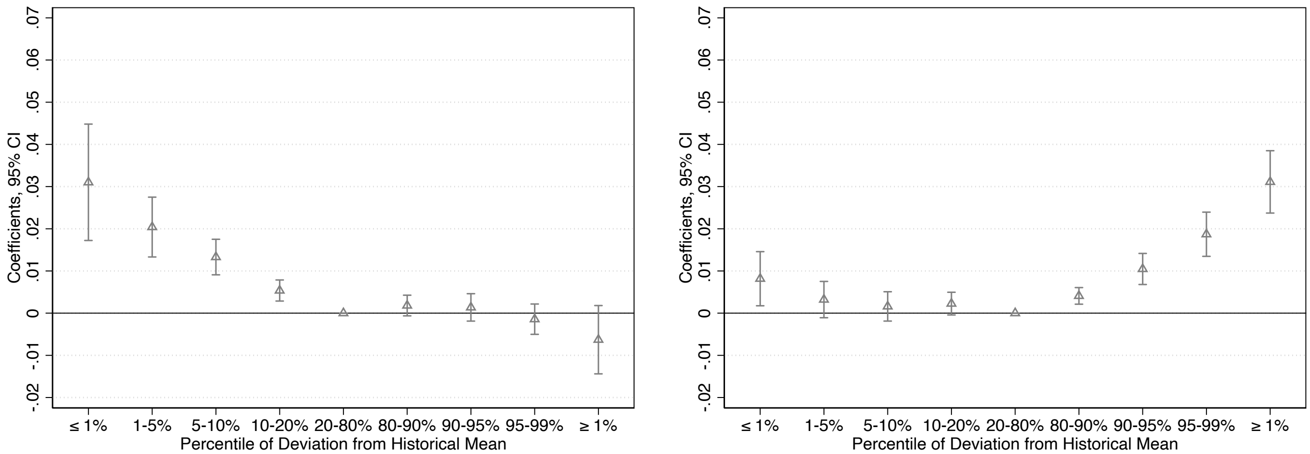
(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events, by media market ideology. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥99. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. The sample is restricted to media markets experiencing at least one weather event in each bin. Standard errors are clustered at the media market level.

Weather Events Defined Based on Monthly Distribution

In this subsection, we reproduce Figures 3, 5, and Figure 7 defining weather events based on the within month distribution of deviations. Specifically, we first narrow down our sample to the months of interest (December, January, February, and March for the winter season and June, July, August, and September for the summer season). Then, we define our weather events depending on percentiles of the national distribution of deviations for each month.

Figure D.6: Editorial Strategies [Within Month Weather Events]

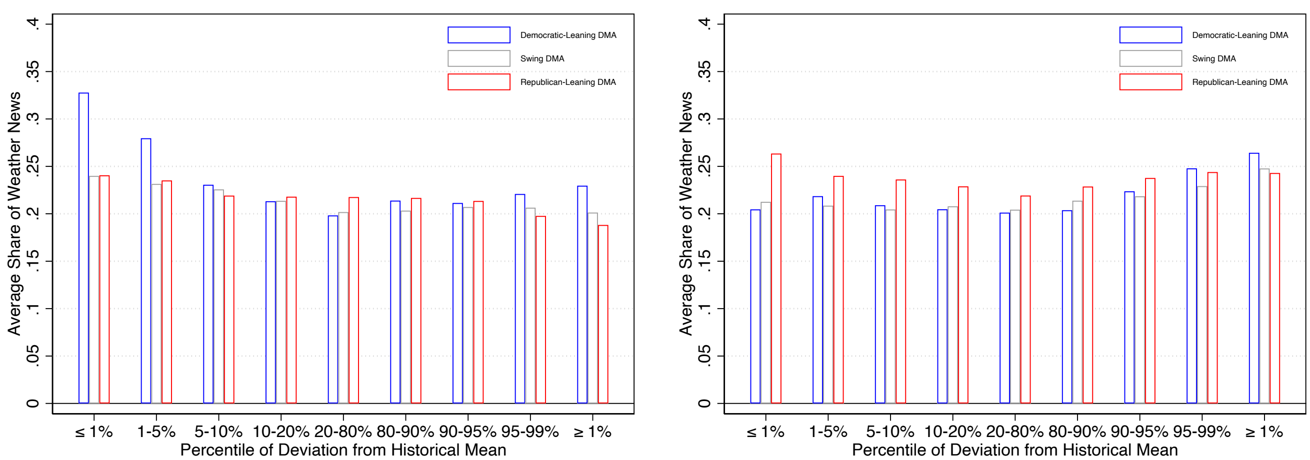


(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution in each month, station fixed effects, and day fixed effects. We consider the following bins: ≤1%, 1%-5%, 5%-10%, 10%-20%, 20%-80%, 80%-90%, 90%-95%, 95%-99%, ≥99%. The omitted category is the 20%-80% bin. Standard errors are clustered at the media market level.

Figure D.7: Mean Coverage of Local Weather [Within Month Weather Events]

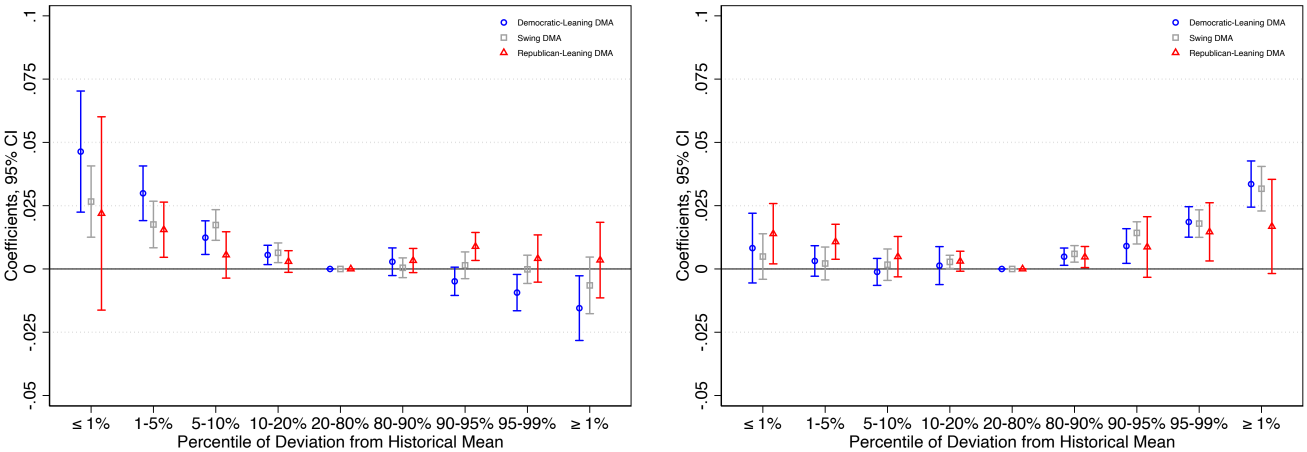


(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the mean coverage of local weather, by weather event and media market ideology. We define coverage of local weather as the share of segments about local weather in a given day. Weather events are deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) that fall in a given bin of the national deviation distribution in each month. We consider the following bins: ≤1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥99. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two.

Figure D.8: Publication Bias [Within Month Weather Events]

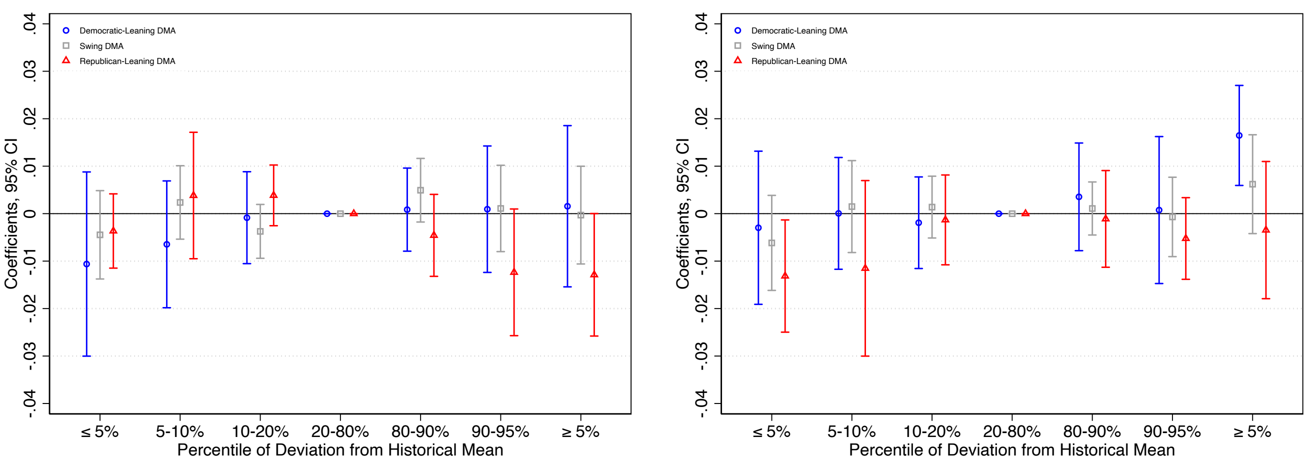


(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between news coverage of local weather and weather events, by media market ideology. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution in each month interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, ≥99. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

Figure D.9: Presentation Bias [Within Month Weather Events]



(a) Minimum Temperatures in Winter

(b) Maximum Temperatures in Summer

Notes: This figure shows the relationship between weather events and coverage of climate change in news about weather, by media market ideology. In particular, we regress an indicator variable equal to one if there is at least one weather segment that mentions climate change on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution in each month interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: ≤5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, ≥95. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

E Regression Tables

Table E.1: Editorial Strategies, Regression Estimates

	Min Temp. Winter (1)	Max Temp. Summer (2)
$\leq$ 1%	0.033	0.009
	(0.008)	(0.004)
1-5%	0.025	0.007
	(0.004)	(0.002)
5-10%	0.017	0.002
	(0.002)	(0.002)
10-20%	0.008	0.001
	(0.001)	(0.002)
80-90%	0.002	0.006
	(0.002)	(0.001)
90-95%	0.001	0.011
	(0.002)	(0.002)
95-99%	-0.003	0.021
	(0.003)	(0.003)
$\geq$ 1%	-0.009	0.037
	(0.005)	(0.006)
Station FEs	✓	✓
Day FEs	✓	✓
Observations	95759	99641
DMAs (Clusters)	66	66
Mean Dep. Variable	0.212	0.212

Notes: This table shows the relationship between news coverage of local weather and weather events. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution, station fixed effects, and day fixed effects. We consider the following bins: $\leq$1%, 1%-5%, 5%-10%, 10%-20%, 20%-80%, 80%-90%, 90%-95%, 95%-99%, $\geq$99%. The omitted category is the 20%-80% bin. Standard errors are clustered at the media market level.

Table E.2: Publication Bias, Regression Estimates

	Min Temp. Winter (1)	Max Temp. Summer (2)
$\leq$ 1%	0.023	0.004
	(0.007)	(0.006)
1-5%	0.025	0.006
	(0.006)	(0.004)
5-10%	0.021	0.001
	(0.003)	(0.003)
10-20%	0.010	0.001
	(0.002)	(0.002)
80-90%	0.002	0.006
	(0.002)	(0.002)
90-95%	0.001	0.015
	(0.003)	(0.003)
95-99%	0.000	0.023
	(0.004)	(0.003)
$\geq$ 1%	-0.010	0.039
	(0.006)	(0.008)
$\leq$ 1% $\times$ Democratic-Leaning Markets	0.037	0.010
	(0.015)	(0.009)
$\leq$ 1% $\times$ Republican-Leaning Markets	0.006	0.014
	(0.021)	(0.009)
1-5% $\times$ Democratic-Leaning Markets	0.007	-0.002
	(0.008)	(0.005)
1-5% $\times$ Republican-Leaning Markets	-0.009	0.007
	(0.010)	(0.005)
5-10% $\times$ Democratic-Leaning Markets	-0.006	-0.001
	(0.005)	(0.005)
5-10% $\times$ Republican-Leaning Markets	-0.008	0.003
	(0.007)	(0.005)
10-20% $\times$ Democratic-Leaning Markets	-0.001	-0.002
	(0.003)	(0.004)
10-20% $\times$ Republican-Leaning Markets	-0.005	0.002
	(0.004)	(0.002)
80-90% $\times$ Democratic-Leaning Markets	-0.002	0.002
	(0.004)	(0.003)
80-90% $\times$ Republican-Leaning Markets	0.003	-0.003
	(0.004)	(0.003)
90-95% $\times$ Democratic-Leaning Markets	-0.007	-0.008
	(0.005)	(0.004)
90-95% $\times$ Republican-Leaning Markets	0.011	-0.003
	(0.005)	(0.006)
95-99% $\times$ Democratic-Leaning Markets	-0.012	-0.003
	(0.005)	(0.004)
95-99% $\times$ Republican-Leaning Markets	-0.003	-0.006
	(0.006)	(0.008)
$\geq$ 1% $\times$ Democratic-Leaning Markets	-0.005	0.009
	(0.009)	(0.011)
$\geq$ 1% $\times$ Republican-Leaning Markets	0.011	-0.023
	(0.013)	(0.012)
Station FEs	✓	✓
Day FEs	✓	✓
Observations	95759	99641
DMAs (Clusters)	66	66
Mean Dep. Variable	0.212	0.212

Notes: This table shows the relationship between news coverage of local weather and weather events, by media market ideology. In particular, we regress the share of segments about local weather in a day on indicator variables for the deviation from historical mean for minimum temperatures in winter (panel (a)) or maximum temperatures in summer (panel (b)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: $\leq$1, 1-5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, 95-99%, $\geq$99. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

Table E.3: Presentation Bias, Regression Estimates

	Min Temp. Winter	Max Temp. Summer
	(1)	(2)
$\leq$ 5%	-0.005	-0.006
	(0.005)	(0.005)
5-10%	-0.001	0.004
	(0.006)	(0.006)
10-20%	-0.002	0.001
	(0.003)	(0.004)
80-90%	0.006	-0.003
	(0.004)	(0.003)
90-95%	0.000	0.009
	(0.006)	(0.006)
$\geq$ 5%	-0.002	0.005
	(0.006)	(0.005)
$\leq$ 5% $\times$ Democratic-Leaning Markets	-0.004	0.007
	(0.009)	(0.008)
$\leq$ 5% $\times$ Republican-Leaning Markets	0.006	-0.011
	(0.007)	(0.009)
5-10% $\times$ Democratic-Leaning Markets	-0.010	0.003
	(0.007)	(0.010)
5-10% $\times$ Republican-Leaning Markets	0.000	-0.015
	(0.007)	(0.011)
10-20% $\times$ Democratic-Leaning Markets	0.007	-0.002
	(0.004)	(0.006)
10-20% $\times$ Republican-Leaning Markets	0.005	-0.005
	(0.007)	(0.007)
80-90% $\times$ Democratic-Leaning Markets	-0.006	-0.001
	(0.006)	(0.005)
80-90% $\times$ Republican-Leaning Markets	-0.007	0.005
	(0.006)	(0.007)
90-95% $\times$ Democratic-Leaning Markets	0.001	0.004
	(0.008)	(0.009)
90-95% $\times$ Republican-Leaning Markets	-0.015	-0.012
	(0.010)	(0.010)
$\geq$ 5% $\times$ Democratic-Leaning Markets	0.010	0.014
	(0.013)	(0.010)
$\geq$ 5% $\times$ Republican-Leaning Markets	-0.008	-0.015
	(0.010)	(0.008)
Station FEs	✓	✓
Day FEs	✓	✓
Observations	95759	99641
DMAs (Clusters)	66	66
Mean Dep. Variable	0.055	0.057

Notes: This table shows the relationship between weather events and coverage of climate change in news about weather, by media market ideology. In particular, we regress an indicator variable equal to one if there is at least one weather segment that mentions climate change on indicator variables for the deviation from historical mean for minimum temperatures in winter (column (1)) or maximum temperatures in summer (column (2)) falling in a given bin of the national deviation distribution interacted with dummies for the ideology of the media market, station fixed effects, and day fixed effects. We consider the following bins: $\leq$5%, 5-10%, 10-20%, 20-80%, 80-90%, 90-95%, $\geq$95. The omitted category is the 20-80% bin. Republican-leaning media markets are media markets with Republican vote share in the 2008 presidential election in the top 25%, Democratic-leaning media markets in the bottom 25%, and swing media markets in-between the two. Standard errors are clustered at the media market level.

F Proofs

F.1 Proofs of the baseline model

We prove slightly general statements of Propositions 1-3 under the assumptions that $h(\cdot)$ and $g(\cdot)$ are $\mathcal{C}^\infty$, strictly increasing, concave (with one of the two functions strictly concave), satisfying $g'(0)/h'(1) > 1$ and $g'(1)/h'(0) < \frac{\min_{\alpha,c\in[0,1]^2} v(c)+\alpha z_D(\mu(c))+(1-\alpha)z_R(\mu(c))}{\underline{u}}$.

Proposition F.1. *Media outlet M's editorial strategy is a function uniquely defined for all $c \in [0,1]$ by:*

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

Proof. From the reasoning in the text, the media outlet engages in pointwise maximization since it would maximize viewership and it is a credible strategy. Hence for all c, the first order condition is:

$$\frac{g'(1-w)}{h'(w)} = \frac{v(c)+\alpha z_D(\mu(c))+(1-\alpha)z_R(\mu(c))}{\underline{u}} \tag{F.2}$$

Notice that for all c, there is a unique interior solution to Equation F.2 as $g'(1-w)/h'(w)$ is strictly increasing with w and given our assumption on $g'(1)/h'(0)$ and $g'(0)/h'(1)$ and $\frac{v(c)+\alpha z_D(\mu(c))+(1-\alpha)z_R(\mu(c))}{\underline{u}} < 1$ for all c and α. □

Proof of Proposition 1

Follows directly from Proposition F.1. □

Proposition F.2. *Suppose $\alpha^d > \alpha^r$, then $w^*(c;\alpha)$ defined by Equation F.1 satisfies:*

- *For all $c < c^0$, $w^*(c;\alpha^d) < w^*(c;\alpha^r)$;*
- *For $c = c^0$, $w^*(c;\alpha^d) = w^*(c;\alpha^r)$;*
- *For all $c > c^0$, $w^*(c;\alpha^d) > w^*(c;\alpha^r)$;*

Proof. Using Equation F.1 and the Implicit Function Theorem (and ignoring argument whenever possible),

$$\frac{\partial w^*(c;\alpha)}{\partial \alpha}\underbrace{\frac{-g''(1-w^*)h'(w^*)-h''(w^*)g'(1-w^*)}{(h'(w^*))^2}}_{>0}=\frac{z_D(\mu(c))-z_R(\mu(c))}{\underline{u}} \tag{F.3}$$

For $c<c^0$, then $\mu(c)<\pi$ (see the reasoning in the main text) and $z_D(\mu(c))-z_R(\mu(c))<0$. Hence, $\frac{\partial w^*(c;\alpha)}{\partial\alpha}<0$, which yields the first point. For $c=c^0$, $z_D(\mu(c))-z_R(\mu(c))=0$, which yields the second point. For $c>c^0$, $z_D(\mu(c))-z_R(\mu(c))>0$, which yields the third point. □

Proof of Proposition 2

Follow directly from Proposition F.2. □

To prove a slightly more general result than Proposition 3 with no functional form, we need to state some additional, sufficient properties of $h'(\cdot)$ and $g'(\cdot)$. To do so, denote

$$K(w)=\frac{g'(1-w)}{h'(w)}$$

Notice that

$$\begin{aligned} K'(w)=&\frac{-g''(1-w)h'(w)-h''(w)g'(1-w)}{(h'(w))^2}>0\\ K''(w)=&\frac{g'''(1-w)h'(w)-h'''(w)g'(1-w)}{(h'(w))^2}-\frac{2h''(w)}{h'(w)}K'(w)\end{aligned}$$

While we cannot generally sign $K''(w)$, we define the following condition:

Condition F.1.

$$\max_{w\in[0,1]}\frac{K''(w)}{(K'(w))^2}<\min_{\alpha,c\in[0,1]^2}\frac{\underline{u}\big(\mu'(c)(z_D'(\mu(c))-z_R'(\mu(c)))\big)}{|(z_D(\mu(c))-z_R(\mu(c))\big(v'(c)+\mu'(c)(\alpha z_D'(\mu(c))+(1-\alpha)z_R'(\mu(c))\big)|}$$

Condition F.1 basically states that the ratio $g'(1-w)/h'(w)$ is not too convex. Using this condition, we then obtain:

Lemma F.1. *Suppose Condition F.1 holds. Then for all $c > c^0$ if $\frac{\partial w^*(c;\alpha)}{\partial c} \geq 0$, then $\frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} > 0$.*

Proof. Using Equation F.1 and the implicit function theorem,

$$\frac{\partial w^*(c;\alpha)}{\partial c} K'(w^*(c;\alpha)) = \frac{v'(c) + \mu'(c)(\alpha z_D'(\mu(c)) + (1-\alpha) z_R'(\mu(c))}{\underline{u}}$$

Similarly,

$$\frac{\partial w^*(c;\alpha)}{\partial c} \frac{\partial w^*(c;\alpha)}{\partial \alpha} K''(w^*(c;\alpha)) + \frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} K'(w^*(c;\alpha)) = \frac{\mu'(c)(z_D'(\mu(c)) - z_R'(\mu(c))}{\underline{u}}$$

Noting that for all $c > c^0$, $z_D(\mu(c)) - z_R(\mu(c)) > 0$ by Proposition F.2 and using Equation F.3 and Condition F.1, we obtain the result. □

Proposition F.3. *Suppose Condition F.1 holds, $\bar{c} \geq c^0$ and $\alpha^d > \alpha^r$ with $v'(c) + \mu'(c)(\alpha^d z_D'(\mu(c)) + (1-\alpha^d) z_R'(\mu(c))) > 0$ for all $c \in [c^0, 1]$, then*

- $\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) > 0$
- $\dfrac{\partial\big(\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r)\big)}{\partial \bar{c}} > 0$

Proof. Using the definition in the main text:

$$\begin{aligned}
&\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) \\
=&\pi \left(\frac{\int_{\bar{c}}^1 w^*(\tilde{c}; \alpha^d) dF_1(\tilde{c})}{1 - F_1(\bar{c})} - \frac{\int_{\bar{c}}^1 w^*(\tilde{c}; \alpha^r) dF_1(\tilde{c})}{1 - F_1(\bar{c})} \right) \\
&- \pi \left(\frac{\int_0^{c^{ref}} w^*(\tilde{c}; \alpha^d) dF_1(\tilde{c})}{F_1(c^{ref})} - \frac{\int_0^{c^{ref}} w^*(\tilde{c}; \alpha^r) dF_1(\tilde{c})}{F_1(c^{ref})} \right) \\
&+ (1-\pi) \left(\frac{\int_{\bar{c}}^1 w^*(\tilde{c}; \alpha^d) dF_0(\tilde{c})}{1 - F_0(\bar{c})} - \frac{\int_{\bar{c}}^1 w^*(\tilde{c}; \alpha^r) dF_1(\tilde{c})}{1 - F_0(\bar{c})} \right) \\
&- (1-\pi) \left(\frac{\int_0^{c^{ref}} w^*(\tilde{c}; \alpha^d) dF_0(\tilde{c})}{F_0(c^{ref})} - \frac{\int_0^{c^{ref}} w^*(\tilde{c}; \alpha^r) dF_0(\tilde{c})}{F_0(c^{ref})} \right)
\end{aligned}$$

We first prove the first statement in the proposition.

We first consider the case when $v'(c) + \mu'(c)(\alpha^r z_D'(\mu(c)) + (1-\alpha^r) z_R'(\mu(c))) > 0$ for all $c \in [c^0, 1]$. In this case, $\frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} > 0$ for all $c \in [c^0, 1]$ and for all $\alpha \in [\alpha^r, \alpha^d]$ by Lemma F.1. As a result,

$\int_{\bar{c}}^{1} w^*(\tilde{c};\alpha^d) - w^*(\tilde{c};\alpha^r) dF_\omega(\tilde{c}) > \int_{\bar{c}}^{1} w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r) dF_\omega(\tilde{c}) = (w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r))(1 - F_\omega(\bar{c}))$. Hence,

$$\begin{aligned}
&\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) \\
&> w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r) \\
&- \pi \left(\frac{\int_0^{c^{ref}} w^*(\tilde{c};\alpha^d) dF_1(\tilde{c})}{F_1(c^{red})} - \frac{\int_0^{c^{ref}} w^*(\tilde{c};\alpha^r) dF_1(\tilde{c})}{F_1(c^{ref})} \right) \\
&- (1-\pi) \left(\frac{\int_0^{c^{ref}} w^*(\tilde{c};\alpha^d) dF_0(\tilde{c})}{F_0(c^{red})} - \frac{\int_0^{c^{ref}} w^*(\tilde{c};\alpha^r) dF_0(\tilde{c})}{F_0(c^{ref})} \right)
\end{aligned}$$

If $c^{ref} < c^0$, then $w^*(c;\alpha^d) - w^*(c;\alpha^r) < 0$ for all $c \in [0, c^{ref}]$ and $\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) > 0$. If $c^{ref} > c^0$, then $\int_0^{c^{ref}} w^*(\tilde{c};\alpha^d) - w^*(c;\alpha^r) dF_\omega(\tilde{c}) < \int_{c^0}^{c^{ref}} w^*(\tilde{c};\alpha^d) - w^*(c;\alpha^r) dF_\omega(\tilde{c})$. Using Lemma F.1 and $\frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} > 0$, $\int_{c^0}^{c^{ref}} w^*(\tilde{c};\alpha^d) - w^*(c;\alpha^r) dF_\omega(\tilde{c}) < (w^*(c^{ref};\alpha^d) - w^*(c^{ref};\alpha^r))(F_\omega(c^{ref}) - F_\omega(c^0)) < (w^*(c^{ref};\alpha^d) - w^*(c^{ref};\alpha^r))F_\omega(c^{ref})$. In which case,

$$\begin{aligned}
&\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) \\
&> \big(w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r)\big) - \big(w^*(c^{ref};\alpha^d) - w^*(c^{ref};\alpha^r)\big)
\end{aligned}$$

Given $\frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} > 0$, $\big(w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r)\big) - \big(w^*(c^{ref};\alpha^d) - w^*(c^{ref};\alpha^r)\big) > 0$, so $\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r) > 0$ as claimed.

Suppose now that there exists $c^- \geq \bar{c}$ such that $v'(c) + \mu'(c)(\alpha^r z_D'(\mu(c)) + (1-\alpha^r) z_R'(\mu(c))) > 0$ for all $c \in [c^0, c^-]$ and $v'(c) + \mu'(c)(\alpha^r z_D'(\mu(c)) + (1-\alpha^r) z_R'(\mu(c))) < 0$ for all $c \in [c^-, 1]$. As such, we can split $\int_{\bar{c}}^{1} w^*(\tilde{c};\alpha^d) - w^*(\tilde{c};\alpha^r) dF_\omega(\tilde{c}) = \int_{c^-}^{1} w^*(\tilde{c};\alpha^d) - w^*(\tilde{c};\alpha^r) dF_\omega(\tilde{c}) + \int_{\bar{c}}^{c^-} w^*(\tilde{c};\alpha^d) - w^*(\tilde{c};\alpha^r) dF_\omega(\tilde{c})$. Since $w^*(\tilde{c};\alpha^r)$ is decreasing with c for all $c \in [c^-, 1]$, $\int_{c^-}^{1} w^*(\tilde{c};\alpha^d) - w^*(\tilde{c};\alpha^r) dF_\omega(\tilde{c}) > (w^*(c^-;\alpha^d) - w^*(c^-;\alpha^r))(1 - F_\omega(c^-)) > (w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r))(1 - F_\omega(c^-))$, with the last inequality using Lemma F.1 and $\frac{\partial^2 w^*(c;\alpha)}{\partial c \partial \alpha} > 0$ for $c \in [\bar{c}, c^-]$. Similarly, $\int_{\bar{c}}^{c^-} w^*(\tilde{c};\alpha^d) - w^*(\tilde{c};\alpha^r) dF_\omega(\tilde{c}) > (w^*(\bar{c};\alpha^d) - w^*(\bar{c};\alpha^r))(F_\omega(c^-) - F(\bar{c}))$ by the same reasoning as above. Hence, we can apply the same logic as above to obtain the result.

Note that the logic we have applied above is also valid for cases when $w^*(c;\alpha^r)$ decreases in an interval in $[\bar{c}, 1]$. Hence, for all possible cases, we have shown the first point of the proposition.

To show the second point, note that

$$\begin{aligned}
&\frac{\partial\big(\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r)\big)}{\partial\bar{c}} \\
\propto&\pi \left(-\big(w^*(\bar{c}; \alpha^r) - w^*(\bar{c}; \alpha^d)\big) f_1(\bar{c})(1 - F_1(\bar{c})) + f_1(\bar{c}) \int_{\bar{c}}^{1} \big(w^*(\tilde{c}; \alpha^d) - w^*(\tilde{c}; \alpha^r)\big) dF_1(\tilde{c})\right) \\
&+ (1-\pi) \left(-\big(w^*(\bar{c}; \alpha^r) - w^*(\bar{c}; \alpha^d)\big) f_0(\bar{c})(1 - F_0(\bar{c}) + f_0(\bar{c}) \int_{\bar{c}}^{1} \big(w^*(\tilde{c}; \alpha^d) - w^*(\tilde{c}; \alpha^r)\big) dF_0(\tilde{c})\right)
\end{aligned}$$

We know from the reasoning above that $\int_{\bar{c}}^{1} \big(w^*(\tilde{c}; \alpha^d) - w^*(\tilde{c}; \alpha^r)\big) dF_\omega(\tilde{c}) > \big(w^*(\bar{c}; \alpha^d) - w^*(\bar{c}; \alpha^r)\big)(1 - F_\omega(\bar{c}))$, so $\frac{\partial\left(\Delta(c^{ref}, \bar{c}; \alpha^d) - \Delta(c^{ref}, \bar{c}; \alpha^r)\right)}{\partial\bar{c}} > 0$. □

Proof of Proposition 3

The proof follows directly from Proposition F.3 after noting that with the assumed functional forms ($g(1-w) = 1-w$ and $h(w) = w^\rho$), we have:

$$\begin{aligned}
K(w) =& \frac{1}{\rho w^{\rho-1}} = \frac{w^{1-\rho}}{\rho} \\
K'(w) =& \frac{1-\rho}{\rho} w^{-\rho} \\
K''(w) =& -(1-\rho) w^{-1-\rho} < 0
\end{aligned}$$

Hence, Condition F.1 is satisfied by our functional forms. □

Proof of Corollary 1

For all $\alpha \in [0,1]$, define $c_{-}^{min}(\alpha) = arg\min_{c \in [c_{-}^{R}, 1]} v'(c) + \mu'(c)(\alpha z_D'(\mu(c)) + (1-\alpha) z_R'(\mu(c)))$. Define α_{-}^{a} as the solution to $v'(c_{-}^{min}(\alpha)) + \mu(c_{-}^{min}(\alpha))(\alpha z_D'(\mu(c_{-}^{min}(\alpha)) + (1-\alpha) z_R'(c_{-}^{min}(\alpha)) = 0$. Notice that due to the linearity in α, $v'(c_{-}^{min}(\alpha)) + \mu(c_{-}^{min}(\alpha))(\alpha z_D'(\mu(c_{-}^{min}(\alpha)) + (1-\alpha) z_R'(c_{-}^{min}(\alpha)))$ is strictly increasing with α. To see that, suppose by way of contradiction that for $\alpha^h > \alpha^l$, $v'(c_{-}^{min}(\alpha^l)) + \mu(c_{-}^{min}(\alpha^l))(\alpha^l z_D'(\mu(c_{-}^{min}(\alpha^l)) + (1-\alpha^l) z_R'(c_{-}^{min}(\alpha^l)) \geq v'(c_{-}^{min}(\alpha^h)) + \mu(c_{-}^{min}(\alpha^h))(\alpha^h z_D'(\mu(c_{-}^{min}(\alpha^h)) + (1-\alpha^h) z_R'(c_{-}^{min}(\alpha^h)))$. Notice that $\alpha^h > \alpha^l$ implies $v'(c_{-}^{min}(\alpha^h)) + \mu(c_{-}^{min}(\alpha^h))(\alpha^h z_D'(\mu(c_{-}^{min}(\alpha^h)) +$

$(1-\alpha^h)z_R'(c_-^{min}(\alpha^h))) > v'(c_-^{min}(\alpha^h)) + \mu(c_-^{min}(\alpha^h))(\alpha^l z_D'(\mu(c_-^{min}(\alpha^h)) + (1-\alpha^l)z_R'(c_-^{min}(\alpha^h)))$. As a result, $v'(c_-^{min}(\alpha^l)) + \mu(c_-^{min}(\alpha^l))(\alpha^l z_D'(\mu(c_-^{min}(\alpha^l)) + (1-\alpha^l)z_R'(c_-^{min}(\alpha^l))) > v'(c_-^{min}(\alpha^h)) + \mu(c_-^{min}(\alpha^h))(\alpha^l z_D'(\mu(c_-^{min}(\alpha^h)) + (1-\alpha^l)z_R'(c_-^{min}(\alpha^h)))$, contradicting that the definition of $c_-^{min}(\alpha^l)$. Further, under the assumptions, $v'(c_-^{min}(0)) + \mu(c_-^{min}(0))(z_R'(c_-^{min}(0))) < 0$ and $v'(c_-^{min}(1)) + \mu(c_-^{min}(1))(z_D'(\mu(c_-^{min}(1))) > 0$, so α_-^a exists, is unique, and is interior. For all $\alpha \geq \alpha_-^a$, $w^*(c;\alpha)$ is increasing with c for all c.

In turn, for all $\bar{c}_- \in (c_-^R, 1)$, define $c_-^{max}(\alpha) = arg\max_{c\in[\bar{c}_-,1]} v'(c) + \mu'(c)(\alpha z_D'(\mu(c)) + (1-\alpha)z_R'(\mu(c)))$. Define $\alpha_-^b(\bar{c}_-)$ as the solution to $v'(c_-^{max}(\alpha)) + \mu(c_-^{max}(\alpha))(\alpha z_D'(\mu(c_-^{max}(\alpha)) + (1-\alpha)z_R'(c_-^{min}(\alpha)) = 0$. By the same reasoning as above, $\alpha_-^b(\bar{c}_-)$ exists, is unique, and is interior and for all $c \geq \bar{c}_-$ and for all $\alpha < \alpha_-^b(\bar{c}_-)$, then $w^*(c;\alpha)$ is strictly decreasing with c.

We can now compute the derivative of our effect:

$$\begin{aligned}\frac{\partial\Delta(c^{ref},\bar{c};\alpha)}{\partial\bar{c}} =& \pi\frac{f_1(\bar{c})}{(1-F_1(\bar{c}))^2}\left(\int_{\bar{c}}^1 w^*(\tilde{c};\alpha)dF_1(\tilde{c}) - w^*(\bar{c};\alpha)\right)\\ &+(1-\pi)\frac{f_0(\bar{c}}{(1-F_0(\bar{c}))^2}\left(\int_{\bar{c}}^1 w^*(\tilde{c};\alpha)dF_0(\tilde{c}) - w^*(\bar{c};\alpha)\right)\end{aligned}$$

For all $\alpha > \alpha_-^a$, we necessarily have $\int_{\bar{c}}^1 w^*(\tilde{c};\alpha)dF_\omega(\tilde{c}) - w^*(\bar{c};\alpha) > 0$ so $\frac{\partial\Delta(c^{ref},\bar{c};\alpha)}{\partial\bar{c}} > 0$ as claimed. In contrast, for all $\bar{c} > \bar{c}_-$, and $\alpha < \alpha_-^b(\bar{c}_-)$, we necessarily have $\int_{\bar{c}}^1 w^*(\tilde{c};\alpha)dF_\omega(\tilde{c}) - w^*(\bar{c};\alpha) < 0$ so $\frac{\partial\Delta(c^{ref},\bar{c};\alpha)}{\partial\bar{c}} < 0$. □

F.2 Proofs of the extensions

Proof of Proposition 4

Denote

$$c_\mu^a(\alpha) = arg\min_{c\in[0,1]}(\alpha v_D'(\mu(c)) + (1-\alpha)v_R'(\mu(c)))$$

$$c_\mu^b(\alpha) = arg\min_{c\in[-1,0]} -(\alpha v_D'(\mu(c)) + (1-\alpha)v_R'(\mu(c)))$$

Suppose $(\alpha v_D'(\mu(c_\mu^a(\alpha))) + (1-\alpha)v_R'(\mu(c_\mu^a(\alpha)))) \leq -((\alpha v_D'(\mu(c_\mu^b(\alpha))) + (1-\alpha)v_R'(\mu(c_\mu^b(\alpha))))$. In this case, define $\overline{\alpha}$ the solution to $(\alpha v_D'(\mu(c_\mu^a(\alpha))) + (1-\alpha)v_R'(\mu(c_\mu^a(\alpha)))) = 0$. In the contrary case, define $\overline{\alpha}$ the solution to $(\alpha v'_D(\mu(c^b_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^b_\mu(\alpha)))) = 0$. In both cases, using a similar reasoning as in the proof of Corollary 1, we can show that $\overline{\alpha}$ exists, is unique, and interior. Notice that for all $\alpha > \overline{\alpha}$, $(\alpha v_D(\mu(c)) + (1-\alpha)v_R(\mu(c)))$ is strictly increasing with $\mu(c)$.

In turn, denote

$$c^c_\mu(\alpha) = arg \max_{c\in[0,1]} (\alpha v'_D(\mu(c)) + (1-\alpha)v'_R(\mu(c)))$$

$$c^d_\mu(\alpha) = arg \max_{c\in[-1,0]} -(\alpha v'_D(\mu(c)) + (1-\alpha)v'_R(\mu(c)))$$

Suppose $(\alpha v'_D(\mu(c^c_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^c_\mu(\alpha)))) \leq -(\alpha v'_D(\mu(c^d_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^d_\mu(\alpha))))$. In this case, define $\underline{\alpha}$ the solution to $(\alpha v'_D(\mu(c^d_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^d_\mu(\alpha)))) = 0$. In the contrary case, define $\underline{\alpha}$ the solution to $(\alpha v'_D(\mu(c^c_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^c_\mu(\alpha)))) = 0$. In both cases, using a similar reasoning as in the proof of Corollary 1, we can show that $\underline{\alpha}$ exists, is unique, and interior. Notice that for all $\alpha < \underline{\alpha}$, $(\alpha v_D(\mu(c)) + (1-\alpha)v_R(\mu(c)))$ is strictly decreasing with $\mu(c)$.

Notice further that under the assumption that for all $c \in (0,1)$, $\frac{\partial \frac{f_1(c)}{f_0(c)}}{\partial c} > \frac{\partial \frac{f_1(-c)}{f_0(-c)}}{\partial(-c)}$, then for all $c \in (0,1]$, $\mu(c) > \mu(-c)$ (see Equation 4). For all $\alpha > \overline{\alpha}$, given the definition of $\overline{\alpha}$, we necessarily have $\alpha v_D(\mu(c)) + (1-\alpha)v_R(\mu(c)) > \alpha v_D(\mu(-c)) + (1-\alpha)v_R(\mu(-c))$ for all $c \in (0,1]$. In turn, for all $\alpha < \underline{\alpha}$, given the definition of $\underline{\alpha}$, we necessarily have $\alpha v_D(\mu(c)) + (1-\alpha)v_R(\mu(c)) < \alpha v_D(\mu(-c)) + (1-\alpha)v_R(\mu(-c))$ for all $c \in (0,1]$. Since the entertainment benefit is the same for c and for $-c$, we obtain the first point of the proposition.

The second point of the proposition follows directly from the first. Notice that our reference category stays the same for $\Delta^+(\cdot)$ and $\Delta^-(\cdot)$, so the only part we need to compare is: $E(w^*(c;\alpha)|c \leq -\bar{c})$ and $E(w^*(c;\alpha)|c \geq \bar{c})$. Under the result above, we know that for all $\alpha > \overline{\alpha}$, $E(w^*(c;\alpha)|c \leq -\bar{c}) < E(w^*(c;\alpha)|c \geq \bar{c})$, so $\Delta^+(c^{ref}, \bar{c}; \alpha) > \Delta^-(c^{ref}, \bar{c}; \alpha)$. In contrast, for all $\alpha < \underline{\alpha}$, $E(w^*(c;\alpha)|c \leq -\bar{c}) > E(w^*(c;\alpha)|c \geq \bar{c})$, so $\Delta^+(c^{ref}, \bar{c}; \alpha) < \Delta^-(c^{ref}, \bar{c}; \alpha)$. □

Proof of Proposition 5

We first define $\underline{\alpha}$ and $\overline{\alpha}$. Denote

$$c^a_\mu(\alpha) = arg \min_{c\in[c^0,1]} \mu'(c)(\alpha v'_D(\mu(c)) + (1-\alpha)v'_R(\mu(c))) - v'(c)$$

Define $\overline{\alpha}$ the solution to $\mu'(c^a_\mu(\alpha))(\alpha v'_D(\mu(c^a_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^a_\mu(\alpha)))) - v'(c^a_\mu(\alpha)) = 0$. Using a similar reasoning as in the proof of Corollary 1, we can show that $\overline{\alpha}$ exists, is unique, and interior. Notice that for all $\alpha > \overline{\alpha}$, $\mu'(c)(\alpha v'_D(\mu(c)) + (1-\alpha)v'_R(\mu(c))) > v'(c)$ for all $c \in [c^0, 1]$.

In turn, denote

$$c^b_\mu(\alpha) = arg \max_{c\in[0,1]}(\alpha v'_D(\mu(c)) + (1-\alpha)v'_R(\mu(c)))$$

Define $\underline{\alpha}$ the solution to $(\alpha v'_D(\mu(c^b_\mu(\alpha))) + (1-\alpha)v'_R(\mu(c^b_\mu(\alpha)))) = 0$. Using a similar reasoning as in the proof of Corollary 1, we can show that $\underline{\alpha}$ exists, is unique, and interior. Notice that for all $\alpha < \underline{\alpha}$, $(\alpha v_D(\mu(c)) + (1-\alpha)v_R(\mu(c)))$ is strictly decreasing with c over $[0, 1]$.

Notice that the introduction of slant does not change the basic problem of the media outlet that maximizes for each c separately: $h(w)\big((1-\lambda)v(c) + (1+\lambda)(\alpha z_D(\mu(c)) + (1-\alpha)z_R(\mu(c)))\big) + g(1-w)\underline{u}$, now with respect to w and λ. Quite simply, the outlet picks $\lambda = \underline{\lambda}$ if $(1-\underline{\lambda})v(c) + (1+\underline{\lambda})(\alpha z_D(\mu(c)) + (1-\alpha)z_R(\mu(c))) \geq v(c) + (\alpha z_D(\mu(c)) + (1-\alpha)z_R(\mu(c)))$, or equivalently $v(c) < \alpha z_D(\mu(c)) + (1-\alpha)z_R(\mu(c))$.

For $\alpha < \underline{\alpha}$, $v(c)$ is strictly increasing with c, whereas $\alpha z_D(\mu(c)) + (1-\alpha)z_R(\mu(c))$ is strictly decreasing with c. Further, note that $\alpha z_D(\mu(c^0)) + (1-\alpha)z_R(\mu(c^0)) = 0$. Hence, if $v(0) < \alpha z_D(\mu(0)) + (1-\alpha)z_R(\mu(0))$, there exists a unique $c^r \in (0, 1)$ such that $\lambda(c) = \underline{\lambda}$ for all $c < c^r$. In turn, if $v(0) \geq \alpha z_D(\mu(0)) + (1-\alpha)z_R(\mu(0))$, then $c^r = 0$.

For $\alpha > \overline{\alpha}$, we know that $\alpha z_D(\mu(c)) + (1-\alpha)z_R(\mu(c)) - v(c)$ is strictly increasing in c. Further, we know that $\alpha z_D(\mu(c^0)) + (1-\alpha)z_R(\mu(c^0)) < v(c^0)$ If $v(1) < \alpha z_D(\mu(1)) + (1-\alpha)z_R(\mu(1))$, then there exists a unique $c^d \in (c^0, 1)$ such that $\lambda(c) = \underline{\lambda}$ if and only if $c > c^d$. In turn, if $v(1) \geq \alpha z_D(\mu(1)) + (1-\alpha)z_R(\mu(1))$, then denote $c^d = 1$. □

Proof of Proposition 6

We first show that the outlets, believer or sceptical, never hide information. Suppose an outlet does. That is, suppose there exists a set $\mathcal{S} = \{c \in [0,1] : r(c) = \emptyset\}$ of cardinality strictly greater than one (otherwise it is the same as reporting the particular value of a shock) and possibly infinite (i.e., $\mathcal{S}$ can contain an interval). We further suppose that $\mathcal{S}$ is closed without loss of generality (otherwise, we can always take a closed subset of $\mathcal{S}$ to prove the result). Denote $c^b = \min \mathcal{S}$ and $c^t = \max \mathcal{S}$. A well known properties of beliefs is that $\mu(c^b) < \mu(\emptyset) < \mu(c^t)$. As such, if the outlet is sceptical, it strictly prefers to report c^b than not reporting it, and so $c^b \notin \mathcal{S}$, a contradiction. If the outlet is a believer, it strictly prefers to report c^t than not reporting it, a contradiction. Hence, the outlet always reports the realised weather shock c absent commitment.

Hence, the only decision of the outlet is how much weather news to report for each shock ($w : [0,1] \to [0,1]$) to impact its audience size. We, therefore, proceeds in two steps. We first find the optimal audience size, which we denote $P = \alpha P_D + (1-\alpha)P_R$). We also denote $\underline{P}$ the minimal feasible audience size and $\overline{P}$ the maximal feasible audience. We then discuss how the media outlet can tailor its amount of reporting to reach the optimal audience size.

We start with a sceptical outlet whose decision problem is:

$$\max_{P \in [\underline{P}, \overline{P}]} \int_0^1 v^s(P\mu(\tilde{c}) + (1-P)\pi) dF^e(\tilde{c})$$

The first and second derivatives of the objective function are respectively:

$$\int_0^1 (\mu(\tilde{c}) - \pi)(v^s)'(P\mu(\tilde{c}) + (1-P)\pi) dF^e(\tilde{c})$$
$$\int_0^1 (\mu(\tilde{c}) - \pi)^2 (v^s)''(P\mu(\tilde{c}) + (1-P)\pi) dF^e(\tilde{c})$$

Under the assumption that $v^s(\cdot)$ is concave, the objective function is also concave. Now, for the first derivative, we obtain:

$$\begin{aligned}
&\int_0^1 (\mu(\tilde{c})-\pi)(v^s)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c})\\
=&\int_0^{c^0} (\mu(\tilde{c})-\pi)(v^s)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c})+\int_{c^0}^1 (\mu(\tilde{c})-\pi)(v^s)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c})
\end{aligned}$$

Notice that since $v^s(\cdot)$ is strictly concave and strictly decreasing and since $(\mu(\tilde{c})-\pi)$ is strictly negative for $\tilde{c}\in[0,c^0)$, we have $\int_0^{c^0}(\mu(\tilde{c})-\pi)(v^s)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c}) < \int_0^{c^0}(\mu(\tilde{c})-\pi)dF^e(\tilde{c})(v^s)'(P\mu(\tilde{c}^0)+(1-P)\pi)$. In turn, since $(\mu(\tilde{c})-\pi)$ is strictly positive for $\tilde{c}\in(c^0,1]$, we have $\int_{c^0}^1(\mu(\tilde{c})-\pi)(v^s)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c}) < \int_{c^0}^1(\mu(\tilde{c})-\pi)dF^e(\tilde{c})(v^s)'(P\mu(c^0)+(1-P)\pi)$. Hence,

$$\begin{aligned}
&\int_0^1 (\mu(\tilde{c})-\pi)(v^s)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c})\\
<&\int_0^{c^0} (\mu(\tilde{c})-\pi)dF^e(\tilde{c})(v^s)'(P\mu(\tilde{c}^0)+(1-P)\pi)+\int_{c^0}^1 (\mu(\tilde{c})-\pi)dF^e(\tilde{c})(v^s)'(P\mu(c^0)+(1-P)\pi)\\
=&\int_0^1 (\mu(\tilde{c})-\pi)dF^e(\tilde{c})(v^s)'(P\mu(\tilde{c}^0)+(1-P)\pi)\\
=&0
\end{aligned}$$

So the objective function is always negative and the sceptical outlet therefore chooses $P^s=\underline{P}$. We can now turn to the choice of the space devoted to weather news: $w:[0,1]\to[0,1]$. Given that the outlet seeks to minimize audience, under the assumption that $\max\{v(0)+z_R(\mu(0)),v(1)+z_D(\mu(1))\}<\underline{u}\le 1$, the best way to do so is to devote all the news broadcast to weather news: $w^s(c)=1$ for all $c\in[0,1]$. It is then immediate that the within outlet variation is then zero as claimed.

We now turn to a believer outlet. As above, the maximization problem is:

$$\max_{P\in[\underline{P},\overline{P}]}\int_0^1 v^b(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c})$$

It can be verified that the objective function is strictly concave. The first derivative is also: $\int_0^1(\mu(\tilde{c})-\pi)(v^b)'(P\mu(\tilde{c})+(1-P)\pi)dF^e(\tilde{c})$. By the same reasoning as above, we obtain that the optimal audience size is $P^b=\underline{P}$. Hence, a believer outlet devotes all the broadcast to weather news as well: $w^b(c)=1$ for all $c\in[0,1]$. This yields no within outlet variation again. $\square$