Measuring Local Climate Change Attention: Does It Affect Households and Firms?

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Abstract

We develop a novel, high-frequency measure of local climate change attention based on a comprehensive dataset covering over 5,000 U.S. newspapers across all major population centers. Heightened attention significantly increases household investment in green ETFs and purchases of flood insurance, prompts local firms to discuss climate risk more frequently, and improves firms' environmental performance. Our measure captures substantial spatial and temporal variation associated with local demographics, social media, and environmental events, and it reflects variation from newspaper ownership and peer attention. By contrast, a widely used existing climate attention measure shows no significant relationship with these household and firm outcomes.

Keywords: Climate Change Attention, ESG, Local News, Media, Social Media, Sustainable Investing, Flood Insurance

JEL Classifications: G11, G14, G20, G29, G39, G41, G50, Q5

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I. Introduction

Many view climate change as one of the most critical global challenges of our time. Despite rising public awareness, concern about climate change varies widely.[1] The drivers of this variation are not well understood, and their economic implications have not been fully evaluated (Giglio, Maggiori, Stroebel, Tan, Utkus, and Xu 2025). Studying local attitudes toward climate change is increasingly important due to the ongoing multi-state effort to exclude environmental, social, and governance (ESG) considerations from public investments.

Recent studies show that attention to climate change influences financial markets, affecting equilibrium prices and stock returns (Choi, Gao, and Jiang 2020; Pástor, Stambaugh, and Taylor 2021, 2022; Ardia, Bluteau, Boudt, and Inghelbrecht 2023). We document that local attention to climate change also substantially influences the behavior of local households and firms. For households, we find that higher local climate attention increases holdings in environmentally friendly stocks and hedging of personal climate risks by purchasing flood insurance. On the corporate side, we find that firms in high-attention areas discuss climate concerns more frequently in earnings calls, suggesting that the firms either face greater pressure from local stakeholders or have heightened internal awareness. These firms also more actively manage their climate risk exposures and exhibit better environmental performance.

We introduce a novel measure, *Local Climate Attention*, constructed from a comprehensive news dataset spanning 2000 to 2022. The dataset encompasses over 5,000

[1] A survey revealed that 78% of Democrats perceive climate change as a significant threat to the country's well-being, compared to just 23% of Republicans. Furthermore, residents of the Pacific region, including California, Washington, Oregon, Hawaii, and Alaska, are more likely than those in other regions to report that climate change is having a substantial local impact (Pew Research Center, 2023).

newspapers, including 510 major publications, covering all major population centers of the United States. This measure improves upon widely used alternatives such as the Yale Climate Opinion Maps (Howe, Mildenberger, Marlon, and Leiserowitz 2015) by capturing high-frequency variation beyond demographics. Using this measure, we identify the factors driving variation in local climate change attention and demonstrate that these variations explain important household and firm outcomes.

Our focus on local news coverage is motivated by a large body of literature arguing that local newspapers hold leaders accountable, increase civic engagement, and play a crucial role in modern representative democracy (Gao, Lee, and Murphy 2020, Ewens, Gupta, and Howell 2022).[2] Since climate change primarily attracts media attention when there is cause for concern, news coverage serves as an indicator of public worry about climate risk (Engle, Giglio, Kelly, Lee, and Stroebel 2020; Pástor et al. 2022; Ardia et al. 2023).[3] We therefore use climate change "attention," "awareness," and "concern" interchangeably, although we recognize that our news-based measure is a proxy for awareness and concern about climate change.

Turning to our main findings, we first examine how retail investment advisory firms' clients adjust their holdings of ESG-focused exchange-traded funds (ETFs) in response to local

[2]The idea goes back to Tocqueville (1835), with more recent work from Gentzkow, Shapiro, and Sinkinson (2011), Hopkins (2018), and Moskowitz (2021). In particular, Ewens et al. (2022) show an increasing trend in private equity acquisitions of local newspapers, which leads to declines in local election participation. Gao et al. (2020) provide evidence that local newspaper closures affect public finance outcomes for local governments by increasing municipal borrowing costs due to the loss of government monitoring. See also Gentzkow and Shapiro (2006) and Dougal, Engelberg, García, and Parsons (2012) for discussions on media bias and its implications.

[3]Our textual analysis also confirms this association, showing that climate pessimist/activist terms dominate our sample of climate-related articles, with only minimal occurrence of optimist/denier terms.

climate attention. We find that more climate attention is associated with increased local investment in ESG ETFs. A one-standard-deviation increase in local climate attention results in a 30 bps increase in ESG ETF ownership, representing 43% of the mean and about 6.4% of the standard deviation of ESG ETF ownership. For the average advisory firm, with $574 million invested in ETFs, this translates to an additional $1.7 million in ESG ETFs.

We next examine whether local climate attention influences households' risk mitigation behavior, specifically through their flood insurance purchasing decisions. We focus on households' flood insurance purchases because standard homeowners insurance typically excludes flood damage, requiring separate coverage. This distinction makes flood insurance purchases a relatively clean proxy for household climate risk mitigation choices.

Using policy-level data from FEMA, we find that a one-standard-deviation increase in climate attention in the current month in a given metro area leads to a 3.6 percentage point larger increase in per capita flood insurance policies over the subsequent 12 months, controlling for water-related disasters, various demographics, and locality and time fixed effects. This corresponds to approximately 23% of the standard deviation of this change in flood insurance take-up. The impact is stronger for metro areas with less-educated residents, with the sensitivity being 84% higher than in more-educated metro areas.

On the corporate side, we first examine whether local climate change awareness influences corporate managers' attention to climate risk exposure. We investigate this through the lens of climate risk discussions during earnings calls, building on recent literature suggesting that earnings call transcripts provide valuable and timely information about climate risks that firms face and that participants view as material factors (Sautner, Van Lent, Vilkov, and Zhang 2023; Li, Shan, Tang, and Yao 2024). Adopting the measure of Li et al. (2024), we find that increases in local climate attention are associated with more frequent discussions of physical risk exposure in the earnings calls of locally headquartered firms, with a one-standard-deviation increase in attention raising discussion intensity by 8% relative to its mean.

We next use firm environmental ratings from MSCI and Refinitiv to study how environmental performance at the corporate level changes with local climate attention. We find that increased climate attention is associated with improved environmental ratings for firms headquartered in the area. A one-standard-deviation increase in local climate attention boosts local firms' environmental ratings by 0.24 standard deviations on average. Heightened climate attention is also associated with measurable reductions in pollution emissions and enhanced green innovation ratings among local firms. These findings suggest that local climate attention influences managerial awareness of climate-related risk exposure and motivates corporate actions that promote environmental innovation and pollution mitigation.

These findings are robust to controlling for geographic area variables, as well as area, time, and firm fixed effects where applicable. We also use two plausibly exogenous instruments: newspaper ownership and climate attention in geographically distant but socially connected areas. The consistency of the results under instrumental variable estimation suggests that the relationships between local climate attention and economic outcomes are plausibly causal.

To benchmark our measure against existing alternatives, we compare it with the Yale Climate Opinion Maps, a widely used data source in recent studies,[4] and find several advantages.

[4]See, for example, Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020), Bakkensen and Barrage (2022), Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2023), Addoum, Ng, and Ortiz-Bobea (2023). The Yale survey uses polling data combined with statistical models to estimate climate change beliefs at the

We evaluate these advantages through three sets of tests comparing the sources of variation in each measure and the degree to which each maps into economic outcomes.

First, we examine the sources of variation in both measures. Local demographics and time fixed effects explain 82% of the variation in the Yale measure but only 24% in our news-based measure. This disparity is consistent with the Yale dataset imputing climate concern using a model that incorporates local demographics in less-populated counties where survey responses are sparse. When we add county fixed effects to demographics, the explained variation in the Yale measure rises to 96%, whereas 46% of the variation in our measure remains unexplained. Our measure thus captures high-frequency, within-area variation that the Yale measure, with its heavy dependence on demographics, does not.

Second, we examine how the two metrics relate to social media attention, measured using a novel geo-coded dataset of Facebook posts on climate-related topics (*FB Climate Posts*) from December 2019 through June 2022. A one-standard-deviation increase in our *Local Climate Attention* measure is associated with a 0.54 bps increase in contemporaneous *FB Climate Posts*, representing 6% of its standard deviation. Our measure also predicts one-month-ahead *FB Climate Posts*. In contrast, $Yale^{Happening}$ does not show a significant relationship with Facebook climate attention. Furthermore, our measure reflects real-time shifts in public concern—aligned with acute environmental events, local protests, and clean energy policy changes—rather than slow-moving demographic composition.

Third, we assess whether the Yale measure can explain the same economic decisions of local households and firms as our *Local Climate Attention* measure. It cannot — $Yale^{Happening}$ has

county level and is available annually since 2014. See Howe et al. (2015) and Leiserowitz, Marlon, Rosenthal, Ballew, Goldberg, Kotcher, and Maibach (2020) for more details of the survey and findings.

no significant association with ESG ETF ownership, flood insurance take-up, or the intensity of climate risk discussions in earnings calls, and has a marginally significant but negative relationship with the change in firms' environmental ratings. These results indicate that the high-frequency variation in our measure enables us to identify the effects of climate attention on economic outcomes—an advantage the Yale measure does not provide.

These comparisons also offer broader guidance on which climate attention measure is best suited for a given research context. Our news-based *Local Climate Attention* measure is well-suited for studying household and firm decisions that vary by geographic location and fluctuate significantly over time, as the high-frequency, within-area variation it captures is what enables identification of causal effects. Time-series measures such as the MCCC Index (Ardia et al., 2023) and the WSJ Index (Engle et al., 2020) are better suited for studying aggregate effects of climate sentiment on economy-wide indicators or financial market returns. In those settings, cross-sectional variation is less relevant. The Yale measure, with its stable demographic foundation, is best suited for studying cross-sectional relationships at the county level — such as the association between local climate beliefs and the local share of the agricultural industry — where time-series variation is less critical and the geographic distribution of long-run beliefs is the object of interest.

More broadly, we provide evidence that our local climate awareness measure aggregates nationwide climate sentiment, local demographics, and observable climate events, but also reflects harder-to-measure forces, including peer effects across socially connected areas, climate legislation, protests, and non-climate factors such as newspaper chain ownership. This highlights the importance of the social, political, and institutional forces captured by our measure. Even after accounting for these observable covariates, the relationships between *Local Climate Attention* and the household and firm outcomes remain robust.

These results highlight the multifaceted nature of climate attention, with our news-based measure capturing meaningful, relatively high-frequency, multi-dimensional variations in local climate awareness that make it well-suited for understanding the interplay between climate change and economic outcomes. Of particular policy relevance is our finding that heightened local climate attention is associated with increased flood insurance adoption, especially among less-educated populations. This addresses a critical gap identified by Harrison, T. Smersh, and Schwartz (2001) and Kousky, Kunreuther, Lingle, and Shabman (2018), who note that only 30–50% of structures in high-flood-risk areas carry flood insurance. Our findings can thus inform the design of targeted climate awareness initiatives for vulnerable households facing substantial climate risks.

Our paper contributes to the literature on how attention to climate change influences economic outcomes such as housing prices (Bernstein et al. 2019; Baldauf et al. 2020; Keys and Mulder 2020; Giglio, Maggiori, Rao, Stroebel, and Weber 2021b) and municipal bond yields (Goldsmith-Pinkham et al. 2023). Recent studies such as Murfin and Spiegel (2020) and Hino and Burke (2021) find that sea-level rise risks are not fully reflected in home prices and that belief heterogeneity matters (Bakkensen and Barrage 2022).[5] We document several novel findings regarding the effects of local climate attention: increased household allocation to green equity

[5]Related to this, recent research shows that investors pay premiums for ESG funds (Baker, Egan, and Sarkar 2022) and climate information increases willingness to pay for carbon offsets (Bernard, Tzamourani, and Weber 2026). Climate awareness also shapes green innovation through consumer environmental concerns (Aghion, Bénabou, Martin, and Roulet 2023; Guzman, Oh, and Sen 2023). See Giglio, Kelly, and Stroebel (2021a), Stroebel

investments, sharper managerial focus on climate risk exposures, faster corporate green innovation, and measurable reductions in pollution emissions.

Our news-based climate awareness measure complements recent studies that employ surveys to identify motives for sustainable investing. These motives range from ethical considerations and social signaling to hedging motives and return expectations (Riedl and Smeets 2017, Giglio et al. 2025). Surveys also show that younger investors are more inclined to support environmental and social issues (Haber, Kepler, Larcker, Seru, and Tayan 2022).[6] Our measure provides comprehensive geographic coverage of climate attention and offers insights into what drives such regional heterogeneity and how it affects household and firm decisions.

Finally, our results contribute to the literature on political and geographic polarization in beliefs. Hong and Kostovetsky (2012) and Di Giuli and Kostovetsky (2014) show how differences in political beliefs affect household and firm decisions related to environmental variables. Other papers describing the effects of political ideology on financial decisions and outcomes include Kempf and Tsoutsoura (2021), Fos, Kempf, and Tsoutsoura (2022), Kempf, Luo, Schäfer, and Tsoutsoura (2023), and Goldman, Gupta, and Israelsen (2024); see Kempf and Tsoutsoura (2024) for a review. Pan, Pikulina, Siegel, and Wang (2022) show that recent growth in geographical differences in stock holdings is driven by media-driven political polarization, while Döttling,

and Wurgler (2021), and Hong, Karolyi, and Scheinkman (2020) for reviews of the broader literature on the influence of climate risk on investments and firm decisions.

[6]Other related research uses surveys or field and laboratory experiments to assess investors' willingness-to-pay (WTP) for sustainable investments (Bauer, Ruof, and Smeets 2021; Heeb, Kölbel, Paetzold, and Zeisberger 2023; Humphrey, Kogan, Sagi, and Starks 2021) or uses investment flows to infer about investors' preferences for sustainable investments (Renneboog, Ter Horst, and Zhang 2011; Hartzmark and Sussman 2019; Döttling and Kim 2022).

Levit, Malenko, and Rola-Janicka (2026) examine how the interplay between political systems and corporate governance regimes may generate ESG backlash. Our measure of climate change attention allows for a better understanding of polarization on this politically contentious subject and its implications on household and firm decisions.

II. Data

We construct our primary variable of interest — local climate attention — from a comprehensive dataset of U.S. newspaper coverage. We measure household outcomes using ESG ETF holdings and flood insurance purchases, and firm outcomes using earnings call climate risk discussions and environmental ratings. In this section, we describe the main variables and their sources. Additional details on the data construction are in Appendix B.1 and all variable definitions can be found in Table A1.

A. News Coverage of Climate Change

Our data on news coverage of climate change come from two main sources: NewsLibrary.com (NL) and Newspapers.com (NP). These two sources are complementary: NL provides more depth in the form of the first 80 words of each article, while NP provides more breadth due to its greater coverage across newspapers. The NL database includes a wide range of large and small newspapers; however, it does not cover approximately one-third of the largest U.S. newspapers. We supplement it with article search counts from the NP database. Finally, we use Factiva to get article search counts for two additional major newspapers, The New York Times and The Washington Post, which are in neither NL nor NP.

For most tests, we restrict our analysis to major newspapers: daily English-language U.S.-based newspapers with at least 10,000 daily circulation, located in Metropolitan Statistical Areas (MSAs).[7] With these restrictions, we have 510 major U.S. newspapers from 352 MSAs, covering all large U.S. population centers. We use keyword searches to find climate-related articles and define our variable of interest, *Local Climate Attention*, for each newspaper-month as the number of climate-related articles scaled by the total number of articles.[8]

For many of our analyses, we aggregate climate attention to the county or MSA levels. We aggregate to the county level by taking the circulation-weighted average across all newspapers in each county-month. For MSA-level analysis, we take the population-weighted average of the county-level variable across all counties in an MSA. We transform monthly variables to quarterly or annual levels by taking the simple average over the given time period.

B. Households' Decisions

Households' Ownership of ESG ETFs We measure local households' holdings of ESG-focused exchange-traded funds (ETFs) using quarterly 13F filings by retail-focused investment advisors, downloaded directly from EDGAR for December 2013 through December 2022. ESG-focused ETFs are identified using the socially conscious indicator from Morningstar Direct, supplemented with fund name keyword searches.

[7]Daily circulation data are from OfficialUSA.com. We determine the location (county and MSA) of each newspaper from its name, which we cross-check with its Wikipedia entry. A small number of major newspapers have closed or merged during our sample period; we identify these from the UNC Hussman School of Journalism U.S. News Deserts website.

[8]The process for construction is described in greater detail in Appendix B.1.A.

Form 13F filings are matched with a registered investment advisor (RIA) that filed Form ADV contemporaneously, using name and business address.[9] We retain investment advisors serving individual (retail) investors, as these advisors' clients are typically local and the clients' investment decisions are most likely to be influenced by local news coverage. For each advisory firm-quarter, we define *ESG ETF Share* as the total value of ESG-focused ETFs divided by the total value of all ETFs in the firm's reported portfolio at the end of the quarter. We use the ZIP code from Form 13F to match each firm to a U.S. core-based statistical area (CBSA), and drop all non-U.S. filers.[10]

Flood Insurance Purchases We measure flood insurance take-up using data from the National Flood Insurance Program (NFIP) policy dataset in OpenFEMA. This dataset includes more than 69 million anonymized policy transactions between 2009 and 2025, including each policy's effective date, termination date, cancellation date (if applicable), and location of the insured property (ZIP code, census tract, county, state). Following Hu (2022), we construct a county-month measure of the stock of in-effect policies. Aggregating this measure across counties within each MSA and dividing by population yields *Policies Per Capita*, the per capita number of in-effect flood insurance policies at the MSA-month level.

C. Firm-Level Variables

Physical Climate Risk Discussions from Earnings Call Transcripts Li et al. (2024) introduce timely measures of firm climate risk based on textual analysis of quarterly earnings conference

[9]Form ADV data are available for download from the SEC's website.

[10]See Appendix B.1.B for a more-detailed discussion.

call transcripts. These metrics quantify the frequency of discussions that simultaneously address acute or chronic weather and climate events and the firm's associated risk exposure.[11] We add together their measures of acute and chronic physical climate risk into one combined measure, *Physical Climate Risk*, available quarterly starting in January 2002.

Environmental Ratings Firm environmental ratings come from two sources: MSCI (formerly KLD) and Refinitiv. We combine the two datasets to maximize coverage, taking the average of the environmental ratings (after standardizing each) for firm-years covered by both datasets and using only one rating when the other is missing.[12] We re-standardize the merged score within each year to define our variable of interest, *ENV Score*.[13] This variable is available for approximately 2,600 firms per year, covering most of the Russell 3000.

Firm Controls We collect firm-level variables from CRSP/Compustat and use them to define the following firm-level controls: *Size* (Log Market Capitalization), *B/M* (Book-to-Market), *Leverage*, *ROA*, and *Returns* (Stock Returns). Because Compustat only reports the current location of each firm, we collect mailing addresses on the headings of 10-K filings from EDGAR, allowing us to match each firm-year to a U.S. core-based statistical area (CBSA) based on its mailing ZIP code. Firms headquartered outside the United States are dropped from the sample.

[11]We thank the authors for making this dataset available at their website.

[12]For MSCI, we add the environmental strengths scores and subtract the environmental concerns scores, following standard practice; for Refinitiv, we take the Environment Pillar Score, which comprises three sub-scores: Emissions, Environmental Innovation, and Resource Use.

[13]One might worry about the variances being different for those observations with dual versus single data coverage. However, this difference is small, with standard deviation of 1.17 for observations with dual coverage compared to 0.93 for those in only one dataset.

D. County-Level Variables

Social Connectedness We follow Bailey, Cao, Kuchler, Stroebel, and Wong (2018b) and measure social connectedness between two U.S. counties using Facebook's *Social Connectedness Index* (SCI).[14] For each focal county, peer counties are those whose SCI with the focal county ranks in the top 10% of the distribution, excluding peers from the same state. We then define *Peer Attention* as the average *Local Climate Attention* across all papers in peer counties.

Demographic and Environmental Controls We collect county-level demographic and socioeconomic control variables, including *Income*, *Education*, *Log Population*, *Unemployment*, and *Democrat Share*, from three sources: the U.S. Census Bureau American Community Survey (ACS), the Local Area Unemployment Statistics (LAUS) program of the Bureau of Labor Statistics (BLS), and the MIT Election Lab.

Environmental control variables include *Greenhouse Gas Emissions* and *Toxic Chemicals Releases* from the EPA. Extreme weather and disaster data are from the NOAA and the OpenFEMA database of presidential disaster declarations. Property damage from natural disasters comes from the Spatial Hazard Events and Losses Database for the U.S. (SHELDUS). All control

[14]SCI is defined as the total number of Facebook friendship links between two U.S. counties (as of April 2016), divided by the product of the two counties' populations. Bailey et al. (2018b); Bailey, Dávila, Kuchler, and Stroebel (2019); Bailey, Farrell, Kuchler, and Stroebel (2020); Bailey, Gupta, Hillenbrand, Kuchler, Richmond, and Stroebel (2021); Bailey, Johnston, Kuchler, Stroebel, and Wong (2022); Kuchler, Li, Peng, Stroebel, and Zhou (2022); Kuchler, Russel, and Stroebel (2020), and Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barberá, Bhole, and Wernerfelt (2022) have all provided evidence that social connections observed on Facebook can serve as a reliable proxy for real-world connections.

variables are defined in Table A1. For MSA-level analyses, we aggregate county-level variables by taking their population-weighted averages over a given MSA.

E. Descriptive Analysis

Table 1 provides summary statistics for the variables used in our empirical analysis (see Table A1 for all variable definitions). Around 1.3% of newspaper articles over our sample period are climate-related. Figure 1 shows both an overall increase in climate awareness and growing polarization over time.[15]

[Table 1 approximately here.]

[Figure 1 approximately here.]

We base most of our analysis on the climate coverage of 510 major newspapers (located in MSAs and with at least 10,000 daily circulation), which gives us climate attention data for geographical areas where 84% of the U.S. population lives. Figure 2 shows how our data coverage varies by state. We have climate attention data covering more than 90% of the populations of large and urbanized states such as California, New York, New Jersey, Massachusetts, and Florida. Our data covers less than half of residents only in the sparsely populated rural states of Montana, Wyoming, Vermont, Mississippi, and the Dakotas.

[Figure 2 approximately here.]

[15]Figure A.1 shows the evolution of *Local Climate Attention* over time, and how it relates to two other indices of national climate sentiment, MCCC and WSJ. Spikes coincide with United Nations climate summits (e.g., December 2009 Copenhagen Summit, December 2015 Paris Summit), as well as the withdrawal of the United States from the Paris Climate Agreement in June 2017.

Despite co-moving with national trends, *Local Climate Attention* exhibits considerable cross-sectional variation. For instance, while San Francisco County, CA has an average *Local Climate Attention* of 5.28%, Cape May County, NJ only has a value of 0.46%.[16]

III. Local Climate Attention and Economic Decisions

In this section of the paper, we examine how local climate attention affects proximate households as well as locally headquartered firms. Our main hypothesis is that more local attention to climate change causes geographically proximate households to shift their portfolio holdings toward more environmentally friendly companies and increase their purchases of flood insurance. Similarly, we expect local firms to be more likely to pay attention to their climate-related risk exposures and take steps to make their operations more green.

Because newspapers typically serve a city and its surrounding region, we aggregate climate attention to the Metropolitan Statistical Area (MSA) level by taking a weighted average of *Local Climate Attention* across all major newspapers in the MSA, as detailed in Section II.A. We define this variable as *Local Climate Attention (M)*, and use it as our main explanatory variable of interest in this section of the paper.

An obvious concern is that newspaper coverage is not random, but instead reflects an omitted variable that simultaneously drives news coverage and household or firm decisions. We

[16]Top five counties based on average *Local Climate Attention* are San Francisco (CA), Boulder (CO), Harris (TX), Dubuque (IA), and Deschutes (OR), while bottom five are Cape May (NJ), Walla Walla (WA), Jefferson (AR), Wayne (NC), and Webb (TX). The San Francisco Bay Area is where the Sierra Club was founded, and it is known for environmental activism, so it is not surprising that it has the most climate-related news coverage in the country.

address this issue by using controls and fixed effects, which absorb time-invariant local characteristics and aggregate time trends. Our primary contribution is measuring and documenting how local climate attention correlates with household and firm outcomes, without claiming to fully isolate exogenous variation. As a robustness check, we also report instrumental variable estimates using two instruments — newspaper chain ownership (*Chain Size*)[17] and the climate attention of socially connected peer counties (*Peer Attention*) — that corroborate the OLS findings. We discuss the construction and validity of these instruments, including their limitations, in Section V.

A. Local Households' Investments in ESG ETFs

We begin by examining how local climate attention shapes household decisions. Specifically, we test whether investors from areas with greater climate attention are more likely to increase their portfolio holdings of environmentally friendly ESG ETFs. Using advisory firm-quarter level panel data, we regress the quarterly change in *ESG ETF Share* on contemporaneous *Local Climate Attention (M)*, while controlling for the size and clientele of the advisory firm. We also control for the lagged value of *ESG ETF Share* because there is significant mean reversion in this variable. We report our results in Table 2.[18]

[Table 2 approximately here.]

[17] *Chain Size* is defined as the total number of newspapers (in our dataset) owned by the focal newspaper's parent company.

[18] The analyses in this table and in Table 4 are at the quarterly level, so we aggregate monthly *Local Climate Attention (M)* to MSA-quarter by averaging across the three months of each quarter.

Greater local newspaper coverage of climate change is associated with a contemporaneous increase in ownership of ESG ETFs from clients of local investment advisory firms. The results in Column 1 of Table 2, which include time fixed effects and MSA-level demographic controls, show a positive and statistically significant estimated coefficient on *Local Climate Attention (M)*. In contrast, the other control variables, with the exception of the lagged share of ESG ETFs, do not significantly affect the change in *ESG ETF Share*. In Column 2, we add advisory firm fixed effects, and the effect of *Local Climate Attention (M)* maintains statistical significance, with the estimated coefficient more than doubling in magnitude.

In Columns 3 through 6, we instrument for climate attention using *Chain Size* and *Peer Attention*, and find that the predicted *Local Climate Attention* from the first stage significantly predicts positive changes in ESG ETF ownership. These IV results are suggestive of at least some causal effect of climate-related news on investor behavior.[19]

In terms of economic magnitude, Column 5 of Table 2 implies that a one-standard-deviation increase in climate attention (about 1.9 percentage points for the sample used in this table) is associated with an approximately 30 bps increase in ESG ETF ownership. While this effect might seem small, the average ESG ETF Share is only 71 bps during our sample period. The average advisory firm in our sample allocates $574 million to ETFs, so 30 bps corresponds to an extra $1.7 million allocated to ESG ETFs from each local advisory firm due to local media attention.

[19]We report the Kleibergen-Paap rk Wald F Statistic for all the IV regressions, and note that while the instrument in Column 5 is somewhat weak (with an F-statistic of 8.422), the other three specifications have instruments that are above the critical values required for a strong instrument.

B. Flood Insurance Purchases by Local Households

We next investigate whether households' flood insurance take-up is influenced by local climate attention. Columns 1 to 3 of Panel A in Table 3 present results from MSA-month level panel regressions. The dependent variable is the percentage change in the MSA's per-capita number of active flood insurance policies over the following 12 months. We use a 12-month horizon to capture the full policy adoption cycle, since flood insurance involves search, underwriting, and annual renewal decisions that may not be reflected immediately in policy counts. We control for the percentage change in per capita number of policies in the previous 12 months, *Water Disaster* (a water-related disaster indicator variable), MSA-level demographic characteristics, and also include MSA and year-month fixed effects. Columns 2 and 3 use *Chain Size* and *Peer Attention* as instruments for *Local Climate Attention*, respectively.

[Table 3 approximately here.]

The estimated coefficients on *Local Climate Attention* are positive in all specifications and statistically significant in three of six. The coefficient of 2.148 in Column 3 indicates that a one-standard-deviation increase in metro-level *Local Climate Attention* in the current month leads to a 0.23-standard-deviation larger change in flood insurance policy take-up over the next 12 months in the same metro area. [20]

Columns 4 through 6 replicate the analysis using county-month observations and find very similar results. For example, Column 6 shows that a one-standard-deviation increase in

[20] The data on *Local Climate Attention* and the per capita number of in-effect insurance policies are both county-month level. Therefore, we aggregate both variables to the MSA-month level by taking their population-weighted averages over the counties that make up a given metro area in a given month.

county-level *Local Climate Attention* leads to approximately 10% standard deviation higher increase in policy take-up over the next 12 months. Collectively, these findings indicate that local climate attention substantially increases flood insurance take-up by local households.

Having established this baseline relationship, we next investigate whether demographic characteristics moderate the climate attention effect. For this heterogeneity analysis, we employ MSA-month-level data and estimate models that interact *Local Climate Attention* with indicator variables for demographic characteristics. Each indicator equals one if a metro area falls in the bottom 10% of the monthly distribution for *Education*, *Unemployment*, or *Income*, and zero otherwise.

Panel B of Table 3 presents these interaction results, with Columns 1 through 4 corresponding to OLS regressions and Columns 5 through 8 corresponding to 2-stage least squares (2SLS) regressions. The variable of interest is the interaction term. Both the OLS and 2SLS specifications suggest that the effect of local climate attention on flood insurance take-up is significantly stronger for MSAs with less-educated residents.

We illustrate the economic magnitude of the effect using the coefficient estimate from Column 8: in MSAs where the share with a bachelor's degree (or higher) is in the bottom decile, the effect of *Local Climate Attention* on flood insurance take-up is approximately 84% larger than in MSAs with higher levels of education. This finding underscores the important role of education in shaping household responsiveness to climate-related information. The policy implication is that targeted communication strategies can enhance flood insurance adoption in less-educated communities. *Unemployment* and *Income* do not alter the relationship between climate attention and flood insurance purchases, suggesting that barriers to adoption might be more informational than financial.

C. Earnings Call Discussions on Climate Risk Exposure

We next investigate whether corporate managers also react to local climate attention. Leveraging the high-frequency variation in our measure, we study whether quarterly earnings calls contain more discussion of climate-related physical risks during periods of heightened local climate attention in the MSA of the firm's headquarters. We obtain *Physical Climate Risk*, the intensity of discussions of a firm's physical risk exposure in earnings calls, from Li et al. (2024). We then regress this measure on contemporaneous *Local Climate Attention (M)*, controlling for firm characteristics, local demographics, and industry-by-time fixed effects, to capture within-industry-quarter variation. The results are reported in Table 4.

[Table 4 approximately here.]

In Column 1 of Table 4, the estimated coefficient on climate attention is 0.007 but is not statistically significant. In Column 2, we add firm fixed effects to absorb cross-firm variation, allowing us to focus on how earnings call discussions about climate risk evolve over time for each firm in response to local climate attention. In this specification, the estimated coefficient on *Local Climate Attention (M)* is 0.011 and it is statistically significant at the 5% level, indicating higher climate attention is associated with a contemporaneous increase in physical risk discussion. In terms of economic magnitude, a one standard-deviation increase in local climate attention is associated with approximately a 2.0 bps increase in physical climate risk. Physical climate risk equals zero for over 95% of earnings calls, and the mean value of this variable is just 26 bps, so a 2.0 bps effect is economically meaningful, representing roughly an 8% increase relative to the mean.

Next, we use our two instruments, *Chain Size* and *Peer Attention*, to examine whether there is a causal effect of *Local Climate Attention (M)*. In Column 3 of Table 4, we use *Chain Size* as an instrument for *Local Climate Attention (M)*, while including the same set of controls and fixed effects as Column 2. The estimated coefficient from the second stage of the IV is positive but is not statistically significant. In Column 4, we instead use *Peer Attention* as an instrument for *Local Climate Attention (M)*. In this specification, the estimated coefficient on our variable of interest is positive and statistically significant at the 1% level (t-statistic of 3.49), suggesting that local climate attention leads to more intense discussion of physical risk exposure in local firms' earnings calls.[21]

Overall, Table 4 provides new evidence that firm managers respond to local climate news coverage, and that this responsiveness shows up in quarterly earnings calls with financial analysts. This finding offers a plausible channel through which climate attention could influence firm decisions, a topic we examine in the next section.

D. Local Firms' Environmental Performance

Finally, we investigate how local climate attention affects firms' environmental performance, using changes in environmental ratings of locally headquartered firms. Using firm-year panel data, we regress the annual change in *ENV Score* on contemporaneous *Local Climate Attention (M)*, while controlling for firm characteristics, 3-digit SIC industry code, and MSA-level demographic variables. We also control for the lagged value of *ENV Score* because of

[21]We do not find a significant relationship between local climate attention and the *transition risk* discussions in earnings calls (as defined by Li et al. 2024). This suggests that concern about physical climate risk exposure is more sensitive to local climate attention shocks than concern about transition risk exposure.

significant mean reversion in this variable. The analysis in this table is at the annual level so we aggregate monthly *Local Climate Attention (M)* to MSA-year by averaging across the twelve months of each year. We include firm, year, and (time-varying) industry fixed effects.

[Table 5 approximately here.]

Column 1 of Table 5 shows a positive and statistically significant relation between climate attention and the contemporaneous change in the firm's environmental score. Consistent with our hypothesis, local climate coverage is associated with improvement in firm-level environmental ratings, reflecting firms' investment of resources to become more environmentally sustainable. We add MSA controls in the remaining columns to control for time-invariant area heterogeneity. In Column 2 of Table 5, the estimated coefficient on climate attention is 0.004, similar to that in Column 1, although no longer statistically significant.

We then implement an IV-based approach in Column 3, using *Chain Size* as an instrument, and find that local climate attention continues to positively predict changes in the firm's environmental score, suggesting that our results are causal.[22] In terms of economic magnitude, Column 3 indicates that a one-standard-deviation increase in local climate attention in a particular year is associated with local firms boosting their environmental ratings that year by 0.24 standard deviations (of the annual change in firm environmental score).

In Columns 4 through 6, we examine the effect of local climate newspaper coverage on changes in three subscores of Refinitiv's Environment Pillar Score: the Emissions Score, Innovation Score, and Resource Use Score. We find that local climate attention is associated with

[22]The *Peer Attention* instrument is unsuitable for these tests because annual data frequency weakens the first-stage estimation.

significant increases in the emissions rating, indicating a reduction in pollution emissions, and an improved innovation rating, indicating more R&D spending on green projects. Climate attention is also associated with an improved resource use score, indicating more efficient use of environmental resources such as minerals, water, and energy.

E. Controlling for Extreme Temperature and Weather Events

One alternative explanation for the previous set of results is the omission of controls for extreme local weather events. Heat waves, floods, hurricanes, wildfires, and other extreme events could simultaneously increase *Local Climate Attention* and lead to changes in investor or firm behavior. We test this explanation by replicating Tables 2–5 while controlling for a comprehensive set of extreme weather events using data from FEMA and NOAA.

In Table A2, we take the strictest specifications from each table and then add *High Temp*, *Tropical/Coastal Storm*, *Other Storm/Tornado/Flood*, *Fire Disaster*, and *Other Weather Disaster* as control variables. All of these variables are county-month indicator variables aggregated to the MSA-month level, so they can be interpreted as the fraction of an MSA's population living in a county that experienced each event in a particular month. The coefficients on *Local Climate Attention* remain largely unchanged. Furthermore, most of the extreme weather variables do not significantly affect the economic decisions of households and firms. These findings support our view that economic behavior is primarily shaped by climate change awareness rather than transient weather events.

IV. Comparison with the Yale Climate Opinion Maps

The Yale Climate Opinion Maps dataset, based on survey results and model estimates, predicts climate change beliefs, risk perceptions, and policy preferences at the state, congressional district, metropolitan area, and county levels, using a concise set of demographic and geographic predictors. We use their model results to define $Yale^{Happening}$, the estimated percentage of the population of each county that believes that global warming is happening, which we compare to our media coverage-based measure of climate attention.[23]

In less-populated counties, where survey responses are sparse, the Yale dataset imputes climate concern using a model that incorporates local demographics. Therefore, we first examine how much of the variation in our *Local Climate Attention* measure versus $Yale^{Happening}$ can be explained by county-level demographics, or more broadly by county fixed effects.[24]

We start by running Fama and MacBeth (1973) regressions of *Local Climate Attention* and $Yale^{Happening}$ on county demographic variables including (log) population, median household income, educational attainment, political leaning, and the unemployment rate. Results appear in Columns 1 and 2 of Table 6, respectively. The rationale for starting with Fama and MacBeth

[23]We thank the Yale Program on Climate Change Communication and the George Mason Center for Climate Change Communication for providing the data. The dataset is available from 2014 onward. Howe et al. (2015) present independently validated high-resolution opinion estimates by using a multilevel regression and post-stratification model. See Ballew, Leiserowitz, Roser-Renouf, Rosenthal, Kotcher, Marlon, Lyon, Goldberg, and Maibach (2019) and Leiserowitz et al. (2020) for more details.

[24]We aggregate the paper-level *Local Climate Attention* measure to the county level by taking a circulation-weighted average over papers published in a given county in a given month.

(1973) regressions is that we aim to focus exclusively on the cross-sectional variation in the two measures that we are comparing.

[Table 6 approximately here.]

Both measures are positively associated with county-level *Income* and *Democrat Share*. On the other hand, *Log Population* and *Education* significantly explain only the Yale measure, while *Unemployment* explains both measures but with opposite signs. The divergence across the two columns is natural, since the two measures use fundamentally different methodologies. More interestingly, the average cross-sectional R^2 for our *Local Climate Attention* measure is 0.100, compared with 0.782 for the Yale measure. This substantial difference in average R^2 between the two columns highlights the main advantage of our measure: it captures other determinants of climate attention, not just local demographic variables.

In Columns 3 and 4 of Table 6, we repeat the analysis but instead use OLS panel regressions with time fixed effects. The R^2 is 0.237 for *Local Climate Attention* and 0.820 for $Yale^{Happening}$, again indicating that the Yale measure is more of a function of local demographics and time fixed effects than our measure. Finally, in Columns 5 and 6, we add county fixed effects to absorb variation from time-invariant county characteristics. This specification increases the R^2 to 0.541 for explaining *Local Climate Attention* and to 0.959 for explaining $Yale^{Happening}$. With an R^2 so close to one, the Yale measure has almost no time series variation that could be used to identify its effect on other economic variables, as we did with *Local Climate Attention* in Section III.

Another way to compare *Local Climate Attention* and $Yale^{Happening}$ is to examine which of the two measures does a better job explaining a third independent measure of climate concern, *FB Climate Posts*, the weekly percentage of Facebook posts in each county related to climate change.[25] In Table 7, we regress *FB Climate Posts* on *Local Climate Attention* and *Yale*^{Happening} at the county-month level. In Columns 1 and 2, which exclude county controls or county fixed effects, the estimated coefficients on *Yale*^{Happening} are positive but not statistically significant. In contrast, *Local Climate Attention* has a positive and significant association with *FB Climate Posts*.

[Table 7 approximately here.]

When we add county-level demographic controls in Columns 3 and 4, the coefficient on *Yale*^{Happening} shrinks significantly, which is unsurprising given that we know from Table 6 that the Yale measure is largely a function of local demographics. And in Columns 5 and 6, which include county fixed effects, the estimated coefficient on *Yale*^{Happening} turns negative. In contrast, across all the specifications, our *Local Climate Attention* measure continues to be positively associated with *FB Climate Posts*. This table illustrates how our news-based measure, but not the Yale measure, picks up high-frequency variation in climate attention that is also picked up by Facebook posts.

Our last comparison of *Local Climate Attention* and *Yale*^{Happening} involves running a "horse race" to see which of the two measures better explains economic outcomes. In Table 8, we run this horse race with the quarterly change in local ESG-linked ETF investments, the same dependent variable we used earlier in Table 2. We aggregate both climate attention measures to the MSA-quarter level, and then regress the change in *ESG ETF Share* on *Local Climate Attention*

[25]We thank Meta and Mike Bailey for providing the aggregated and anonymized data. Unfortunately, we are unable to use this measure in other parts of the paper because of a very short sample period (December 2019 through June 2022), but we use it in this section to run a horse race between our measure and the Yale measure.

(M) and *Yale*^{Happening} *(M)*. We only include observations for which both measures are available to ensure a true apples-to-apples comparison.

[Table 8 approximately here.]

Columns 3 and 5 of Table 8 show that *Local Climate Attention (M)* is positively associated with the change in *ESG ETF Share*, with or without advisor firm fixed effects. In contrast, *Yale*^{Happening} *(M)* has a significant positive association with the change in *ESG ETF Share* only in Column 1, where we omit MSA demographic controls. When we include those controls in Column 2 or add advisory firm fixed effects in Column 4, the estimated coefficient on*Yale*^{Happening} *(M)* becomes insignificant or turns negative.

Overall, this evidence suggests that our climate attention measure outperforms the Yale measure in both capturing social media climate discussions and investment behavior. The Yale measure's weaker performance, particularly after controlling for demographic variables or advisory firm fixed effects, likely stems from its reliance on model imputation, which generates limited cross-sectional and time-series variation beyond local demographics.

In Table A3, we further test the ability of *Yale*^{Happening} to explain the variation in our economic variables. We examine its association with household financial decisions, namely ESG ETF holdings and flood insurance purchases, and with corporate behavior, including local firms' discussions of climate risk in earnings calls and their overall environmental performance. For comparison, each column replaces *Local Climate Attention* with *Yale*^{Happening} in the corresponding regression from Section III.[26]

[26]Specifically, Column 1 of Table A3 is the analogue of Column 2 of Table 2, Column 2 is the analogue of Column 1 of Table 3, Column 3 is the analogue of Column 2 of Table 4, and Column 4 is the analogue of Column 2 of Table 5

Each specification includes all control variables used in its counterpart, including local demographics. They also include the same time fixed effects used in the original regressions. However, the MSA or firm fixed effects used in the original regressions are excluded from the table because of multicollinearity caused by the high persistence of $Yale^{Happening}$. The coefficient on $Yale^{Happening}$ is insignificant in Columns 1 to 3. In Column 4, the coefficient is negative and marginally significant, at the 10% level. The results in Table A3 suggest that $Yale^{Happening}$ has trouble explaining the economic variables studied in Section III.

One major difference is that while the Yale measure covers a wider cross-section, its time series is more limited, with data availability only starting in 2014, compared to 2000 for our measure. In Table A3, we use all the available Yale data and find that it does not have the same economic effects that our measure had in Section III. The lack of significant results may reflect the Yale measure's high correlation with local demographics or its shorter sample period.

V. Determinants of Local Climate Attention

As shown in Table 6, local demographic variables, such as *Income* and *Democrat Share*, are important determinants of local climate attention. In this section, we examine additional candidate variables that might explain variation in climate news coverage. These include: (1) national or global news about climate change such as international climate conferences or federal government climate policies; (2) extreme local weather phenomena that bring the issue of climate change to the forefront; (3) local pollution and carbon emissions; (4) other events such as local climate policies, protests, or lawsuits, and (5) climate attention in socially connected (peer) areas, and newspaper ownership decisions.

We examine the determinants of climate attention in Table 9, where we use newspaper-month level data to regress *Local Climate Attention* on different sets of possible determinants in a series of OLS panel regressions. All specifications include the county demographic controls from Table 6, as well as lagged *Local Climate Attention* to account for persistence in climate coverage. We also include newspaper fixed effects in all regressions, and various time fixed effects depending on the specification.

[Table 9 approximately here.]

A. National Climate News Coverage

In the first two columns of Table 9, we formally relate our *Local Climate Attention* measure to two previously used measures of nationwide climate change sentiment, the *MCCC Index* from Ardia et al. (2023) and the *WSJ Index* from Engle et al. (2020), both standardized to have zero mean and unit standard deviation to simplify interpretation. Each column includes year, instead of year-month, fixed effects since the nationwide measures only vary over time and do not vary cross-sectionally within a month.

Both nationwide climate sentiment measures significantly explain *Local Climate Attention*. Column 1 of Table 9 shows that a one-standard-deviation increase in *MCCC Index* is associated with a statistically significant 28.7 bps, or 0.16-standard-deviation, increase in contemporaneous *Local Climate Attention*. Likewise, in Column 2, a one-standard-deviation increase in *WSJ Index* is associated with a somewhat smaller but still significant 13.3 bps, or 0.07-standard-deviation, increase in *Local Climate Attention*. This correlation of climate attention with nationwide climate sentiment helps to validate our measure.

B. Extreme Local Weather

Next, we examine the association between *Local Climate Attention* and local extreme natural events. In Column 3 of Table 9, we regress *Local Climate Attention* on county-month indicator variables for extreme high temperatures, a highly damaging natural disaster, a tropical or coastal storm, an inland storm with tornadoes or floods, wildfires, or other weather disasters. The list of affected counties is based on FEMA disaster declarations, indicating the disasters had significant adverse effects. We include year-by-month fixed effects to absorb any national climate attention effect from a particularly salient weather event, such as Hurricane Katrina.

Column 3 shows that three of the six event types, *High Temp*, *Fire Disaster*, and *Other Weather Disaster*, are significant positive predictors of *Local Climate Attention*. While it is somewhat surprising that salient events like hurricanes, floods, or highly damaging natural disasters are not associated with greater climate attention, there is likely to be a crowding-out effect, as news coverage around the disaster is often focused on more urgent issues like emergency response, human and economic costs, and post-disaster recovery and rebuilding. This effect would cancel out any expected increase in climate attention due to the disaster.

One important question is to what extent our climate attention measure is just an aggregate of the various extreme weather events or whether it is mostly a function of other non-weather phenomena. We answer this by looking at the increase in R^2 from including the extreme weather events. The R^2 in Column 3 of Table 9 is 0.635, but most of this explanatory value comes from fixed effects, local demographics, and lagged *Local Climate Attention*. If we run this specification without the extreme natural events, the R^2 is almost identical (0.635 after rounding); the incremental R^2 from these local disaster variables, beyond the fixed effects, local demographics, and lagged *Local Climate Attention*, is only 0.0005. This indicates that the natural events add very little explanatory value. Therefore, local climate attention can be explained by many different variables, not just short-lived episodes of extreme weather.

C. Pollution, Policy, and Other Events

Next, we examine four additional determinants of local climate attention: local pollution, climate-related legislation, litigation, and protests.

We investigate the role of local pollution and carbon emissions in explaining climate attention. In Column 4 of Table 9, we regress *Local Climate Attention* on the county-level *Greenhouse Gas Emissions* and *Toxic Chemicals Releases* from all production facilities, along with other non-weather explanatory variables. We do not find a significant relationship between *Local Climate Attention* and either measure. The result suggests that local residents are not attentive to local pollution, either because it is not directly observable to them or because they do not respond to such signals.

We also examine whether climate attention reacts to state government climate transition policies. Cornaggia and Iliev (2023) show that the implementation of state-level Renewable Portfolio Standards (RPS) and Clean Energy Standards (CES) affects local municipal bond yields and credit ratings. Since many RPS were implemented before our sample period begins, we focus on CES, which states began adopting from 2017 onward. We collect data on each state's year of enactment of these programs from the U.S. State RPS and CES 2024 Report.[27] Column 4 of Table

[27]Information on state enactments of RPS and CES can be found on page 10 of the U.S. State Renewables Portfolio and Clean Electricity Standards 2024 Report. For a discussion of the adoption of these standards, see Cornaggia and Iliev (2023).

9 includes *Post Clean Energy Standard*, an indicator for whether the state had implemented a CES, thus comparing climate attention before and after CES adoption. We find a positive and significant effect, with an additional 10.7 bps of climate attention (equivalent to 8.1% of the mean) after CES adoption.

Another potential reason for heightened local climate attention is climate-related litigation. We add *Climate Lawsuits*, the number of climate-related lawsuits filed in a particular county-month, as an explanatory variable to Column 4 of Table 9.[28] Climate litigation is associated with a statistically significant increase (t-statistic of 6.65) in *Local Climate Attention*. Each extra lawsuit increases climate attention by 19.6 bps (14.8% of the mean).

Finally, we investigate how *Local Climate Attention* responds to local climate-related protests. Because the sample period for this variable is short (2020–2022), we examine it separately from the other explanatory variables in Table 9.

Column 5 of Table 9 presents the results of regressing *Local Climate Attention* on *Climate Protests*, an indicator for whether a climate-related protest occurred in an MSA, with the same controls and fixed effects as Column 4. Despite the short sample period, local climate protests are associated with a positive and statistically significant increase in climate attention of 22.4 bps (equivalent to 16.9% of the mean).

We also examine the temporal decay of climate protests at the MSA-month level by regressing *Local Climate Attention (M)* on leads and lags of the number of protests occurring in an MSA, while controlling for MSA fixed effects and year-month fixed effects. Figure A.2 reports

[28]The month and county of each lawsuit are based on the court where it was filed and the date of the first filing.

the coefficient estimates, showing that for each protest, *Local Climate Attention* contemporaneously increases by 0.31 bps, and the effect persists for the following two months.

Overall, our findings suggest that local climate attention responds to tangible climate events, both natural (weather-related) and human-caused (climate policies, lawsuits, and protests). The lack of association between news coverage and local pollution suggests that media attention focuses on acute climate events rather than chronic environmental issues.

D. Newspaper Ownership

Next, we investigate newspaper ownership, the first of two instruments for *Local Climate Attention* we used in Section III. We hand-collect ownership data from Wikipedia entries for each newspaper, supplemented with Google searches, tracking ownership changes of each newspaper back to the start of our sample period. Newspapers often belong to chains owned by a single parent company. *Chain Size* is defined as the total number of newspapers (in our dataset) owned by the parent company.

Figure A.3 shows how ownership of U.S. newspapers changed over our sample period. The red line shows that chain size increased from an average of 17 papers per chain at the start of our sample period, to just under 60 papers by the end. Much of this consolidation happened from 2015 to 2020, when several large newspaper chains like Gannett and Gatehouse, underwent mergers. The blue line shows that the trend is not driven solely by mergers of large chains. Stand-alone newspapers, those not part of a chain, declined from 20% of our sample to 12% during this period, as circulation has declined, forcing locally owned family papers to sell to more economically efficient chains. We argue that these trends in local newspaper ownership are largely exogenous to climate issues.

We examine the relation between *Local Climate Attention* and *Chain Size*, the total number of newspapers in our sample with the same owner as that of the focal newspaper, and report the results in Column 4 of Table 9. Climate coverage is significantly lower for newspapers belonging to larger chains. A one-standard-deviation increase in *Chain Size* is associated with a decrease in *Local Climate Attention* of approximately 6.7 bps (equivalent to 5.1% of the mean). The exact mechanism for this result is unclear, but Gibson (2016) suggests that large newspaper chains' focus on cost-cutting leads to layoffs of journalists specializing in science and environmental topics.

Because *Chain Size* is significantly associated with *Local Climate Attention*, it serves as a potential instrument. The key question is whether it satisfies the exclusion restriction. We argue that the secular consolidation process into chains and each newspaper's association with a particular chain are based on the economics of the news industry and the liquidity needs of the newspapers' legacy ownership. These factors are exogenous to local climate attention and thus the instrument should satisfy the exclusion restriction.

Alternatively, one could argue that newspaper chain managers might select specific newspapers to add to their portfolio based on criteria related to climate coverage, in which case, our instrument would not satisfy the exclusion restriction. In Table A4, we investigate whether ownership changes can be predicted by newspaper characteristics or local demographic variables. We find that the probability of an ownership change is significantly associated with only one variable, the population size of the county where the paper is located. This positive relation between county population and ownership change also holds in subsample tests for small-chain/independent newspapers and large-chain newspapers, while no determinants are statistically significant (at the 5% level) for medium-sized chains. Importantly, none of the newspaper variables, including the paper's prior climate coverage, predict ownership changes. These results support the use of newspaper ownership as an instrument.

E. Peer Attention

Extensive research has documented significant peer influence on household beliefs and financial decisions (see Bailey, Cao, Kuchler, and Stroebel 2018a; Bailey et al. 2019, 2022; Bailey, Johnston, Koenen, Kuchler, Russel, and Stroebel 2024; Hu 2022 for studies that used Facebook-based measures). Motivated by these studies, we examine whether climate attention in socially connected areas influences local climate awareness. We examine the relation between *Local Climate Attention* and *Peer Attention*, defined as the average *Local Climate Attention* of counties with strong social connections to the home county of the newspaper, based on Facebook's SCI, and excluding same-state peers, and report the results in Column 4 of Table 9. There is a positive and statistically significant relation (t-statistic of 6.93) between local and peer newspaper attention. A one-standard-deviation increase in *Peer Attention* corresponds to an increase in *Local Climate Attention* of 29.8 bps (equivalent to 22.5% of the mean).

Peer Attention is also a potential instrument for *Local Climate Attention*. We argue that *Peer Attention* might satisfy the exclusion restriction because climate coverage in geographically distant but socially proximate areas of the country is unlikely to be related to local climate coverage except through the social connections. This helps mitigate concerns that omitted, time-varying local factors, such as climate disaster shocks, might drive both climate attention and the associated economic outcomes. Nevertheless, we are cautious about the identification based on *Peer Attention* since we lack an exogenous shock to peer attention.

The estimated coefficients from the IV regressions can be understood as local average treatment effects — specifically, the effect on economic outcomes for households and firms whose local climate attention was shifted by the relevant instrument. For the peer attention IV, peer groups may be more responsive to climate attention than the average agent, which could explain why the estimates based on this IV tend to be larger than the OLS estimates.

We also investigate whether socially connected areas share similar climate-related reporting content. We analyze headlines and opening paragraphs of climate-related articles from over 5,000 newspapers in NewsLibrary to compare topic coverage across regions. Using Latent Dirichlet Allocation (LDA), we extract 20 topics and measure the distance between counties' topic shares averaged across the entire time period using the Jensen-Shannon distance (*JD20*). This metric ranges from zero (identical distributions) to one (completely different distributions).[29] Appendix B.2 details our textual analysis methodology.

Table A5 examines how social connectedness relates to similarity in climate reporting content. The dependent variable, *Topic Similarity*, is computed as one minus the topic distance between counties as measured by the Jensen-Shannon distance *JD20*. Our analysis considers three measures of county similarity: social connectedness (*SCI*), demographic and economic characteristics (*Socioeconomic Similarity*), and geographic proximity (*GeoProx*), and we also control for focal and peer county fixed effects in all regressions.

[29] Results remain consistent using five or ten topics.

Column 1 of Table A5 shows that moving from the bottom to the top rank of *SCI* corresponds to a 63.8 bps increase in *Topic Similarity* (14.47% of its standard deviation). In other words, reporting is more similar for more connected counties. Alternative similarity measures, *Socioeconomic Similarity* and *GeoProx*, are also significant in explaining *Topic Similarity*. Together, the results suggest that social connections play a distinct role in shaping climate reporting, fostering topical similarity across socially connected regions and supporting our use of peer climate attention as an instrument.

VI. Conclusion

We develop a novel, high-frequency measure of local climate change attention based on a comprehensive dataset of over 5,000 U.S. newspapers covering all major U.S. population centers from 2000 to 2022. Using this measure, we find that local climate attention shapes household and corporate behavior in economically meaningful ways. A one-standard-deviation increase corresponds to a 43% increase in ESG ETF ownership relative to the mean (an additional $1.7 million in ESG holdings for the average advisory firm) and a 0.23-standard-deviation increase in flood insurance take-up, with effects stronger in less-educated communities. For firms, local climate attention raises the intensity of physical climate risk discussions in earnings calls by approximately 8% relative to the mean and boosts environmental ratings by 0.24 standard deviations, with measurable emissions reductions and increased green innovation.

These results have direct policy implications: targeted communication strategies can meaningfully shift climate-risk mitigation behavior, particularly flood insurance adoption in less-educated communities where informational rather than financial barriers appear to dominate.

Our measure also offers researchers a validated tool for studying the effect of climate awareness on decision making. Unlike the Yale Climate Opinion Maps, it captures high-frequency within-area variation beyond local demographics, aggregating a myriad of signals that reflect not only nationwide climate sentiment, local demographics, and observable climate events, but also less tangible forces such as social media attention, peer effects in socially connected areas, climate legislation, protests, and other non-climate factors.

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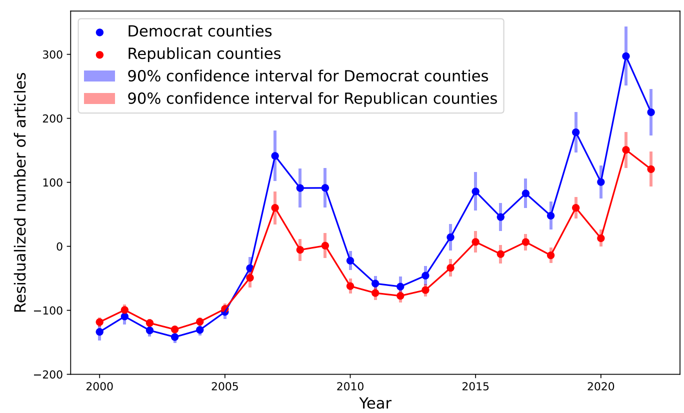
FIGURE 1

Climate-Related Articles and ESG ETF Shares in Democratic Versus Republican Counties

This figure shows the residualized average number of climate-related articles published by newspapers, comparing Democratic and Republican counties in Panel A. Panel B presents average residualized ESG-focused ETF shares by year across Democratic and Republican Core Based Statistical Areas (CBSAs). Both measures are residualized on log(population) and a constant. A Democrat (Republican) county/CBSA is defined as a region with a vote share that is more than (less than) 50% Democrat. The bars indicate 90% confidence intervals.

Panel A: *Local Climate Attention*



Panel B: ESG share

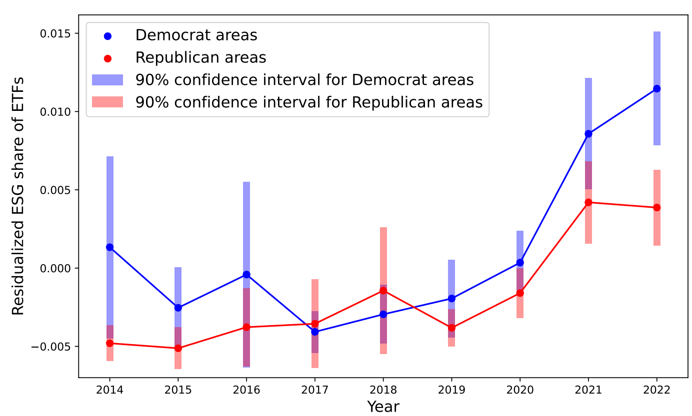


FIGURE 2

Heat Map of Data Coverage Across U.S. States

This figure shows the percentage of each state's population that lives in an MSA covered by our newspaper local climate attention data. Darker blue shades indicate states with better data coverage.

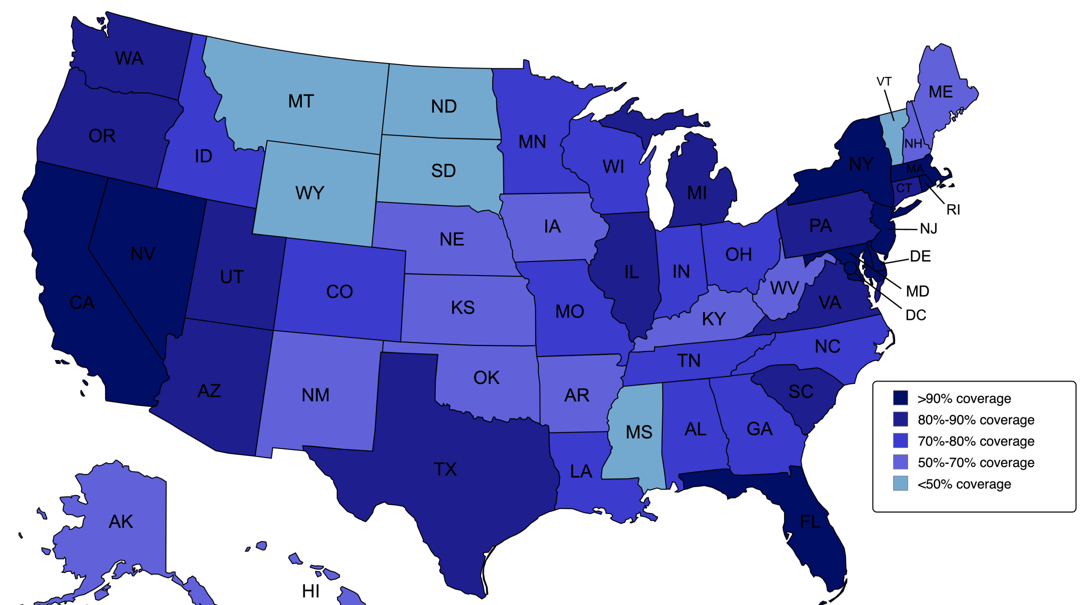


TABLE 1

Summary Statistics

This table presents summary statistics for the main variables used in the analyses. The statistics are calculated for only those areas that have local newspaper coverage. Variable definitions appear in Table A1.

	Frequency	N	Median	Mean	SD	25%	75%
MCCC Index	Month	236	1.085	1.180	0.504	0.801	1.468
WSJ Index	Month	210	0.592	0.629	0.210	0.487	0.719
Local Climate Attention (%)	Paper-Month	123,293	0.803	1.326	1.807	0.231	1.776
Local Climate Attention (M) (%)	Metro-Month	88,388	0.832	1.323	1.677	0.277	1.791
Chain Size	Paper-Month	123,283	14.000	26.532	33.746	3.000	29.000
Peer Attention (%)	Paper-Month	134,881	1.161	1.430	1.083	0.623	1.921
FB Climate Posts (%)	County-Month	13,658	0.122	0.142	0.092	0.078	0.183
Δ Policy Per Capita (t, t+12) (%)	County-Month	64,186	-4.460	-3.159	12.607	-7.959	-0.550
Δ Policy Per Capita (t, t+12) (M) (%)	Metro-Month	47,606	-4.389	-2.923	15.538	-7.914	-0.352
High Damage	County-Month	122,268	0.000	0.007	0.082	0.000	0.000
High Temp	County-Month	122,268	0.000	0.007	0.085	0.000	0.000
Tropical Storm	County-Month	122,268	0.000	0.006	0.074	0.000	0.000
Other Storm	County-Month	122,268	0.000	0.008	0.090	0.000	0.000
Fire Disaster	County-Month	122,268	0.000	0.002	0.045	0.000	0.000
Other Disaster	County-Month	122,268	0.000	0.000	0.006	0.000	0.000
$\text{Yale}^{\text{Happening}}$ (%)	County-Year	4,430	68.025	68.382	6.509	63.770	72.948
Greenhouse Gas Emissions	County-Year	4,565	13.370	13.293	2.237	12.172	14.797
Toxic Chemicals Releases	County-Year	9,337	14.138	13.871	2.584	12.620	15.538
Log Population	County-Year	10,624	12.334	12.472	0.942	11.773	13.111
Education (%)	County-Year	10,624	26.500	28.033	9.578	20.800	33.500
Median Household Income (2023 Dollars)	County-Year	10,624	68,245	71,983	16,524	60,811	78,793
Unemployment Rate (%)	County-Year	10,486	5.200	5.722	2.466	4.000	6.900
Democrat Share (%)	County-Year	10,608	49.581	49.759	13.755	39.751	58.469
Δ ESG ETF Share (%)	Adv Firm-Qtr	101,341	0.000	0.026	2.498	0.000	0.000
ESG ETF Share Lag (%)	Adv Firm-Qtr	104,246	0.000	0.706	4.635	0.000	0.001
Log AUM Lag	Adv Firm-Qtr	104,246	19.683	20.036	1.646	18.936	20.777
Physical Climate Risk	Firm-Quarter	224,054	0.000	0.262	1.489	0.000	0.000
ROA	Firm-Quarter	201,564	0.028	-0.012	0.205	-0.018	0.075
B/M	Firm-Quarter	206,121	0.493	0.804	2.259	0.271	0.823
Leverage	Firm-Quarter	213,934	0.334	0.366	0.321	0.088	0.544
Size	Firm-Quarter	206,121	13.960	13.993	1.915	12.721	15.215
Returns	Firm-Quarter	200,797	0.021	0.033	0.289	-0.104	0.142
Δ ENV Score	Firm-Year	47,080	-0.023	0.013	0.441	-0.078	0.059
Δ Emissions Score	Firm-Year	26,156	0.000	0.030	0.116	0.000	0.034
Δ Innovations Score	Firm-Year	26,143	0.000	0.016	0.114	0.000	0.000
Δ Resource Use Score	Firm-Year	26,156	0.000	0.032	0.119	0.000	0.027

TABLE 2

Local Climate Attention and ESG ETF Ownership

This table examines how local climate news coverage influences retail investors' investment in ESG ETFs. We run panel regressions at the MSA-quarter level from 2013 through 2022, focusing on advisory firms serving primarily individual investors. *ESG ETF Share* represents an advisory firm's holdings in ESG-focused ETFs as a fraction of total ETF holdings, based on its Form 13F portfolio. The key independent variable, *Local Climate Attention (M)*, measures the quarterly average fraction of climate-related articles in an MSA's newspapers. Control variables include *Log AUM Lag* (logarithm of prior-quarter assets under management), *High Net Worth* (indicator for majority high-net-worth clientele), and prior quarter's *ESG ETF Share*. All specifications also include MSA-level demographic controls and quarter-year fixed effects, with advisor fixed effects in selected columns. For instrumental variable specifications, for each MSA, we use population-weighted averages of county-level *Newspaper Chain Size* and *Peer Attention* as instruments for *Local Climate Attention* (see Table A1 for variable definitions). Standard errors are double-clustered at the year-by-quarter and MSA levels, and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Δ ESG ETF Share					
	1	2	$3_{\text{IV=CS}}$	$4_{\text{IV=Peer}}$	$5_{\text{IV=CS}}$	$6_{\text{IV=Peer}}$
Local Climate Attention (M)	0.008**	0.018***	0.023*	0.042**	0.156**	0.109***
	(2.196)	(4.893)	(1.831)	(2.530)	(2.565)	(4.106)
ESG ETF Share Lag	−0.090***	−0.325***	−0.091***	−0.091***	−0.326***	−0.326***
	(−5.454)	(−6.944)	(−5.487)	(−5.463)	(−7.021)	(−6.825)
Log AUM Lag	−0.006	0.026	−0.006	−0.005	0.023	0.024
	(−1.197)	(0.986)	(−1.149)	(−0.877)	(0.917)	(0.948)
High Net Worth	−0.032	−0.007	−0.032	−0.031	−0.013	−0.011
	(−1.323)	(−0.196)	(−1.307)	(−1.270)	(−0.387)	(−0.327)
MSA Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Firm FE	No	Yes	No	No	Yes	Yes
Cluster-Robust 1st Stage F-stat	-	-	19.319	20.720	8.422	38.172
Observations	58,543	58,543	58,543	58,543	58,543	58,543
R^2	0.041	0.208	0.041	0.040	0.200	0.204

TABLE 3

Local Climate Attention and Flood Insurance Take-Up

This table examines how local climate news coverage influences households' flood insurance take-up. In Columns 1–3 of Panel A, we conduct panel regressions at the MSA-month level from 2011 to 2021. The dependent variable, Δ *Policies Per Capita (t, t+12)*, is the percent change in the per capita number of in-effect NFIP flood insurance policies in a given MSA/county over the next 12 months. Δ *Policies Per Capita (t-12, t)* is the percent change in the per capita number of in-effect NFIP flood insurance policies over the preceding 12 months. *Water Disaster* is a dummy variable equal to one if a water-related disaster (excluding droughts) occurred in the current month. *Local Climate Attention* is the fraction of climate-related articles aggregated to the MSA level. Columns 4–6 of Panel A repeat the same analysis using county-month level data. In Columns 2 and 5 (Columns 3 and 6), *Local Climate Attention* is instrumented by *Chain Size* (*Peer Attention*). All specifications in Panel A include demographic controls at the MSA/county level and MSA/county fixed effects, as well as year-by-month fixed effects. In Columns 1–3, standard errors are double-clustered at year-by-month and MSA levels, while in Columns 4–6, they are clustered at year-by-month and county levels. In Panel B, we run MSA-month level panel regressions that include interactions of *Local Climate Attention* with *Low Education*, *Low Unemployment*, and *Low Income*, where "low" indicates being in the bottom 10% of MSAs with respect to the corresponding demographics in the current month. Columns 1–4 use OLS regressions, while the remaining columns use 2SLS, where *Local Climate Attention* and its interactions with demographic dummies are instrumented by *Peer Attention* and its interactions. All specifications in Panel B include metro-level demographic controls, year-by-month fixed effects, and MSA fixed effects. Standard errors are double-clustered at year-by-month and MSA levels. In both panels, t-statistics are given in parentheses, and *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

TABLE 3

Local Climate Attention and Flood Insurance Take-Up

Panel A: Baseline Regressions

	Δ Policies Per Capita (t, t+12)					
	MSA Level			County Level		
	1	$2_{\text{IV=CS}}$	$3_{\text{IV=Peer}}$	4	$5_{\text{IV=CS}}$	$6_{\text{IV=Peer}}$
Local Climate Attention	0.315^{**}	1.940	2.148^{***}	0.197	1.822	0.817^{*}
	(2.056)	(1.196)	(2.717)	(1.200)	(1.495)	(1.649)
Δ Policies Per Capita (t-12, t)	-0.117^{***}	-0.117^{***}	-0.117^{***}	-0.099^{***}	-0.094^{***}	-0.097^{***}
	(-4.099)	(-4.103)	(-4.082)	(-2.786)	(-2.591)	(-2.721)
Water Disaster	5.953^{***}	5.935^{***}	5.933^{***}	5.428^{***}	5.411^{***}	5.421^{***}
	(4.007)	(3.945)	(3.938)	(5.449)	(5.388)	(5.431)
MSA Controls	Yes	Yes	Yes	-	-	-
MSA FE	Yes	Yes	Yes	-	-	-
County Controls	-	-	-	Yes	Yes	Yes
County FE	-	-	-	Yes	Yes	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-Robust 1st Stage F-stat	-	12.107	86.072	-	14.475	78.373
Observations	42,672	42,669	42,672	58,265	58,262	58,265
R^2	0.142	0.124	0.120	0.180	0.138	0.173

Panel B: Interactions with Demographics

	Δ Policies Per Capita (t, t+12)							
	OLS				2SLS (IV=Peer)			
	1	2	3	4	5	6	7	8
Local Climate Attention	0.265*	0.286*	0.311**	0.233	1.910**	1.978***	2.210***	1.753**
	(1.692)	(1.726)	(1.986)	(1.352)	(2.417)	(2.712)	(2.665)	(2.289)
Local Cl. Att. × Low Education	0.725***			0.759***	1.453***			1.466***
	(2.904)			(3.052)	(2.693)			(2.807)
Local Cl. Att. × Low Unemployment		0.173		0.198		0.623		0.702
		(0.578)		(0.651)		(0.670)		(0.754)
Local Cl. Att. × Low Income			0.101	−0.081			0.779	0.320
			(0.423)	(−0.330)			(0.703)	(0.289)
Low Education	−4.164***			−4.179***	−4.376***			−4.315***
	(−3.269)			(−3.261)	(−3.136)			(−3.039)
Low Unemployment		−0.642		−0.637		−1.408		−1.503
		(−0.776)		(−0.760)		(−0.853)		(−0.910)
Low Income			0.045	0.290			−0.724	−0.112
			(0.042)	(0.273)			(−0.483)	(−0.075)
Δ Policies Per Capita (t-12, t)	−0.117***	−0.117***	−0.117***	−0.117***	−0.117***	−0.117***	−0.117***	−0.117***
	(−4.104)	(−4.088)	(−4.099)	(−4.094)	(−4.090)	(−4.069)	(−4.085)	(−4.081)
Water Disaster	5.940***	5.953***	5.949***	5.937***	5.929***	5.939***	5.926***	5.932***
	(4.005)	(4.010)	(4.000)	(4.002)	(3.946)	(3.934)	(3.923)	(3.932)
MSA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,672	42,672	42,672	42,672	42,672	42,672	42,672	42,672
R^2	0.143	0.142	0.142	0.143	0.124	0.121	0.117	0.124

TABLE 4

Local Climate Attention and Climate Risk Discussions in Earnings Calls

This table examines how local climate attention affects earnings conference call discussions of physical climate risk at locally-headquartered firms. Using firm-quarter panel data from 2002 through 2022, we regress *Physical Climate Risk* on *Local Climate Attention (M)*, and include controls and fixed effects. The dependent variable, *Physical Climate Risk*, is the intensity of discussions of a firm's physical risk exposure in earnings calls, as constructed by Li et al. (2024). *Local Climate Attention (M)* is news-based climate attention at the MSA level. Firm control variables include *Size* (log market capitalization), *B/M* (book-to-market ratio), *ROA* (return on assets), *Leverage* (book leverage ratio), and *Return* (contemporaneous quarterly stock return). All columns also include MSA-level demographic variables. All specifications include year-by-quarter-by-SIC 3-digit industry fixed effects; Columns 2 through 4 also add firm fixed effects. In Columns 3 and 4, we use MSA-aggregated *Newspaper Chain Size* and *Peer Attention*, respectively, as instruments for *Local Climate Attention (M)*. Standard errors are double-clustered at the year-by-quarter and MSA levels, and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Physical Climate Risk			
	1	2	$3_{\text{IV=CS}}$	$4_{\text{IV=Peer}}$
Local Climate Attention (M)	0.007	0.011**	0.041	0.114***
	(1.619)	(2.115)	(0.877)	(3.488)
Size	−0.006	−0.005	−0.005	−0.006
	(−1.356)	(−0.523)	(−0.519)	(−0.601)
B/M	0.004	−0.004	−0.004	−0.005
	(0.388)	(−0.405)	(−0.448)	(−0.600)
ROA	0.093***	−0.006	−0.009	−0.019
	(3.916)	(−0.210)	(−0.312)	(−0.632)
Leverage	−0.008	−0.077***	−0.079***	−0.080***
	(−0.384)	(−2.960)	(−3.044)	(−3.075)
Return (Qtr)	−0.005	0.006	0.006	0.007
	(−0.311)	(0.363)	(0.338)	(0.373)
MSA Controls	Yes	Yes	Yes	Yes
Year×Quarter×SIC3 FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes
Cluster-Robust 1st Stage F-stat	-	-	14.638	17.801
Observations	180,305	180,305	179,838	179,838
R^2	0.207	0.316	0.316	0.312

TABLE 5

Local Climate Attention and Firm Environmental Ratings

This table examines how local climate attention influences corporate environmental performance of locally-headquartered firms. We analyze the effect of MSA-level climate coverage, *Local Climate Attention (M)*, on annual changes in firms' environmental scores, using firm-year panel regressions from 2000 through 2022. In Columns 1 through 3, the dependent variable is Δ*ENV Score*, which combines standardized environmental ratings from MSCI and Refinitiv. Columns 4 through 6 examine changes in Refinitiv's Emissions, Innovation, and Resource Use subscores, respectively. Control variables include *Size* (log market capitalization), *B/M* (book-to-market ratio), *ROA* (return on assets), *Leverage* (book leverage ratio), and *Return Lag* (prior-year stock return). All specifications include the one-year lagged level of the dependent variable, as well as year, industry, and firm fixed effects. Columns 2 through 6 include MSA-level demographic variables. Column 3 uses MSA-aggregated *Chain Size* as an instrument for *Local Climate Attention (M)*. Standard errors are double-clustered at the year and MSA levels, and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Δ ENV Score			Δ Emissions Score	Δ Innovation Score	Δ Resource Use Score
	1	2	$3_{\text{IV=CS}}$	4	5	6
Local Climate Attention (M)	0.004*	0.004	0.062**	0.002**	0.002*	0.003*
	(1.746)	(1.490)	(2.449)	(2.138)	(2.067)	(1.954)
Size	0.031***	0.032***	0.029***	0.023***	0.003*	0.021***
	(3.824)	(3.992)	(3.464)	(9.108)	(1.874)	(6.458)
B/M	0.010	0.011	0.003	0.017***	−0.004	0.015***
	(0.737)	(0.833)	(0.271)	(3.565)	(−1.152)	(4.292)
ROA	−0.012	−0.010	−0.018	0.008	−0.002	−0.009
	(−0.583)	(−0.487)	(−0.842)	(0.999)	(−0.218)	(−1.023)
Leverage	0.027	0.029	0.020	0.016**	−0.016	0.018***
	(1.322)	(1.382)	(0.881)	(2.182)	(−1.661)	(3.008)
Return Lag	−0.012***	−0.012***	−0.012**	−0.005***	−0.001	−0.005***
	(−3.093)	(−3.011)	(−2.779)	(−5.473)	(−1.481)	(−3.659)
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-Robust 1st Stage F-stat	-	-	10.796	-	-	-
Observations	44,097	44,058	44,058	24,371	24,360	24,371
R^2	0.207	0.208	0.196	0.268	0.248	0.276

TABLE 6

Explaining News Climate Attention and Yale Climate Opinions with County Demographic Variables and Fixed Effects

This table compares how well county demographic variables and/or county fixed effects explain news-based climate attention versus Yale climate opinions. Columns 1 and 2 show estimated coefficients from Fama and MacBeth (1973) regressions, while the remaining columns use coefficient estimates from pooled OLS regressions. The sample period is 2014 through 2022. In Columns 1, 3, and 5, the dependent variable is *Local Climate Attention*, the fraction of climate-related articles published in a newspaper, averaged across the newspapers in a county, with circulation numbers used as weights. In Columns 2, 4, and 6, the dependent variable is $Yale^{Happening}$, the estimated percentage of respondents who believe that global warming is happening, from the Yale Climate Opinion Maps surveys. The explanatory variables are the following county-level demographics: *Log Population* is the natural logarithm of the county population, *Income* is the county median household income, measured in thousands of 2023 dollars; *Education* is the percentage of the population with a Bachelor's degree or higher; and *Democrat Share* is the share of the two-party vote in the county won by the Democratic candidate in the previous presidential election. Columns 3 through 6 include year-by-month fixed effects, and Columns 5 and 6 also add county fixed effects. Standard errors are double-clustered at the year and county levels and t-statistics are given in parentheses. In Columns 1 and 2, the reported R^2 values are averages of the cross-sectional R^2 values. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

TABLE 6

Explaining News Climate Attention and Yale Climate Opinions with County Demographic Variables and Fixed Effects

	Local Climate Attention $1_{\text{F-M}}$	$\text{Yale}^{\text{Happening}}$ $2_{\text{F-M}}$	Local Climate Attention 3_{OLS}	$\text{Yale}^{\text{Happening}}$ 4_{OLS}	Local Climate Attention 5_{OLS}	$\text{Yale}^{\text{Happening}}$ 6_{OLS}
Log Population	−0.070	0.329***	−0.060	0.373**	−1.918	−1.946
	(−1.568)	(4.206)	(−0.708)	(2.056)	(−0.848)	(−0.588)
Income	0.010***	0.027***	0.010*	0.024**	0.021	−0.011
	(3.595)	(5.127)	(1.915)	(2.565)	(1.543)	(−0.812)
Education	−0.001	0.099***	0.003	0.109***	0.038	0.242***
	(−0.116)	(5.492)	(0.277)	(3.917)	(1.070)	(2.864)
Democrat Share	0.033***	0.274***	0.031***	0.268***	0.006	0.082**
	(4.906)	(16.275)	(4.295)	(12.869)	(0.638)	(2.418)
Unemployment	−0.068***	0.267***	−0.059*	0.285***	0.068	0.003
	(−5.975)	(4.525)	(−1.772)	(3.145)	(1.308)	(0.045)
Year×Month FE	No	No	Yes	Yes	Yes	Yes
County FE	No	No	No	No	Yes	Yes
Observations	108	108	44,115	44,115	44,115	44,115
R^2	0.100	0.782	0.237	0.820	0.541	0.959

TABLE 7

Explaining Social Media Climate Attention with News-Based Climate Attention and Yale Climate Opinions

This table compares news-based climate attention with the Yale climate opinion variable in explaining social media climate attention. We estimate a panel regression of *FB Climate Posts* on county-level *Local Climate Attention*, $Yale^{Happening}$, and their lagged values. *FB Climate Posts* is the fraction of Facebook posts in a given county-month that are climate-related. *Local Climate Attention* is the fraction of climate-related articles published in a newspaper, averaged across newspapers in a county, with circulation numbers used as weights. $Yale^{Happening}$ is the estimated percentage of respondents who believe that global warming is happening, from the Yale Climate Opinion Maps surveys. All specifications include the one-month lag of *FB Climate Posts*. Although not shown in the table, all columns further control for the one-year lag of $Yale^{Happening}$; Columns 2, 4, and 6 also control for the one-month lag of *Local Climate Attention*. Columns 3 and 4 also control for the county-level demographic variables from Table 6. Year-by-month fixed effects are included in all specifications. Columns 5 and 6 also include county fixed effects. Standard errors are double-clustered at the year-by-month and county levels, and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	FB Climate Posts					
	1	2	3	4	5	6
Local Climate Attention		0.003**		0.003**		0.002***
		(2.700)		(2.675)		(3.055)
$\text{Yale}^{\text{Happening}}$	0.001	0.001	0.0001	0.0001	−0.002*	−0.002*
	(1.473)	(1.491)	(0.255)	(0.174)	(−1.780)	(−1.760)
FB Climate Posts Lag	0.735***	0.713***	0.687***	0.663***	0.332**	0.328**
	(7.313)	(6.920)	(6.426)	(6.056)	(2.444)	(2.434)
County Controls	No	No	Yes	Yes	No	No
County FE	No	No	No	No	Yes	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,658	12,658	12,426	12,426	12,658	12,658
R^2	0.816	0.820	0.821	0.824	0.860	0.861

TABLE 8

Horse Race in Explaining Local Investor ESG ETF Ownership

This table shows the results of a horse race between Yale climate opinions and news-based local climate attention in explaining local investor ESG ETF holdings. Using MSA-quarter-level data from 2013 through 2022, we regress changes in ESG ETF portfolio shares on Yale climate opinions and climate attention. $Yale^{Happening}$ *(M)* measures the MSA-level percentage of respondents who believe global warming is happening, based on Yale Climate Opinion Maps surveys. *Local Climate Attention (M)* is the fraction of climate-related newspaper articles, averaged across newspapers within each MSA-quarter. Additional controls (not reported) include *Log AUM Lag* (logarithm of prior-quarter assets under management), *High Net Worth* (indicator for majority high-net-worth clientele), and prior quarter's *ESG ETF Share*, as in Table 2. Columns 2 through 5 also control for the county-level demographic variables from Table 6. All specifications include year-by-quarter fixed effects, while Columns 4 and 5 add advisory firm fixed effects. Standard errors are double-clustered at the year-by-quarter and MSA levels, and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Δ ESG ETF Share				
	1	2	3	4	5
$Yale^{Happening}$ (M)	0.007***	0.003	0.002	−0.011	−0.012
	(4.885)	(1.240)	(0.905)	(−0.644)	(−0.733)
Local Climate Attention (M)			0.008**		0.019***
			(2.100)		(4.433)
MSA Controls	No	Yes	Yes	Yes	Yes
Year×Quarter FE	Yes	Yes	Yes	Yes	Yes
Advisor Firm FE	No	No	No	Yes	Yes
Observations	58,637	58,543	58,543	58,465	58,465
R^2	0.041	0.041	0.041	0.207	0.208

TABLE 9

Determinants of Climate Coverage: National News, Local Weather, and Non-Weather Variables

This table reports estimated coefficients from pooled OLS regressions examining the relationship between *Local Climate Attention*—defined as the fraction of climate-related articles in a newspaper—and various explanatory variables. Columns 1 and 2 use national news-based indices: the *MCCC Index* (Media Climate Change Concern Index from Ardia et al. (2023)) and the *WSJ Index* (Wall Street Journal Climate Change Index from Engle et al. (2020)). Both indices are normalized to have a standard deviation of one. Column 3 includes indicators of extreme local weather: high temperatures, high-damage events, and FEMA-declared disasters, categorized as *Tropical/Coastal Storm*, *Other Storm/Tornado/Flood*, *Fire Disaster*, and *Other Weather Disaster*. Column 4 introduces non-weather variables: *Greenhouse Gas Emissions*, *Toxic Chemicals Releases*, *Newspaper Chain Size* (the number of newspapers in the same chain), Clean Energy Standards (CES) policy in the state, *Peer Attention*, and *Climate Lawsuits*. Column 5 includes local *Climate Protests* as the independent variable of interest. All explanatory variables are defined in Table A1. All specifications control for lagged *Local Climate Attention* and the county demographic variables from Table 6. Columns 1 and 2 also control for the lagged version of the main explanatory variable from that column. Columns 1 and 2 have year fixed effects; Columns 3 through 5 instead include year-by-month fixed effects; and all specifications contain newspaper fixed effects. Standard errors are double-clustered at the year-by-month and county levels, and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Local Climate Attention				
	1	2	3	4	5
MCCC Index	0.287***				
	(8.039)				
WSJ Index		0.133***			
		(4.322)			
High Temp			0.099**		
			(2.185)		
High Damage Event			0.042		
			(1.176)		
Tropical/Coastal Storm			−0.000		
			(−0.001)		
Other Storm/Tornado/Flood			0.009		
			(0.343)		
Fire Disaster			0.133**		
			(2.067)		
Other Weather Disaster			0.155**		
			(2.089)		
Greenhouse Gas Emissions				−0.000	
				(−0.020)	
Toxic Chemicals Releases				0.005	
				(0.624)	
Post Clean Energy Standard (CES)				0.107*	
				(1.756)	
Climate Lawsuits				0.196***	
				(6.649)	
Newspaper Chain Size				−0.002***	
				(−3.131)	
Peer Attention				0.275***	
				(6.933)	
Climate Protests					0.224**
					(2.260)
County Controls	Yes	Yes	Yes	Yes	Yes
Year×Month FE	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No
Paper FE	Yes	Yes	Yes	Yes	Yes
Observations	106,729	91,467	120,990	120,981	15,497
R^2	0.597	0.573	0.635	0.638	0.665

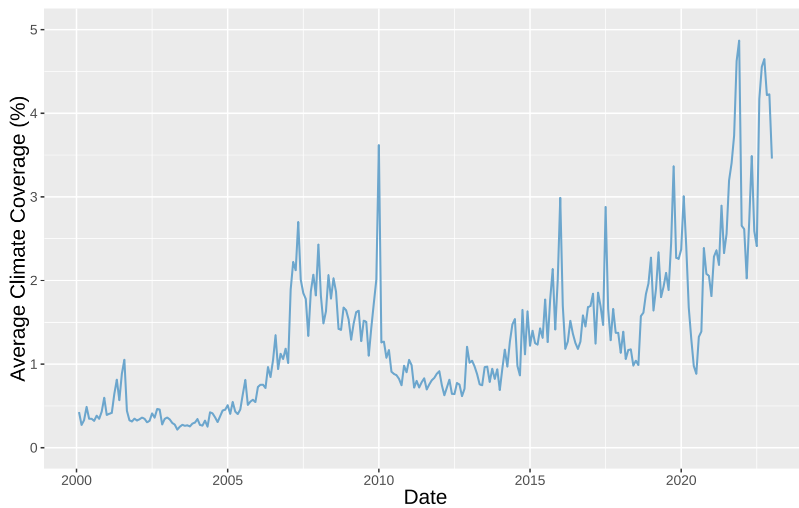
Appendix A

FIGURE A.1

Time Series of Climate Attention Measures

Panel A plots average news-based *Local Climate Attention* across 510 major U.S. newspapers from January 2000 to December 2022, measured as the monthly percentage of climate-related articles. Panel B compares *Local Climate Attention* with the Media Climate Change Concern Index (MCCC) of Ardia et al. (2023) and the climate-related news coverage index based on Wall Street Journal articles (WSJ) of Engle et al. (2020). All measures are expressed in percentages.

Panel A: Local Climate Attention



Panel B: Local Climate Attention, MCCC, and WSJ

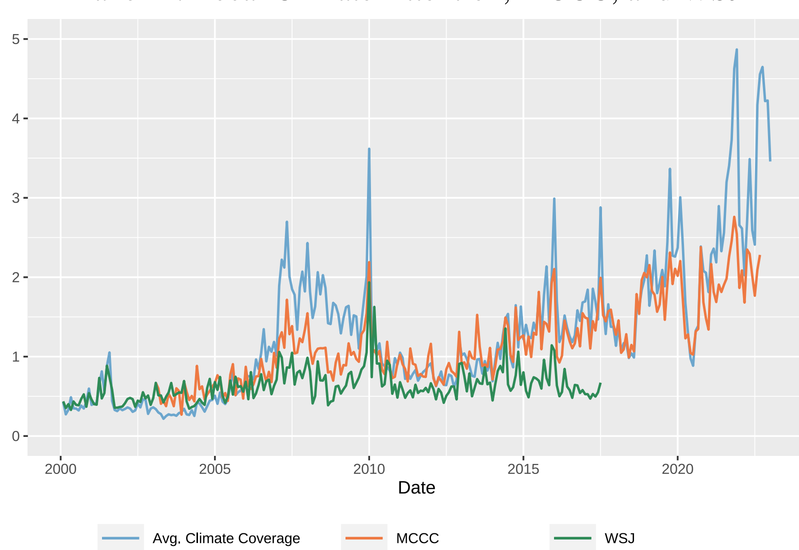


FIGURE A.2

Protests, Riots, and Climate Attention

This figure plots coefficients and 95% confidence intervals from a regression of *Local Climate Attention* on leads and lags of climate-related unrest, controlling for MSA and year-month fixed effects.

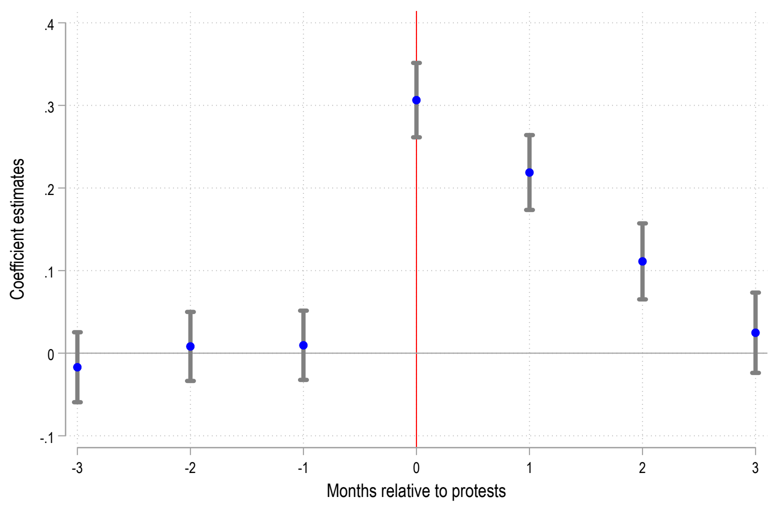


FIGURE A.3

Newspaper Chain Characteristics, 2000-2022

This figure plots the average *Chain Size* (red) and the proportion of stand-alone newspapers (blue) from January 2000 through August 2022.

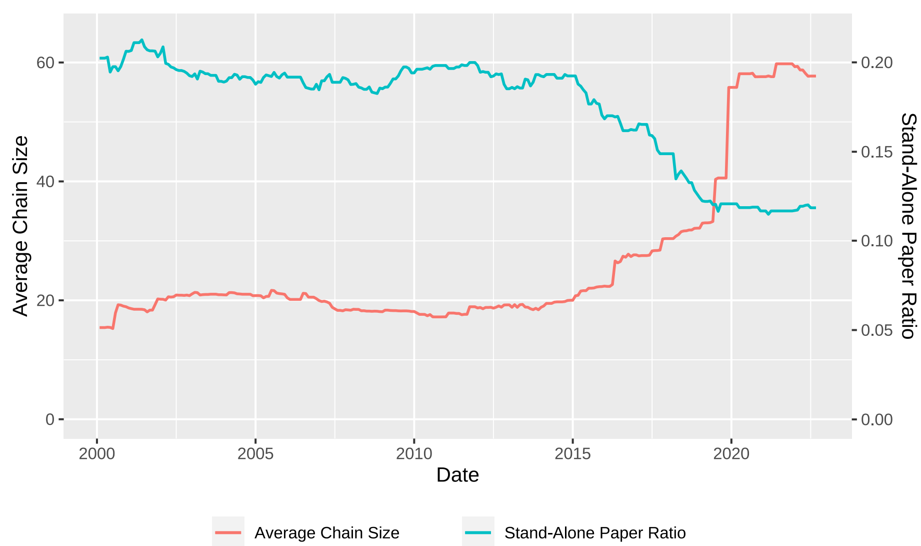


TABLE A1

Variable Descriptions

Variable	Definition
B/M	Ratio of book value of equity to market value of equity at the start of the year.
Chain Size	The total number of newspapers in our sample with the same owner as the focal newspaper.
Climate Lawsuits	The number of climate-related lawsuits in each county-month. The data are obtained from the U.S. Climate Litigation Database at Columbia Law School's Sabin Center for Climate Change Law.
Climate Protests	An indicator equal to one if the newspaper is located in an MSA where a climate protest occurred (in the relevant month), and zero otherwise. Data on protests are from the Armed Conflict Location and Event Data Project (ACLED) (Raleigh, Kishi, and Linke, 2023).
Democrat Share	County-level share of two-party votes cast for the Democratic candidate in the previous presidential election, obtained from the MIT Election Lab. Expressed as a percentage.
Education	County-level percentage of the population with a Bachelor's degree or higher, obtained from the U.S. Census Bureau's American Community Survey.
ESG ETF Share Lag	Prior quarter's proportion of ETFs that are ESG-related.
FB Climate Posts	Aggregated, anonymized data from Meta (formerly Facebook) measuring the weekly percentage of climate-related posts in a given county. *FB Climate Posts Lag* is the one-month lag of *FB Climate Posts*.
Fire Disaster	A county-month-level indicator equal to one if a declared disaster with type "fire" occurs. The MSA-level version is the population-weighted average of the county-level variable across counties in the MSA. Obtained from FEMA's Disaster Declaration Summaries dataset.
GeoProx	Geographic proximity between two counties, defined as the inverse of the physical distance between them.
Greenhouse Gas Emissions	Natural logarithm of the total greenhouse gas emissions by production facilities in a given county in a given year; obtained from the Environmental Protection Agency (EPA) Inventory of Greenhouse Gas Emissions and Sinks.
High Damage	A dummy variable that equals one if the sum of property and crop damage due to natural disasters/hazards for a given county-month observation exceeds one million dollars. Damage data are obtained from the Spatial Hazard Events and Losses Database for the U.S. (SHELDUS) maintained by Arizona State University. *High Damage Lag* is the one-month lag of *High Damage*.
High Net Worth	An indicator equal to one if the firm has more client assets from high-net-worth individuals than from non-high-net-worth individuals, and zero otherwise.
High Temp	A county-level indicator equal to one if the county's average temperature in the current month exceeds any prior monthly average ever recorded in the county. *High Temp Lag* is the one-month lag of *High Temp*.

Variable	Definition
Income	County-level median household income, in thousands of 2023 dollars, from the U.S. Census Bureau's American Community Survey.
Innovation Score Lag	Prior year's Environmental Innovation Score from Refinitiv.
$1 - JD20$ (Topic Similarity)	$JD20$ is the Jensen-Shannon distance between the 20-topic LDA distributions of two counties; it takes values between zero (identical distributions) and one (non-overlapping distributions). Therefore, we define $1 - JD20$ as Topic Similarity.
Leverage	Book leverage, defined as total debt divided by the sum of total debt and book equity at the start of the year.
Local Climate Attention	Number of climate-related articles scaled by the total number of articles in each paper-month observation; expressed as a percentage. *Local Climate Attention Lag* is the one-month lag of *Local Climate Attention*. *Local Climate Attention (M)* is *Local Climate Attention* aggregated to metropolitan statistical area (MSA) level.
Log AUM Lag	Natural logarithm of the advisory firm's assets under management at the end of the prior quarter, measured as the market value of its Form 13F reported holdings.
Log Population	Natural logarithm of the county population. Population data are from the U.S. Census Bureau's American Community Survey (ACS) and Population and Housing Unit Estimates Program (PEP) databases.
MCCC Index	The Media Climate Change Concern Index of Ardia et al. (2023); reported monthly and standardized to have zero mean and unit standard deviation.
Other Storm/Tornado/Flood	A county-month-level indicator equal to one if a declared disaster with one of the following types occurs: "flood", "severe storm", "tornado", "winter storm", "severe ice storm", and "snow storm". The MSA-level version is the population-weighted average of the county-level variable across counties in the MSA. Obtained from FEMA's Disaster Declaration Summaries dataset.
Other Weather Disaster	A county-month-level indicator equal to one if a declared disaster with one of the following types occurs: ”mud/landslide”, ”dam/levee break”, ”freezing”, ”drought”, ”human cause”, ”straight-line winds”, ”fishing losses”, and ”other”. The MSA-level version is the population-weighted average of the county-level variable across counties in the MSA. Obtained from FEMA's Disaster Declaration Summaries dataset.
Peer Attention	Equal-weighted average of *Local Climate Attention* across peer papers, defined as the top 10% of papers ranked by their counties' SCI with the focal paper's county, excluding papers in the same state as the focal paper.
Physical Climate Risk	The firm's physical climate risk in the current quarter, based on textual analysis of earnings call transcripts, as constructed by Li et al. (2024).
Post Clean Energy Standard (CES)	An indicator equal to one if the state in which the newspaper is headquartered has implemented Clean Energy Standards (CES), and zero otherwise.
Return Lag	Prior year's annual stock return.
ROA	Earnings before extraordinary items divided by start-of-year assets.
SCI	Meta's Social Connectedness Index, defined as the number of Facebook friendship links between two U.S. counties, scaled by the product of their populations.
Size	Natural logarithm of the firm's market capitalization at the start of the year.

Variable	Definition
Socioeconomic Similarity	The inverse of the Euclidean distance between two counties in the rank-normalized socioeconomic variable space. The vector components are rank-normalized county population, education (fraction of the population with a Bachelor's degree or higher), median household income, unemployment rate, and Democratic share of the vote. Ranks are normalized to the [0,1] interval.
Toxic Chemicals Releases	Natural logarithm of the total chemicals released by production facilities in a given county in a given year; obtained from the Environmental Protection Agency (EPA) Toxic Release Inventory.
Tropical/Coastal Storm	A county-month-level indicator equal to one if a declared disaster with one of the following types occurs: "tropical storm", "coastal storm", "typhoon", and "hurricane". The MSA-level version is the population-weighted average of the county-level variable across counties in the MSA. Obtained from FEMA's Disaster Declaration Summaries dataset.
Unemployment	County-level unemployment rate (in percent), from the Bureau of Labor Statistics' LAUS program.
Water Disaster	An indicator equal to one if a water-related disaster occurred in a given geography (MSA or county) in a given month, based on FEMA's Disaster Declaration Summaries dataset. Water-related disasters include: "Flood", "Severe Storm(s)", "Hurricane", "Coastal Storm", "Dam/Levee Break", "Typhoon", and "Tsunami".
WSJ Index	Index of climate attention derived from Wall Street Journal articles by Engle et al. (2020); reported monthly and standardized to have zero mean and unit standard deviation.
$\text{Yale}^{\text{Happening}}$	The estimated percentage of each county's population that believes global warming is happening, from the Yale Climate Opinion Maps.
Δ Emissions Score	Change from last year in the firm's Emissions Score from Refinitiv.
Δ ESG ETF Share	Change from last quarter in the proportion of ETFs that are ESG-related, as reported on the advisor's Form 13F.
Δ ENV Score	Change from last year in the firm's Environmental Score (averaged over MSCI and Refinitiv).
Δ Innovation Score	Change from last year in the firm's Environmental Innovation Score from Refinitiv.
Δ Policies Per Capita (t, t+k)	The percent change in the per capita number of in-effect NFIP flood insurance policies between the end of month t and the end of month $t+k$.
Δ Resource Use Score	Change from last year in the firm's Resource Use Score from Refinitiv.
Climate Pessimist/Activist	Terms relating to climate change risks and the need for mitigation: global warming, greenhouse gas emissions, renewable energy, sustainability, environmental justice, carbon footprint, climate crisis, biodiversity loss, ecological conservation, and carbon neutral.
Climate Optimist/Denier	Terms relating to climate change skepticism and downplaying the need for government action on this issue: climate realism, climate alarmism, clean coal, lower emissions fuels, advancing climate solutions, economic growth, energy independence, technological innovation, climate adaptation, and environmental overreach.

TABLE A2

Controlling for Temperature and Weather Events

This table examines whether the economic effects of local climate attention can be explained by local weather events. In each column, we augment a specific regression from the main text by adding as controls indicators of extreme local temperature and FEMA-declared disasters, categorized as *Tropical/Coastal Storm*, *Other Storm/Tornado/Flood*, *Fire Disaster*, and *Other Weather Disaster*. Specifically, Columns 1 and 2 are the counterparts of Columns 5 and 6 from Table 2, Columns 3 and 4 are counterparts of Columns 2 and 3 from Panel A of Table 3, Columns 5 and 6 are counterparts of Columns 3 and 4 from Table 4, and Column 7 is the counterpart of Column 3 from Table 5. Each column includes all control variables used in its counterpart. Standard errors in each column are clustered using the same clustering technique in the corresponding regression in the main text, and t-statistics are shown in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

TABLE A2

Controlling for Temperature and Weather Events

	Δ ESG ETF Share		Δ Policies Per Capita (t, t+12)		Physical Climate Risk		Δ ENV Score
	$1_{\text{IV=CS}}$	$2_{\text{IV=Peer}}$	$3_{\text{IV=CS}}$	$4_{\text{IV=Peer}}$	$5_{\text{IV=CS}}$	$6_{\text{IV=Peer}}$	$7_{\text{IV=CS}}$
Local Climate Attention	0.154**	0.111***	2.432*	1.880***	0.041	0.113***	0.062**
	(2.346)	(3.815)	(1.710)	(2.814)	(0.872)	(3.389)	(2.135)
High Temperature	0.283	0.406	0.571	0.658	0.072	0.002	−0.131
	(0.509)	(0.787)	(0.845)	(0.984)	(0.635)	(0.015)	(−0.804)
Tropical/Coastal Storm	0.203	0.179	1.940**	1.942**	0.004	0.025	−0.135
	(1.513)	(1.323)	(2.535)	(2.542)	(0.049)	(0.302)	(−1.242)
Other Storm/Tornado/Flood	0.017	0.009	2.602***	2.606***	0.034	0.045	0.006
	(0.176)	(0.107)	(4.334)	(4.369)	(0.905)	(1.262)	(0.132)
Fire Disaster	−0.051	−0.048	−1.204	−1.091	0.048	0.039	−0.060
	(−0.651)	(−0.565)	(−1.509)	(−1.428)	(1.112)	(0.816)	(−0.594)
Other Weather Disaster	0.818***	0.709***	5.578**	5.688**	−0.299*	−0.304	0.314
	(4.930)	(5.342)	(2.222)	(2.077)	(−1.687)	(−1.464)	(0.998)
Original Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	-	-	Yes	Yes	-	-	-
Year FE	-	-	-	-	-	-	Yes
Year×Quarter FE	Yes	Yes	-	-	-	-	-
Year×Month FE	-	-	Yes	Yes	-	-	-
Year×Quarter×SIC3 FE	-	-	-	-	Yes	Yes	-
Advisor Firm FE	Yes	Yes	-	-	-	-	-
Firm FE	-	-	-	-	Yes	Yes	Yes
Cluster-Robust 1st Stage F-stat	8.394	35.364	12.781	87.929	14.151	15.732	7.478
Observations	58,376	58,376	42,796	42,799	179,467	179,467	44,252
R^2	0.199	0.202	0.161	0.186	0.317	0.313	0.196

TABLE A3

Testing the Yale Data

This table examines the association between Yale$^{\text{Happening}}$ and various firm and household level variables. Each column is obtained by replacing *Local Climate Attention* with $Yale^{Happening}$ in a corresponding regression in the main text. Specifically, Column 1 is the analogue of Column 2 of Table 2, Column 2 is the analogue of Column 1 of Table 3, Column 3 is the analogue of Column 2 of Table 4, and Column 4 is the analogue of Column 2 of Table 5. Each column includes all control variables used in its counterpart, as well as the same time fixed effects used in the original regressions. MSA and/or firm fixed effects used in the original regressions are excluded here because of the high persistence of $Yale^{Happening}$. Standard errors in each regression are clustered using the same scheme as in the corresponding regression in the main text, and t-statistics are shown in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Δ ESG ETF Share	Δ Policies Per Capita (t, t+12)	Physical Climate Risk	Δ ENV Score
	1	2	3	4
Yale$^{\text{Happening}}$	0.003	0.098	−0.004	−0.001*
	(1.213)	(0.959)	(−0.642)	(−1.670)
Original Controls	Yes	Yes	Yes	Yes
MSA Controls	Yes	Yes	Yes	Yes
Industry FE	-	-	-	Yes
Year FE	-	-	-	Yes
Year×Quarter FE	Yes	-	-	-
Year×Month FE	-	Yes	-	-
Year×Quarter×SIC3 FE	-	-	Yes	-
Observations	62,860	31,335	87,034	20,858
R^2	0.041	0.038	0.198	0.122

TABLE A4

Predicting Ownership Changes

This table reports estimated coefficients from OLS regressions of a newspaper ownership change indicator on newspaper characteristics and local demographic variables. Column 1 shows results for the full sample, while Columns 2 through 4 use sub-samples based on the size of the newspaper chain to which the paper belonged prior to the ownership change. Explanatory variables are lagged by one month. All specifications include year-by-month fixed effects. Standard errors are double-clustered at the year-by-month and paper levels, and t-statistics are shown in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Coefficients in this table are multiplied by 100 (i.e., expressed in percentages) for presentation purposes.

	All Transactions	Sale of Small Chains or Independents (size < 4)	Sale of Medium Chains (size 4–20)	Sale of Big Chains (size > 20)
	1	2	3	4
Local Climate Attention	−0.0004	−0.0018	−0.0060	0.0076
	(−0.12)	(−0.81)	(−1.49)	(0.97)
Chain Size	−0.0002	−0.0552	−0.0207	0.0028
	(−0.02)	(−0.71)	(−0.79)	(0.20)
Publicly Owned	0.4386	0.6544	0.6527*	0.3141
	(1.61)	(1.64)	(1.73)	(0.65)
Log Population	0.0959***	0.1162**	0.0452	0.0972*
	(3.11)	(1.97)	(0.69)	(1.77)
Income	0.0018	−0.0011	0.0138	−0.0030
	(0.42)	(−0.19)	(1.27)	(0.69)
Education	−0.0017	−0.0129	−0.0031	0.0068
	(−0.33)	(−1.55)	(−0.27)	(0.73)
Democrat Share	−0.0001	0.0058	0.0041	−0.0038
	(−0.04)	(1.11)	(0.88)	(−0.75)
Unemployment	0.0057	−0.0313	0.0096	0.0370
	(0.29)	(−1.22)	(0.46)	(0.75)
Year×Month FE	Yes	Yes	Yes	Yes
Observations	117,465	32,795	35,955	48,715
R^2	0.08	0.01	0.07	0.31

TABLE A5

Peer Effects on Climate News Similarity across County Pairs

This table reports county-pair-level analysis of how social connections relate to topic similarity (defined as $1 - JD20$) in climate reporting. *SCI* is the Social Connectedness Index. *Socioeconomic Similarity* and *GeoProx* denote the socioeconomic similarity and geographic proximity between two counties, respectively. Socioeconomic similarity is based on the 2021 values of county-level population, median household income, percentage of college-educated population, unemployment rate, and Democratic vote share in the previous presidential election. We rank these five variables across counties and normalize the ranks to the [0,1] interval. *Socioeconomic Similarity* between two counties is then defined as the inverse of the Euclidean distance between the counties in the rank-normalized socioeconomic variable space. All independent variables are rank-normalized to the [0,1] interval within each focal county. All regressions include focal-county and peer-county fixed effects. Standard errors are clustered at the county level, and t-statistics in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Topic Similarity (%)					
	1	2	3	4	5	6
SCI	0.638***			0.549***	0.463***	0.349***
	(22.022)			(20.566)	(13.792)	(11.885)
Socioeconomic Similarity		0.579***		0.470***		0.483***
		(15.352)		(13.197)		(13.573)
GeoProx			0.609***		0.276***	0.312***
			(18.639)		(7.201)	(8.302)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,168,256	2,165,312	2,168,256	2,165,312	2,168,256	2,165,312
R^2	0.895	0.895	0.895	0.895	0.895	0.895

Appendix B

B.1. Data Description

A. Calculation of Local Climate Attention Measure

The corpus of local newspaper articles comes from the news aggregator NewsLibrary.com (NL). We search for the keyword “climate” and download all headlines (and up to the first 80 words of the article) containing this keyword.[1] This search provides 718,144 snippets. After dropping observations lacking state and county information (mostly online-only newspapers), we have 472,026 article previews across 5,139 newspapers for the period of January 2000 through August 2022. After restricting the sample to articles covering environmental issues according to FinBERT (Huang, Wang, and Yang 2023), we are left with 345,909 articles. We use the snippets for textual analysis in Section V.E of the paper, while performing the rest of our analysis using article counts from the smaller set of major newspapers.

We use data from NP to supplement the NL dataset. We run a keyword search for “climate change” or “global warming” and collect the number of articles which include either of those phrases in the headline or body for each newspaper-month from 2000 through 2022. We also conduct a more general keyword search, using three commonly used words (“have”, “new”, and “good”) to obtain the total number of articles in a newspaper-month. We apply the same

[1] See Widmer, Abed Meraim, Galletta, and Ash (2025) for more details on the NewsLibrary dataset. We cannot run precise searches for phrases such as ‘climate change’ or ‘global warming’ because the NewsLibrary search tool does not reliably match multi-word expressions. In addition, we do not have access to the full article lead that is being searched, only the first 80 words are provided, so we also cannot use the full article text to further refine our searches.

procedure in Factiva for The New York Times and The Washington Post. We then define our main variable of interest, *Local Climate Attention*, as the number of climate-related articles scaled by the total number of articles.

Since we only have the scaling variable for the NP dataset, we use the subsample of all newspapers that are in both NL and NP to find the average conversion factor from the raw article count in NL to the scaled article count in NP (allowing this factor to vary by year). We then apply the conversion factor to the NL-only count data to impute *Local Climate Attention* for those newspapers not in NP.

We use textual analysis to validate our measure as a proxy for climate awareness. We prompt ChatGPT to provide polarizing terms used in the climate debate. The first set of terms, which we refer to as climate pessimist/activist terms, relates to climate change risks and the need for mitigation, while the second set of terms, which we refer to as optimist/denier terms, relates to climate change skepticism and downplaying the need for government action to address this issue.[2] Figure B.1 shows that pessimist/activist terms consistently dominate, with minimal occurrence of optimist/denier terms, confirming that climate coverage primarily reflects climate-risk concerns rather than climate change skepticism.

B. Description of Household and Firm Variables

Households' Ownership of ESG ETFs We measure local households' holdings of ESG-focused exchange-traded funds (ETFs) through quarterly 13F filings by retail-focused investment advisors. ETFs are section 13(f) securities, whereas open-end mutual funds generally

[2]The full lists of terms for each category are provided at the end of Table A1.

are not, so Form 13F captures manager holdings of ETFs but not of open-end funds. Thus, we can track how institutional filers in different geographic locations change their exposure to ESG ETFs over time. We identify ESG-focused ETFs using the socially conscious indicator variable from Morningstar Direct, supplemented with fund name searches using the following keywords: ESG, green, sustainable, clean, social, environment, solar, water, wind, alternative energy. This procedure yields 297 ESG-focused ETFs over our sample period.

We download Form 13F filings directly from EDGAR for the period from December 2013 through December 2022. In 2013, the SEC required filers to submit forms using a standardized (XML) format enabling automated parsing. In addition, there were almost no ESG ETFs prior to 2013. The main advantage of using EDGAR filings instead of getting holdings data from Thomson Reuters (TR) is that holdings are consolidated at the parent company level on TR while the division-level owners of each holding is shown on the forms themselves. For example, in its latest 13F filing, Bank of New York Mellon filed on behalf of itself and 28 different asset management affiliates.

We match each institutional investor filer of Form 13F with a registered investment advisor (RIA) that filed Form ADV, using name and business address. We focus on investment advisors serving individual investors, as these advisors' clients are typically local and the clients' investment decisions are most likely to be influenced by local news coverage.[3] Large institutions such as banks, insurance companies, foundations and endowments, mutual funds, hedge funds, and pension funds typically have clients from all over the country. These institutions also hold

[3]Form ADV data are available for download from the SEC's website.

smaller stakes in ETFs than individual investors do, as they prefer to invest in the underlying securities to avoid fund fees.

For each advisory firm-quarter, we define *ESG ETF Share* as the total value of ESG-focused ETFs divided by the total value of all ETFs in the firm's reported portfolio at the end of the quarter. We define two additional variables: *Log AUM Lag*, the natural logarithm of the market value of reported holdings at the end of the prior quarter, and the indicator variable *High Net Worth*, based on whether a majority of the advisory firm's individual clients are high-net-worth individuals. We use the ZIP code from Form 13F to match each firm to a U.S. core-based statistical area (CBSA), and drop all non-U.S. filers.

Flood Insurance Purchases We collect data on flood insurance take-up from the National Flood Insurance Program (NFIP) policy dataset in OpenFEMA. NFIP, established by Congress in 1968, provides federally backed flood insurance to property owners in participating communities (Gallagher 2014; Hu 2022). The dataset is updated monthly and includes more than 69 million anonymized policy transactions between 2009 and 2025. For each transaction, we observe the policy effective date, termination date, cancellation date (if applicable), and location of the insured property (ZIP code, census tract, county, state).

We construct a county-month measure of the stock of in-effect policies as follows. Since most policies have a twelve-month term, a policy enters the stock on its effective date and exits on its termination or cancellation date. Following Hu (2022), we initialize the stock at the end of January 2010 by cumulating net policy additions — new policies minus terminations and cancellations — from January 2009 onward, allowing sufficient time for any pre-2009 policies to expire.[4] We then update the stock each month by adding that month's net change. Aggregating across counties within each MSA and dividing by population yields the per capita number of in-effect flood insurance policies at the MSA-month level.

We also collect data on water-related disasters from FEMA's Disaster Declaration Summaries (DDS). After merging with the NFIP data, we define an indicator variable *Water Disaster* that equals one if there was a water-related disaster in a given month in a given MSA or county.

B.2. Text Analysis of Documents

For articles sourced from NewsLibrary.com (NL), we have access to the first 80 words, which allows us to analyze the information in more depth. Our goal in analyzing the text of the documents is threefold. First, we want to study the content written in a given place and time period. This will allow us to study how events shape reporting. Second, we want to compare reporting across regions. This will tell us how similar reporting is at a given point in time and whether differences can be explained by events. Third, we want to study whether reporting predicts changes in firm outcomes and decisions.

As a first step, we want to make sure that all of our articles are related to climate in the environmental sense. Given that we used "climate" as the search term, we also have articles referring to climate in a social sense, such as the climate in a team or an office. We therefore make use of FinBERT (Huang et al. 2023), a pre-trained Large Language Model (LLM), to classify the

[4] All policy transactions in the data have a policy effective date of January 2009 or later; policies that became effective before that date are not covered.

articles as Environmental, Social, or Governance. We then retain all articles that are either classified as Environmental with greater than 50% probability or that contain the term “climate change”. This leaves us with 345,909 articles.

A. Summarizing News into Topics

We use Latent Dirichlet Allocation (LDA), developed by Blei, Ng, and Jordan (2003), to compute topic shares of each article preview combined with the headline. Once we know what articles are about, we can compute average reporting for each state and county over time. The distribution of topics in a given year or month then allows us to compute the distance between the reporting of two regions. In the following, we outline these two procedures.

Before feeding the documents into LDA, an unsupervised machine learning model, we apply standard pre-processing to the text. We remove a set of stopwords (using a standard dictionary), as well as overly frequent and overly rare words, and then apply a lemmatizer to harmonize expressions. Since LDA is a bag-of-words model—word order plays no role—we also include bigrams and trigrams (i.e., two- and three-word combinations).

LDA is a generative statistical model used to discover topics in large collections of documents. It assumes that each document in a corpus is a mixture of several topics, and that each word in a document is generated from one of these topics. Specifically, it assumes that each topic is represented by a distribution over words, and that each document is a mixture of these topic distributions.

The model works by taking a set of documents and assigning each word in each document to a topic, based on a probability distribution over topics. Through iterative Bayesian updating, it then refines the assignment of words to topics—and the distribution of topics in each document—until a stable solution is found. The parameters of the LDA model are estimated using Bayesian inference, with the Dirichlet distribution used as a prior distribution for both the topic distributions and the per-document topic distributions.

The final output of interest is the distribution of topics across documents. In Table B1, we present the top 15 keywords for each topic when the topic model is estimated with 20 topics. In Figure B.2, we present the top keywords of four topics, with text sizes indicating the relative importance of the top 1,000 keywords within each topic. In the top left panel (a), we see a topic capturing reporting about the rising 'sea', 'flood', and 'drought', as well as more general disasters such as 'hurricane'. In the top right panel (b), the reporting covers emissions, as indicated by 'emission' and 'greenhouse gas' appearing among the top keywords. In the bottom left panel (c), we present a topic related to energy, exemplified by the terms 'fuel', 'energy', and 'oil'. In the bottom right panel (d), the topic relates to scientific studies, as indicated by the words 'study', 'research', and 'scientist'.

1. Similarity between Topic Distributions

The Jensen-Shannon distance is a measure of dissimilarity between two probability distributions. It is a modification of the Kullback-Leibler divergence. The Jensen-Shannon distance measures the dissimilarity between two probability distributions as follows. It computes the average of the Kullback-Leibler divergences between each distribution and a third distribution—the average of the two—and then takes the square root.[5]

It ranges from 0 (identical distributions) to 1 (completely different distributions). The Jensen-Shannon distance, which is the square root of the Jensen-Shannon divergence, is symmetric, non-negative, and bounded. It is commonly used in applications such as information retrieval, document classification, and clustering, where comparing the similarity of probability distributions is important. We transform the measure into topic similarity by taking $1 - JD$.

[5] In mathematical terms, the Jensen-Shannon distance between two probability distributions P and Q is given by $JD(P\|Q) = \sqrt{\frac{1}{2}D_{\text{KL}}(P\|M) + \frac{1}{2}D_{\text{KL}}(Q\|M)}$, where M is the mean distribution $M = \frac{P+Q}{2}$ and the Kullback-Leibler divergence is given by $D_{\text{KL}}(P\|M) = \sum_{x\in\mathcal{X}} P(x)\log_2\left(\frac{P(x)}{M(x)}\right)$.

FIGURE B.1

Frequency of Climate Pessimist/Activist Versus Optimist/Denier Terms

We classify newspaper content using two sets of polarizing terms generated by ChatGPT. Climate pessimist/activist terms include “global warming, greenhouse gas emissions, renewable energy, sustainability, environmental justice, carbon footprint, climate crisis, biodiversity loss, ecological conservation, carbon neutral”. Optimist/denier terms include “climate realism, climate alarmism, clean coal, lower emissions fuels, advancing climate solutions, economic growth, energy independence, technological innovation, climate adaptation, environmental overreach”. The figure plots the frequencies of these terms over time.

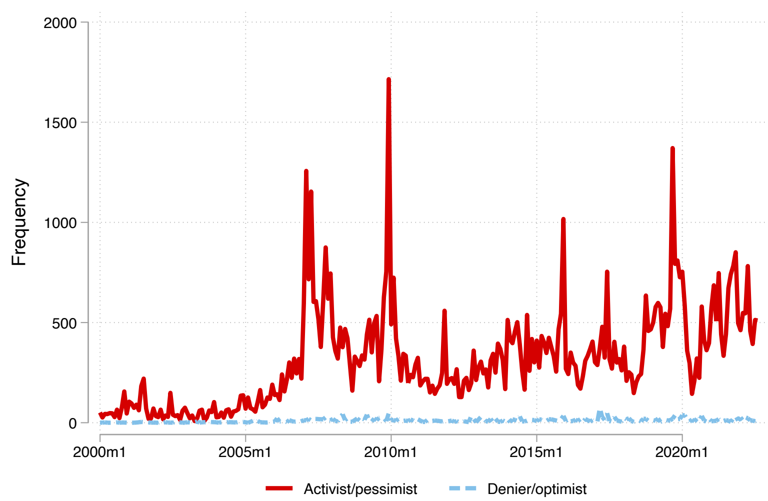


FIGURE B.2

Word Clouds for Selected LDA Topics

This figure presents word clouds for four of the 20 topics produced by applying Latent Dirichlet Allocation (LDA) to the headlines and up to the first 80 words of all climate-related articles in the full sample of 5,139 local newspapers from NewsLibrary. The sample period is January 2000 through August 2022.

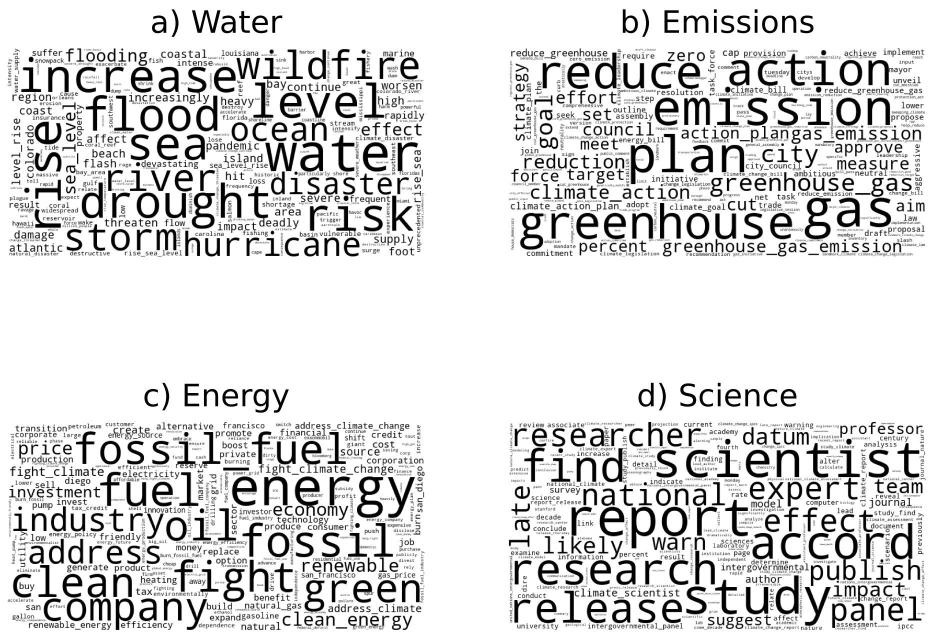


TABLE B1

Top Keywords of the 20-topic LDA Model

Topic 0: need use crisis way future planet climate_crisis lead today action challenge solar system protect wind
Topic 1: water rise level drought increase sea risk flood wildfire storm river hurricane ocean disaster flooding
Topic 2: report scientist study accord research find release researcher effect expert panel national publish late likely
Topic 3: city begin friday control activist run turn build street raise building line start road thousand
Topic 4: bill president health house senate act democrats pass vote legislation washington care sen congress republican
Topic 5: earth human cause letter science recent editor real believe opinion happen fact scientific write read
Topic 6: world united country nation leader states united_states talk sign deal international conference agreement reach nations
Topic 7: weather heat temperature warm record month extreme hot degree ice past high break wave expect
Topic 8: public environmental policy news environment wednesday national hold justice general director office town meeting follow
Topic 9: carbon power air environmental federal administration court agency pollution electric protection coal plant dioxide vehicle
Topic 10: come long billion big major face bad want government right end threat far concern decade
Topic 11: global warming global_warming tell point view global_climate story question reality appear book age course global_climate_change
Topic 12: community event school student focus center local host april open discuss high free series sustainability
Topic 13: energy fuel fossil fight fossil_fuel clean oil company green industry address clean_energy economy renewable price
Topic 14: gas plan emission greenhouse reduce action greenhouse_gas city goal climate_action reduction gas_emission greenhouse_gas_emission cut set
Topic 15: grow plant winter season park early summer area fall dry rain snow garden spring region
Topic 16: people issue work group good problem support base recently solution consider important organization offer ask
Topic 17: know home look live life think thing feel leave old ago little place lot close
Topic 18: state include california county project program impact business department gov lake official announce resident development
Topic 19: help million fire tree large forest food land provide specie agriculture conservation small farmer animal