Measuring Local Climate Change Attention: Does it Affect Investors and Firms?

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December 8, 2024

Abstract

We construct a novel measure of local climate change attention using a comprehensive news dataset extracted from over 5,000 newspapers covering all major population centers in the U.S. from 2000-2022. We document an increasing trend in climate attention and growing polarization in climate-related coverage across the U.S. While local climate attention co-moves with national trends, it shows significant regional variation and correlates with local demographic characteristics and aligns with geographical social media attention as reflected in Facebook user posts. Climate attention responds to acute environmental events like natural disasters and extreme heat episodes, but not to chronic environmental conditions. Exploiting exogenous variations in newspaper ownership and peer effects, we show that higher local climate attention leads to increased individual investment in ESG-focused ETFs and improved environmental performance of local firms. Our measure offers distinct advantages over the Yale Climate Opinion Survey's estimated climate concern measure, providing researchers a novel tool for causal inference and offering policymakers and climate communicators actionable insights about the geographic and temporal dynamics of public climate engagement.

Keywords: Climate change, ESG, Local News, Media, Social Media, Sustainable investing
JEL Classifications: G11, G14, G20, G41, G29, G39, G50, Q5

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1 Introduction

Many view climate change as one of the most critical global challenges of our time. Investor attention to climate change has also been shown to be associated with equilibrium prices and the returns of green versus brown stocks (Choi, Gao and Jiang 2020; Pástor, Stambaugh and Taylor 2021, 2022, Ardia et al. 2022).

Despite the rising public awareness of climate change, concern on this topic varies widely across the United States. A 2023 Pew Research 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.[1] However, the drivers of these variations are not well-understood, and their economic implications have not been fully evaluated (Goldstein et al. 2022; Giglio et al. 2024). The importance of studying local attitudes toward climate change is heightened by the ongoing multistate effort to exclude environmental, social, and governance (ESG) considerations from public investments.[2]

This paper constructs a novel measure of local climate change concerns using a comprehensive dataset of newspaper coverage from 2000-2022, encompassing over 5,000 US newspapers, including 510 major newspapers, covering all the large population centers in the United States. Using this measure, we identify the factors influencing variation in local climate change concerns and show that this variation affects the behavior of investors and firms.

The news-based measure of local climate concerns offers several key advantages over measures provided by the Yale Climate Opinion Survey data, a highly influential data source that has been used in recent studies (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).[3]

First, our data is more comprehensive, spanning a longer time period with coverage from actual news articles across nearly every U.S. metropolitan area, rather than relying on survey data and model imputation using demographic and geographic variables like the Yale data. Second, it captures dynamic variations beyond demographic and geographic

[1] Source: Pew Research (2023).

[2] See, for example, ESG Legislation in the First Six Months of 2023 (Plural, 2023).

[3] The Yale survey uses polling data combined with statistical models to estimate climate change beliefs at the county level and is available annually since 2008. See Howe et al. (2015) and Leiserowitz et al. (2020) for more details of the survey and findings.

predictors, with changes that aligns with social media attention metrics from Facebook as well as local investors' holdings of green investments. Third, and most importantly, it enables identification through plausibly exogenous variations, allowing us to examine the causal effect of local climate attention on economic decisions by investors and firm managers.

Our approach of measuring local awareness towards climate change with news coverage is motivated by a large body of literature that has argued that local newspapers hold local leaders accountable, increase civic engagement, and are crucial to modern representative democracy (Gao, Lee and Murphy 2020, Ewens, Gupta and Howell 2022).[4] Since climate change primarily rises to the media's attention when there is a cause for concern, news coverage serves as an indicator of public concern about climate risk (Engle et al. 2020; Pástor et al. 2022; Ardia et al. 2022). Our textual analysis confirms this association, showing climate pessimist/activist terms dominate our sample of climate-related articles, with minimal occurrence of optimist/denier terms.[5] Accordingly, we use the phrases "climate change attention," "climate change awareness," and "climate change concern" interchangeably throughout the paper.

Our measure shows both an overall increase in climate change awareness and an increasing degree of polarization. Figure 1, Panels (a) and (b), illustrates this by plotting the measures of climate awareness for Democratic versus Republican regions. Panel (a) shows the evolution of climate attention in Democratic versus Republican counties by year. While the general trend indicates an increase in awareness, Democratic counties feature more reporting on climate, and the difference in reporting levels between Democrat and Republican counties is increasing over time. The increased polarization is also associated with more divergence in individuals' holdings of ETFs that are dedicated to ESG investments. As shown in Panel (b), the residualized mean holding share of ESG-focused ETFs by Core Based Statistical Areas (CBSA), has been increasing since 2019, again with a more pronounced rise in Democratic areas.

More formally, our analysis shows that while local attention to climate change correlates with national attention levels, there exists considerable heterogeneity across locations. Cross-

[4]The idea goes back to Tocqueville (1835), with more recent work from Snyder and Strömberg (2010), Gentzkow et al. (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.

[5]While most of our tests focus on the 510 major daily newspapers that cover MSAs, such as the New York Times, Chicago Tribune, Philadelphia Inquirer, Miami Herald, Nashville Tennessean, et al., we perform textual analysis using articles from over 5000 local newspapers that also include the Cambridge Chronicle, Princeton Packet, Los Alamos Monitor, and Staten Island Advance, et al.

sectionally, our local news-based climate attention measure, *Climate Attention*, strongly correlates with the county-level estimates of climate beliefs from the Yale Climate Opinion Maps dataset, based on whether individuals think climate change is happening ($Yale^{Happening}$) and whether they are worried about it ($Yale^{Worried}$), as well as county-level climate-related share of Facebook posts (*FB Climate Posts*).

We conduct two sets of horse race tests to assess our local climate awareness measure against the Yale measure. First, examining social media attention, we find that a 1 percentage point increase in our measure correlates with a 0.3 bps increase in the contemporaneous *FB Climate Posts*, representing 5.2% of the variable's standard deviation. Our measure also predicts the one-month-ahead *FB Climate Posts*. In comparison, $Yale^{Happening}$ and $Yale^{Worried}$ show no significant relationship with Facebook climate attention.

Second, we compare these measures' ability to explain local investors' holdings of ESG-focused ETFs, using quarterly 13F filings by retail-focused investment advisors. Our measure significantly correlates with changes in ESG ETF shares, persisting after controlling for advisor firm fixed effects. A one-percentage-point increase in our measure corresponds to a 1.7 percentage point increase in contemporaneous in ESG ETF share, which corresponds to 79% of the variable's sample standard deviation. In contrast, the Yale measures show substantially weaker associations that become insignificant after including advisor firm fixed effects.

These tests suggest our news-based measure better captures dynamic variations in geographical differences in climate change awareness, making it potentially more suitable for causal inference.

We next show that local climate attention can be attributed to local demographic variables and political inclination. For instance, a 1 percentage point increase in the percentage of college graduates in a county is associated with a 1.5 bps increase in local climate attention. Likewise, a 1 percentage point increase in the share of votes cast for the Democratic candidate in the last presidential election is associated with a 1.6 bps increase in the local climate attention.

Climate attention is also associated with local natural events such as the occurrence of extreme heat episodes or damage due to natural hazards. We find that attention is 5.8 bps higher in months when total property and crop damage due to natural hazards exceeds 1 million dollars. Likewise, if the average temperature in a month is an all-time high, local coverage is 9.8 bps higher. These effects are notably larger than those of demographic factors, suggesting that direct experience with climate-related events drives public attention more strongly than background characteristics. In contrast, local climate attention is not significantly associated with greenhouse gas emissions or toxic chemical releases from local production facilities.

These results offer important insights for policymakers and climate communicators, they suggest that climate messaging may be most effective when linked to concrete local events rather than abstract environmental metrics, and that different communication strategies may be needed for communities with varying demographic profiles.

We next turn to investigating the causal effects of local climate attention on economic decisions. We identify two exogenous factors that affect climate attention. The first factor is based on the the newspaper's ownership. Specifically, we show that newspapers which belong to larger chains offer less coverage of climate change, consistent with their more standardized news offerings and less interest in politically-charged or scientific topics (see Gibson 2016).[6] Since ownership is typically based on industry economics or liquidity shocks to prior owners, our instruments are likely to satisfy the exclusion restriction.

Our second instrument utilizes climate attention from peer locations, leveraging Facebook's Social Connectedness Index (SCI) to measure social connections within and across U.S. counties (see Bailey et al., 2018b).[7] We construct peer climate attention as the average attention from highly connected counties whose SCI with the focal county rank within the top 10% of the distribution. By further excluding same-state peers and controlling for geographical proximity-based peer attention, we mitigate concerns about omitted local variables affecting both climate attention and outcomes. We find strong peer influence—a one-percentage-point increase in peer attention correlates with a 28.5 basis point increase in focal county attention. We also perform textual analysis of climate news articles and find that higher social connectedness between counties increase their news articles' topic similarities, supporting peer attention's relevance as an instrument.

Using newspaper chain size and peer attention as instruments, we next analyze the impact of news-based climate attention on economic outcomes.[8] Specifically, we examine effects on retail investors' ESG investments and local firms' environmental performance.

[6]For more on the coverage decisions of large chains, see New Jersey Globe, June 10, 2022. Ewens et al. (2022) provide similar findings for newspapers owned by private equity firms.

[7]As the world's largest online social networking service, Facebook's enormous scale and coverage (over 258 million active users in the United States as of 2020) and the relative representativeness of its user base makes SCI a unique measure of the real-world geographic structure of U.S. social networks at a population scale. Research using Facebook friendship data has documented social influence on product adoption, house price expectations, Covid-19 social distancing behavior, and flood insurance purchases (Bailey et al. 2018a, 2019, 2022, 2023; Hu 2022). See, Bailey et al. (2018b) and Kuchler et al. (2020) for further discussion on the data and related applications.

[8]We also use ownership by Gannett, the largest newspaper chain in the U.S., as an alternative instrument to chain size. Results are similar.

We first examine how retail investment advisory firms' clients adjust their holdings of ESG-focused exchange-traded funds in response to local climate attention. We find that more climate attention is associated with increased local investment in ESG ETFs, a result that holds both in OLS and IV panel regressions with firm fixed effects. A one-standard deviation increase in local climate attention results in a 36 bps increase in ESG ETF ownership, representing 59% of the mean and about 10% of the standard deviation of the ESG ETF ownership. For an average advisory firm in our sample with $574 million invested in ETFs, this translates to an additional $2 million allocation to ESG ETFs.

We next use firm environmental ratings from MSCI and Refinitiv to study how environmental performance at the corporate level changes in response to local climate attention. We find that increase in local climate attention is associated with improved environmental ratings of firms headquartered in the area. A one-standard deviation increase in local climate attention is associated with local firms boosting their environmental ratings by an average of 0.2 standard deviations. The result holds in IV regressions using ownership instruments. Together, the IV evidence suggests that local climate attention causally affects both investor behavior and firm decisions.

Our new measure of geographic climate attention has significant policy and welfare implications. Several recent papers underscore the importance of climate beliefs for housing prices, municipal bond yields, and other household decisions. For example, Bernstein et al. (2019); Baldauf et al. (2020) and Keys and Mulder (2020) show that housing price discounts associated with sea level rising risks (SLR) are significantly higher and volume lower in areas with high climate change "worry" as measured in the Yale data. Similarly, areas with greater public climate concern (based on Yale data) exhibit higher premiums on SLR-exposed municipal bonds tend to have a higher premium on SLR-exposed municipal bonds (Goldsmith-Pinkham et al. 2023). Additionally, Giglio et al. (2021b) create a "climate attention index" for the coastal states of Florida, New Jersey, North Carolina, and South Carolina, based on the frequency with which terms such as hurricanes or flood zones are mentioned in housing listings and find that the index predicts flood risk capitalization.[9]

A more comprehensive understanding of local climate beliefs could facilitate more informed decisions and the appropriate reflection of such risks in market outcomes. Our measure complements existing indices from Yale and Giglio et al. (2021b) by providing broader geographic coverage across major U.S. population centers over an extended period. Com-

[9]Relately, recent studies such as Murfin and Spiegel (2020) and Hino and Burke (2021) find that sea level rising risks (SLR) are not fully reflected in home prices and that belief heterogeneity matter (Bakkensen and Barrage 2022). See Giglio et al. (2021a), Stroebel and Wurgler (2021), and Hong et al. (2020) for reviews of this rapidly evolving broader literature on the influence of climate risk on investments and firm decisions.

pared to the Yale measure, our index captures greater variation in climate attention both across locations and over time, making it particularly valuable for research examining causal relationships.

Moreover, our measure and analysis provide new insights into how climate attitudes evolve and their relationship with social media attention and real outcomes. These insights can inform policy development. For example, recent research shows that investors pay premiums for ESG funds (Baker et al. 2022) and climate information increases willingness to pay for carbon offsets (Bernard et al. 2023). Climate awareness also shapes green innovation through consumer environmental concerns (Aghion et al. 2023; Guzman et al. 2023). Yet gaps remain in climate risk management—only 30-50% of structures in high flood risk areas carry flood insurance (Harrison et al. 2001, Kousky et al. 2018). Our measure can help policymakers target and evaluate initiatives to promote climate awareness and its downstream effects on green innovation, emissions reduction, and risk mitigation behaviors.

Our news-based climate awareness measure also complements recent studies employ surveys to identify motives for sustainable investing. These motives range from no reason, ethical considerations, social signaling, hedging motives, to return expectations (Riedl and Smeets 2017, Giglio et al. 2024). They also suggest that younger investors are more inclined to support environmental and social issues than older investors (Haber et al. 2022).[10] Our measure provides comprehensive geographic coverage of climate attention and offers insights into its regional heterogeneity can help inform future survey design.

Finally, our results are also 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 investor 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 et al. (2022), Kempf et al. (2023), and Goldman et al. (2024) (see Kempf and Tsoutsoura 2024 for a review). Additionally, Pan et al. (2022) show how recently growing geographical differences in portfolio stock holdings are driven by media-driven political polarization. Our comprehensive measure of local attention to climate change allows for a better understanding of the rising polarization on this politically-contentious subject and its implications on individual and firm decisions.

The paper is outlined as follows. Section 2 describes our main data sources and reviews descriptive statistics on newspapers' climate attention. Section 3 compares our measure of

[10]Other related research use surveys or field and laboratory experiments to assess investors' willingness-to-pay (WTP) for sustainable investments (Bauer et al. 2021; Heeb et al. 2023; Humphrey et al. 2023) or use investment flows to infer about investors' preferences for sustainable investments (Renneboog et al. 2011; Hartzmark and Sussman 2019; Döttling and Kim 2022).

climate attention to other frequently used measures. Section 4 examines the variables that explain media coverage of climate change. Section 5 looks at the effect of climate attention at the investor and firm levels. Section 6 concludes.

2 Data

2.1 News Coverage of Climate Change

Our data on news coverage of climate change comes from two main sources: NewsLibrary.com (NL) and Newspapers.com (NP). While the NL database includes many large and small newspapers, it does not cover approximately one-third of the largest newspapers in the United States. We therefore 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 not in either of our primary databases. For most tests, we restrict our analysis to daily English-language U.S.-based newspapers with at least 10,000 daily circulation, and that are located in Metropolitan Statistical Areas (MSAs).[11] With these restrictions, we have data on 510 major U.S. newspapers from 352 different MSAs, covering all the large population centers in the United States.

Our primary corpus of local newspaper articles comes from the news aggregator NewsLibrary. We download all headlines and up to first 80 words, which is the information we had access to, containing the keyword 'climate' of all published articles for a large number of US newspapers.[12] This search provides 718,144 snippets.

For many newspaper outlets the database does not provide information about the state or county. In these cases we use various methods to generate matches: (i) we search for information by googling the newspaper name, (ii) if we know the state but not the county we search whether names of any major cities in the state appear in the newspaper name, and (iii) if the county field contains a city name instead of a county name we assign the newspaper to the county for the largest city with the given name in the respective state. After dropping article snippets for which we do not have state and county information, we are left with 472,026 article previews across 5,139 newspapers for the period of January 2000 through August 2022.

We use the news aggregator Newspapers.com to supplement the NL dataset. We perform a keyword search for 'climate change' or 'global warming' and download the number of

[11] Daily circulation data is from OfficialUSA.com.

[12] See Widmer et al. (2022) for more details on the database.

articles which includes either of those phrases in the headline or body for each newspaper in each month from January 2000 through December 2022. We also do a more general keyword search, using commonly-used words, to get the total number of articles each month in each newspaper. We repeat this procedure in Factiva for The New York Times and The Washington Post.

We define our main variable of interest, *Climate Attention*, for each newspaper-month, as the number of climate-related articles scaled by the total number of articles.[13] To validate our measure as a proxy for climate awareness and concerns, we evaluate our newspaper corpus's content orientation. Using ChatGPT, we identify two sets of terms: Climate pessimist/activist ("global warming, greenhouse gas emissions, renewable energy, sustainability, environmental justice, carbon footprint, climate crisis, biodiversity loss, ecological conservation, carbon neutral") and optimist/denier terms ("climate realism, climate alarmism, clean coal, lower emissions fuels, advancing climate solutions, economic growth, energy independence, technological innovation, climate adaptation, environmental overreach"). Figure 2 shows that pessimist/activist terms consistently dominate across our sample period, with minimal occurrence of optimist/denier terms, confirming that these articles primarily reflect climate-related concerns.

Newspaper Ownership and Location We hand-collect ownership data from Wikipedia entries of each newspaper, supplemented with Google searches, tracking ownership changes of each newspaper going back to the start of our sample period. Most newspapers are part of chains, owned by the same parent company. We use ownership data to generate two variables, *Chain Size* and *Chain Gannett*, which we use as instruments for climate coverage. The first of these is the total number of newspapers (in our dataset) owned by the parent company and the second is an indicator variable based on whether the newspaper's parent company is Gannett, the largest chain in the country.

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, and we identify these from the UNC Hussman School of Journalism U.S. News Deserts website.

[13]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 *Climate Attention* for those newspapers not in NP.

2.2 Other Climate Concern Measures

National Measures Engle et al. (2020) introduce the WSJ-based climate news index. The authors construct their first index based on news coverage in the Wall Street Journal (WSJ). They then create a 'Climate Change Vocabulary' (CCV) from 74 documents found in 19 climate change white papers (IPCC, EPA, etc.). Subsequently, they employ the term-frequency and inverse document-frequency (tf-idf) methodology to compare both the CCV and the WSJ daily news. The final index is built by calculating the 'cosine similarity' scores of tf-idf between the CCV and WSJ daily news. Days in which the WSJ uses the same terms in the same proportion as the CCV earn an index value of one, while days in which the WSJ uses no words from the CCV receive an index value of zero.

Ardia et al. (2022) construct the Media Climate Change Concern Index (MCCC). They utilize the news articles from top U.S. newspapers and newswires to assess media coverage of climate change risk. First, they employ the LIWC2015 lexicon model to identify climate risk-related words. Then, they aggregate the risk coverage ratio and news sentiment. The MCCC index is the average of all news sources, standardized using standard deviation.

County-level Measures The Yale Climate Opinion Maps is based on data from 2010 through Fall 2023. Howe et al. (2015) present independently validated high-resolution opinion estimates by using a multilevel regression and post-stratification model.[14] The model predicts climate change beliefs, risk perceptions and policy preferences at the state, congressional district, metropolitan and county levels, using a concise set of demographic and geographic predictors. We use their model results for the estimated percentage of the population of each county that believes that global warming is happening and/or is worried about it to define $\text{Yale}^{\text{Happening}}$ and $\text{Yale}^{\text{Worried}}$, two local climate sentiment measures that we compare to our climate attention measure based on local media coverage.

Social Media Posts by Local Users We obtain aggregated and anonymized data from Meta (formerly Facebook) on users' climate-related posts by county. Our second measure of local climate sentiment, *FB Climate Posts*, captures the weekly percentage of posts related to climate in each county from December 2019 to June 2022.[15]

[14] We thank the Yale Program on Climate Change Communication and the George Mason Center for Climate Change Communication for providing the data. See Ballew et al. (2019) and Leiserowitz et al. (2020) for more details.

[15] We thank Meta and Mike Bailey for providing the data.

2.3 Ownership of ESG Exchange-Traded Funds

We collect a list of Environmental-Social-Governance (ESG)-focused exchange-traded funds (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 look at ETFs and not regular mutual funds because holdings of the former are reported quarterly on Form 13F, allowing us to track how institutional investors in different geographic locations change their exposure to ESG ETFs over time.

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 allowing them to be read. 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.[16]

We match each institutional investor filer of Form 13F with a registered investment advisor (RIA) that filed Form ADV, using name and business address.[17] Large institutions such as banks, insurance companies, mutual funds, hedge funds, and pension funds typically have clients from all over the country and/or they rarely hold ETFs. Thus, we focus our analysis on investment advisors to individual investors who invest their clients' funds and must then report these holdings on Form 13F. Their clients are usually local and their investment decisions are the 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 also use the total market value of reported 13F assets to generate *Log AUM Lag*, the natural logarithm of the market value of reported holdings at the end of the prior quarter. We use Form ADV to define 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 of each Form 13F filer to match it to a U.S. core-based statistical area (CBSA), and drop all filers from outside the United States from our sample.

[16]For example, in its latest 13F filing, Bank of New York Mellon filed on behalf of itself and 28 different asset management affiliates.

[17]Form ADV data is also available for download from the SEC's website.

2.4 Firm-level Variables

We collect data on firm environmental ratings from two sources: MSCI (formerly KLD) and Refinitiv. MSCI ratings coverage ends in 2018 while Refinitiv covers fewer firms than MSCI in most years. Therefore, to maximize coverage, we combine the two datasets, taking the average of the two ratings (after standardizing each) for firm-years covered by both datasets and using only one rating when the other is missing.

For each firm-year, MSCI provides a discrete rating of 0 or 1 along a number of dimensions related to community involvement, corporate governance, diversity, employee relations, environment, human rights, and product quality. Categories are defined as either strengths and concerns. We proceed using the standard practice of adding the strengths scores and subtracting the concerns scores to define an overall environment score, which we then standardize within each year to have mean zero and standard deviation of one.

For each firm-year, Refinitiv defines a continuous Environment Pillar Score from 0 to 1 based on three broad sub-scores: Emissions, Environmental Innovation, and Resource Use. We standardize the Environment Pillar Score within each year to have mean zero and standard deviation of one. For each firm-year, we then average the standardized scores from MSCI and Refinitiv to define the variable *Environmental Rating*. We also use the three Refinitiv sub-scores for several tests in Table 11. *Environmental Rating* is available for 60,099 firm-years from 2000 through 2022, or an average of approximately 2,600 firms per year, almost fully covering the Russell 3000 Index.

We also collect firm-level variables from CRSP/Compustat and use them to define the following firm-level controls: *Log Marketcap*, *Book-to-Market*, *Leverage*, *ROA*, and *Stock Returns* (see Appendix Table A1 for all variable definitions.) Because Compustat only reports the current location of each firm, we collect mailing addresses from the headings of 10-K filings, 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.

2.5 County-level Variables

Social Connectedness We follow Bailey et al. (2018a) and measure social connectedness between two U.S. counties using Facebook's *Social Connectedness Index* (SCI). The measure is the total number of Facebook friendship links between two U.S. counties (as of April 2016), divided by the product of the populations of the two counties. As the world's largest online social networking service, Facebook's scale and the relative representativeness of its user body make SCI a comprehensive measure of the geographic structure of the U.S. social networks.[18] For each focal county, we define peer counties as 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 Coverage* as the average *Climate Attention* across these peer counties.

Demographic Variables We collect county-level demographic and socioeconomic data from three sources. Median household income, *Income*, and percentage of college graduates, *Education*, are from the U.S. Census Bureau's American Community Survey. Population for calculating *Log Population* and the unemployment rate, *Unemployment* are from the U.S. Department of Agriculture's database. Finally, the county's share of two-party votes cast for the Democratic candidate in the previous presidential election, *Democrat Share*, is from the MIT Election Lab.

Greenhouse Gas Emissions Since 1990, Environmental Protection Agency (EPA) develops an annual report called the Inventory of U.S. Greenhouse Gas Emissions and Sinks (Inventory), which tracks U.S. greenhouse gas emissions and sinks by source, economic sector, and greenhouse gas. This annual report provides a comprehensive accounting of total greenhouse gas emissions for all man-made sources in the United States. The gases covered by the Inventory include carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluoride. We use this database to aggregate the greenhouse gas emissions by individual facilities to county level. Our variable, *Log GHG*, is the logarithm of the total annual greenhouse gas emission in a given county.

Toxics Release The Toxics Release Inventory (TRI) dataset contains all chemical components released by facilities in the United States. We follow Hsu et al. (2023), who construct each firm's emission intensity by dividing the total toxic chemical releases by the total assets of the firm. Our measure, *Log TCR*, is the natural logarithm of the aggregate toxic chemical release in a given county-year.

[18]For example, Facebook had more than 2.1 billion monthly active users globally and 239 million active users in the United States and Canada as of 2017. This represents 68% of the adult population and 79% of online adults in the United States (Duggan et al., 2016). Facebook usage rates among U.S.-based online adults were relatively constant across various demographics and locations. Bailey et al. (2018b, 2019, 2020, 2022, 2021); Kuchler et al. (2022, 2020), and Chetty et al. (2022) have all provided evidence that social connections observed on Facebook can serve as a reliable proxy for real-world connections, even in eras prior to the widespread use of computers and the internet.

Extreme Temperature We obtain the average monthly temperature data from the National Oceanic and Atmospheric Administration (NOAA). The division temperature data encompass all stations within a climate division, including both airports and National Weather Service (NWS) cooperative stations. To calculate our extreme temperature dummy *High Temp* for a given county in a given month, we look at the full history of average temperature values. *High Temp* equals one if the average temperature measured in the current month is larger than any past measurement made in the county in any month, and zero otherwise.

Economic Damage data We collect data on the total property and crop damage (in 2000 dollars) from the Spatial Hazard Events and Losses Database for the U.S. (SHELDUS) maintained by Arizona State University. SHELDUS provides monthly county-level data on damage due to major natural hazards and disasters.[19] We define a dummy variable *High Damage*, which equals one if the total damage from SHELDUS in a given month is larger than one million dollars, and zero otherwise.

2.6 Descriptive Analysis

Table 1 provides summary statistics on the variables used in our empirical analysis. Panel A shows the variables used for tests at the paper-month level, where we have 123,239 observations for *Climate Attention*, our main variable of interest. This variable is converted to percentage points so the mean value of 1.312 indicates that around 1.3% of newspaper articles are climate-related.

Panel B of Table 1 shows summary statistics for variables at the advisory firm-quarter level, which we use to examine the effect of climate attention on ESG ETF ownership. We aggregate climate attention and control variables to the MSA level since newspapers typically cover, and are circulated, at that geographic level. The mean value of lagged *ESG ETF Share* is 0.610 (which is in percentage points) indicating that 0.61% of ETFs are ESG-related for the typical investment advisory firm. This small magnitude is consistent with ESG-related ETFs having a tiny share of the multi-trillion dollar ETF AUM. The median value of this variable is zero indicating that most advisory firms hold no ESG ETFs among their ETF holdings.

[19]Natural hazards and disasters categories included in the SHELDUS database in our sample period (2000-2022) are "heat", "hurricane/tropical storm", "wind", "severe storms/thunder storm", "tornado", "flooding", "coastal", "hail", "winter weather", "lightning", "drought", "wildfire", "landslide", "avalanche", "tsunami/seiche", and "fog". Top five disasters in terms of the total damage between 2000-2022 are flooding, hurricane/tropical storm, wildfire, tornado, and drought. The damage due to these five disasters makes up 93% of the total natural disaster damage in this period.

Panel C of Table 1 shows summary statistics for variables at the firm-year level, which we use to examine the effect of climate attention on changes in environmental ratings of locally-headquartered companies. The firm overall rating is calculated by averaging standardized ratings from Refinitiv and MSCI, so its mean is close to zero and standard deviation is close to one. Panel D shows the summary statistics for topic similarity measures *JD20* and *Embedding Similarity* based on county pairs.

Figure 3 Panel A shows the evolution of *Climate Attention* over time. The spikes coincide with United Nations climate summits (e.g., December 2009 Copenhagen Summit, December 2015 Paris Summit) as well as the United States withdrawal from the Paris Climate Accords in June 2017. More recent spikes have come from national political debate and Congressional votes on the Build Back Better Framework/Inflation Reduction Act of 2022, which included significant spending on climate-related initiatives. We can also see a general upward trend in climate attention as the issue has gained salience over our sample period. We use time fixed effects in our tests to absorb time-series variation.

Figure 3 Panel B superimposes two indices of nation-wide climate sentiment, MCCC and WSJ, on average *Climate Attention*. We can see that the spikes on all three series coincide with each other. Also, *Climate Attention* closely follows MCCC, and WSJ to a lesser degree. This figure helps validate our *Climate Attention* variable, by showing that it moves in concert with earlier measures of nation-wide climate sentiment.

Despite co-moving with national trends, *Climate Attention* exhibits considerable cross-sectional variation. Figure 4 shows the heat map for the average *Climate Attention* for the counties in continental U.S. between January 2000 and December 2022. Grey areas are counties outside of MSAs or without major newspapers. Darker shades of blue indicate higher average *Climate Attention*. We see a large variation in climate attention across counties. For instance, while San Francisco County, CA had an average *Climate Attention* of 5.28% between 2000-2022, Cape May County, NJ had only 0.46%.[20] San Francisco and the surrounding Bay area are where the Sierra Club was founded by John Muir and are known for their environmental activism, so it's not surprising that it has the most climate-related news coverage in the country.

[20] Top five counties based on average *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).

3 Comparing Measures of Climate Attention

In this section, we validate our measure of climate attention by examining its relation to other measures that have been used in the literature. We conduct this validation both with national (time-series) measures as well as local measures that vary both across time and county. We also run horse race tests between our news-based measure and the measure drawn from the Yale Climate Opinion Maps which has been widely used in the literature (see Bernstein et al. (2019); Baldauf et al. (2020), Keys and Mulder (2020), and Goldsmith-Pinkham et al. 2023).

We start by formally relating our climate attention measure to national measures using panel regressions with newspaper-month observations. The main explanatory variables are the two previously-used measures of nation-wide sentiment about climate change are *MCCC* and *WSJ*, both standardized to have zero mean and unit standard deviation to simplify interpretation. All specifications also include a control for lagged climate attention to account for persistence in coverage.

Table 2 presents the results. Column 1 shows that a one-standard deviation increase in *MCCC* is associated with a statistically-significant 25.7 bps increase in the contemporaneous *Climate Attention*. Likewise, in column 4, a one-standard deviation increase in *WSJ* is associated with a somewhat smaller but still significant 11.7 bps increase in *Climate Attention*. When we instead include lagged versions of these national measures in columns 2 and 5, we find no connection between the prior month's national climate attention and the current month's local climate attention. Similarly, when we include both lagged and contemporaneous of *MCCC* and *WSJ* in columns 3 and 6, only the contemporaneous measures show up with a positive and significant coefficient. Thus, Table 2 confirms that local climate attention is correlated with the nation-wide climate sentiment, helping to validate our measure. Still the regression R^2 in Table 2 are all below 0.6, indicating that there is significant residual variation in local *Climate Attention* that is not explained by national attention.

We next examine the relationship between *Climate Attention* and two local climate concern proxies, $Yale^{Happening}$ and *FB Climate Posts*. Table 3 shows that both measures correlate positively with *Climate Attention*, with *FB Climate Posts* showing stronger associations. A one-percentage point increase in $Yale^{Happening}$ corresponds to a 2.8 basis point increase in contemporaneous *Climate Attention* (column 1), though this effect weakens substantially with county controls (column 2).

In comparison, a one-standard deviation increase in *FB Climate Posts* corresponds to a 28.2 basis point increase in *Climate Attention* (column 4). When including both measures (column 5), only the Facebook-based measure remains positive and significant. Moreover, with county fixed effects (column 6), the coefficient of $Yale^{Happening}$ switches sign and becomes marginally negative, consistent with its construction from slow-moving county characteristics.

To compare our news-based measure of climate attention with the Yale-based measure that uses survey data and model imputations, we run a horse race to determine which measure better captures the climate attention as reflected in local users' social media posts. In Table 4, we regress *FB Climate Posts* on *Climate Attention* and $Yale^{Happening}$ using a monthly, county-level panel regression. Column 5 shows that a 1 percentage point increase in *Climate Attention* is associated with a 0.3 bps increase (with a t-statistics of 2.522) in the contemporaneous *FB Climate Posts*, which corresponds to 5.2% of the sample standard deviation of *FB Climate Posts*. In the same column, the coefficient of $Yale^{Happening}$ is both economically and statistically insignificant. Thus, *Climate Attention* can explain *FB Climate Posts* better than $Yale^{Happening}$.

Next, we run a second horse race to see which of the two measures does a better job in explaining economic outcomes. For this purpose, we examine the extent to which the two local climate attention measures explains local investors' holding of ESG-linked ETFs. We argue that ESG ETF investment is a natural consequence of higher climate attention, as these vehicles are specifically named and marketed so as to attract investors concerned about the environment.

To that end, we first aggregate our newspaper-month level variable *Climate Attention* to MSA-quarter level by taking its county population weighted average within an MSA. We then take the quarterly average of this MSA-level version to obtain *Climate Attention (M)*. We then run an advisory firm-quarter level panel regression of changes in local ESG-linked ETF investments on *Climate Attention (M)*. We only include observations for which both measures are available so that we can do a true apples-to-apples comparison, and report the results in Table 5. For robustness, we use two Yale-based variables, based on whether individuals think climate change is happening ($Yale^{Happening}$) and whether they are worried about it ($Yale^{Worried}$). These variables are in county-year level. Thus, we also aggregate them to MSA-year level by taking their county population weighted averages within each MSA to obtain $Yale^{Happening}$ *(M)* and $Yale^{Worried}$ *(M)*. The results are very similar for both as the two measures are highly correlated when aggregated at the metro area level. Since ETF ESG share shows strong mean reversion, we include the one quarter lagged ETF ESG share as a control in all regressions.

Columns 1 and 4 of Table 5 show that the MSA-level version of our news-based measure, *Climate Attention (M)*, has a significant correlation with the changes in ETF ESG share with or without advisor firm fixed effects. Specifically, in Column 4, a 1 percentage point increase in *Climate Attention (M)* is associated with 1.7 percentage point increase in contemporaneous change in ETF ESG share, which corresponds to 79% of the sample standard deviation of the change in ETF ESG share share. In contrast, Columns 2 and 5 show that $Yale^{Happening}$ *(M)* has a marginally significant association with the change in ETF ESG share only when we exclude the advisor firm fixed effects, and even then, its effect is about 60% of that of *Climate Attention (M)*. Finally, Columns 3 and 6 show that $Yale^{Worried}$ *(M)* does not have significant explanatory power for ESG-linked ETF ownership.

The evidence indicates that our news-based measure of climate concerns outperforms the Yale measure in capturing both 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 demographic changes.

4 Determinants of Climate Attention

In this section of the paper, we investigate the cross-sectional variables that explain local climate coverage, in order to get a better understanding of what explains the geographic heterogeneity in climate attention. Some candidates for determinants of climate attention include local demographic and socioeconomic variables, variables related to emissions and natural events caused by climate change, as well as variables related to ownership of the local newspapers that report on climate.

4.1 Demographics, Climate Shocks, and Environmental factors

We first examine the relationship between *Climate Attention* five demographic/socioeconomic variables: logarithm of the population (*Log Population*), median household income in $1,000 (*Income*), college graduation rate (*Education*), unemployment rate (*Unemployment*), and political inclination (*Democrat Vote Share*). We perform panel regression analysis at newspaper-month level. We do not include paper fixed effects because most of these variables are stable over time, so we are mainly focused on how their cross-sectional variation affects climate attention.

Panel A of Table 6 shows that, in univariate regressions, all five variables are highly significantly correlated with *Climate Attention*: all variables except unemployment rate are positively associated with coverage of climate-related news. In a multivariate regression, *Education*, *Democrat Share*, and *Unemployment* retain their significance and signs, while *Log Population* and *Income*, although retaining their signs, become insignificant. The analysis shows that climate attention is more prevalent in counties with higher education levels and Democratic-leaning voters, but lower in areas with higher unemployment.

Table 7 examines the relationship between *Climate Attention* and local extreme natural events, as well as pollution, while controlling for time and paper fixed effects along with county demographic variables. In column 1, we regress *Climate Attention* on *High Damage*, a dummy variable that indicates the occurrence of natural disaster/hazard that causes a total damage exceeding $1,000,000. In column 2, we replace *High Damage* with *High Temp*, another dummy variable indicating an all-time high average monthly temperature. Both variables are significantly associated with *Climate Attention*: *Climate Attention* is 5.8 bps higher in a *High Damage* month and 9.8 bps higher in a *High Temp* month. In columns 3 and 4, *Climate Attention* is regressed on the county-level log greenhouse gas emissions (*Log GHG*) and log toxic chemical release (*Log TCR*) from all production facilities. Results show that, there is no significant relationship between *Climate Attention* and these two pollution measures.

These findings suggest that local climate coverage responds significantly to tangible climate events—major natural disasters and record-high temperature. However, the lack of correlation between news coverage and local pollution measures (greenhouse gas emissions and toxic chemical releases) suggests that media attention focuses on acute climate events rather than chronic environmental conditions.

4.2 Newspaper Ownership

Figure 5 shows how ownership of U.S. newspapers has changed over our sample period. In red, we can see that the average chain size has gone up over time, with the average newspaper being in a chain with 17 total papers at the start of our sample period, to just under 60 total papers at the end. Much of this consolidation has happened in the period from 2015 to 2020, when several large newspaper chains like Gannett and Gatehouse, underwent mergers. In blue, we can see that the overall trend is not only coming from mergers of large chains. Stand-alone newspapers, those not part of a chain, went from 20% of our sample to 12% over our sample period, as circulations have declined, forcing locally-owned family papers to sell to more economically efficient chains. These trends in ownership are largely exogenous to climate issues, but they provide us with time-series variation in climate-related articles that allows us to make causal inferences about the effects of climate attention.

In Table 8, using newspaper-month level panel regressions, we examine the relationship between *Climate Attention* and two measures related to the newspaper ownership: *Chain Size*, which is defined as the total number of newspapers (in our sample) with the same owner as that of the newspaper, and *Chain Gannett*, which is an indicator variable which equals one if the newspaper's owner is the Gannett company and zero otherwise. We also control for the high temperature indicator (*High Temp*), county-level socioeconomic/demographic variables given in Table 6, and time fixed effects in all columns. We further control for paper fixed effects in columns 3 and 4. We can see that *Climate Attention* is significantly and negatively associated with both of the ownership variables. For instance, columns 3 and 4 show that a one standard deviation increase in *Chain Size* is associated with a 11.2 bps increase in *Climate Attention*, while ownership by Gannett is associated with a 19.1 bps increase in the same variable. Hence, being owned by a large chain has a significant and negative effect on the local climate-related news coverage. The effect of newspaper ownership on climate coverage makes it a potentially useful instrument in the next section where we will want to understand how climate attention affects investor and corporate behavior.

One potential concern about using using ownership variables as instruments is that newspapers chain managers might be selecting specific newspapers to add to their portfolio based on some criteria related to their climate coverage. In that case, our instrument would not satisfy the exclusion restriction. In Appendix Table A2, we investigate whether ownership changes can be predicted by newspaper characteristics or local demographic variables. We find that across all types of newspapers, including small-chain, mid-sized chain, and large-chain papers, the probability of an ownership change is significantly associated with only one variable, the population size of the county where the paper is located. None of the newspaper variables, including the paper's prior climate coverage, predict that the paper will change hands. These results support the validity of using newspaper ownership as an instrument.

4.3 Peer Attention

A large literature has documented significant peer influence on household beliefs and financial decisions (see Bailey et al. 2018a, 2019, 2022, 2023; Hu 2022 for studies that used Facebook-based measures). Motivated by this, we examine how climate attention in socially connected areas influences local climate awareness.

We regress *Climate Attention*, the focal paper climate attention, on *Peer Attention*, the average *Climate Attention* of counties with strong social connections based on Facebook's

SCI, excluding same-state peers. We also control for lagged peer attention (*Peer Attention Lag*), both focal and peer temperatures, focal county socioeconomic variables, month-by-year fixed effects, and focal newspaper fixed effects. Table 9 presents the results, showing a positive and significant relationship between local and peer newspaper attention: a 1.0 percentage point increase in *Peer Attention* corresponds to a 28.5 bps increase in *Climate Attention*.

We also measure social connections using geographic proximity. We define *Peer Attention Geo* as the average *Climate Attention* of counties whose physical distance to the focal county ranks in the bottom 10% of the distribution. Thus, in column 2, we replace *Peer Attention* with *Peer Attention Geo*, which is defined as the equal weighted *Climate Attention* over bottom 10% of the peer papers based on the physical distance between the focal paper's county and peer counties. We once again exclude same state peers to make the variable comparable to *Peer Attention*. Results show that this distance-based measure of peer climate attention is also significantly associated with *Climate Attention*, although its coefficient is smaller than that of *Peer Attention* in column 1.

In column 3, we include both measures of peer attention together. We can see that *Peer Attention* remains highly significant while *Peer Attention Geo* is no longer significant, which indicates that the association between peer and focal climate attention is primarily driven by social ties and that physical proximity is a noisier measure of such ties compared to SCI.[21] Because peer attention is independent of local variables but affects local climate attention, it will be a potentially useful instrument in the next section of the paper.

Beyond examining the volume of climate coverage across socially connected areas, we investigate whether these areas share similar climate-related reporting content. We analyze headlines and opening paragraphs (up to 80 words) of climate-related articles from over 5,000 newspapers in NewsLibrary to compare topic coverage across regions. Using the Latent Dirichlet Allocation (LDA), we extract 20 topics and measure the distance between topic distributions between counties using the Jensen-Shannon distance (*JD20*). This metric ranges from zero (identical distributions) to one (completely different distributions).[22] Appendix B.1 details our textual analysis methodology.

Panel B of Table 9 examines how social connectedness relates to similarity in climate reporting content. The dependent variable, *Topic Similarity*, is the negative of the topic distance between counties as measured by *JD20*. Our analysis considers three measures of

[21] Similarly, Kuchler et al. (2022) find that geographical proximity loses its significance and even changes its sign after SCI is included in their analysis of institutional investor portfolio allocations.

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

county similarity: social connectedness (*SCI*), demographic and economic characteristics (*Socioeconomic Similarity*), and geographic proximity (*GeoProx*), which is defined as the negative of the distance between the counties.[23] In the regressions, all three of these measures are rank-normalized to [0,1] within each focal county. Apart from county similarities, we also control for focal and peer county fixed effects in all regressions. Column 1 shows that, when moving from the bottom to the top rank of *SCI* corresponds to a 63.79 basis point 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 content, providing both content similarity across socially connected regions and support for our use of peer climate attention as an instrument in subsequent analysis.

5 The Effects of Climate Attention

In this section of the paper, we examine how local climate attention affects decisions of investors who live close by as well as the decisions of firms headquartered in the area. Our main hypothesis is that more local attention to climate change causes geographically proximate investors to shift their portfolio holdings toward more environmentally-friendly companies and also causes local firms to make their operations more green.

Because newspapers typically cover news, and are read in, a city or town and its surrounding region, we aggregate climate attention to the Metropolitan Statistical Area (MSA) level by taking a weighted (by circulation) average of *Climate Attention* of all major newspapers located in the MSA. We define this variable as *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 is picking up some other omitted variable that is both driving news coverage and investor or firm decisions. We address this issue by using controls and fixed effects, and by using an instrumental variable approach, with the ownership variables, *Chain Size* and *Chain Gannett*, and the peer-based variable, *Peer Attention*, as instruments. As we saw earlier in Table 8, newspapers that are owned by larger chains or the Gannett company, are less likely to cover climate change. Since

[23] *Socioeconomic Similarity* is based on the 2021 values of county-level population, median household income, percentage of college-educated population, unemployment rate, and percentage of the votes cast for the Democratic candidate in the last presidential election. We rank these five variables across counties and normalize the ranks to [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.

ownership is typically based on the economics of the news industry and the liquidity needs of families that own newspapers, they are unlikely to be related to climate coverage, and thus these instruments are likely to satisfy the exclusion restriction. Also, climate coverage in other areas of the country is unlikely to be related to local factors and thus more likely to be exogenous to local climate coverage. We aggregate the instruments to the metro level and proceed with the subsequent analysis of economic outcomes at that level.

5.1 Climate Attention and Portfolio Decisions

We start by examining how local climate attention shapes investor decisions. Using advisory firm-quarter level panel data, we regress the quarterly change in *ESG ETF Share* on *Climate Attention (M)*, while controlling for the size and clientele of the advisory firm. We also control for the presence of an extreme heat event, *High Temp*, to ensure that climate attention is not just picking up unusual local weather. Finally, we control for the lagged value of *ESG ETF Share* because there is significant mean reversion in this variable. We report our results in Table 10.

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 10, which include time fixed effects, show a positive and statistically significant estimated coefficient on *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 *Climate Attention (M)* maintains statistical significance with a more than doubling in the magnitude of its estimated coefficient.

In Columns 3 through 8, we instrument for climate attention using our two ownership-based instrumental variables, *Chain Size* and *Chain Gannett*, and our peer-based instrumental variable, *Peer Attention*. We find that the fitted *Climate Attention* variable from the first stage still significantly predicts positive changes in ESG ETF ownership. These findings are important because they suggest that newspaper coverage is not just acting as a barometer of local interest or sentiment toward climate change but that it is directly affecting investor behavior as exogenous ownership changes or peer attention changes increase or reduce newspaper coverage of this issue.

In terms of economic magnitude, Column 7 shows that a one standard-deviation (1.6 percentage point) increase in climate attention is associated with approximately a 36 bps cross-sectional increase in ESG ETF ownership. While this effect might seem small, the average ESG ETF Share is only 61 bps during our sample period. The average advisory firm in our sample allocates $574 million dollars to ETFs, so 36 bps corresponds to an extra $2,000,000 allocated to ESG ETFs from each local advisory firm due to local media attention.

5.2 Climate Attention and Firm Decisions

We also investigate how firms respond to local climate attention using changes in environmental scores of locally-headquartered firm. Using firm-year level panel data, we regress the annual change in *ENV Rating* on *Climate Attention (M)* while controlling for firm characteristics (such as lagged size, book-to-market, stock returns, 3-digit SIC code for industry, etc.) We also control for the presence of an extreme heat event, *High Temp*, to ensure climate coverage is not just picking up unusual local weather. Finally, we control for the lagged value of *ENV rating* because there is significant mean reversion in this variable. We report our results in Table 11.

The results in Column 1 of Table 11 show a positive and statistically significant relation between climate attention and the change in the environmental score. Consistent with our hypothesis, more local newspaper climate coverage is associated with firms getting better environmental ratings due to the investment of firm resources into becoming environmentally greener.

We add firm fixed effects in the remaining columns to control for time-invariant firm heterogeneity. In Column 2, the positive effect of climate attention persists and is about twice the magnitude of that in Column 1. We then implement an instrumental variable-based approach in Columns 3 and 4 using two related instruments, *Chain Size* and *Chain Gannett*, and find that local climate attention continues to positively predict improvements in the firm's environmental score, suggesting that our results are causal. In terms of economic magnitudes, Column 4 shows 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 an average of 0.18 standard deviations.[24]

In Columns 5 through 7, 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 significant increases in the emissions rating, indicating a reduction in polluting emissions, and an improved resource use rating, indicating more efficient use of natural resources. However, there is no significant change in the innovation rating. This could be due to in-

[24]The peer coverage instrument is unsuitable for these tests as annual data frequency weakens the first-stage estimation.

novation requiring more and continued investment than reducing pollution or having better resource use.

Other than climate attention, we find that firm size is a significant predictor of improvements in the environmental rating. This is consistent with the literature showing that larger firms are more capable of making the major investment required to make their operations more environmentally friendly. The other firm-level variable that significantly predicts changes in environmental firm performance is last year's stock return, but the sign on that coefficient is negative. This result suggests that firms with poor recent stock performance might be trying to clean up their firm's environmental record to attract green-conscious investors to get the stock price back up. On the other hand, firms whose stock price has been going up don't need to spend valuable firm resources to attract environmentally-conscious investors.

6 Conclusion

Our study advances understanding of local climate attitudes and their economic impacts through a novel news-based measure covering major U.S. population centers from 2000-2022. Compare to the Yale Climate Opinion Survey, our measure offers several key advantages: it spans a longer time period, captures dynamic variations beyond demographic and geographic predictors, and enables stronger causal inference through exogenous variation.

We document rising climate attention and growing regional polarization. While our measure tracks national trends, it reveals substantial geographic heterogeneity, with climate attention varying considerably across locations. Specifically, climate attention is higher in areas with more educated populations and Democratic voters, but lower in areas with high unemployment. Climate attention also responds to acute environmental events like natural disasters and extreme heat episodes. However, chronic environmental conditions—local greenhouse gas emissions and toxic chemical releases—show no significant relationship with attention. Additionally, our news-based climate attention measure correlates significantly with local users' social media climate attention.

By exploiting exogenous variations in climate attention due to factors based on the newspaper's ownership or the climate attention of distant peers, we provide causal evidence that increased climate change coverage boosts local individual investors' ESG ETF investments. A one-standard deviation increase in local climate attention corresponds to a 59% increase in ESG ETF ownership (relative to the mean), representing a $2,000,000 increase in ESG ETF holdings for an average-sized local advisory firm. Furthermore, we find that local climate change coverage is associated with improved environmental ratings of firms headquartered in the area, as well as better scores on emission reduction and more efficient use of natural resources by these local firms. A one-standard deviation increase in local climate attention is associated with local firms boosting their environmental ratings by an average of 0.18 standard deviations.

These findings demonstrate that local climate concerns directly influence investor behavior and corporate environmental performance. These findings are important for several reasons: First, by identifying factors shaping local climate attitudes, our results inform policy development aimed at climate mitigation and adaptation. Second, our evidence that climate attention drives ESG investment and corporate environmental responsibility can guide policy initiatives promoting green innovation and climate-risk awareness in household decisions. Third, the documented peer effects across regions highlight how interconnected public discourse shapes climate action, emphasizing the importance of coordinated responses to climate change. Finally, our local attention measure provides a novel tool for future research examining the causal effect of climate change awareness and attitudes on decision making.

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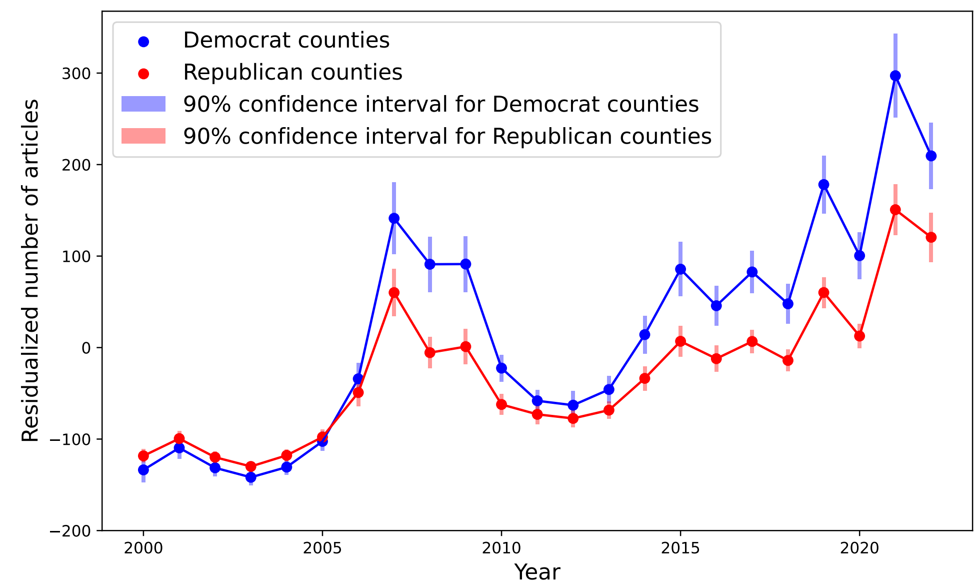
Figure 1: Climate-related articles and ESG ETF shares in Democratic versus Republican counties. Panel A shows the average number of climate-related articles published by newspapers, comparing Democratic and Republican counties. Panel B presents average ESG-focused ETF shares across Democratic and Republican Core Based Statistical Areas (CBSAs) by year. Both measures are residualized by 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: *Climate Attention*



Panel B: ESG share

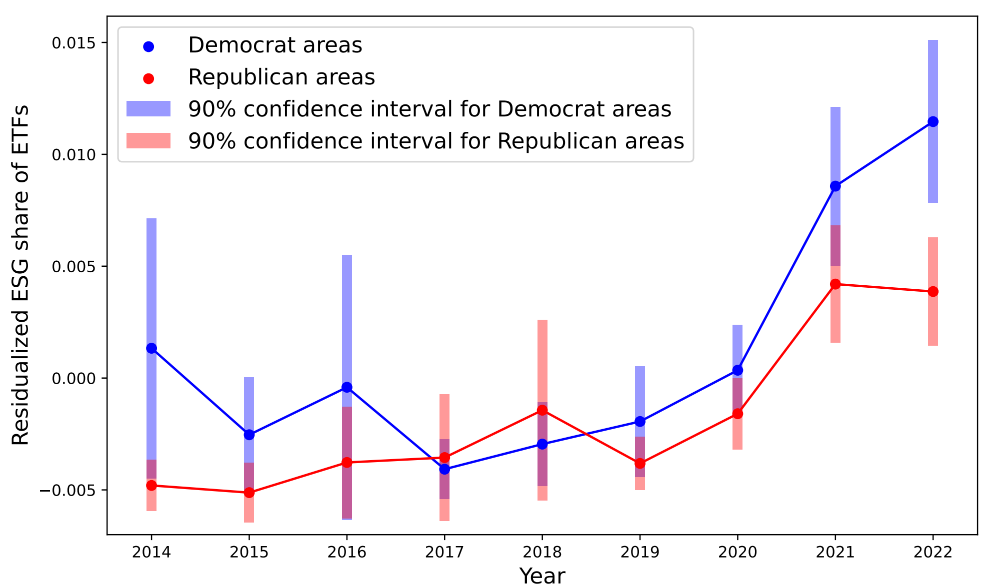


Figure 2: Frequency of climate pessimist/activist versus optimist/denier terms. We classify newspaper content using ChatGPT to identify two sets of terms. Climate pessimist/activist terms include "global warming, greenhouse gas emissions, renewable energy, sustainability, environmental justice, carbon 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 frequency of these terms over time.

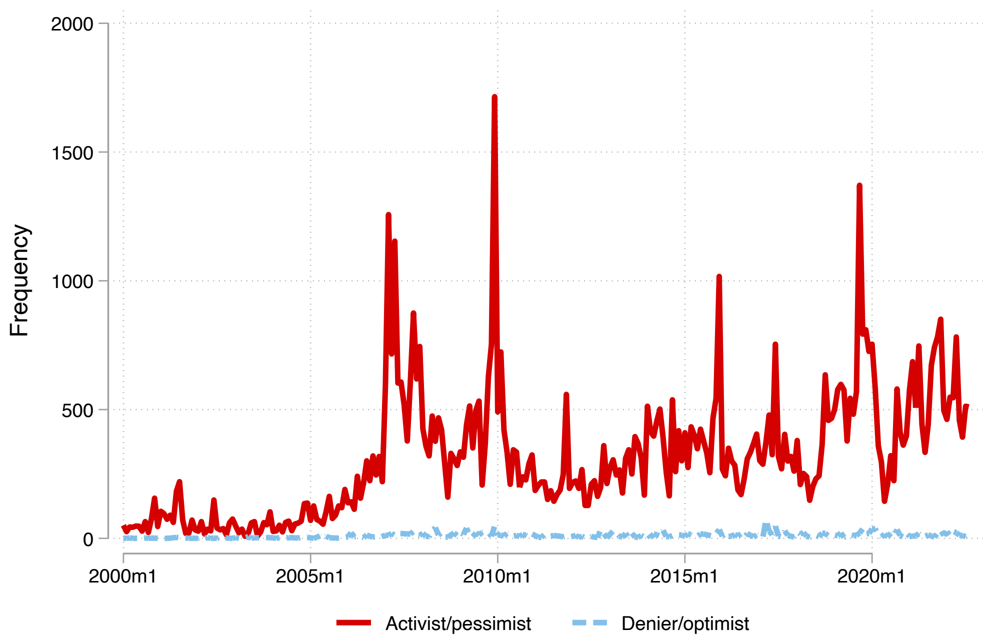
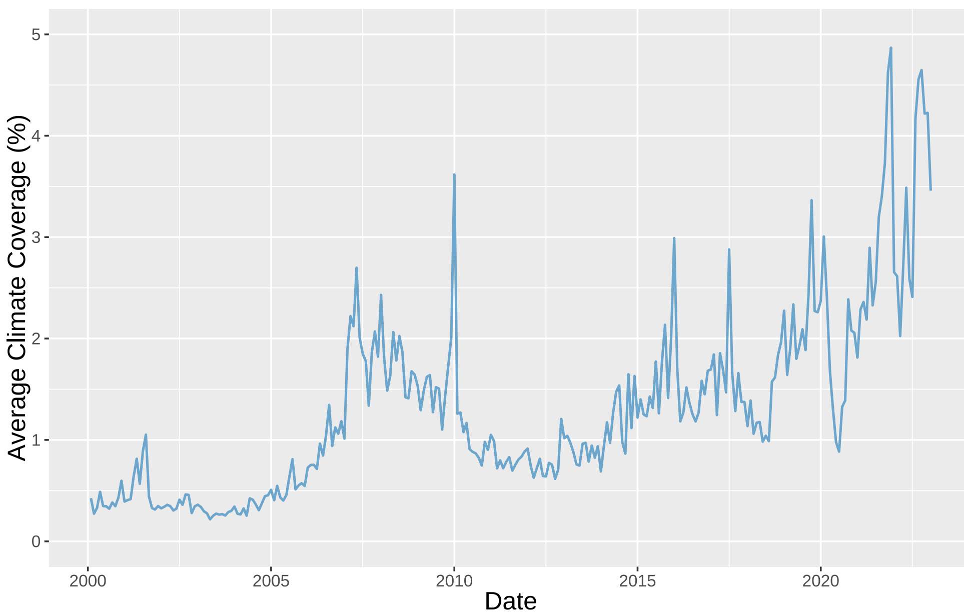


Figure 3: Time series of climate attention measures. Panel A plots average news-based *Climate Attention* across 510 major U.S. newspapers from January 2000 to December 2022, measured as the monthly percentage of climate-related articles. Panel B compares *Climate Attention* with the Media Climate Change Concern Index (MCCC) of Ardia et al. (2022), and 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: Climate Attention



Panel B: Climate Attention, MCCC, and WSJ

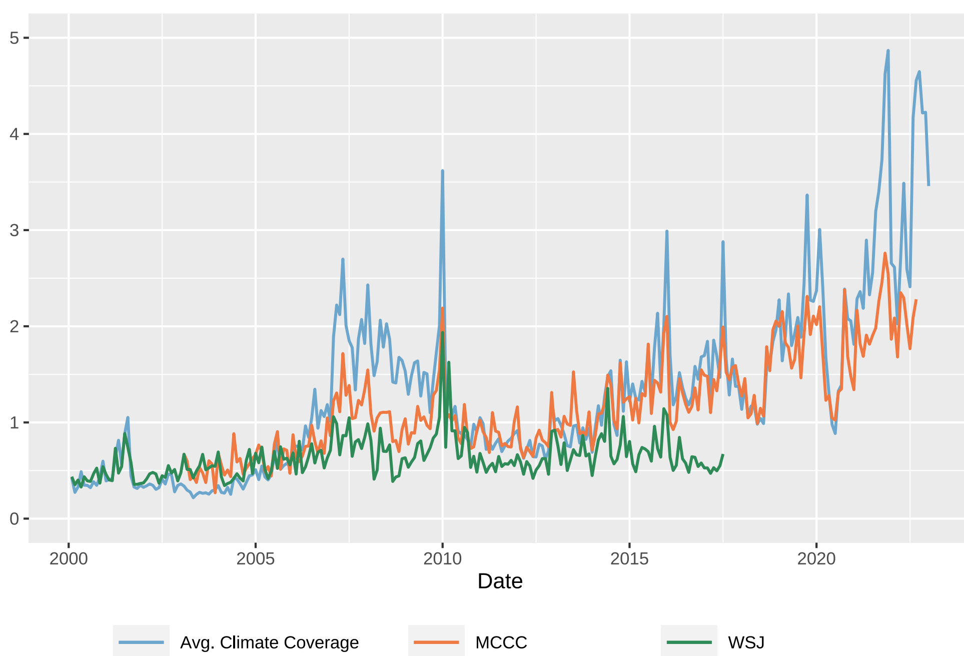


Figure 4: Heat map of Climate Attention across U.S. counties, 2000-2022. Average Climate Attention (in percent) is shown for counties in the continental United States. Darker blue shades indicate higher Climate Attention. Grey areas represent counties without major newspapers in our sample.

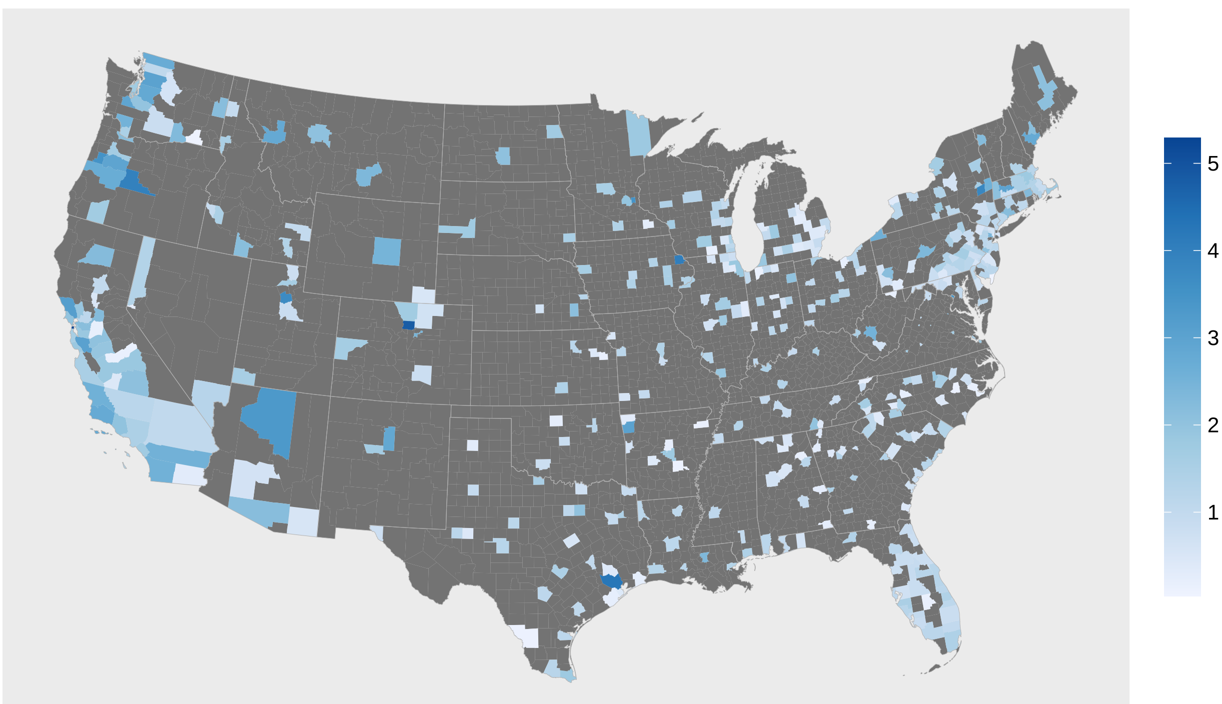


Figure 5: Newspaper chain characteristics, 2000-2022. The figure plots average Chain Size (red) and the proportion of stand-alone newspapers (blue) from January 2000 through August 2022.

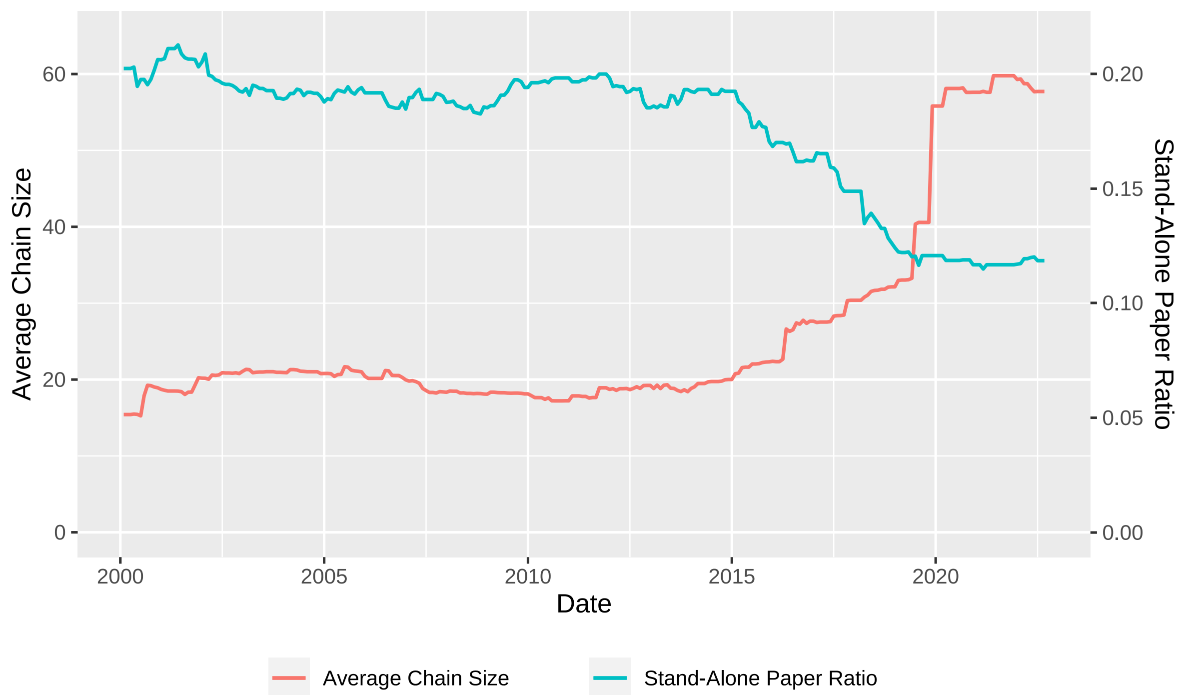


Table 1: **Summary Statistics**

Table 1 presents the summary statistics for the main variables used in the analyses. Variable definitions can be found in A1. Panel A includes newspaper and county level variables used in Tables 2, 6, 7, 8, and 9, while Panel B and Panel C report statistics for MSA-level variables used in Tables 10, 11, and 5.

Panel A: Paper-Level Variables

	N	Median	Mean	SD	Min	25%	75%	Max	Skew	Kurt
Climate Attention	123,293	1.055	1.312	1.341	0.005	0.442	1.765	12.317	3.320	24.647
Log Population	122,993	12.500	12.657	1.070	9.860	11.880	13.319	16.104	0.773	0.768
Income	118,202	47.639	50.195	11.184	29.104	42.683	54.957	95.003	1.153	1.631
Education	118,202	23.093	23.826	7.343	10.324	18.010	28.065	46.848	0.625	0.031
Democrat Share	122,704	51.270	51.635	14.228	16.872	41.244	60.301	92.790	0.264	-0.161
Unemployment	118,178	5.733	5.946	1.729	2.434	4.849	6.782	20.745	2.373	17.833
$\text{Yale}^{\text{Happening}}$	38,632	69.124	69.373	5.859	55.789	64.897	73.328	84.805	0.216	-0.431
FB Climate Posts	14,994	0.128	0.142	0.058	0.051	0.105	0.162	0.472	1.948	6.269
High Damage	134,881	0.000	0.007	0.052	0.000	0.000	0.000	0.489	11.615	164.468
High Temp	134,881	0.000	0.007	0.026	0.000	0.000	0.004	0.152	8.372	104.261
Log GHG	134,881	6.326	5.857	2.069	0.000	5.681	7.053	8.475	-2.022	3.323
Log TCR	134,881	13.155	11.724	4.695	0.000	10.363	14.649	18.250	-1.632	2.019
Chain Size	123,283	16.442	26.372	27.970	1.000	3.068	45.622	78.663	1.084	-0.144
Chain Gannett	123,283	0.000	0.178	0.376	0.000	0.000	0.138	1.000	1.759	1.311
Peer Attention	134,881	1.357	1.431	0.366	0.749	1.154	1.669	2.457	0.621	-0.314
Peer High Temp	134,881	0.003	0.007	0.009	0.000	0.001	0.009	0.040	2.476	8.191
Peer Chain Size	134,881	25.423	25.566	4.937	14.214	21.930	28.870	39.768	0.240	-0.310
Peer Gannett	134,881	0.170	0.180	0.065	0.041	0.133	0.221	0.371	0.480	-0.217
PeerAttentionGeo	134,881	1.185	1.279	0.378	0.705	0.994	1.459	2.239	0.804	-0.143
PeerHighTempGeo	134,881	0.002	0.007	0.011	0.000	0.000	0.009	0.045	3.588	26.059
Climate Attention (IV=CS)	118,274	1.049	1.220	0.986	-0.196	0.587	1.584	8.210	2.247	11.470
Climate Attention (IV=G)	118,274	1.050	1.220	0.987	-0.192	0.586	1.584	8.209	2.247	11.465

Panel B: Quarterly MSA-Level Variables

	N	Median	Mean	SD	Min	25%	75%	Max	Skew	Kurt
Climate Attention (M)	102,572	2.314	2.554	1.579	0.038	1.696	2.923	11.814	2.047	7.581
Δ ESG ETF Share	104,117	0.000	0.023	2.142	-53.933	-0.000	0.001	56.924	0.790	769.601
ESG ETF Share Lag	107,050	0.000	0.610	4.047	0.000	0.000	0.131	91.412	17.343	380.263
Log AUM Lag	107,050	19.677	20.035	1.647	11.749	18.931	20.787	28.453	0.901	2.231
High Net Worth	63,638	1.000	0.778	0.409	0.000	0.556	1.000	1.000	-1.408	0.198
High Temp	107,050	0.000	0.000	0.004	0.000	0.000	0.000	0.083	21.436	502.869

Panel C: Annual MSA-Level Variables

	N	Median	Mean	SD	Min	25%	75%	Max	Skew	Kurt
Δ ENV Score	52,463	-0.031	0.007	0.435	-2.656	-0.067	0.049	3.361	1.067	15.773
ENV Score Lag	52,463	-0.122	-0.010	0.883	-3.499	-0.243	0.191	4.138	0.259	5.053
Size	55,359	14.108	14.281	1.600	9.474	13.114	15.245	20.153	0.524	0.320
B/M	53,531	0.481	0.585	0.452	0.028	0.270	0.774	2.845	1.911	5.867
ROA	54,982	0.032	0.007	0.168	-0.938	-0.006	0.078	0.344	-2.741	12.727
Leverage	55,149	0.336	0.360	0.297	0.000	0.106	0.532	1.525	0.958	1.398
Return Lag	52,340	0.102	0.194	0.640	-0.885	-0.106	0.350	12.032	5.913	109.409
Δ Emissions Score	29,584	0.000	0.030	0.123	-0.573	-0.004	0.040	0.826	1.600	9.433
Δ Innovation Score	29,537	0.000	0.017	0.120	-0.712	-0.001	0.000	0.876	2.391	23.369
Δ Resource Use Score	29,584	0.000	0.033	0.128	-0.560	-0.003	0.038	0.806	1.820	9.695
Emissions Score Lag	29,684	0.103	0.241	0.301	0.000	0.000	0.415	0.992	1.084	0.058
Innovation Score Lag	29,638	0.000	0.139	0.241	0.000	0.000	0.216	0.985	2.042	4.454
Resource Use Score Lag	29,684	0.102	0.244	0.305	0.000	0.000	0.420	0.991	1.084	0.150
High Temp	53,767	0.000	0.009	0.041	0.000	0.000	0.000	0.348	16.471	485.200

Table 2: **National Climate Sentiment and Local Newspaper Climate Attention**

The table presents monthly panel regression analysis of newspaper climate attention on national climate sentiment measures. *Climate Attention* is the fraction of climate-related articles published in a newspaper. *MCCC* is the *Media Climate Change Concern Index* introduced by Ardia et al. (2022) and *WSJ* is the Wall Street Journal climate change index introduced by Engle et al. (2020), both normalized to have unit standard deviation. The sample period is from January 2000 through December 2022. All specifications include year, month of the year, and paper fixed effects. Standard errors are double-clustered at the month-by-year and paper levels. T-stats in brackets. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Climate Attention					
	(1)	(2)	(3)	(4)	(5)	(6)
MCCC	0.257***		0.267***			
	(30.877)		(30.551)			
MCCC Lag		0.002	−0.045***			
		(0.228)	(−5.417)			
WSJ				0.117***		0.122***
				(21.144)		(20.776)
WSJ Lag					−0.004	−0.025***
					(−0.606)	(−4.067)
Climate Attention Lag	0.538***	0.543***	0.542***	0.550***	0.547***	0.553***
	(25.156)	(25.019)	(24.839)	(17.869)	(17.581)	(17.791)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Paper FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103,940	103,538	103,538	91,790	92,266	91,790
R^2	0.592	0.581	0.592	0.575	0.567	0.575

Table 3: **Comparison of Local Climate Concern Measures**

The table presents panel regression analysis of the news-based local climate attention measure on other measures of local climate concerns at the newspaper-month level. *Climate Attention* is the fraction of climate-related articles published in a newspaper. $Yale^{Happening}$ is the "estimated percentage of who think that global warming is happening" obtained from the Yale Climate Opinion Maps (2008-2021) survey. *FB Climate Posts* is the fraction of climate-related Facebook posts made by users in a given month in a given county. All specifications control for the county-level demographic variables: *Log Population* is the natural logarithm of the county population, *Income* is the county median household income (in $1,000); *Education* is the percentage of the population with a college degree; and *Democrat Share* is the percentage of the two-party vote in the county won by the Democratic candidate in the last presidential election. Month-by-year fixed effects are included in all specifications. Standard errors are double-clustered at the month-by-year and paper levels. T-stats in brackets. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Climate Attention					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Yale}^{\text{Happening}}$	0.028***	0.015**			0.006	−0.079*
	(6.414)	(2.551)			(0.769)	(−1.825)
FB Climate Posts			5.427***	4.896***	4.877***	4.812***
			(7.550)	(6.386)	(6.410)	(5.317)
Climate Attention Lag	0.685***	0.675***	0.658***	0.667***	0.667***	0.356***
	(18.570)	(16.227)	(11.740)	(9.680)	(9.659)	(4.370)
County Controls	No	Yes	No	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	No	No	Yes
Observations	38,625	33,759	14,513	11,497	11,497	11,497
R^2	0.578	0.569	0.563	0.590	0.590	0.669

Table 4: **Explaining Social Media Climate Attention**

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 *Climate Attention* and $Yale^{Happening}$ and their lagged values. *FB Climate Posts* is the fraction of climate-related Facebook posts made by users in a given month in a given county. *Climate Attention* is the fraction of climate-related articles published in a newspaper, averaged across the newspapers for a county. $Yale^{Happening}$ is the "estimated percentage of who think that global warming is happening" obtained from the Yale Climate Opinion Maps (2010-2023) survey. All specifications control for the county-level demographic variables: *Log Population* is the natural logarithm of the county population, *Income* is the county median household income (in $1,000); *Education* is the percentage of the population with a college degree; and *Democrat Share* is the percentage of the two-party vote in the county won by the Democratic candidate in the last presidential election. Month-by-year fixed effects are included in all specifications. In all regressions, standard errors are double-clustered at the month-by-year 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)
Climate Attention Lag	0.001**				−0.001
	(2.013)				(−1.399)
Climate Attention		0.002**			0.003**
		(2.392)			(2.433)
$\text{Yale}^{\text{Happening}}$ Lag			0.0005		0.0005
			(1.565)		(1.059)
$\text{Yale}^{\text{Happening}}$				0.0004	−0.00004
				(1.529)	(−0.131)
FB Climate Posts Lag	0.669***	0.656***	0.681***	0.682***	0.658***
	(5.579)	(5.542)	(5.821)	(5.823)	(5.505)
County Controls	Yes	Yes	Yes	Yes	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes
Observations	10,100	10,100	10,100	10,100	10,100
R^2	0.818	0.820	0.817	0.817	0.821

Table 5: **Explaining Local Investor ESG ETF Holdings**

This table examines how news-based climate attention and Yale climate opinions explain local institutional investors' ESG ETF holdings. We regress quarterly changes in 13F-reported ESG ETF portfolio shares on climate attention and climate opinion measures. *Climate Attention (M)* represents the fraction of climate-related newspaper articles, averaged across newspapers within each MSA-quarter. $Yale^{Happening}$ *(M)* and $Yale^{Worried}$ *(M)* measure the MSA-level percentage of residents who believe global warming is happening and who are worried about global warming, respectively, from Yale Climate Opinion Maps (2008-2021). All specifications include MSA-level demographic controls listed in Table 3. In all regressions, standard errors are double-clustered at the quarter-by-year and MSA levels and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Change in ETF ESG Share					
	(1)	(2)	(3)	(4)	(5)	(6)
Climate Attention (M)	0.010**			0.017***		
	(2.423)			(3.595)		
$\text{Yale}^{\text{Happening}}$ (M)		0.006*			−0.005	
		(1.830)			(−0.310)	
$\text{Yale}^{\text{Worried}}$ (M)			0.005*			−0.001
			(1.687)			(−0.071)
ETF ESG Share Lag	−0.085***	−0.085***	−0.085***	−0.325***	−0.325***	−0.325***
	(−5.530)	(−5.540)	(−5.539)	(−7.274)	(−7.262)	(−7.264)
MSA Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Firm FE	No	No	No	Yes	Yes	Yes
Observations	49,591	49,591	49,591	49,591	49,591	49,591
R^2	0.035	0.035	0.035	0.218	0.218	0.218

Table 6: **Climate Attention and County Characteristics**

This table examines the relationship between county demographics and local climate change attention using newspaper-month panel regressions. The dependent variable *Climate Attention* measures the fraction of climate-related articles. Independent variables include *Log Population* (natural logarithm of county population), *Income* (median household income in $1,000), *Education* (percentage with college degree), and *Democrat Share* (Democratic candidate's percentage of two-party presidential vote in most recent election). All specifications include month-by-year fixed effects. In all regressions, standard errors are double-clustered at the month-by-year and paper levels and t-statistics are given in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Climate Attention					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Population	0.163***					0.018
	(4.054)					(0.367)
Income		0.016***				0.003
		(4.265)				(0.802)
Education			0.035***			0.015**
			(5.831)			(2.206)
Democrat Share				0.021***		0.016***
				(6.746)		(4.893)
Unemployment					−0.042***	−0.034*
					(−2.631)	(−1.839)
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122,993	118,202	118,202	122,704	118,178	117,513
R^2	0.241	0.222	0.235	0.262	0.211	0.246

Table 7: **Environmental Events, Pollution, and Local Climate Attention**

This table examine how natural disasters, extreme temperatures, and pollution levels affect local climate attention using panel regressions. The dependent variable *Climate Attention* measures the fraction of climate-related articles at the newspaper-month level. Key independent variables include *High Damage* (indicator for natural hazard damages exceeding $1 million from SHELDUS), *HighTemp* (indicator for record monthly average temperature), *Log GHG* (logarithm of annual greenhouse gas emissions), and *Log TCR* (logarithm of annual toxic chemical releases from TRI). All specifications include socioeconomic controls at in Table 3, month-year fixed effects, and newspaper fixed effects. The sample spans 2000-2022. All specifications include month-by-year and paper fixed effects. All columns include the county-level socioeconomic variables as in Table 3. Standard errors are double-clustered at the month-by-year and paper levels. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively

	Climate Attention			
	(1)	(2)	(3)	(4)
Climate Attention Lag	0.569***	0.569***	0.569***	0.569***
	(16.250)	(16.252)	(16.256)	(16.252)
High Damage	0.058*			
	(1.793)			
High Damage Lag	−0.019			
	(−0.502)			
High Temp		0.098**		
		(1.995)		
High Temp Lag		0.076		
		(1.260)		
Log GHG			−0.003	
			(−0.690)	
Log TCR				−0.002
				(−0.248)
County Controls	Yes	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes
Paper FE	Yes	Yes	Yes	Yes
Observations	117,011	117,011	117,011	117,011
R^2	0.623	0.623	0.623	0.623

Table 8: **Newspaper Chain Size and Climate Attention**

This table examines the relationship between newspaper ownership structure and climate change coverage using panel regressions. The dependent variable *Climate Attention* measures the fraction of climate-related articles at the newspaper-month level. Key ownership variables include *Chain Size* (number of newspapers under same ownership in our sample) and *Chain Gannett* (indicator for Gannett ownership). All specifications include the *High Temp* indicator for record monthly average temperature, demographic controls as in Table 3, and month-year fixed effects, with newspaper fixed effects added in Columns 3 and 4. The sample spans 2000-2022. Standard errors are double-clustered at the month-by-year and paper levels. T-stats in brackets. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

	Climate Attention			
	(1)	(2)	(3)	(4)
Chain Size	-0.002^{**}		-0.004^{***}	
	(-2.292)		(-3.514)	
Chain Gannett		-0.157^{**}		-0.157^{**}
		(-2.518)		(-2.518)
High Temp	0.191^{**}	0.191^{**}	0.082	0.191^{**}
	(2.063)	(2.075)	(1.327)	(2.075)
County Controls	Yes	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes
Paper FE	No	No	Yes	Yes
Observations	117,505	117,505	117,505	117,505
R^2	0.248	0.248	0.446	0.248

Table 9: **Peer Effects on Climate Attention and News Content**

This table presents the relationship between focal and peer climate attention (Panel A) and news content (Panel B). Panel A focuses on *Climate Attention*, which is a newspaper's climate coverage. *Peer Attention* is the average *Climate Attention* of newspapers in counties whose social connectedness (SCI) with the focal county ranks in the top 10% of the distribution, excluding same-state peers. *Peer Attention Geo* captures the average *Climate Attention* of newspapers in counties whose geographic distance to the focal county ranks in the bottom 10%, excluding same-state peers. *High Temp* equals one if the focal county's monthly average temperature reaches an all-time high.All specifications include month-by-year and focal paper fixed effects, along with county-level demographic controls from Panel A of Table 6. Standard errors are double-clustered at the month-by-year and paper levels. Panel B conducts analysis at county-pair level and examines how social connections relate to topic similarity in climate reporting across county pairs. Topic similarity is defined as the negative of the Jensen-Shannon distance based on 20 topics extracted from news articles. We measure county connections using the Social Connectedness Index (*SCI*), socioeconomic similarity (*Socioecon. Sim.*, based on demographic variables in Table 6), and geographic proximity (*GeoProx*, defined as the negative physical distance between county centroids). All independent variables are rank normalized to [0,1] within each focal county. The analysis includes focal and peer county fixed effects. Standard errors are double clustered at month-by-year and county levels. In both panels, t-statistics are given in parentheses, and *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Peer Effects on Climate Attention (Newspaper-level Analysis)

	Climate Attention		
	(1)	(2)	(3)
Climate Attention Lag	0.561***	0.563***	0.561***
	(16.154)	(16.186)	(16.153)
Peer Attention	0.285***		0.256***
	(4.773)		(3.831)
Peer Attention Lag	0.024		0.013
	(0.482)		(0.246)
Peer Attention Geo		0.210***	0.039
		(4.032)	(0.704)
Peer Attention Geo Lag		0.031	0.011
		(0.757)	(0.273)
High Temp	0.089*	0.086*	0.088*
	(1.927)	(1.886)	(1.913)
County Controls	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes
Paper FE	Yes	Yes	Yes
Observations	117,011	117,011	117,011
R^2	0.625	0.624	0.625

Panel B: Peer Effects on Climate News Content (County-pair Analysis)

	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)
Socioecon. Sim.		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

Table 10: **Climate Attention and ESG Share of ETF Ownership**

This table examines how local climate news coverage influences retail investors' ESG ETF holdings. We conduct panel regressions at the MSA-quarter level from 2013-2022, focusing on advisory firms serving primarily individual investors. The dependent variable *ESG ETF Share* represents ESG-focused ETFs as a fraction of total ETF holdings in 13F portfolios. The key independent variable *Climate Attention* 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 *High Temp* (indicator for record monthly temperatures). All specifications include quarter-year fixed effects, with advisor fixed effects in selected columns. For instrumental variable specifications, we use MSA-level averages of *Chain Size*, *Chain Gannett*, and *Peer Attention* as instruments for *Climate Attention*.

	Δ ESG ETF Share							
	(1)	(2)	$(3)_{\text{IV=CS}}$	$(4)_{\text{IV=G}}$	$(5)_{\text{IV=Peer}}$	$(6)_{\text{IV=CS}}$	$(7)_{\text{IV=G}}$	$(8)_{\text{IV=Peer}}$
Climate Attention (M)	0.014^{**}	0.021^{***}	0.030^{**}	0.039^{***}	0.063^{***}	0.171^{**}	0.230^{**}	0.179^{***}
	(2.296)	(4.983)	(2.423)	(3.364)	(3.073)	(2.380)	(2.322)	(4.198)
ESG ETF Share Lag	-0.089^{***}	-0.325^{***}	-0.089^{***}	-0.089^{***}	-0.090^{***}	-0.326^{***}	-0.327^{***}	-0.326^{***}
	(-4.383)	(-6.966)	(-5.029)	(-5.474)	(-5.489)	(-7.060)	(-7.092)	(-6.989)
Log AUM Lag	-0.005	0.027	-0.005	-0.004	-0.004	0.026	0.025	0.026
	(-0.952)	(1.062)	(-0.918)	(-0.878)	(-0.731)	(1.018)	(0.995)	(1.010)
High Net Worth	-0.027	-0.007	-0.029	-0.029	-0.031	-0.010	-0.012	-0.010
	(-1.150)	(-0.200)	(-1.190)	(-1.220)	(-1.270)	(-0.311)	(-0.350)	(-0.321)
High Temp	0.215^{***}	0.185	0.195^{***}	0.183^{***}	0.153^{**}	0.147	0.132	0.145
	(7.951)	(1.675)	(5.494)	(3.939)	(2.057)	(0.639)	(0.472)	(0.629)
Year*Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Firm FE	No	Yes	No	No	No	Yes	Yes	Yes
Robust 1^{st} Stage F-stat	-	-	20.640	27.725	10.838	7.994	9.727	9.457
Observations	59,975	59,975	59,975	59,975	59,975	59,975	59,975	59,975
R^2	0.041	0.207	0.040	0.040	0.038	0.199	0.192	0.199

Table 11: **Climate Attention and Firm Environmental Ratings**

This table examines how local climate news coverage influences corporate environmental performance. We analyze the effect of MSA-level climate coverage (*Climate Attention (M)*) on firms' annual Environmental Score changes using panel regressions from 2000-2022. In columns 1–4, the dependent variable is *ENV Score*, which combines standardized environmental ratings from MSCI and Refinitiv. Columns 5–7 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* ratio, and *Return lag* (prior-year stock return). All specifications include year, industry, and *High Temp* indicator controls, with firm fixed effects in most models. Column 3 uses MSA-aggregated *Chain Size* and Column 4 uses MSA-aggregated *Chain Gannett* as instruments for *Climate Attention (M)*. Standard errors are double-clustered at the year and MSA levels. T-stats in brackets. *, **, *** 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)	$(3)_{\text{IV=CS}}$	$(4)_{\text{IV=G}}$	(5)	(6)	(7)
Climate Attention (M)	0.003***	0.006*	0.043**	0.070*	0.002*	0.001	0.002
	(3.027)	(1.970)	(2.483)	(1.909)	(1.903)	(1.396)	(1.719)
Size	0.057***	0.032***	0.030***	0.029***	0.024***	0.002	0.022***
	(4.071)	(3.829)	(3.564)	(3.230)	(8.431)	(1.218)	(6.640)
B/M	0.030***	0.008	0.005	0.002	0.018***	−0.004	0.017***
	(3.419)	(0.669)	(0.364)	(0.139)	(3.411)	(−1.137)	(4.385)
ROA	0.015	−0.014	−0.015	−0.015	0.012	−0.001	−0.007
	(0.762)	(−0.632)	(−0.671)	(−0.679)	(1.521)	(−0.118)	(−0.791)
Leverage	0.041*	0.029	0.023	0.019	0.018**	−0.017	0.017**
	(1.962)	(1.357)	(1.033)	(0.765)	(2.159)	(−1.699)	(2.631)
Return Lag	−0.016***	−0.012***	−0.012***	−0.012**	−0.005***	−0.001	−0.005***
	(−3.508)	(−2.943)	(−2.826)	(−2.716)	(−5.617)	(−1.451)	(−3.582)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust 1st Stage F-stat	-	-	10.573	9.011	-	-	-
Observations	42,837	42,837	42,837	42,837	23,644	23,633	23,644
R^2	0.105	0.208	0.203	0.194	0.269	0.244	0.276

Appendix A

Table A1: Variable Descriptions

Variable	**Definition**
Climate Attention	Number of climate-related articles scaled by the total number of articles for every paper-month observation; reported in percentages. *Climate Attention Lag* is the one-month-lagged *Climate Attention*. *Climate Attention (M)* is *Climate Attention* aggregated to metropolitan statistical area (MSA) level. *Climate Attention (IV)* is the first-stage fitted value of *Climate Attention* in a two-stage least squares (2SLS) regression that uses either *Chain Size*, *Chain Gannett*, or *Peer Attention* to instrument *Climate Attention*.
MCCC	The Media Climate Change Concern Index of Ardia et al. (2022); reported monthly and standardized to have zero mean and unit standard deviation.
WSJ	Index of climate attention derived form Wall Street Journal articles by Engle et al. (2020); reported monthly and standardized to have zero mean and unit standard deviation.
Log Population	Logarithm of the county population. Population data is from the U.S. Department of Agriculture database.
Income	County-level median household income in one thousand dollars, obtained from the U.S. Census Bureau's American Community Survey.
Education	County-level percentage of college graduates in the population, obtained from the U.S. Census Bureau's American Community Survey.
Unemployment	County-level unemployment rate in percentages, obtained from the U.S. Department of Agriculture database.
Democrat Share	County-level share of two-party votes cast for the Democratic candidate in the previous presidential election, Democrat Share, obtained from the MIT Election Lab. Reported in percentages.
$\text{Yale}^{\text{Happening}}$	The estimated percentage of the population of each county that believes that global warming is happening, obtained from the Yale Climate Opinion Maps.
$\text{Yale}^{\text{Worried}}$	The estimated percentage of the population of each county that is worried about global warming, obtained from the Yale Climate Opinion Maps.
FB Climate Posts	Aggregated and anonymized data from Meta (formerly Facebook) on the weekly percentage of all posts made in a given county that are related to climate. *Climate Posts Lag* is the one-month-lagged *Climate Posts*.

Variable	Definition
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 is 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-lagged *High Damage*.
High Temp	A county-level dummy variable that equals one if the average temperature measured in the county in the current month is larger than any past measurement made in the county in any month. *High Temp Lag* is the one-month-lagged *High Temp*.
Log GHG	Natural logarithm of the total greenhouse gas emissions by production facilities in a given county in a given year; obtained from Environmental Protection Agency's (EPA) Inventory of Greenhouse Gas Emissions and Sinks.
Log TRI	Natural logarithm of the total chemical release by production facilities in a given county in a given year; obtained from Environmental Protection Agency's (EPA) Toxic Release Inventory.
Chain Size	The total number of newspapers (in our sample) with the same owner as that of the newspaper.
Chain Gannett	A dummy variable that equals one if the newspaper's owner is the Gannett company and zero otherwise.
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.
ESG ETF Share Lag	Prior quarter's proportion of ETFs that are ESG-related.
Log AUM Lag	Natural logarithm of the advisory firm's assets under management, based on the market value of its 13F reported holdings.
High Net Worth	A dummy variable that equals one if the firm has more client money from high-net worth individuals than from non-high net worth individuals, and zero otherwise.
Δ ENV Score	Change from last year in the firm's Environmental Score (averaged over MSCI and Refinitiv).
ENV Score Lag	Last year's firm Environmental Score (averaged over MSCI and Refinitiv).
Size	Natural logarithm of the firm's market capitalization at the start of the year.
B/M	Ratio of book value of equity to market value of equity, at the start of the year.

Variable	Definition
ROA	Earnings before extraordinary items divided by start of year assets.
Leverage	Book leverage, defined as total debt divided by the sum of total debt and book equity, at the start of the year.
Return Lag	Prior year's annual stock return.
Δ Emission Score	Change from last year in the firm's Emissions Score from Refinitiv.
Δ Innovation Score	Change from last year in the firm's Environmental Innovation Score from Refinitiv.
Δ Resource Use Score	Change from last year in the firm's Resource Use Score from Refinitiv.
Emission Score Lag	Prior year's Emissions Score from Refinitiv.
Innovation Score Lag	Prior year's Environmental Innovation Score from Refinitiv.
Resource Use Score Lag	Prior year's Resource Use Score from Refinitiv.
Peer Attention	Equal weighted average of *Climate Attention* over peer papers, defined as the top 10% of papers based on their counties' SCI with the focal paper's county, excluding the papers in the same state as the focal paper.
Peer Attention Geo	Equal weighted average of *Climate Attention* over top 10% of papers based on the physical distance between their counties and the focal paper's county, excluding the papers in the same state as the focal paper.
JD20	The Jenson-Shannon distance between counties based on the LDA-based distribution for twenty topics; takes values between zero (non-overlapping distributions) and one (identical distributions).
Embedding Similarity	Cosine similarity between the 512 embeddings that represent the topics covered in each county. The embeddings are derived by using the Universal Sentence Encoder (Cer et al. 2018) developed by Google based on Vaswani et al. (2017).

Table A2: **Predicting Ownership Changes**

This table shows estimated coefficients from OLS regressions of newspaper ownership changes (dummy variable) 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 belongs to prior to the ownership change. Explanatory variables are lagged by one month. All specifications include month-by-year fixed effects. Standard errors are double-clustered at the month-by-year and paper levels. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Coefficients in this table are multiplied by 100 (i.e., are in percents) 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)
Climate Articles	−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

Appendix B

B.1 Text Analysis of Documents

Our goal of analyzing the text the documents is threefold. First, we want to study the content that is being written in a given place and time period. This will allow us to study how events shape reporting. Second, we want to compare the writing in two regions to each other. This will inform us how similar reporting is at the same point in time and whether we can explain these differences through events. Third, we want to study whether reporting predicts changes in firm outcomes and decisions.

As a first step 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, a pre-trained Natural Language Processing (NLP) model, to classify the articles into Environmental, Social or Governance articles. We then keep all articles that are either classified as Environmental with more than 50% probability or which contain the term "climate change". This leaves us with 345,909 articles.

B.1.1 Summarizing News into Topics

We use the Latent Dirichlet Allocation (LDA) developed by Blei et al. (2003) in order 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. Given the distribution of topics in a certain year or month then allows us to compute the distance between reporting of two regions. In the following we will outline these two procedures.

Before we feed the documents into the LDA, an unsupervised machine learning, we have the text undergo some standard pre-processing procedures. We remove a set of stopwords following a dictionary, overly frequent and rare words, and then use a lemmatizer to harmonize expressions. Since LDA is a bag-of-word model, meaning the location of a word 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 of 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. It then iteratively through Bayesian updating 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 for the topic distributions and the per-document topic distributions.

The final output we are after is the distribution of topics across documents. In Table B1 we present the top 15 keywords when estimating the topic model with 20 topics. The top keywords indicate the themes of each project, but the actual distributions across the entire dictionary. In Figure B.1 we present the top keywords of four of the topics indicating the relative importance of the top 1,000 keywords within a topic. In the top left panel (a) we see a topic concerned about the rising 'sea' and 'flood' as well as 'drought', but also disasters more general such as 'hurricane'. In the top right panel (b) reporting covers emissions, indicated by 'emission' and 'greenhouse gas' belonging to the top keywords. In the bottom left panel (c) we present a topic related to energy as 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.

B.1.1.1 Distance between Topic Distributions

The Jenson-Shannon distance is a measure of similarity between two probability distributions. It is a modification of the Kullback-Leibler divergence. The Jenson-Shannon distance measures the similarity between two probability distributions by computing the average of the Kullback-Leibler divergences between each distribution and a third distribution that is the average of the two.[1]

It ranges from 0 to 1, with 0 indicating that the two distributions are identical, and 1 indicating that the two distributions are completely different. The Jenson-Shannon divergence is symmetric, non-negative, and bounded and is commonly used in applications such as information retrieval, document classification, and clustering, where it is important to compare the similarity of probability distributions.

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

B.1.2 Summarizing News into Embeddings using the Universal Sentence Encoder

The Universal Sentence Encoder (Cer et al. 2018) developed by Google based on Vaswani et al. (2017) is designed to obtain sentence-level embeddings. The Universal Sentence Encoder uses neural networks as the core of its architecture to encode textual data into high-dimensional vectors, known as embeddings, which are numerical representations of the text. Texts are reduced to a vector of 512 dimensions, similar to a latent factor model, based on a model that has been pre-trained on millions of documents from Wikipedia, web news, web question-answer pages, and discussion forums. Word embeddings, in particular, are famous for their ability to solve analogy tasks through algebraic manipulations (e.g., the classic example "king - man + woman = queen" in the word vector space).

B.1.2.1 Similarity between Embeddings

Cosine similarity is a metric used to measure how similar two entities, in our case two text documents. Mathematically, it measures the cosine of the angle between two vectors projected in a multi-dimensional space. The cosine similarity is bounded between -1 and 1, with -1 for complete dissimilarity and 1 for similarity.[2]

[2] For two embedding vectors, A and B, the cosine similarity, $\cos(\theta)$, is represented using a dot product and magnitude as $\cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$, where $A \cdot B$ is the dot product of the vectors A and B, and $\|A\|$ and $\|B\|$ are the Euclidean norms of the vectors.

Figure B.1: The figure presents the word clouds of four of the 20 topics obtained by applying Latent Dirichlet Allocation (LDA) to the headlines and up to first 80 words of all climate-related articles from the full sample of 5,139 local newspapers, obtained from NewsLibrary. The sample period is January 2000 through August 2022.

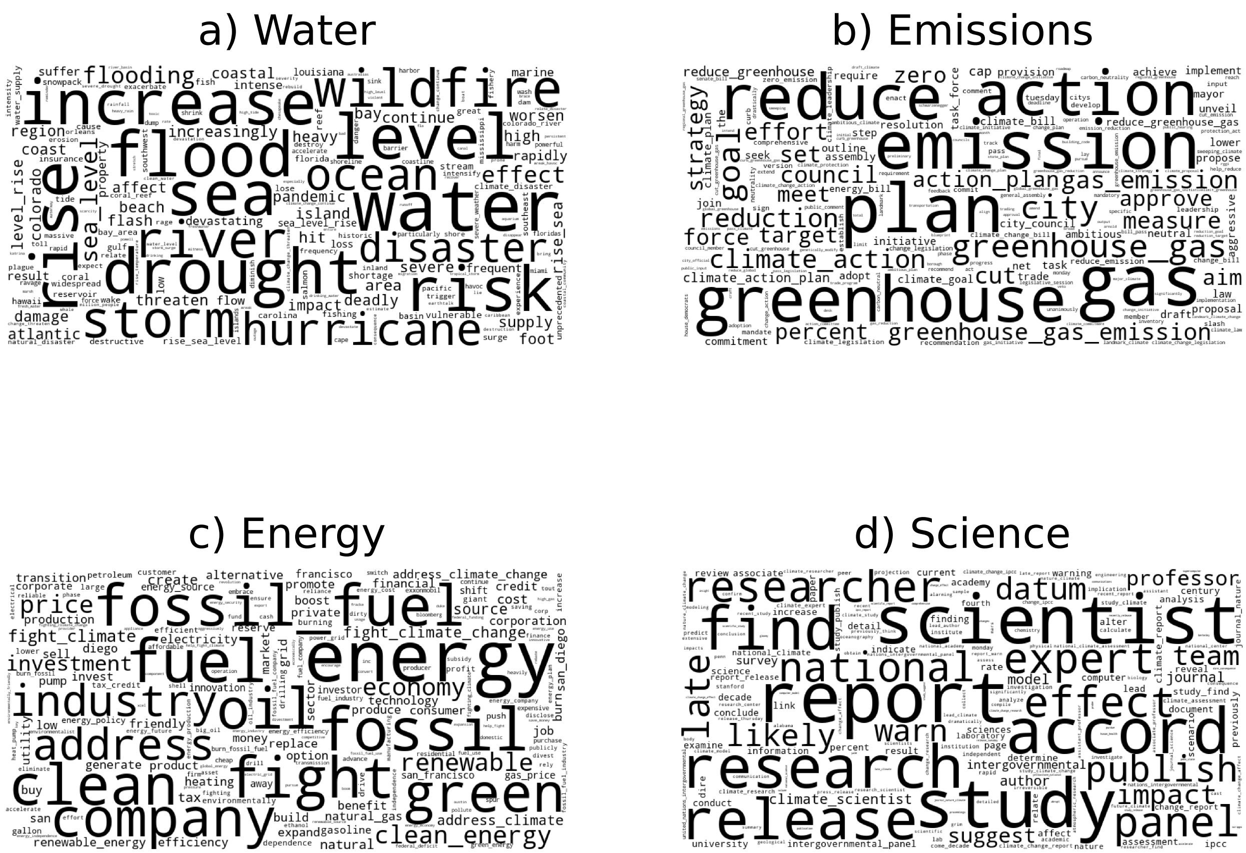


Table B1: Top keywords of 20 topic LDA model

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