What a Disaster Means: Interpretation and the Demand for Green Assets

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Abstract

How events are interpreted substantially shapes portfolio choices, fund flows, and asset prices. Focusing on extreme weather events, I analyze 1.5 million articles from U.S. news outlets using fine-tuned large language models to construct a new measure of local climate interpretation that distinguishes general attention to a disaster from coverage explicitly linking it to climate change. I combine this measure with geolocated portfolios of wealthy U.S. households and mutual fund managers. Among counties affected by these events, local coverage attributing the event to climate change leads to substantial reallocation in household portfolios toward funds labeled as environmentally friendly. Similarly, nearby mutual fund managers actively rebalance toward greener and away from browner stocks. Predetermined county and investor characteristics and the direct economic effects of the disaster are not driving the responses. Using changes in the ownership structure of the county's newspapers, I provide causal evidence that locally supplied climate interpretation narratives move households' and fund managers' portfolios. Nesting these estimates in a calibrated model, I find an interquartile increase in climate interpretation implies a relative appreciation of green stocks equivalent to up to 15% of the observed annual green return spread.

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1 Introduction

Many events that affect portfolio decisions and asset prices, such as elections, technological innovations,[1] or natural disasters, do not directly concern individual firms, and their implications for those firms can be ambiguous. Differences in interpretation may lead investors to make different portfolio decisions in response to the same event (Kandel and Pearson, 1995). Yet isolating the role of interpretation in portfolio choices, trading, and prices is empirically challenging. Investors may also differ in whether and what they learn about an event, their exposure to its fundamental consequences, and how readily they assess its implications (Fedyk, 2021; Wagner et al., 2018).[2]

In this paper, I use extreme weather events to distinguish the role of interpretation in investors' portfolio decisions from that of information and attention. I examine whether households and mutual fund managers who experience salient events such as floods, hurricanes, or wildfires reallocate toward sustainable assets when these events are interpreted locally as evidence of climate change, compared to other investors exposed to the same disaster but to a different interpretation of it. I find that differences in how the same event is interpreted have substantial consequences for portfolio choices and capital allocation, beyond the information the event conveys or the attention it attracts.

Extreme weather events help separate interpretation from information. They can affect investors across several counties simultaneously, allowing me to compare how the same event, with the same objective characteristics and implications for climate change, is interpreted in different places. Although climate change is already affecting many extreme weather events (IPCC, 2023), the extent to which a particular disaster can be attributed to it remains uncertain, leaving room for different interpretations and disagreement.[3] After Hurricane Ian, the share of respondents associating the storm with climate change differed by 21 to 41 percentage points between liberals and conservatives (Djourelova et al., 2024).

My empirical strategy compares the portfolio changes of investors with similar exposure to the same or comparable disasters, in counties with similar levels of local news coverage, political views, and climate beliefs, but differing in their local interpretation of the event (proxied by how local newspapers frame it). In addition, I provide causal evidence of the effect of local interpretation narratives using changes in the ownership of local newspapers, which shift how these outlets interpret disasters for reasons other than changes in their audiences' beliefs and preferences.

Interpretation is also hard to separate from attention. When investors do not respond in the expected direction, this may reflect either a different interpretation of the event or simply inattention to it. Extreme weather events help distinguish these explanations because they are salient events known to affect the portfolio decisions of impacted and nearby investors regardless

[1] For instance, following the release of DeepSeek's cheaper AI model, analysts and investors disagreed about whether it would reduce demand for Nvidia's chips, as fewer chips would be needed, or increase demand by encouraging wider adoption of AI. See FT Alphaville (2025) and Reuters (2025).

[2] Wagner et al. (2018) find that after the 2016 election, returns are consistent with investors incorporating tax consequences quickly and taking longer to work out trade consequences.

[3] See also Druckman and McGrath (2019) and Hazlett and Mildenberger (2020).

of their climate interpretation (Alok et al., 2020), as I confirm in my setting. Indeed, I also compare the portfolio responses of exposed investors with those of unaffected or more distant investors around the same disaster to account for the overall response to the event's salience. Because exposed investors respond to the disaster, inattention cannot explain why some of them do not shift toward green assets. Together, these comparisons make differences in portfolio responses to the same disaster more plausibly attributable to heterogeneous interpretations than to differences in objective information or attention.

To study the effect of climate interpretation on asset demand, I consider two complementary settings. The first is wealthy U.S. households' demand for funds labeled as environmentally friendly, which I observe through the portfolios of their local investment advisers (Pan et al., 2025; Kostovetsky et al., 2026). Labeled products provide a direct mapping from observed investment decisions to demand for green assets. The second is active rebalancing by mutual fund managers toward greener and away from browner stocks. This setting allows me to relate portfolio choices more closely to the views and local information environment of the individual making the decision, and to examine how climate interpretation affects the active trading of professional investors.

To capture investors' local interpretation environment, I use local newspapers as a proxy for how disasters are discussed in the community. Newspapers help set the agenda of these discussions, reaching beyond their direct readership. I support this choice with evidence on newspapers' local reach through their online audiences and Twitter followings.[4] I therefore measure how local newspapers cover each disaster and how they frame it. The corpus holds 1.5 million disaster articles from 527 outlets. I classify every paragraph of these articles with fine-tuned large language models. The classifier records whether a paragraph discusses a specific disaster and the link it draws with climate change, including how strongly it suggests connection and whether it negates it or expresses skepticism. I assign this measure to investors by matching their offices to the newspapers circulating in the same ZIP code or county, weighted by each newspaper's circulation share.

I find that households move toward green assets when a disaster is interpreted locally as climate change. In particular, I focus on the share of their exchange-traded fund (ETF) holdings invested in funds labeled as environmentally friendly. In counties affected by floods and hurricanes, a 10-percentage-point higher share of local news coverage explicitly linking the disaster to climate change is associated with an increase in the green share of their ETF holdings of approximately 20% of its average pre-event level over two quarters, a 19-basis-point rise in the share. Disaster coverage raises households' portfolio turnover without a net tilt toward green ETFs, suggesting that the absence of a green tilt reflects differences in interpretation, not inattention.

The effect of climate interpretation extends beyond green ETFs held through local advisers

[4]Newspapers originate most of the stories that set the agenda of other media and reach readers beyond print through websites, aggregators, and social media (Section 2.2). Even small outlets can spark wider discussion (King et al., 2017), and aggregators matter most for the audiences of small and local outlets (Calzada and Gil, 2020; Athey et al., 2021). Newspapers' web audiences are concentrated in the same counties as their print circulation, and their Twitter followings scale with it (Appendix Figures D.1 and D.2).

to the broader market for funds with environmental, social, and governance (ESG) objectives.[5] Among funds headquartered in affected states, net inflows into ESG funds relative to non-ESG funds are larger after disasters with high climate interpretation, by 8.5 percentage points of pre-disaster assets over two quarters, with no such difference in neighboring unaffected states.

Mutual fund managers themselves respond to local interpretation through their own active trading. I define greener and browner stocks by their environmental score, which rates a firm's environmental performance (Engle et al., 2020; Pástor et al., 2022).[6] Following Alekseev et al. (forthcoming), I validate this measure by showing that managers tilt toward greener stocks after local heat waves, shocks more easily associated with climate change.[7] I find that a 10-percentage-point higher share of climate-linked coverage reaching managers within 50 miles of a disaster raises their active tilt toward greener firms by 69 basis points in the quarter of the disaster, about as large as the response to a local heat wave severe enough to cause injuries or fatalities. I compare funds of the same investment style that hold the same stock around the same disaster, so that the stock's fundamentals, returns, and exposure to the disaster cannot explain the response.

Exploiting differences between managers' office locations and their funds' headquarters, I show that portfolio responses follow the interpretation prevailing where managers work, not where their funds are headquartered or where investors are. Moreover, the results persist after controlling for managers' political views, suggesting that local interpretation matters beyond pre-existing political preferences.

To interpret these results as the effect of interpretation, the identifying assumption is that, absent differences in how disasters are interpreted, investors in otherwise similar locations would have adjusted their portfolios similarly, given comparable disaster exposure and local coverage. Two main challenges arise. First, places that interpret disasters more strongly as climate change may already be shifting toward green assets. Pre-disaster portfolio changes do not differ by interpretation, and the interpretation effect is absent or much smaller among investors farther from the disaster.

Second, investors in these places may respond more strongly to any salient shock, regardless of how it is interpreted, because of their prior beliefs or preferences. I account for investors' prior political views, climate beliefs, demographics and climate attention, allowing these characteristics to shape the response to the disaster. County fixed effects account for counties' usual portfolio changes around disasters. After earthquakes, which local coverage does not interpret as climate change, counties that interpret other disasters more strongly as climate change show no differential green tilt. In both settings, saturated fixed effects and detailed controls address the main alternative

[5] I classify a mutual fund as ESG if its name contains a sustainability keyword or if Morningstar classifies it as focused on sustainability, impact, or ESG factors, based on its prospectus (Section 2.1).

[6] I use the Environmental Pillar score from LSEG, the environmental component of its ESG rating, covering emissions, resource use and environmental innovation (Section 2.1).

[7] People more readily link heat waves to climate change, including conservatives (Deryugina, 2013). Heat waves are also the type of extreme event most confidently attributed to climate change (National Academies of Sciences, Engineering, and Medicine, 2016). Unusually warm local temperatures have been shown to increase attention to climate change and retail selling of carbon-intensive stocks (Choi et al., 2020).

explanations, including non-belief motives such as misaligned incentives between intermediaries and their investors, mechanical portfolio adjustments induced by disaster-related damage and fund flows, and confounding factors such as common national narratives.

To separate the effect of climate interpretation narratives from the prior beliefs and preferences of their readers (Schwartzstein and Sunderam, 2021), I instrument the local interpretation of a disaster with the size of the chain that owned the county's newspapers. Acquisitions by larger chains, increasingly owned by private equity, lead to newsroom cuts and greater reliance on centrally produced copy (Ewens et al., 2022; Gao et al., 2020). Anecdotal evidence suggests that these cuts have affected climate reporting. National news organizations, including newspapers, radio stations, and television networks, have dismissed their climate desks following ownership changes and cost reductions, with similar patterns reported among local newspapers.[8]

The first stage shows that the climate-interpreted share of disaster coverage falls with chain size, within the same outlet over time and within the same county across its disasters.

Identification comes from changes in the size of the chains owning a county's newspapers between disasters. Chain size changes when a newspaper passes to another owner, or when its owner merges with, buys, or sells newspapers elsewhere. I therefore compare the portfolio responses of the same county to disasters of the same type that occurred when its newspapers belonged to a larger and to a smaller chain. The exclusion restriction is that, conditional on county and calendar-quarter fixed effects, coverage volume and local losses, a change in chain size moves portfolio responses only through the climate interpretation of the coverage investors receive. Consistent with this, changes in chain size do not predict the county's politics, climate beliefs, or pre-event portfolio changes.

The two-stage least squares estimates support the conclusion that the portfolio response is not driven solely by the prior beliefs and preferences of readers. The instrumented response of advisers is in line with the estimates above, and that of managers has the same sign and is about two and a half times as large.

Having documented large causal responses to interpretation, I further investigate the mechanism behind these responses. I provide suggestive evidence that it is a revision of perceived climate harm, beyond a shift in preferences for sustainable investments. To distinguish these explanations, I examine first-time purchases of flood insurance, which respond to perceived climate risks but not to sustainability preferences. A flood makes flood risk salient directly, so take-up rises in affected counties regardless of how the flood is interpreted. A wildfire does not directly signal greater flood risk, yet flood insurance take-up after wildfires rises with the climate interpretation of the event, suggesting that households generalize from a specific disaster to broader climate risks. This is consistent with the survey findings of *Climate Change in the American Mind*.[9] Respondents

[8] After Skydance acquired Paramount in 2025, CBS News dismissed its climate unit and reduced climate coverage by 61 percent over the following year (Media Matters). The Washington Post and NPR have dissolved their climate desks amid cost cuts (Covering Climate Now, NPR Public Editor, 2026). Climate coverage declined for a fourth consecutive year in 2025 (Yale Environment 360, 2026). In 2025, there were only 79 dedicated local climate reporters across 577 outlets (Grist, 2025).

[9] See Ballew et al. (2019) for a description of the surveys.

interviewed in the four weeks after a local flood are more likely to report that global warming is harming Americans now or will within ten years than those interviewed in the four weeks before. Within the same year, advisers hold larger green ETF shares in media markets where a greater share of residents hold this belief.

Finally, I study the effect of interpretation on aggregate flows and asset prices. Whether climate interpretation moves the prices of green stocks depends on how widely that interpretation is shared. When investors read the same disaster differently, they can trade against one another and therefore not necessarily affect the prices of green stocks. However, a common interpretation can shift aggregate demand and prices (van der Beck et al., 2025). The climate interpretation of national disaster coverage predicts flows into ESG funds beyond the attention a disaster receives.[10] From the 25th to the 75th percentile of the national interpretation share, the three-month inflow response to the same disaster-attention surprise rises by the equivalent of 80% of these funds' net inflows in a normal quarter, 58 basis points of fund assets.

These aggregate flows, however, do not isolate the underlying demand response to interpretation, as they may also reflect investors' expectations about how others will respond. Moreover, the national analysis identifies variation in interpretation by comparing different disasters, which may also differ in what they reveal about climate risk. To quantify the price implications of the underlying demand response to interpretation, I therefore use my micro estimates, which compare investors exposed to the same disaster but receiving different interpretations. I consider a counterfactual in which each institutional investor experiences one of the year's disasters and responds to its local climate interpretation as the households in my adviser sample do, reallocating the same share of capital toward ESG assets. I price the resulting demand with a calibrated market response.[11] Holding disaster attention fixed, an interquartile increase in climate interpretation would generate $79 billion of ESG demand over the year and imply roughly 34 basis points of ESG-stock appreciation relative to other stocks. This price effect is equivalent to 15% of the observed annual green return spread (van der Beck, 2026).

Related literature. This paper contributes to research on disagreement, political views and financial responses to common events, which documents partisan differences in investment beliefs and capital allocation (Meeuwis et al., 2022; Kempf et al., 2023; Cookson et al., 2020). These studies proxy investors' worldviews with their political ideology. They infer how investors interpret a common event by relating differences in political views to differences in observed beliefs or portfolio responses around it. Instead, I study the effect of local narratives and interpretations *specific* to each event, beyond political views. I measure these interpretations directly from local news, sepa-

[10] This is consistent with evidence that newsworthy disasters raise flows into green funds and the relative returns of sustainable assets (Marshall et al., 2021; Fiordelisi et al., 2023; Misev and Balles, 2024). I add to this evidence by separating how coverage interprets a disaster from the attention it receives.

[11] The calculation uses estimates of how much demand moves prices (van der Beck, 2026). It assumes that institutional investors respond to climate interpretation as the households in my sample do, that the market accommodates their demand as it accommodated the ESG flows on which these estimates rest, and that investors do not adjust their demand in response to others' trading. Section 6 and Appendix J derive the calculation and state these assumptions.

rately from the portfolio responses I seek to explain. My constructed measure captures geographic differences and changes over time in the explanations linking events to climate change. It reflects how a specific outlet reads a specific disaster, well beyond stable differences across outlets and their audiences. More stable, cross-sectional differences in political views alone cannot capture this variation. I find that local interpretations predict portfolio responses even when political views are allowed to shape the response to the disaster.

The paper also relates to research linking climate attention to trading and asset returns (Choi et al., 2020; Pástor et al., 2022; Ardia et al., 2023).[12] I contribute by identifying local portfolio responses to disaster experience and examining how these responses depend on whether local narratives attribute the event to climate change. I therefore distinguish the attention an event receives from its attribution to climate change and trace how geographically dispersed investors translate disaster experience and local information into portfolio adjustments.

I further contribute to research on institutional investors' responses to climate-related shocks. Prior work documents reduced exposure to disaster-zone stocks, greater support for environmental proposals, and portfolio responses to climate-related belief shocks (Alok et al., 2020; Fich and Xu, 2025; Alekseev et al., forthcoming).[13] These studies compare investors with different exposure to the event. I also compare investors who have similar exposure to the same disaster and comparable levels of local coverage but vary in how strongly their local narratives attribute the disaster to climate change.

In addition, the paper relates to research linking investors' beliefs and preferences to observed portfolio holdings (Riedl and Smeets, 2017; Giglio et al., 2025; Anderson and Robinson, 2026). These studies link survey data on beliefs and preferences to cross-sectional heterogeneity in green ownership. My evidence is complementary. I examine portfolio adjustments around particular disaster experiences instead, using pre-event allocations to distinguish investment responses from pre-existing differences in holdings.[14] Investors rarely adjust their portfolios. Changes in beliefs explain little about whether they trade, even though they help explain the direction and magnitude of trading conditional on adjustment (Giglio et al., 2021). The reallocations I observe suggest that disaster experience and its local interpretation can overcome this inertia.

[12] Pástor et al. (2022) link green assets' realized outperformance to unexpectedly strengthening climate concerns. Ardia et al. (2023) construct a daily newspaper-based climate-concern index and show that green stocks outperform brown stocks on days when climate concerns rise unexpectedly. Their daily stock-return regressions also associate green outperformance with shocks to concerns about specific physical risks, including hurricanes and floods.

[13] Alok et al. (2020) find that funds headquartered within 100 miles of a disaster-zone firm reduce their portfolio weight in that firm more than distant funds, with evidence consistent with salience bias. Alekseev et al. (forthcoming) use local extreme heat and changes in shareholder disclosures to identify climate-belief shocks and connect them to industry reallocations, like buying automobile and semiconductor stocks and selling real estate. Fich and Xu (2025) find increased support for environmental proposals after hurricanes and increased holdings in firms where their votes could help environmental proposals pass, providing evidence consistent with both managers' own preferences and career concerns about investor flows.

[14] Closest to my paper, Anderson and Robinson (2026) study climate-belief revisions following wildfires and global warming attention, and link it to cross-sectional differences in allocations to fossil-fuel-exclusion mutual funds within Sweden's premium pension system, measured about three and a half years after the wildfires. Instead, I compare active portfolio changes from pre-event allocations, tracing the timing and subsequent path of portfolio adjustments over shorter horizons around disasters.

Finally, the paper is related to a broader literature on how experience, political views, and media shape climate attitudes (Deryugina, 2013; Ash et al., 2023; Djourelova et al., 2024). These studies measure the response in stated beliefs and attitudes. I show that the local interpretation of disaster experience also shapes consequential financial decisions, through active portfolio reallocations toward green assets. Complementary survey evidence also examines how responses to disaster experience vary with political views and local media coverage, distinguishing perceived climate risks from beliefs about human causation and policy preferences. These patterns suggest that risk perceptions can respond to experience among conservatives despite persistent political differences in climate attitudes.[15] Read alongside the portfolio responses, they point to the role of perceived risk in prompting green investment adjustments.

The rest of the paper proceeds as follows. Section 2 describes the data, institutional setting, measurement of climate interpretation, and the local information environment and determinants of interpretation. Section 3 examines how local climate interpretation affects household demand for green ETFs through investment advisers, extends the analysis to ESG mutual fund flows, and addresses the main alternative explanations. Section 4 turns to active portfolio rebalancing by mutual fund managers, examining whether local climate interpretation also shapes their trading decisions. Section 5 exploits changes in newspaper ownership to isolate variation in the climate narratives supplied by local outlets, independently of readers' pre-existing beliefs and preferences, and examines the resulting portfolio responses of both advisers and mutual fund managers. Section 6 studies how national disaster coverage and climate interpretation affect aggregate ESG fund flows and asset prices, and quantifies the potential price effects of climate interpretation when a year's disasters collectively activate institutional investors. Section 7 discusses the mechanisms underlying these responses, distinguishing changes in beliefs from shifts in preferences. Section 8 concludes.

2 Data and Measurement

This section describes the data (Section 2.1) and the climate interpretation measure constructed to capture the local information environment (Section 2.2). I draw on four types of data: the portfolio holdings of households and of mutual fund managers, records of climate disasters, and local newspaper coverage of each disaster.

2.1 Data

Households: local investment advisers. To represent household portfolio decisions, I use the portfolios reported by local U.S. registered investment advisers (RIAs) that predominantly serve

[15] This pattern is consistent with Deryugina's (2013) finding that abnormally warm weather makes conservatives more likely to report that the effects of global warming have already begun. Similarly, Myers et al. (2013) find that personal experience raises certainty that global warming is happening, mainly among respondents initially less engaged with the issue.

household accounts. Advisers file Form ADV with the SEC, where they report their client composition, assets under management, and office locations. I combine quarterly Form ADV filings with raw Form 13F holdings to obtain the location and the clientele of each 13F filer. Following Pan et al. (2025), I define an adviser as serving predominantly household accounts when individuals and high-net-worth individuals make up a strict majority of its clients, and as local when all its offices are in one county. The final sample contains 4,040 advisers in 490 counties, covering all 50 states, the District of Columbia, and Puerto Rico (Table 1). FactSet classifies most of these advisers as investment advisers (66.4 percent) or as private banking and wealth-management firms (30.6 percent).

Table 1: Registered investment adviser sample characteristics

Statistic	All registered advisers (1)	Household-serving, single-county (2)
Registered investment advisers	8,489	4,040
Adviser-quarters	222,832	87,853
U.S. counties represented	1,439	490
States and U.S. jurisdictions represented	52	52
Median regulatory assets under management ($ millions)	593.8	426.1
Median client accounts	439	681
Median advisory offices	10.0	6.0
Advisers ever holding any ETF (%)	87.1	97.1
Advisers ever holding a green ETF (%)	36.3	44.0

Notes. Characteristics of the registered investment advisers in the sample. All registered advisers are those with a direct Form ADV filing or listed as relying advisers on Schedule R. Exempt reporting advisers are excluded. Regulatory assets under management, client accounts and offices are measured at each adviser's latest observation.

Advisers that serve households hold a large share of ETFs, and an even larger share of green ETFs. Advisers whose clients are mostly high-net-worth individuals held 47 percent of their reported 13F assets in ETFs by 2023, against less than 7 percent for pensions and endowments.[16] Registered advisers held 41 percent of the $10.3 trillion U.S. ETF market at the end of 2024 and 45 percent of its green segment, against 20 and 18 percent for every other Form 13F institution combined.[17] Of the $38 billion of green ETFs held by all registered advisers at the end of 2024, local household advisers alone held about $12 billion. The final sample of local household-serving RIAs holds 7 percent of the regulatory assets reported by all registered advisers, while holding 21 percent of their ETF dollars and 31 percent of their green ETF dollars (Appendix Table C.2). Almost all of these advisers have ever held an ETF, and almost half have held a green ETF.

The local and household-account restrictions keep the part of an adviser's 13F portfolio that most likely reflects its clients' choices, especially for green ETFs. ETFs are held largely by households, directly or through their advisers. In 2024, 17 million U.S. households, 13 percent of the

[16]Source: Moussawi et al. (2025).

[17]Appendix Table C.1 shows ETF adoption, portfolio allocation, and market shares for registered advisers and for the household-serving group.

total, owned ETFs. These households are relatively wealthy, with a median income of $140,000 and median financial assets of $500,000, against a national median household income of about $87,000 in 2025. Since 58 percent of U.S. families hold equity directly or indirectly, more than one in five investing households owns ETFs.[18]

I combine 13F filers into stable adviser-level portfolio units[19] and assign each unit to a county. I restrict the sample to advisers that never change county, so that within-county portfolio changes are not mechanically driven by relocations. Then, I pool ETF holdings across local advisers to measure the allocation of the combined ETF wealth of the households they serve. Under the assumption that these households reside in their advisers' county, pooling holdings gives each household's ETF investment its corresponding weight in the county portfolio. Advisers serving more households or managing larger household investments therefore contribute more to the aggregate. The county green share is

$$g_{ct} = \frac{\sum_{a \in c} \sum_f V_{aft} G_f}{\sum_{a \in c} V_{at}^{ETF}} = \sum_{a \in c} \frac{V_{at}^{ETF}}{\sum_{b \in c} V_{bt}^{ETF}} g_{at}, \tag{1}$$

where G_f identifies green ETFs, V_{aft} denotes adviser a's holdings in ETF f, $V_{at}^{ETF} = \sum_f V_{aft}$, and g_{at} is the adviser's green ETF share.[20]

I define an ETF as green if its name in CRSP contains at least one of a list of climate and transition keywords, or if Morningstar assigns it one of a selected set of climate and clean-technology themes. ESG labels influence investor demand beyond differences in underlying holdings (Baker et al., 2024). Even as investors differ in which assets they think are green, buying a product labeled as environmentally friendly is a direct way to act on a climate shock. I exclude sectors whose climate mandate is ambiguous[21] and funds with only a social mandate. The rule classifies 227 funds as green over 2009–2024. Since green ETFs became common in adviser portfolios only around 2015, the main analysis covers 2015–2024 (Section 3).[22] At the end of 2024, about 180 green ETFs were active, with a market value of about $94 billion, or approximately 1 percent of the U.S. ETF market.

To ensure that an adviser's county is also where its clients live, I manually review the names of all retained advisers. I exclude internet-based advisers and advisers whose offices are all in

[18]Sources: Investment Company Institute (2025) for the ETF-owning households, U.S. Census Bureau (2026) for the national median household income, and Board of Governors of the Federal Reserve System (2023) for the share of families holding equity.

[19]The FactSet parent rollup and the S34 manager identity define the candidate aggregations. I split a parent into separate portfolios only when they belong to distinct advisers and are reported separately throughout. This keeps a portfolio's holdings unchanged when it is reported under a different filer identity.

[20]Adviser-level regressions weighted by pre-disaster shares of county ETF holdings approximate this aggregate response and yield very close estimates, as reported in Appendix Table C.3. They capture changes in green shares within advisers but omit the contribution of changes in advisers' relative ETF holdings; Appendix B.4 derives the conditions for equivalence. Equal-adviser-weighted regressions instead measure the average adviser's response, giving advisers equal importance regardless of the number of households they serve or the ETF wealth they manage. Although this differs from my target, I report these estimates in the Appendix (Appendix Table C.3, Panel B): the results remain statistically significant, while their magnitudes change with the different estimand.

[21]Metals and mining, resource extraction, upstream and midstream energy, commodities, agriculture and food, nuclear, water, and batteries.

[22]Green ETF market value grew from $2 billion in 2009 to a peak of $106 billion in 2021.

one county but whose clientele is not local. To validate the local definition, I verify that the share of an adviser's stock portfolio invested in firms headquartered in its own state exceeds the share obtained by randomly reassigning adviser locations. I compute the green share within an adviser's ETF holdings, so that changes in mutual fund holdings reported on the same Form 13F do not enter the household measure.[23]

Mutual fund managers. I combine fund holdings from the Thomson Reuters S12 database, fund characteristics and manager names from Morningstar Direct, manager profiles from Revelio Lab., and the filings of the managing firms with the SEC to build a panel of fund portfolios located where their managers work. Since mutual fund investors cannot be located, I study the portfolio managers who actively rebalance the funds, whose location I observe. I locate each fund at the offices of its sub-adviser, or of its adviser when it has none, from Form N-SAR until 2017 and Form N-CEN thereafter, following Alekseev et al. (forthcoming), and from Morningstar portfolio-manager records. This way, I am able to locate the managing office for 76,652 fund-quarters. This office often differs from the fund's headquarters (Section 4.4). I also match 1,161 funds to 2,348 named managers by combining Morningstar Direct and Revelio, which allows me to measure the managers' political views from their political donations.

I construct fund-quarter holdings from S12 and compute changes only between consecutive quarterly reports. I also restrict the sample to actively managed U.S. equity funds.[24] Appendix Figure A.3 maps the county-weighted geography of fund management.

I classify a mutual fund as having an ESG mandate if its name includes a sustainability term or if Morningstar classifies it as focused on sustainability, impact, or environmental, social, and governance factors, based on its prospectus. I exclude funds with an ESG mandate from the analysis of managers (Section 4), because their portfolios follow climate considerations and incentives unrelated to local disasters (Alekseev et al., forthcoming).

Climate disaster episodes. I build disaster data from the NOAA Storm Events Database, which records storms and other weather events at the county level. I group related county records into disaster episodes, so that a disaster that affects several counties counts as a single event while each county keeps its own exposure.[25] I assign each episode a dominant hazard type and measure its severity from inflation-adjusted property and crop losses, fatalities, and injuries. I combine these measures into an index of the episode's aggregate impact.[26] For each sample, I retain the episodes

[23] Some advisers also manage mutual funds, and their 13F filings then include the funds' holdings. This overlap matters little for ETF positions. In the same quarter, mutual funds in S12 hold only 1.23 percent of ETF market value and 2.11 percent of green ETF market value, and only 0.59 percent of S12 funds hold any green ETF.

[24] I exclude funds whose Thomson Reuters objective is international, municipal bonds, bond and preferred, or balanced (Alok et al., 2020; Kacperczyk et al., 2008), passive funds and exchange-traded funds, identified by CRSP flags and fund names (Appel et al., 2016; Sammon and Shim, 2023; Alok et al., 2020), and funds with less than $5 million in assets or fewer than ten stocks (Alok et al., 2020).

[25] I audit every multi-event episode for coherence and split those that fail into sub-episodes, so that each episode approximates the footprint of one physical shock.

[26] The construction of this index builds on a Pareto approximation of the tail of disaster losses (Barro and Jin, 2011).

occurring in the period of analysis that are in the top 15 percent of this index within their hazard type, and exclude episodes that had another local episode in their pre-period. Appendix Table A.1 reports the characteristics of the episodes, and Figure C.1 maps them by county.

Local news. To measure how disasters are discussed locally, I collect newspaper articles from ProQuest TDM Studio. I query articles whose text includes climate and global-warming vocabulary, as well as extreme-weather and disaster vocabulary, yielding 1,485,896 disaster articles from 527 outlets. Restricting to articles that cover a disaster over 2015–2024, the corpus holds 782,714 articles, of which 724,969 come from local outlets and 57,745 from national ones. I combine the articles with local newspaper circulation data from the Alliance for Audited Media and Editor & Publisher, complemented by device-measured readership from Comscore. The circulation data give ZIP-level newspaper market shares, which I use to aggregate outlet-level measures to the ZIP and county level. Using these weights, I construct a sample of 433 outlets reaching 2,134 counties.

Additional data. To construct the instrument for local interpretation (Section 5), I combine newspaper ownership data from Ewing (2026) with the ownership panels of the Northwestern Medill Local News Initiative. I date ownership changes to the quarter using SEC Form 8-K filings and reports of newspaper and company acquisitions.

To measure the environmental profile of the stocks the funds trade, I use the Environmental Pillar score from Refinitiv (LSEG, 2024), the environmental dimension of the ESG rating, covering resource utilization, emissions, and innovation. I take the firms' GICS sectors and industries from Compustat and the location of their headquarters from the business addresses in their SEC filings.

The remaining sources enter as controls, such as characteristics of ZIP codes, counties, advisers, mutual funds, and disasters, or serve to construct placebo events and other newsworthy events that coincide with disasters.

2.2 Local Information and Interpretation Environment

Climate beliefs are shaped by local discourse, through family and friends, news from different sources, and social media. Thirty-nine percent of Americans hear about global warming in the media at least once a month, and 17 percent hear people they know talk about it as often (Leiserowitz et al., 2026). Local news reaches people through the same channels. Seventy-three percent of Americans get local news from friends, family, and neighbors, 64 percent from local television, half from local social media groups or forums, and a third directly from local daily newspapers, down from 43 percent in 2018 (Pew Research Center, 2024a,b).

Although only a third of residents read a local daily directly, newspapers shape much of what circulates locally. First, they originate most of the stories that set the agenda of other media,[27] and even small outlets can spark wider discussion (King et al., 2017). Second, their articles reach readers

[27] Pew Research Center, *How News Happens*, 2010, https://www.pewresearch.org/journalism/2010/01/11/how-news-happens/.

beyond print, through websites, news aggregators, and social media.[28] Finally, local newspapers also reach investors. Retail and institutional investors rely on geographically proximate information (Engelberg and Parsons, 2011; Baik et al., 2010; Bernile et al., 2015), and local newspapers are "a key channel through which institutional investors acquire geographically scattered information" (Kang and Nam, 2025).

To construct a measure of local climate interpretation that captures the narratives shared locally and the discussions they trigger, I quantify how much local newspapers cover each disaster and how they frame it. To do so, I classify every paragraph of the disaster articles with a hierarchical teacher–student pipeline of large language models. I first define the classes and hand-label about 300 paragraphs, which I use to tune the prompts of a teacher model, GPT-5.5. The teacher then labels a training set, on which I train two local student models, DeBERTa and Qwen. DeBERTa classifies the full corpus and passes uncertain cases to Qwen.

The classifier first detects whether a paragraph discusses a specific disaster event, identified in time and place. If it does, the classifier records whether the paragraph links the event to climate change and how strongly, and its stance on climate change. The stance can be affirming, denying, neutral, lukewarm (accepting global warming but minimizing its importance), or reporting contested opinions, and the classifier also records whether the stance is the reporter's own. In addition, I identify other common topics in each paragraph, the most frequent being damages and the human toll (damage to homes and victims), and whether the paragraph tells the event episodically, through the experience of a specific affected person, or thematically, through facts and aggregates (Iyengar, 1991).

Against my hand labels on held-out paragraphs, the two student models reach an F_1 score of 0.87 and 0.88 on the climate link, above general-purpose models such as gpt-4.1-mini (0.85) and gpt-5.4-mini (0.77).[29] The classifier substantially outperforms the keyword rule in detecting paragraphs on a specific event among paragraphs mentioning disasters in general, and keywords cannot read the intensity and stance of the attribution (Appendix Tables A.2 and A.3).[30]

The classifier yields two measures, the first one being local disaster coverage. Let o index outlets, c counties, and e disaster episodes, and let w_{co} be outlet o's circulation share in county c, normalized to sum to one within the county, and A_{oe} the number of articles on episode e that outlet o publishes in the four weeks from the episode's start. Local disaster coverage of episode e in county c is the circulation-weighted number of articles,

[28] Of the 546 local newspapers in the sample, at least 468 have an active website and 293 a Twitter account. Across counties, their print circulation shares track their web audience shares (correlation 0.82; Appendix Figure D.1), within a county their print market shares track their web market shares (correlation 0.78), and their Twitter audiences track their print circulation (rank correlation 0.84; Appendix Figure D.2). News aggregators matter most for the audiences of small and local outlets (Calzada and Gil, 2020; Athey et al., 2021).

[29] Appendix Figure A.1 shows the pipeline. Appendix Tables A.2 and A.3 report the performance of each model on every classification task, and Appendix A details the training and validation procedures.

[30] Appendix Table A.4 shows two examples. The first, from the coverage of Hurricane Helene, links the storm to the burning of fossil fuels without ever mentioning "climate change," so a keyword search would miss it, while the classifier labels it as an affirming climate link. The second, from the coverage of Hurricane Katrina, tells the human toll through one person's story and makes no link to climate change.

$$A_{ce} = \sum_{o} w_{co} A_{oe}. \tag{2}$$

When coverage enters the regressions, I use $\log(1 + A_{ce})$ to allow for diminishing returns to additional coverage.

The second measure is local climate interpretation, the extent to which local coverage of a disaster interprets the event as a result of climate change. Let C_{oe} be the number of outlet o's articles on episode e that link the event to climate change, and $m_{oe} = C_{oe}/A_{oe}$ the outlet's interpretation ratio, defined for outlets with $A_{oe} > 0$. I aggregate these ratios to the county with the same circulation weights, renormalized over the outlets that cover the episode

$$M_{ce} = \frac{\sum_o w_{co} \mathbf{1}\{A_{oe} > 0\} m_{oe}}{\sum_o w_{co} \mathbf{1}\{A_{oe} > 0\}}. \tag{3}$$

M_{ce} is the share of climate-linked articles in the coverage of the average local outlet that covers the episode, with outlets weighted by their readership in the county.[31] The measure averages 0.172 across county–episode observations, with a standard deviation of 0.157, so an increase of 10 percentage points corresponds to 0.64 standard deviations. In a county served by a single outlet, such an increase means one more climate-linked article in every ten articles on the episode. In a county served by two outlets with equal circulation, it means either one more climate-linked article in ten in both outlets, or two more in ten in one outlet and no change in the other.

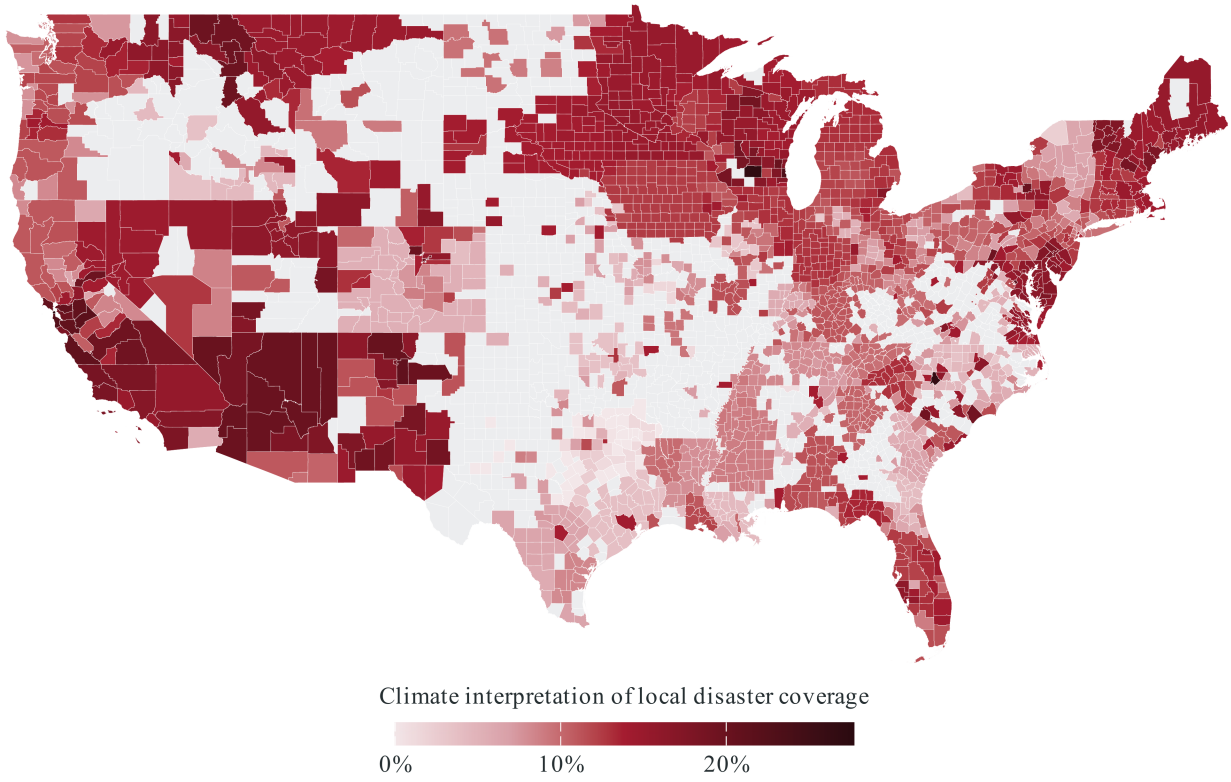
Figure 1 shows the average local climate interpretation of disaster coverage in each county. Interpretation varies widely across the country: it is highest along the West Coast and in the Southwest, and lowest in Texas and much of the South. It also rises over time, from 6.5 percent of a county's local disaster coverage before 2015 to 17.9 percent from 2015 on.

To separate the role of the outlet from that of the disaster, I decompose the variance of coverage and of climate interpretation across outlet–episode pairs into an outlet component, an episode component, and their match, as in the literature on matched employer–employee data (Abowd et al., 1999; Kline et al., 2020). The outlet component captures stable differences across outlets, such as the political views and green attitudes of their audience and owner. The episode component captures the characteristics of the disaster, such as its year, hazard type, and damages. The match captures how a given outlet covers a given disaster beyond what the outlet and the disaster predict on their own. Appendix Figure D.3 shows that coverage depends mostly on the episode, which accounts for 55.4 percent of its variance against 19.5 percent for the outlet, mainly through the hazard type.

Climate interpretation instead lies mostly in the match, at 54.1 percent of its variance, against 40.7 percent for the episode and 5.5 percent for the outlet. The year and hazard type of the event explain part of the episode component, and over 90 percent of that part comes from the year, because the interpretation of each hazard type changes over time. Stable outlet and audience

[31] As a robustness check, I also use the pooled share $\sum_o w_{co} C_{oe} / \sum_o w_{co} A_{oe}$, which weights outlets by both their readership and the number of articles they publish on the episode.

FIGURE 1: LOCAL CLIMATE INTERPRETATION OF DISASTER COVERAGE

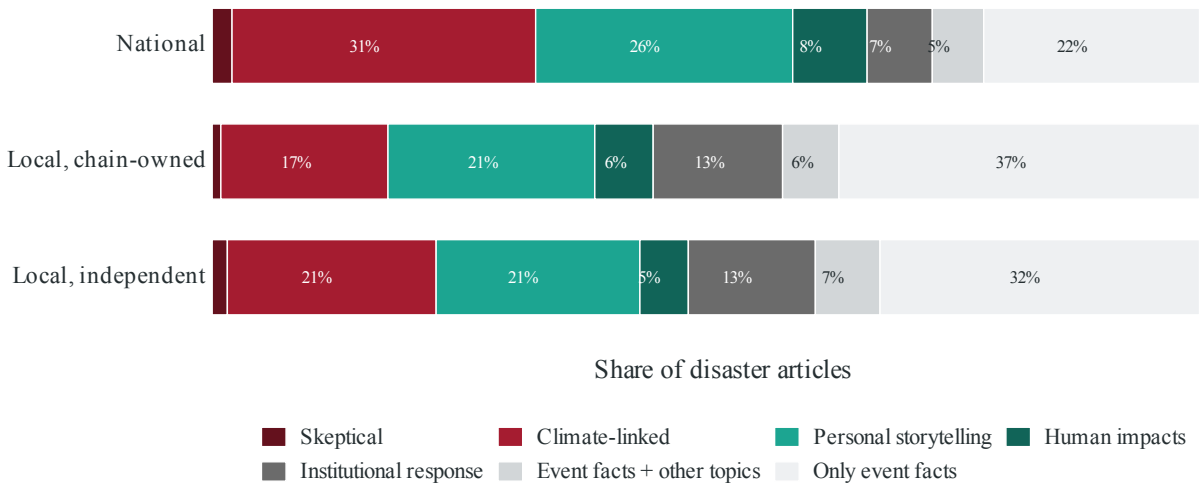


Notes. Mean local climate interpretation of disaster coverage in each county, over the disasters covered by its local outlets. Local climate interpretation is the share of the local coverage of a disaster that links it to climate change, with outlets weighted by their readership in the county. Gray counties have no local coverage of disasters in the sample.

differences, together with common event characteristics, including time, still leave more than half of the variation unexplained. A substantial part of the variation therefore concerns how a specific outlet interprets a specific disaster, while serving a given audience at that time.

Part of the match reflects how articles reach an outlet. Many local newspapers belong to chains, groups of newspapers under the same owner, and a chain often writes an article once and prints it in several of its newspapers. Among the outlet-event pair characteristics I observe, chain copies account for 92 percent of the variation in the match that these characteristics explain. I leverage this variation to provide causal evidence on the effect of local interpretation in Section 5.

Figure 2: Composition of disaster coverage by outlet ownership



Notes. Composition of disaster coverage by category and outlet type. A local outlet is chain-owned when its owner holds two or more newspaper titles in the quarter of publication, and independent when its owner holds one. Articles with skeptical content are classified as Skeptical, and the remaining articles that link the disaster to climate change as Climate-linked, even when they also cover other topics. Only event facts are articles that report only the specific event. Event facts + other topics are articles that also discuss hazards in general, trends or projections, green products, sustainability or climate regulation.

The way a disaster is represented in the news therefore depends on the type of outlet that covers it. Figure 2 shows the composition of disaster coverage for national outlets, chain-owned local outlets, and independent local outlets. The key difference is in the share of disaster articles linked to climate change, which is 30.8 percent for national outlets, 16.9 percent for chain-owned local outlets, and 21.1 percent for independent local outlets. Across all disaster articles, chain-owned local outlets link disasters to climate change 4.2 percentage points less often than independent ones, and the gap remains statistically significant within the same quarter (Appendix Table D.1).

3 Households and Fund Investors: Green ETFs and ESG Fund Flows

I find that a higher share of local news coverage reading the extreme weather event as climate change is associated with a significantly larger increase in the green-ETF share of household

portfolios over the following two quarters. The observed increase in sustainability comes on the extensive margin. Disaster coverage alone moves portfolio turnover without a net tilt toward sustainable funds (Section 3.4).

To show this, I begin with a difference-in-differences design that compares affected counties with clean comparison counties around the same episode and, among affected counties of the same hazard in the same year, counties whose newspapers read the disaster differently. The estimate is stable, conditional on detailed controls for the county's politics, climate beliefs, demographics and climate attention before the event, and with county fixed effects. I then present and rule out the alternative explanations by progressively saturating the specification, and by introducing a within-episode design.

3.1 Empirical Strategy

My objective is to estimate how the local interpretation of a disaster affects the green share of household portfolios. The ideal experiment would compare the response of investors in otherwise identical counties, with the same level of exposure to the same disaster at the same time, and differing only in how the local discourse (proxied by newspapers) has interpreted the disaster.

I approximate it by exploiting two sources of variation. First, because the timing of a disaster is exogenous, comparing the change in the green share of affected counties with that of unaffected counties around the same episode identifies the response to the disaster at average interpretation. Second, among the affected counties, I compare those with similar observable characteristics, exposed to the same type of disaster in the same year, differing in the climate-interpreted share of their local newspapers' coverage. In practice, I implement this comparison by estimating the following local-projection regression at each horizon h from the start of the extreme weather event:

$$\Delta_h q_{ie} = \gamma_h M_{ie} + \theta_h D_{ie} \cdot M_{ie} + D_{ie} \cdot \delta^h_{k(e),y(e)} + X'_{it}\big(\Gamma_h + D_{ie} \cdot \Lambda_h\big) + \alpha^h_{s(i)} + \eta^h_e + \varepsilon_{ieh}. \tag{4}$$

The unit i is a county or an adviser, observed around episode e starting in quarter $t(e)$, at horizon h.

Treatment is repeated and non-absorbing. A county can be affected by several episodes over the sample, and the comparison counties of one episode can be the affected counties of another. Therefore, I construct the sample of treatment and control units around each episode with a clean-window design. Treated units are those in the disaster zone of the episode with no earlier local disaster in the two quarters before the start, and control units are clean comparison counties[32] not affected by that episode or by any other major disaster within a window.[33]

[32] More precisely, clean comparisons are defined relative to each episode and each horizon. For horizon h, control county-quarters have no local disaster in the stabilization window before the reference quarter and none between it and $t + h$. Treated county-episodes have no other local disaster through horizon h. Episodes starting in the same quarter are kept, each county–episode weighted by one over the number of episodes of its county in that quarter.

[33] Following Dube et al. (2025), the first comparison is a local-projection difference-in-differences with clean controls. Because episode fixed effects absorb everything common to an episode, the effect of D_{ie} is estimated within each episode. The regression is a stacked version of their quarter-level event study estimator in which each episode forms its own

The outcome is the change in the share of a county's exchange-traded fund holdings in environmentally focused funds, q_{it}, aggregated to the county of the adviser's office.[34] I define the cumulative portfolio change from the quarter before the event as $\Delta_h q_{ie} \equiv q_{i,t+h} - q_{i,t-1}$.

To isolate active rebalancing from valuation drift, I construct the portfolio weight change at fixed pre-event price. For each episode starting in quarter t and each horizon h, I rebuild the county portfolio using quantities observed at $t+h$, valuing every ETF at the pre-event price vector $P_{j,t-1}$,

$$q_{i,t+h|t-1} = \frac{\sum_j G_j P_{j,t-1} Q_{ij,t+h}}{\sum_j P_{j,t-1} Q_{ij,t+h}}, \tag{5}$$

and $\Delta_h q^{FP}_{ie} \equiv q_{i,t+h|t-1} - q_{i,t-1|t-1}$.[35] The pre-event-price measure isolates active reallocation, while the total measure captures the net observed green exposure. When both are positive and close in magnitude, the observed increase in relative exposure is neither an artifact of revaluation nor a counterbalancing of negative drift to maintain the desired exposure. It is an active change to a new desired allocation. The main text reports the two-quarter cumulative pre-event-price portfolio change, rescaled to basis points, and Appendix Table E.1 adds the current-price change.[36]

D_{ie} is an indicator function and takes value 1 when i is in the disaster zone of episode e, while M_{ie} is the climate-interpreted share of local coverage of the episode.[37] The coefficients of interest are θ_h, the differential effect of interpretation in affected relative to unaffected units, and $\gamma_h + \theta_h$, the total interpretation effect among affected units.

$\delta^h_{k(e),y(e)}$ are affected × hazard × year fixed effects, where $k(e)$ and $y(e)$ are the hazard type and year of episode e, capturing the average response of affected counties in each hazard type and year. $\alpha^h_{s(i)}$ are state fixed effects, where $s(i)$ is the state of unit i. η^h_e are episode fixed effects, absorbing the level of each disaster. The episode fixed effects compare units in the disaster zone with the unaffected units of the same disaster, while the affected × hazard × year fixed effects compare the interpretation effect among affected units within the same year and the same hazard type.

X_{it} is a vector of county controls that may be correlated with both local interpretation and the portfolio response. It always includes disaster coverage, among both affected and unaffected units, to control for news attention to the disaster, with additional controls depending on the analysis. The additional controls hold fixed what could make a county both receive a climate reading of the disaster and buy green assets in any case. They are the county's Democratic vote share at the last presidential election and the share of its residents worried about global warming, its income, college share, share of white residents, total population and population density, the size of its advised portfolio in the previous quarter, the share of its local coverage devoted to climate policy

stack, as in Cengiz et al. (2019).

[34] As described in Section 2, holdings are pooled across the county's advisers before taking the share, and adviser-level regressions are weighted by pre-disaster shares of county ETF holdings.

[35] This follows the same logic as Calvet et al. (2009), adapted to fit the local projection estimation framework.

[36] For ease of exposition, most tables and figures in the main text report the pre-event-price portfolio change. The Appendix shows, for each of these tables and figures, the version at both pre-event and current prices side by side (Tables E.1 and G.1, Figures E.1 and G.1). Magnitudes are consistent throughout.

[37] M_{ie} is missing for county-episodes with no local coverage, so the interaction is estimated on covered county-episodes.

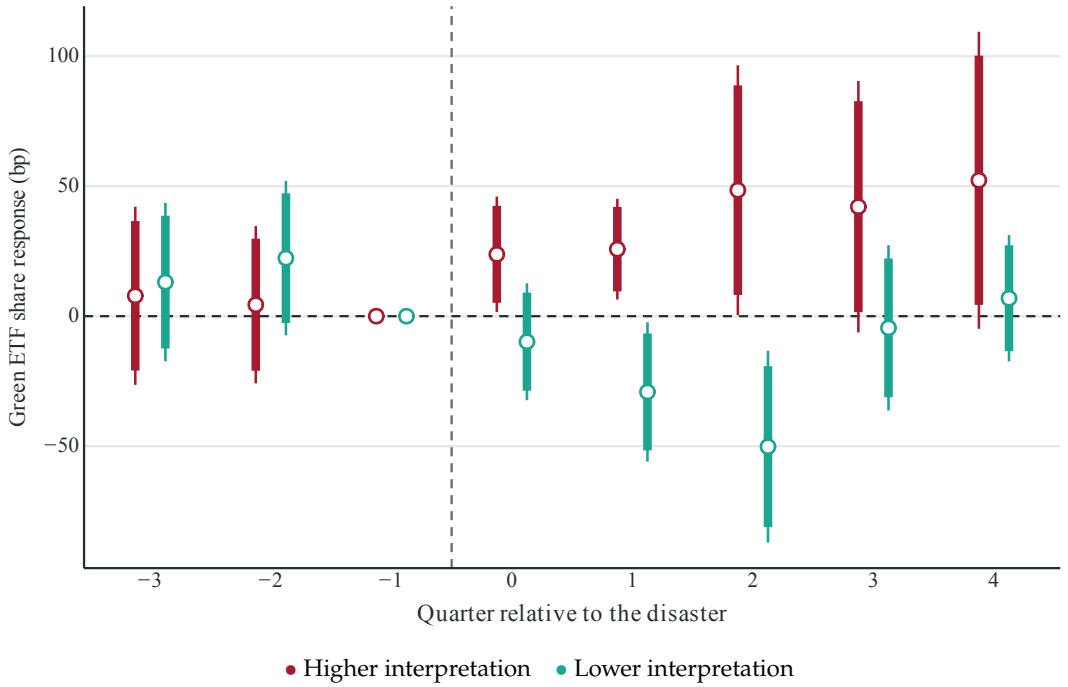
and green topics in the quarter before the episode, and its own damage, fatalities and injuries.

Each control enters alone (Γ_h) and interacted with the affected indicator (Λ_h), so θ_h is net of how the green share of counties with these characteristics changes around any episode and of how they respond to a disaster.[38] Section 3.3 discusses the specific confounders each set of controls rules out. Standard errors are clustered by county.[39]

3.2 Results

Interpretation Effect on Green Household Demand. The full results are presented in Table 2. I find that a one-standard-deviation increase in local climate interpretation of the disaster raises the pre-event-price green share of affected counties by 30 basis points relative to the unaffected counties of the episode (Column 4). The estimate for observed prices (Appendix Table E.1) is within one basis point of the pre-event-price estimate, so price drift does not drive the increase in either direction.

FIGURE 3: DISASTER RESPONSE OF COUNTY GREEN ETF SHARES BY LOCAL INTERPRETATION, BY QUARTER



Notes. Disaster response of the county green-ETF share by quarter relative to the disaster, separately for counties with local interpretation above and below the median. The outcome at each quarter is the change in the county green-ETF share from the quarter before the disaster to that quarter, so the paths are cumulative. The regressions include calendar-quarter and episode fixed effects and Affected × year terms. Controls are lagged portfolio assets, prior political lean, demographic characteristics, Attention, and Interpretation as a continuous variable. The joint test that the gap between the two groups is zero in quarters −4 to −2 gives $p = 0.463$. The figure shows 95% and 90% confidence intervals, with standard errors clustered by county and episode. Appendix Figure E.1 shows the same estimates at pre-event and current prices.

[38] Damage, fatalities and injuries are zero outside the affected counties, so they enter once. Coverage of climate policy and green topics enters alone.

[39] See Appendix Table E.2 for the standard errors clustered two-way by county and episode, which differ by less than one basis point and leave every significance level unchanged.

TABLE 2: COUNTY GREEN-ETF PORTFOLIO RESPONSE

Dependent variable: Green-ETF share response (basis points, pre-event prices)					
	(1)	(2)	(3)	(4)	(5)
Affected × Interpretation	25.48**	25.86**	22.46*	30.31**	22.76*
	(10.13)	(12.33)	(12.18)	(12.58)	(12.44)
Affected × Attention	.86	4.91	3.64	1.69	−9.36
	(10.93)	(10.92)	(10.30)	(10.06)	(10.01)
Total Interpretation effect among affected counties	26.70**	27.08**	23.47*	31.32**	22.73*
	(10.45)	(12.44)	(12.26)	(12.53)	(12.31)
Observations	105,662	105,662	105,662	105,662	105,662
R^2	.028	.029	.031	.032	.102
Affected county-episodes	244	244	244	244	244
Episode and quarter FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	
County FE					✓
Affected × hazard × year FE		✓	✓	✓	✓
Financial and demographic controls			✓	✓	✓
County damages, fatalities and injuries			✓	✓	✓
Political and belief controls				✓	✓
Lagged climate attention				✓	✓
Affected × controls				✓	✓

Notes. Effect of local climate interpretation on the county green-ETF share after disasters. The sample covers high-salience flood, hurricane and coastal episodes. The outcome is the mean county green-ETF share over the quarter of the episode and the two following quarters minus its mean over the two quarters before. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage. Both are measured over the first four weeks of the episode and standardized. All columns include episode and quarter fixed effects. Columns 1 to 4 include state fixed effects, and Column 5 county fixed effects. Columns 2 to 5 add Affected × hazard × year fixed effects. Columns 3 to 5 control for financial and demographic characteristics (lagged log portfolio assets, income, college share, white share, population and population density) and for the county's damages, fatalities and injuries. Columns 4 and 5 add political and belief controls (prior Democratic vote share and share of residents worried about global warming) and lagged climate attention (share of local coverage on climate policy and green topics in the quarter before the episode), and interact the controls with Affected. Standard errors in parentheses are clustered at the county level. Appendix Table E.1 reports the same estimates at pre-event and current prices. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Of two counties exposed to the same disaster, the one whose local coverage reads the event as climate change ten points more often, thirty percent of articles in place of twenty, holds 19 more basis points of green share at pre-event prices two quarters later. For the mean county, with $2.6 billion in ETFs, that is about $5 million more in green ETFs. This is 19.6 percent of the mean county's green-ETF holdings before the disaster. This change is at the 82nd percentile of all absolute two-quarter changes in the green share among the county-quarters of Table 2. The one-standard-deviation effect of 30 basis points is at the 86th percentile. Figure 3 plots the change in the green share from the quarter before the disaster to each quarter after it, separately for counties above and below the median interpretation. The paths are cumulative. A path that stays at its level means that the counties keep the green ETFs bought after the disaster and do not sell them back, while a rising path would mean further purchases.

The estimate is similar with interpretation measured over the calendar quarter and at the adviser level (Appendix Tables E.3 and E.5). It does not rest on the comparison counties. The slope among affected counties alone is comparable, while the same contrast among unaffected counties is indistinguishable from zero (Appendix Figure E.2).

Extensive Margin. Per standard deviation of interpretation in affected counties, the share of advisers in the county holding a green ETF rises about 6 percentage points, and as much among advisers reporting from the same county across the two quarters, so the increase comes from advisers already there. That is more than four times the ordinary movement of this share after a disaster (Appendix Table E.6).

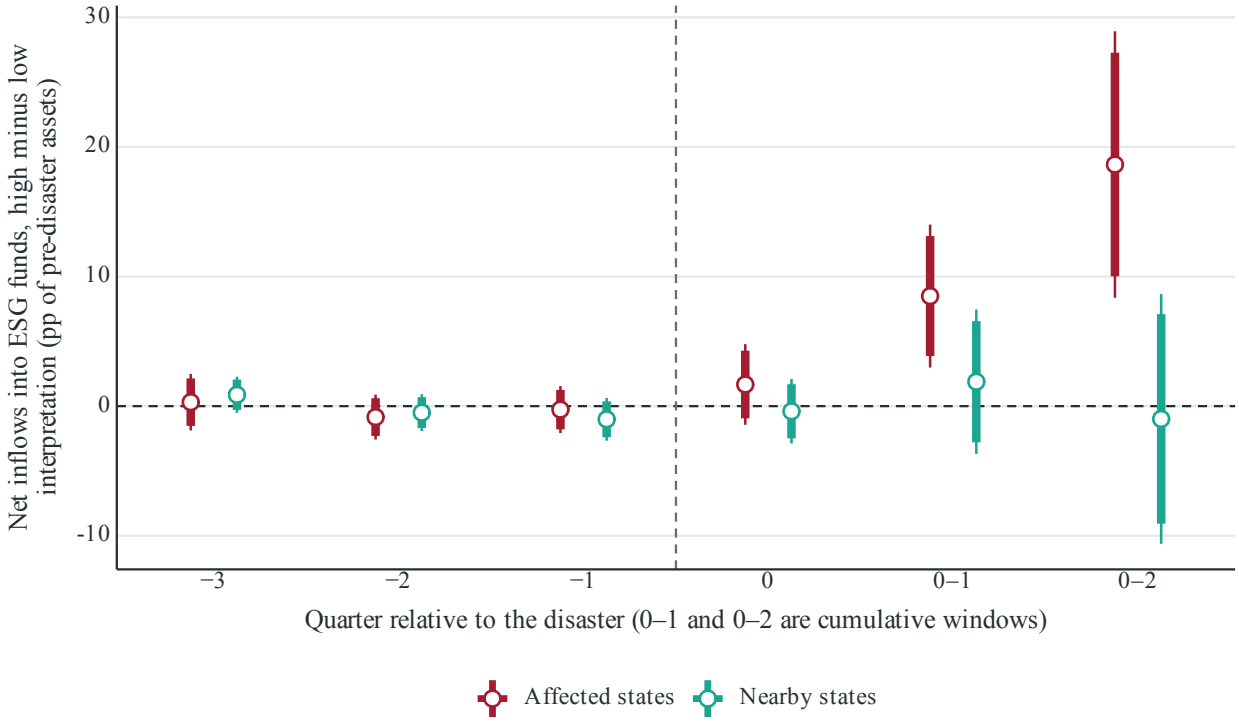
Extension to ESG Mutual-Fund Flows. To establish external validity beyond green ETFs, I extend the analysis to ESG mutual-fund flows.[40] Disaster exposure is assigned at the fund's headquarters state. The assumption is that headquarters location proxies for clientele exposure. With the same assignment, Marshall et al. (2021) find higher net inflows into green mutual funds relative to matched nongreen funds when disasters occur in the funds' headquarters states. In Figure 4 I compare relative net ESG inflows, measured against net inflows into non-ESG funds, across disasters with high and low climate interpretation, holding disaster coverage in the headquarters state and other covariates constant.

Fund fixed effects absorb persistent differences in fund flows. ESG-status-by-quarter fixed effects absorb broad national trends in ESG investment by allowing ESG and non-ESG fund flows to vary separately each quarter. Hazard-by-exposure-group fixed effects account for average differences across disaster types and geographic exposure.

Among funds headquartered in disaster-affected states, relative net ESG inflows are larger following high-interpretation disasters, by 8.5 percentage points of pre-disaster assets cumulated over two quarters, and by more over three (Figure 4). The corresponding differences in neighboring unaffected states are indistinguishable from zero.

[40] ESG funds are identified by a dated green or sustainable fund-name classification, a Morningstar intentional-ESG designation effective before the disaster, or a Morningstar climate-theme flag. The comparison group comprises confirmed non-ESG mutual funds. ETFs, low-carbon-only funds and funds with ambiguous classifications are excluded.

Figure 4: Climate interpretation and flows into ESG mutual funds



Notes. Difference in relative net inflows into ESG mutual funds between disasters with high and low climate interpretation, separately for funds headquartered in affected states and in neighboring unaffected states. Relative net inflows are net inflows into ESG funds measured against non-ESG funds. High and low interpretation are split at the median interpretation among affected states. The regressions also include ESG status × Affected, fund, ESG status × calendar quarter, and hazard × group of states fixed effects. Controls are log disaster damage, its interactions with ESG status and with the group of states, and log pre-disaster assets. The figure shows 95% and 90% confidence intervals, with standard errors clustered at the episode level.

3.3 Identification

Equation (4) nests two designs. The first identifies the response to the disaster, through the experience of the event, its salience and the attention it receives, by comparing affected units with the clean comparison counties of the same episode. The response is therefore identified under no anticipation and parallel trends between affected and comparison counties.[41]

The second measures the interpretation effect among the affected counties by comparing those exposed to the same type of disaster in the same year, with similar observable characteristics and damage, whose local interpretation of the disaster differs. For the purpose of identifying θ_h, the design is equivalent[42] to a regression on the affected counties alone in which the fixed effects, the

[41] No anticipation means that the green share of a county does not move before an episode in response to it. Parallel trends means that, absent the episode and given the controls, the green share of affected and comparison counties would have followed the same path. With repeated disasters, this holds for each episode a county is exposed to (Dube et al., 2025). The clean window of two quarters keeps earlier local episodes out of the pre-period of affected counties and any change in exposure out of the comparison counties through the horizon.

[42] The unaffected counties enter θ_h only through these components, and the total effect among affected counties,

controls and the baseline interpretation response γ_h are held at their estimates from the entire sample.

The identifying assumption is that, conditional on these controls, the climate reading of a county's coverage of a disaster is unrelated to how its green share would have changed under a different reading. Namely, affected counties discussing the disaster more as climate change would otherwise have changed their green share similarly to those discussing it less as climate change. A bias would arise if the readers who demand climate interpretation of a disaster would have bought green assets after it without that interpretation. Appendix Figure E.2 shows the event-study path with the coefficients on leads and lags. The leads show no pre-trend.

By exploiting progressively more fine-grained variation, the columns of Table 2 restrict the level at which a confound would have to operate. The episode fixed effect absorbs the disaster itself, its size, its national coverage, everything common to the affected and unaffected counties of each specific episode, including anything else in the quarter the episode starts. Because each horizon is estimated separately, the episode fixed effect also absorbs common shocks in the following quarters, such as national events or news. Furthermore, the state fixed effects absorb the average change in the green share of the counties in each state. On top of this, column 2 controls for the average response of affected counties in each hazard type and year, so that the interpretation effect does not come from comparing fundamentally different disasters, or from underlying trends in climate salience or market trends in sustainable products picked up by comparing disasters in different years.

Column 3 adds financial and demographic controls, including the size of the advised portfolio in the previous quarter, and the county's own damage, fatalities and injuries to check that the interpretation effect is not driven by how strongly a specific county was affected by the event.[43] Column 4 adds the county's prior Democratic vote share, its share worried about global warming and its coverage of climate policy and green topics in the quarter before the event, which absorbs the change in the green share that goes with how much its newspapers already write about climate. It also interacts the controls with the affected indicator, except that coverage, so that the interpretation effect is estimated net of the disaster response of richer, more Democratic and more worried counties.

Column 5 replaces state with county fixed effects. On the stacked panel a county appears in every episode it is exposed to, almost always as a nearby or distant comparison county,[44] so the county effect absorbs its trend in the green share and its usual change around large disasters, wherever they occur. The interpretation effect is then read from how an affected county's change

$\gamma_h + \theta_h$, through their own slope, γ_h. In this sense θ_h is a triple difference, across interpretation, between affected and unaffected counties, around the event.

[43] Damage could itself be the confounder. A county more strongly impacted may be less likely to buy green or may be forced to liquidate assets, and local news in a severely affected county may turn to fatalities, losses and emergency information, at the expense of climate interpretation articles, so that both lower interpretation and lower rebalancing toward green appear in the most affected counties.

[44] Even a county that is affected by some episode is affected in only 0.4 percent of the episodes it enters, and is a comparison county in the rest.

after its own disaster departs from that usual change, compared with the other affected counties in the same hazard and year. The interpretation effect survives county fixed effects. If the estimate only reflected counties that react strongly to every disaster, it would have vanished once each county is compared with its own usual response.

Nor is interpretation a stable trait of local outlets. A fixed outlet component explains only 5.5 percent of its variance, and most of it reflects how a specific outlet reads a specific disaster (Section 2.2). This suggests that the effect is tied to the interpretation of the current event. At the county level, 72 percent of the variance of Interpretation across the county-episodes of Table 2 is within county, across the episodes a county is linked to.

Remaining confounds must operate within a county and among affected counties of the same hazard type and year. For example, an affected county whose newspapers read a flood as climate change would have to raise its green share around the event, by more than the other counties affected by similarly impactful floods that year, for reasons other than interpretation-driven climate concern, and those reasons would have to be correlated with how its newspapers read the flood.

Section 3.4 addresses the remaining identification concerns. The first is that the interpretation effect picks up predetermined county beliefs, attitudes or trends unrelated to disasters, which I address with placebo tests and with the newspaper-ownership design of Section 5, where the interpretation that local outlets supply shifts with ownership changes. The second is that it reflects comparisons across disasters, which the within-episode design of Section 3.4 replaces with a comparison of advisers at the same distance from the same disaster in the same state. The third is that it mostly captures attention to the disaster, which I address by controlling for coverage and by showing that turnover rises with coverage but does not respond to interpretation. Section 3.4 also discusses threats to reading the response as a demand shock for sustainability.

3.4 Alternative Explanations

Confounders of Interpretation. The interpretation effect could capture something else that happened in the county in the same quarter, such as climate policy events and their coverage. Appendix Table F.1 adds the share of local coverage devoted to climate policy and green topics, in the same quarter and in the quarter before. It adds them as controls and interacted with the affected indicator, with interpretation and with their product, allowing other forms of climate attention to compete against the interpretation of the disaster in explaining the portfolio response. The climate-attention interactions are all indistinguishable from zero, and the interpretation effect, estimated against them, remains unchanged.

The interpretation effect could reflect attitudes the county already held, with the disaster as the occasion on which they are acted upon. If residents more concerned about climate change buy green assets whenever a salient local event occurs, and if coverage in those same counties is also more climate-interpreted, the correlation between interpretation and green reallocation would be spurious. The rows of Appendix Table F.1 that add the county's share of residents worried about global warming, its perceived scientific consensus, its Democratic vote share and its college share

suggest that this is not the case.

If local climate interpretation mainly captured a general propensity of climate-concerned counties to buy green assets after any salient local shock, the same pattern would appear after earthquakes, which no coverage reads as climate change. There is no differential green tilt after earthquakes in counties whose coverage of other disasters was more climate-interpreted (Appendix Table F.2). Finally, Section 5 uses changes in the ownership of the county's newspapers, which shift the climate-interpreted share of their disaster coverage, to isolate the interpretation that local outlets supply.

Interpretation could proxy for attention to the disaster. More heavily affected places may be both covered more and interpreted more. Affected counties most likely pay attention to the disaster in any case. The main specification controls for its damage, and every specification controls for coverage.

If interpretation only measured attention, advisers in high-interpretation counties would trade more after the disaster, as advisers do where coverage is heavier. I examine how the gross turnover[45] of advisers' books after the disaster changes with local disaster coverage and with interpretation, in affected and unaffected counties (Appendix Table F.3). Turnover of the whole reported book rises with coverage in both affected and unaffected counties, by 0.107 and 0.081 log points per standard deviation. It does not rise with interpretation in affected counties. Advisers in high-interpretation counties tilt toward green ETFs without trading more than advisers in low-interpretation counties. Interpretation is therefore not a proxy for attention to the disaster.[46] The newspaper-ownership design of Section 5, which shifts the interpretation that local outlets supply while holding coverage fixed, separates the two further. Section 7 separates them in household insurance demand.

Threats to Event Link and Specificity. A concern with the county estimates in Table 2 is how much of the interpretation effect comes from comparing different disasters, and how much from differences in interpretation within one disaster.[47] The fixed effects and controls of Section 3.1 compute the interpretation effect only across disasters of the same type, in the same year, with comparable damage. Such disasters may still differ in the national attention and the national interpretation they receive, in the state where they occur and its politics and policies, and in the local economy of the affected counties, and these can correlate with the local interpretation. The within-episode design removes these differences. It compares advisers at the same distance from the same disaster in the same state.

To compare portfolio responses to the same disaster, I use advisers in affected counties and nearby advisers within 50 miles of the affected area, and I measure local interpretation at the

[45] Following Calvet et al. (2009), turnover is the value of absolute quantity changes over the quarter at start-of-quarter prices, divided by the starting reported book value, aggregated to the county and measured as log(1 + turnover in basis points).

[46] The event-study plots dividing counties at the median of interpretation (Figure 3) show that low-interpretation counties tend to reduce their green share in the quarters after the disaster, suggesting, if anything, that they are reacting by accommodating the demand.

[47] NOAA splits one storm system into separate episodes at state and forecast-office boundaries and by hazard type, so many episodes have a single affected county with observed advisers, and a separate intercept for the affected counties of each episode is too demanding at the county level.

adviser's office ZIP code. I estimate

$$\Delta_h q_{ie} = \theta_h M_{ie} + X'_{ie}\gamma_h + \alpha^h_{e,s(i)} + \lambda^h_{e,b(i,e)} + \mu^h_{c(i)} + u_{ie,h}, \qquad h \in \{0,1\}, \tag{6}$$

where $\Delta_h q_{ie}$ is the change in green-ETF share from the previous quarter to the disaster quarter or the following quarter, measured in basis points at pre-event prices. M_{ie} measures interpretation in ten-percentage-point units, with a common coefficient across affected and nearby advisers. X_{ie} contains the same four groups of controls as the main design, namely attention, financial, demographic and political, and their group interactions.[48] Interpretation and attention are measured at the adviser's ZIP code and the financial controls at the adviser level. Standard errors are clustered by disaster episode and ZIP.

Episode by state fixed effects absorb the disaster itself, with its footprint, impact and national coverage, and everything common to the state, such as differential trends in political or climate views, in the insurance market and in state policy. Episode by band fixed effects allow affected advisers and nearby advisers 0–25 and 25–50 miles from the affected area to have different average responses to each disaster. With county fixed effects, the comparison is relative to the county's average portfolio response across episodes in which its advisers are affected or nearby.

The identifying assumption is that, conditional on the controls, advisers in the same state at the same distance from the same disaster would otherwise have changed their green share by the same amount. A ten-percentage-point increase in interpretation is associated with a 7-basis-point increase in green-ETF share in the disaster quarter and a 12-basis-point increase by the following quarter, both relative to the previous quarter (Appendix Table F.4, column 3).

Threats to Revealed Demand Shock. The response could reflect the advisers' views and not their clients'. I restrict the sample to local advisers serving predominantly household accounts, but most of their assets are managed on a discretionary basis, so the adviser decides the trades. I therefore compare county voting, which proxies for clients' political views, with advisers' political views measured from staff donations, including both in the regression. If advisers' own views drive the response, their political leanings should help explain it. The response is stronger in less Democratic counties but does not vary significantly with advisers' own political views (Appendix Table F.7).

Less Democratic advisers are less likely to hold any green ETF to begin with. However, conditional on holding a green ETF, their own views do not significantly affect the disaster response and the interpretation effect.[49] This evidence suggests that the green ETF response to the local interpretation reflects the views of the households the advisers serve, and not the advisers' own, consistent with what Pan et al. (2025) find.

The effect could be mechanical. Disasters may generate liquidity needs, withdrawals, or precautionary adjustments that change ETF shares even without any active move toward green

[48] See Appendix Table F.4.

[49] Only smaller advisers show an effect of the firm's own leaning on the average disaster response, and none on the interpretation response.

assets. In particular, advisers may cut ETFs first to meet their liquidity needs because ETFs tend to be particularly liquid and easy to trade, and may be held as a liquidity buffer. If, among ETFs, the non-green ones are liquidated more aggressively, the ETF denominator can fall and green ETF shares can rise even without a genuine tilt toward green funds. Instead, I find that green ETF assets rise alongside non-green and total ETF assets, while total observed 13F holdings show no statistically significant change (Appendix Table F.9).

Moreover, ETF and whole-portfolio flows show no systematic contraction in counties and episodes with higher climate interpretation (Appendix Table F.8). The interpretation effect also holds among advisers in nearby counties not directly affected by the disaster (Appendix Tables F.5 and F.6). These findings do not support liquidation as the explanation for the increase in the green ETF share.

Advisers may also act on their own incentives. One is to encourage clients to buy their green products, or to buy green ETFs and then accommodate that demand by selling the underlying stocks. About 2% of the local advisers in my sample sponsor or manage the ETFs in their holdings. I find that when advisers purchase green ETFs, they also tend to purchase the underlying constituent stocks directly (Appendix Table F.10). This pattern does not support systematic offsetting sales within the observed portfolios. Another is to use a disaster as an occasion to rebalance client portfolios and justify their fees. I control for advisers' prior ETF and whole-portfolio turnover. The interpretation response does not vary significantly with a one-standard-deviation increase in either measure (Appendix Table F.11).

Affected advisers may buy green ETFs because they expect higher returns (Giglio et al., 2025). Since a single local disaster event provides little information about either climate risk trends or green firms' cash flows, the return expectation motive requires anticipating that many investors will buy these products as a result of the event[50] and push up their prices. These expectations would be shared by affected and unaffected advisers. The common component of this response is therefore absorbed by the episode fixed effects.

For return expectations to explain the stronger response of affected and nearby advisers, and the interpretation effect among them, affected advisers in higher-interpretation places would need to expect a stronger reaction from others than unaffected advisers do. They would also need to expect a stronger reaction than affected advisers in places where the disaster was interpreted less as a climate event. Expectations about other investors would follow the national coverage of the event, so I add national coverage and national interpretation, alone and interacted with local interpretation, to the county and adviser regressions of Section 3 (Appendix Table F.12). The local interpretation response among affected counties and advisers remains positive after accounting for national news. If anything, national attention strengthens this response and widens the gap between affected places with high and low local interpretation,[51] while national interpretation

[50] Morris and Shin (2002) show how public information can influence behavior through expectations of others' actions. Schmidt-Engelbertz and Vasudevan (2025) document speculation motivated by beliefs about other investors, even when it conflicts with investors' own valuations.

[51] The strengthening is statistically significant for counties and book-weighted advisers, and remains positive but is

does not significantly change it.

Finally, if advisers instead bought green ETFs on momentum, chasing past returns, the response would be larger after green ETFs had done well. The response does not differ after strong and weak years for green ETFs (Appendix Table I.7).

4 Mutual-Fund Managers and Active Rebalancing

The second setting I study is actively managed mutual funds. In this context, I can observe the investment teams that make the decisions and measure the political views of the managers themselves, as well as the local information environment they are embedded in. This allows me to separate the decisions of delegated portfolio managers from those of fund investors and to study the effect among professional institutional investors.

I find that a higher share of local news coverage reading the disaster as climate change raises the shift of nearby mutual fund managers' portfolios toward stocks of environmentally friendly firms in the quarter of the event.

4.1 Empirical Strategy

The hypothesis is that managers are influenced by the narratives surrounding a disaster that occurred near where they work, and that these narratives affect their portfolio decisions, moving them toward more sustainable assets when local coverage interprets the disaster as climate change. To show this, I compare the shift toward stocks of more relative to less environmentally friendly firms in the quarter of the event across funds with offices within 50 miles of the affected area whose local newspapers read the event differently. In each quarter, I link a fund to the nearest disaster and to every disaster that affects one of its offices.[52] For fund f and episode e, I estimate the following regression

$$\Delta_h q_{fe} = \theta_h^n D_{fe}^n M_{fe} + \sum_{b \neq n} \theta_h^b D_{fe}^b M_{fe} + X_{fe}' \Gamma_h + \sum_g D_{fe}^g Z_{fe}' \Lambda_h^g + \delta_{g(f,e),e}^h + \mu_{c(f,e)}^h + \kappa_{s(f)}^h + \varepsilon_{feh}. \quad (7)$$

The outcome, $\Delta_h q_{fe}$, is the green tilt of the fund's trading, the change in its weight in stocks in the top tercile of the score minus the change in its weight in stocks in the bottom tercile, over the quarter of the disaster, in basis points of the fund's scored stock portfolio. I measure each stock's environmental profile with its Environmental Pillar score (Section 2.1), after validating this measure with local heat waves (Section 4.4). As for households (Equation 5), I compute the weight changes holding constant prices at the beginning of the quarter.

not statistically significant with equal adviser weights.

[52] As disasters I consider floods, hurricanes, storms, and wildfires. I exclude a fund from the analysis of a disaster when one of its offices was affected by another disaster in the same or the previous quarter. I also exclude it when it has an office within 100 miles whose county had no local coverage of the disaster, since local interpretation is not defined there, and when stocks with an Environmental Pillar score make up less than half of its stock portfolio before the disaster. The latter excludes few observations, and the median fund's stock portfolio before the disaster is almost fully scored.

M_{fe} is the share of local coverage that interprets the disaster as climate change where the managers are (Equation 3), and D^b_{fe} indicates the distance band of the fund's managers. The bands are the affected counties (affected managers), within 50 miles of them (nearby managers, $b = n$), between 50 and 100 miles, and more than 100 miles away (the comparison group).[53] Each band has its own slope, θ^b_h. The coefficient of interest is θ^n_h, the total effect of interpretation among nearby managers.

$g(f, e)$ is the fund's exposure group in the disaster. The groups are affected managers, managers within 100 miles, and the comparison group. $\delta^h_{g(f,e),e}$ are exposure-group-by-disaster fixed effects, which capture each group's average response to each disaster, including its damage, and give the comparison group its own level in each disaster. $\mu^h_{c(f,e)}$ are fixed effects for the county from which the fund is managed. $\kappa^h_{s(f)}$ are fund-style fixed effects, so that each fund is compared with funds of the same investment style. The strongest specification also includes fund fixed effects, so that each fund's change in green tilt is measured against its own average quarterly change across the disasters in the sample.

X_{fe} contains the size, age and turnover of the fund before the disaster and an indicator for nearby managers, which gives them a level common to all disasters. Z_{fe} contains, for the fund's offices in each exposure group g, the volume of local coverage and, depending on the column, county and political controls, as well as damage for the offices in the affected counties.[54] I also control for how the county's outlets interpret the other large disasters they cover, so that the comparison holds fixed the county's usual reading of climate events. I cluster standard errors by disaster.

4.2 Identification

The effect of interpretation is identified by comparing the response of managers at the same distance from the same disaster, managing funds of the same investment style, whose local coverage interprets it more or less as climate change, relative to how funds managed from their county usually respond to a disaster. The identifying assumption is that, conditional on the controls, the climate reading of a manager's local coverage is unrelated to how the fund's green tilt would have changed under a different reading. Namely, managers whose coverage reads the disaster more as climate change would otherwise have changed their green tilt similarly to managers at the same distance whose coverage reads it less as climate change. A bias would arise if managers whose newspapers read the disaster as climate change would have tilted toward greener stocks after it without that reading.

[53] Most funds are managed from a single county. For funds with offices in several bands, each indicator is the fraction of the fund's offices in the band, with equal weight on each office, and M_{fe} averages M over these offices. The results are robust to keeping only the funds with all their offices in one county, and to placing the fund at all its offices or only at the office closest to the disaster (Appendix Table G.4).

[54] Political controls are the county's Democratic two-party vote share and the managers' political score, from the political donations of the named portfolio managers or, without them, of the management company. Appendix Table G.3 shows that the results are robust to including funds whose managers and management companies have no matched donations.

Isolating the effect of local interpretation on managers has two main challenges. First, how local outlets interpret a disaster may be endogenous and reflect stable characteristics of the place and of the managers who live there, and not the event itself. Namely, counties whose outlets often write about climate change, or with a given political leaning, may also host managers who respond differently to any disaster. Second, the disaster itself can change the stocks the managers hold and the flows into their funds, whatever its coverage.

The first challenge is addressed by the fixed effects for the county from which the fund is managed, $\mu^h_{c(f,e)}$, which absorb how funds managed from that county respond to disasters in general. The second challenge is addressed by the exposure-group-by-disaster fixed effects, $\delta^h_{g(f,e),e}$, which absorb the movements of greener and browner stocks in the quarter of the disaster that are common to managers in the same exposure group.

The mutual fund manager design combines the advantages of each of the two main designs I run for counties and advisers. As in the within-episode design (Equation 6), it compares only managers at the same distance from the same disaster. As in the main design (Equation 4), it still includes a clean (unaffected and far) comparison group, allowing me to control for how funds managed from each county (and funds of the same style and characteristics) usually respond to a disaster.[55] The comparison group starts more than 100 miles away because the effects of a disaster spill over beyond the affected area.

To assess the identifying assumption, Figure 5 plots the effect quarter by quarter. In the three quarters before the disaster, the estimates are close to zero and jointly not significant, so there is no evidence of pre-trends. Appendix Table G.6 reports the estimates behind the figure.

4.3 Results

Table 3 reports the interpretation coefficient for nearby managers, θ^n_h. Appendix Table G.14 shows the change in the tilt of nearby funds around one episode, Tropical Storm Isaias. Panel A shows that nearby managers tilt their portfolios toward greener stocks when local coverage interprets the disaster as climate change. A ten percentage point higher interpretation share raises their green tilt by 69 basis points at beginning-of-quarter prices in the quarter of the disaster (Column 2), about as large as the response to a local heat wave that causes injuries or fatalities (Appendix Table G.2).[56] The tilt is driven by an increase in the weight of greener stocks as well as a reduction in the weight of browner stocks (Appendix Table G.5). The estimates are similar with political controls (Column

[55] For the purpose of identifying the interpretation effect, the design is equivalent to a regression on the exposed managers alone, as in the within-episode design for advisers, in which the county fixed effects, the fund-style fixed effects and the fund controls are held at their estimates from the entire sample. Managers more than 100 miles away enter the interpretation effect only through these components. Restricting the sample to managers near the disaster would leave those components to be estimated only from the few disasters in which each county is affected or nearby. Because a county is far from most disasters, the comparison group pins down how funds managed from each county usually respond.

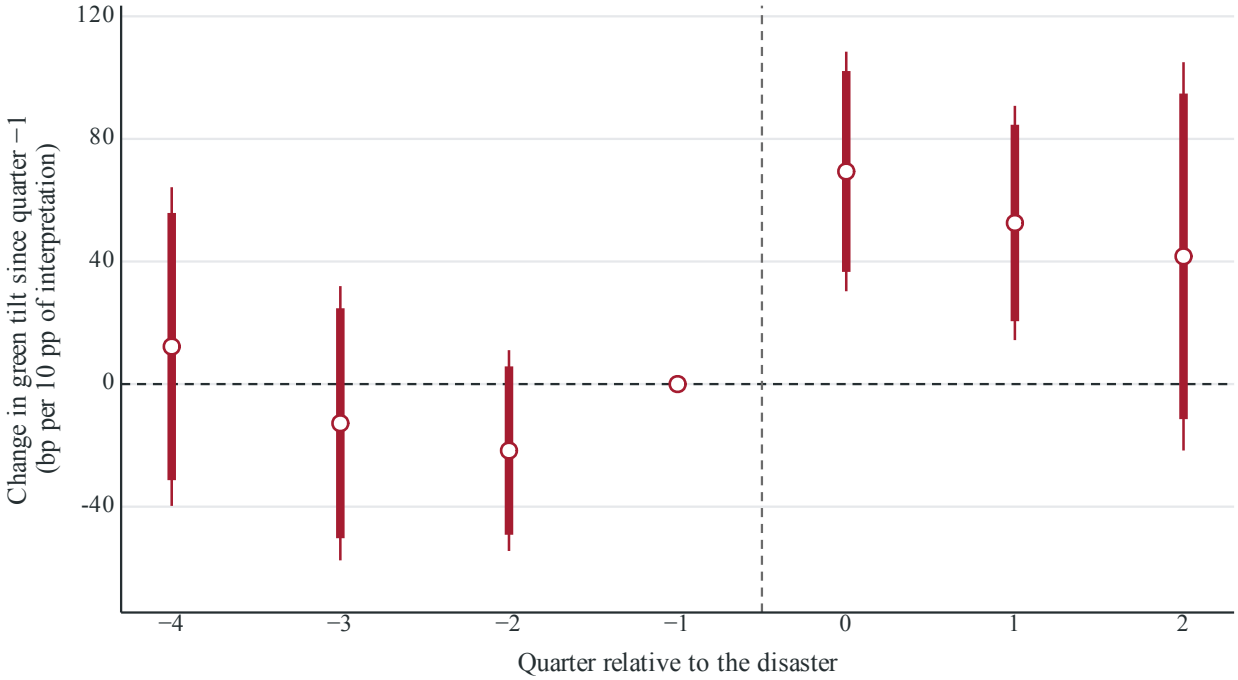
[56] The results are robust to measuring each stock's environmental profile with its continuous Environmental Pillar score (Appendix Table G.4).

TABLE 3: MUTUAL FUND PORTFOLIO RESPONSE

Dependent variable: response in basis points (pre-event prices)				
	(1)	(2)	(3)	(4)
Panel A. Fund level: change in the fund's green tilt				
Interpretation	69.34***	69.38***	66.25***	67.58***
	(20.11)	(19.87)	(18.99)	(19.86)
Attention	−2.05	−.85	−1.09	−1.95
	(2.84)	(3.12)	(3.09)	(3.36)
Observations (fund-episodes)	37,047	37,047	37,047	36,964
Nearby fund-episodes	1,712	1,712	1,712	1,710
R^2	.031	.032	.033	.093
Exposure × episode FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓
Fund FE				✓
Fund controls	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × county controls		✓	✓	✓
Exposure × political controls			✓	✓
Panel B. Stock level: change in the fund's weight in a stock, top minus bottom tercile				
Interpretation		3.57***	3.56***	
		(1.28)	(1.28)	
Attention		.04	.03	
		(.27)	(.28)	
Observations (fund-episode-stocks)		5,426,327	5,426,327	
Fund-episodes		53,028	53,028	
R^2		.577	.577	
Fund × episode FE		✓	✓	
Fund style × stock × episode FE		✓	✓	
Exposure × episode FE		✓	✓	
Damage and coverage controls		✓	✓	
Exposure × political controls			✓	

Notes. Effect of local climate interpretation on the green tilt of mutual funds whose managers are near the disaster. The green tilt is the fund's weight in stocks in the top tercile of the Environmental Pillar score minus its weight in bottom-tercile stocks. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is per 10 percentage points and Attention per 10 log points. In Panel A, all columns include exposure group × episode, county and fund-style fixed effects, fund controls, and damage and coverage controls. Column 2 adds county controls and Column 3 political controls, both interacted with the exposure group. Column 4 adds fund fixed effects. In Panel B, all columns include fund × episode, fund style × stock × episode and exposure group × episode fixed effects and damage and coverage controls. Column 3 adds political controls interacted with the exposure group. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the volume of local coverage for the fund's offices in each exposure group and damage for its offices in affected counties. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. Standard errors in parentheses are clustered at the episode level. Appendix Table G.1 reports the same estimates at pre-event and current prices. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

FIGURE 5: INTERPRETATION EFFECT AMONG NEARBY MANAGERS, BY QUARTER



Notes. Effect of local climate interpretation on the green tilt of mutual funds with managers within 50 miles of the affected counties, by quarter relative to the disaster. The green tilt is the weight of stocks in the top tercile of the Environmental Pillar score minus the weight of bottom-tercile stocks. Each regression includes exposure group × episode, county and fund-style fixed effects and controls for Attention, fund characteristics (lagged log total net assets, log age and turnover), damage and coverage. It also includes county controls interacted with the exposure group (the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share). The figure shows 95% and 90% confidence intervals, with standard errors clustered at the episode level. Appendix Figure G.1 shows the same estimates at pre-event and current prices.

3) and with fund fixed effects (Column 4).[57] In contrast, the volume of local coverage does not move the tilt, with the coefficient on attention small and never significant.

A one standard deviation increase in the interpretation share raises the tilt by 1.1 percentage points, about a tenth of the gap in the tilt between a conventional fund and a fund with an ESG mandate. In dollar terms, the average nearby fund, with $4.3 billion in assets, moves about $49 million from bottom-tercile to top-tercile stocks. Summed over the nearby funds of the average disaster, the shift reaches about $1.4 billion.

The effect is concentrated near the disaster. Appendix Table G.7 reports, from the same regressions, the effect for affected managers and for managers more than 100 miles away. It is as large for affected managers as for nearby managers, while among managers more than 100 miles away a ten percentage point higher interpretation share raises the tilt by 4 basis points, about a twentieth of the effect among nearby managers.

Unlike for households and labeled products, one concern with the results of Panel A is that

[57] The estimates are smaller but remain significant when I replace the exposure-group-by-disaster and county fixed effects with episode fixed effects and fixed effects for each combination of exposure group, hazard and calendar quarter (Appendix Table G.3, Columns 5 and 10).

they could be driven by differences in the fundamentals of the stocks held by managers whose local coverage interprets the disaster differently. A disaster can move the fundamentals and prices of the firms it affects, and it can affect greener and browner firms differently. For example, funds whose local coverage interprets the disaster as climate change may hold more of the greener stocks, which could be directly affected by the policy response or the news about climate risk that the disaster brings.

To address this concern, I use more granular data at the level of the fund, stock and disaster, with the change in the fund's weight in the stock as the outcome. I can then include fixed effects for each stock around each disaster, separately for each fund style, which absorb everything common to the funds of that style that hold the stock, such as its return and fundamentals, the location of the firm and its own exposure to the disaster, national coverage of the firm and the shock to its industry. Since I compare funds of the same style that hold the same stock around the same disaster, the stock's cash-flow news from the disaster, the part agreed by everyone, cannot explain the effect.

In addition, I include fixed effects for each fund around each disaster, which absorb everything common to the fund's stocks, such as the attention and interpretation of its local coverage, its distance from the disaster, the damage in its county, its flows and its average trading, as well as the fund and county controls of Panel A. Interpretation, attention, damage and the exposure-group-by-disaster fixed effects therefore enter interacted with indicators for the top and bottom terciles of the Environmental Pillar score, as do the political controls in Column 3. The estimate therefore compares how managers whose local coverage interprets the same disaster more or less as climate change reweight the same stocks, relative to the other stocks in their portfolios and to funds of the same style that hold the same stocks.

Panel B shows the results. A ten percentage point higher interpretation share raises the weight of nearby managers in top-tercile relative to bottom-tercile stocks by 4 basis points (Column 2). The estimates are similar with political controls (Column 3) and at current prices (Appendix Table G.1).

4.4 Alternative Explanations

Investors or Managers. Differences in portfolio responses may also reflect the pressure of the funds' investors. This is especially relevant for smaller funds, whose clientele is often local, so that a disaster can be experienced and interpreted both by the manager and, sometimes, by a significant part of the clientele. Managers whose clients are more concerned about climate change may face stronger incentives to demonstrate that their funds have responded to a disaster. It is much easier to show investors that the fund acted on climate change risk by showing a higher Environmental Pillar score than through adjustments based on the firms' exposure to physical risk, which are harder to explain and appear less transparent. Conversely, managers facing less pressure may still adjust their portfolios in response to perceived climate risks, but along different dimensions. The differences in the observed environmental tilt may then reflect client pressure and the margins along which managers choose to respond, regardless of their interpretation of the disaster.

To distinguish managers from their clients, I exploit differences between the locations of fund headquarters and managers' offices. Studies of mutual funds and local disasters typically use headquarters as a proxy for manager location (e.g., Fich and Xu, 2025). Yet, headquarters is also a natural proxy for investor location, since individual investors favor locally managed funds (Bailey et al., 2011). Instead, I use more granular data on managers' locations and treat headquarters as the approximate location of the investors. While managers' offices are usually in the same county as headquarters, the locations differ in 35 percent of cases and are more than 100 miles apart in 30 percent. For sub-advised funds, whose portfolios are run by an outside firm, the locations are more than 100 miles apart in 63 percent of cases. If client pressure drives the environmental tilt, the response should follow the climate interpretation near headquarters and not near managers' offices.

Appendix Table G.12 exploits this separation for funds with known headquarters, using the main specification. I estimate the effect of the interpretation near managers' offices separately for managers near a disaster whose funds' headquarters are within or beyond 100 miles of the disaster. I also estimate the effect of the interpretation near headquarters for funds whose headquarters are within 50 miles of the disaster but whose managers are more than 100 miles away. Nearby managers respond equally strongly whether their headquarters are near or far from the disaster. Conversely, funds with nearby headquarters but distant managers exhibit a smaller, statistically insignificant response. The contrast is stronger when including all fund-episodes, and stronger still among below-median-size funds, whose investors are more likely to live near headquarters (Appendix Table G.13). These results suggest that the response depends more on the location of managers than on that of their funds' investors.

Measure of Green Stocks. A related concern is that managers respond along dimensions of climate risk that the Environmental Pillar score does not capture. Managers may disagree on how green a firm is (the ESG ratings of the same firm from different providers correlate only between 0.38 and 0.71, Berg et al., 2022), as well as on how to respond to a higher perceived climate risk, for example by tilting toward sustainable firms or away from firms exposed to certain types of physical or transition risk. The choice of measure biases the interpretation effect only if the part of the response that the score misses is correlated with the interpretation of the disaster. In any case, using the approach and (extended) data of Alekseev et al. (forthcoming), I take local heat waves as the climate shock, since they raise managers' climate concerns, and check that the response goes in the direction of the score. A fund with all its offices exposed to such a heat wave raises its green tilt by 65 basis points at beginning-of-quarter prices (Appendix Table G.2).[58]

Sale of Firms in the Disaster Area. The estimated tilt could reflect managers selling firms

[58] In an ideal experiment, I would observe each climate shock as the manager perceives it and let the portfolio response reveal which stocks managers treat as green. Such shocks cannot be isolated. A disaster bundles the damage it causes, the policy responses it triggers and the news it brings about climate risk. Comparing managers at different distances from it still requires that the response to the bundle is the sum of the responses to its elements. Any more sophisticated approach would rest on the same assumption. I therefore use a sustainability rating, which investors chase (Hartzmark and Sussman, 2019) and fund managers trade to obtain (Gantchev et al., 2024; Ceccarelli et al., 2024). The validation exercise is then an indirect approximate version of the ideal experiment.

located in the disaster area because of expected losses or concerns about investors' exposure, if these firms are disproportionately brown. I decompose the tilt of Table 3, Column 2, into reallocations across firms at different distances from the disaster and reallocations among firms at similar distances (Appendix Table G.10). The former component is small and insignificant, while the latter is nearly identical to the main estimate. Consistently, the stock-level effect outside the disaster area is unchanged, while within the affected area the effect is larger, at 19 basis points (Appendix Table G.11). Managers thus do not sell local firms as a block, but reweight toward the greener ones. Managers affected by or near a disaster sell and underweight the stocks of firms located within 50 miles of the affected counties, relative to distant managers holding the same stocks in the same episode (Appendix Table G.8). This tendency does not vary systematically with the climate interpretation of the disaster, a further indication that the reaction to the disaster itself and the response to its interpretation are separate channels.

Fund Flows or Liquidity Shocks. The effect could also capture fund flows and not the managers' own choices. Funds managed in the affected counties can face outflows from local investors (Tubaldi, 2021), which raises two concerns. First, outflows may correlate with climate interpretation through disaster severity or other local characteristics.[59] Second, flow-induced sales may disproportionately affect certain stocks (Coval and Stafford, 2007) and generate an environmental tilt even after accounting for proportional portfolio adjustments.

To address the first concern, I measure active trades net of proportional adjustments to flows, following Sammon and Shim (2023). A ten percentage point higher interpretation share raises the net active purchases of nearby managers in top-tercile relative to bottom-tercile stocks by 30 basis points of assets before the disaster (Appendix Table G.9, Column 2). To address the second, I have estimated the effect on managers outside the affected counties, and kept the affected managers in a band of their own. Nearby managers do not face the outflows of local investors in the affected counties (unless their fund is headquartered there). Nearby managers respond equally strongly whether their headquarters are near or far from the disaster (Appendix Table G.12), so forced sales cannot explain their tilt.

5 Separating Interpretation Narratives from Prior Beliefs and Preferences

The previous household, adviser and fund-manager designs compare units whose local coverage gives different interpretations to the same type of disaster, holding fixed the climate and political views of the county as well as those of advisers and fund managers. Event-study leads, placebo tests and additional fixed effects ruled out confounders such as a trend in green investment and a general propensity of climate-concerned counties to buy green assets even after salient but non-climate shocks. So far, I have estimated the response to local interpretation as it emerges

[59]For instance, in counties where the disaster was more destructive, climate narratives may be less common, and liquidity needs might raise outflows. As a result, the interpretation effect would pick up differences in outflows.

in equilibrium from local discussions and narratives, regardless of whether the county's outlets supply them or cater to their readers' predispositions.

Next, I move to the role of locally supplied interpretation models and narratives (Schwartzstein and Sunderam, 2021), by testing whether the local interpretation moves portfolios when it is driven by changes in the narrative that the outlets supply, independently of the prior beliefs or preferences of their readers. I do so by adapting an instrumental variable approach that uses media ownership as a shifter of content (Martin and McCrain, 2019; Garz and Rickardsson, 2023; Ananyev and Volkova, 2024; Ewens et al., 2022; Kostovetsky et al., 2026). In particular, I instrument the interpretation of the disaster in local news with the size of the chain that owned the county's newspapers. Larger newspaper chains are more detached from the counties they serve and cater less to local demand, supplying centrally produced copy.[60]

In practice, the instrument exploits changes in the ownership of the newspapers serving a county between two disasters of the same type. For each county, I compare the disasters of the same type that affected it directly or occurred within 50 miles, in particular those that occurred before with those that occurred after the chain size of its newspapers changed.

Specification and estimation. The sample contains the counties directly affected or within 50 miles and with positive local coverage of the event. I define the chain size of newspaper o in calendar quarter t, $ChainSize_{ot}$, as the number of newspapers in the sample held by the outlet's owner as recorded prior to the event, so that an independent newspaper has a chain size of one. The county instrument is the mean of the logarithm of chain size[61] across the chained newspapers serving the county, weighted by their circulation.

$$Z_{c,t(e)} = \frac{\sum_{o \in C_{c,t(e)}} w^D_{oc} \, \log ChainSize_{o,t(e)}}{\sum_{o \in C_{c,t(e)}} w^D_{oc}}, \tag{8}$$

where C_{ct} is the set of chained newspapers serving county c and w^D_{oc} is the fixed circulation weight. The first-stage equation is

$$M_{ce} = \tilde{\pi} Z_{c,t(e)} + \tilde{\beta}_A A_{ce} + X'_{ce}\tilde{\gamma} + \tilde{\mu}_c + \tilde{\tau}_{t(e)} + \tilde{\lambda}_{h(e)\times b(c,e)} + u_{ce}, \tag{9}$$

where $Z_{c,t(e)}$ is the county instrument of equation (8), A_{ce} is local disaster coverage in logs, X_{ce} collects the logs of one plus own-county fatalities and damage, the county Democratic two-party vote share at the previous presidential election and, in columns 2 and 4 of Table 4, the audience overlap of the county's newspapers with the event footprint, $\tilde{\mu}_c$ are county fixed effects, $\tilde{\tau}_{t(e)}$ calendar-quarter fixed effects, and $\tilde{\lambda}_{h\times b}$ hazard-by-exposure-band fixed effects, where the two

[60] Outside the United States, newspapers held by one owner share that owner's slant (Garz and Rickardsson, 2023), and acquisitions shift slant in a direction that depends on the acquirer (Ananyev and Volkova, 2024); in American local broadcasting, ownership changes shift content (Martin and McCrain, 2019).

[61] I use the natural logarithm to measure proportional changes in chain size, since the same change in the number of newspapers is more meaningful and impactful for a small chain than for a large one.

exposure bands are the directly affected counties and the counties within 50 miles; the comparison is among counties at the same exposure to disasters of one hazard family.[62] I estimate

$$Y_{ue} = \beta_M M_{ce} + \beta_A A_{ce} + X'_{ce}\gamma + \mu_c + \tau_{t(e)} + \lambda_{h(e)\times b(c,e)} + \varepsilon_{ue}, \tag{10}$$

where u is a county or an adviser in county c and M_{ce} is instrumented with $Z_{c,t(e)}$. Adviser regressions weight each adviser by its share of the county-episode ETF book in the quarter before the episode. Standard errors are clustered by county.

Relevance and exclusion. The climate-interpreted share of disaster coverage differs persistently across owners, and newspaper chain size predicts that share at the outlet level; under a larger prior owner, local disaster coverage has a lower climate-interpreted share (Table H.1). Chain size is measured at the newspaper–quarter level; Panel A of Table 4 shows that its relation to the interpretation share extends to the event-specific share of the county's coverage.

The identifying assumption is that, conditional on the fixed effects, coverage volume and own losses, a change in the chain size of a county's newspapers is unrelated to any change in how its investors respond to the disaster, other than through the climate interpretation of the coverage they receive. Calendar-quarter fixed effects absorb everything common to the counties exposed in the same quarter, such as a rise in chain size or a fall in green shares across the country. Hazard-by-exposure-band fixed effects restrict the comparison to counties exposed to the same hazard type in the same exposure band: affected counties are compared with affected counties and nearby counties with nearby counties.

County fixed effects absorb permanent differences between counties with larger and smaller chains, such as market size, politics, climate beliefs and the usual reading of their newspapers. They also absorb a steady trend in a county's green share, since it adds the same amount to each of the county's changes around its disasters. What remains is the county's log chain size at each disaster minus its average over the county's disasters.[63]

The remaining concern is that changes in chain size systematically occur in counties that, even without such shocks, would have bought fewer green assets and whose newspapers would have interpreted disasters less as climate change. How likely this selection bias is depends on the nature of the change.

Two kinds of ownership shock account for most of the changes in chain size. The first is an upstream shock, a change at the level of the owner: the owner expands or contracts through a merger or an acquisition by or of other owners, or through purchases and sales of other newspapers,

[62] For mutual fund managers, as in Section 4, I focus on managers whose offices are outside the affected counties but within 50 miles of the disaster footprint, to address outflows from local investors. With a single exposure band, the band fixed effects reduce to hazard fixed effects. The county is the county of the manager's offices, and the instrument is averaged over those offices.

[63] For example, the Hartford Courant, which holds 97 percent of the circulation of Hartford County, Connecticut, was owned by Tribune Publishing, a chain of 18 newspapers, at the time of the flood of 28 June 2020 and by Alden Global Capital, a chain of 56, at the time of the flood of 1 September 2021, both within 50 miles of the county.

TABLE 4: PORTFOLIO RESPONSE TO INSTRUMENTED INTERPRETATION

	Portfolio response (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. First stage				
Outlet level	−2.29***	−2.29***	−2.29***	−2.29***
	(.50)	(.50)	(.50)	(.50)
County level	−8.81***	−8.82***	−8.81***	−8.82***
	(2.89)	(2.89)	(2.89)	(2.89)
Newspaper-quarters	6,711	6,711	6,711	6,711
County-events	694	694	694	694
First-stage F, outlet level	20.85	20.85	20.85	20.85
First-stage F, county level	9.32	9.33	9.32	9.33
Panel B. County ETF holdings				
Interpretation (IV)	22.75	22.47	24.96*	24.60*
	(14.30)	(14.21)	(14.69)	(14.59)
Observations	694	694	694	694
Anderson–Rubin p	.064	.067	.051	.054
Anderson–Rubin 90% set	[2.5, 61.9]	[2.3, 61.2]	[3.9, 64.7]	[3.6, 63.9]
Panel C. Adviser ETF holdings				
Interpretation (IV)	19.34*	19.18*	22.54**	22.38**
	(10.51)	(10.53)	(11.30)	(11.31)
Observations	4,342	4,342	4,342	4,342
County-events	660	660	660	660
First-stage F	9.43	9.44	9.43	9.44
Anderson–Rubin p	.029	.032	.025	.027
Anderson–Rubin 90% set	[4.7, 48.4]	[4.5, 48.2]	[6.3, 52.8]	[6.0, 52.5]
Panel D. Mutual fund managers				
Interpretation (IV)	176.56**	209.87**	107.27	164.27*
	(84.17)	(97.94)	(82.25)	(97.44)
Observations	2,052	2,052	2,052	2,052
County-events	136	136	136	136
First-stage F	11.47	11.13	11.47	11.13
Anderson–Rubin p	.062	.043	.190	.073
Anderson–Rubin 90% set	[26.5, 350.6]	[47.1, 429.3]	[−31.0, 287.6]	[14.5, 400.3]
Coverage, county fatalities and damages	✓	✓	✓	✓
Democratic vote share	✓	✓	✓	✓
Audience reach		✓		✓
Fund size, age and turnover (Panel D)	✓	✓	✓	✓
County, quarter and hazard × distance-band FE	✓	✓	✓	✓

Notes. Two-stage least squares estimates of the effect of local climate interpretation on portfolio responses. Panel A reports the first stage, the effect of chain size on the interpretation share in percentage points, per log point at the outlet level and per standard deviation at the county level. The outlet-level first stage includes newspaper and calendar-quarter fixed effects. In Panel B, the outcome is the mean county green-ETF share over the quarter of the episode and the two following quarters minus its mean over the two quarters before. In Panel C, the outcome is the change in the adviser green-ETF share from the quarter before the episode to the quarter after it. In Panel D, the outcome is the change in the green tilt of mutual funds whose managers' offices are all within 50 miles of the disaster. Interpretation effects are per 10 percentage points of interpretation. All columns include county, quarter and hazard × distance-band fixed effects and control for coverage, county fatalities and damages, and the Democratic vote share. Columns 2 and 4 also control for audience reach. Panel D also controls for fund size, age and turnover. Standard errors in parentheses are clustered at the county level and, for the outlet-level first stage, at the newspaper level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

as in the 2019 merger of Gannett and GateHouse.[64]

Owners take these decisions at the chain level, for reasons that follow from the economics of the newspaper industry, such as declining advertising revenue, and are plausibly unrelated to the climate concern of the county's readers.[65] Upstream shocks are the most common.

The second is a direct change in ownership, in which the county's newspaper itself passes from one owner to another, as in the 2023 sale of the San Diego Union-Tribune by NantMedia to Alden Global Capital. Although acquisitions and sell-offs also follow the economics of the newspaper industry, a chain buying an independent newspaper is the only case where one could argue that the owner chooses the county's market. Removing these purchases leaves the county and adviser results similar (Appendix Table H.5). Changes in chain size do not predict the county's latest presidential vote share, its climate beliefs measured before the sample, its portfolio change before the event, or the losses, distance and coverage of the disaster (Table H.4).

Separating attention. Disasters that receive more news coverage may also generate more discussion of their climate implications. The estimated effect of interpretation could therefore reflect differences in attention. To distinguish the two, both stages control for the volume of local disaster coverage, while hazard-by-exposure-band fixed effects compare counties exposed to the same type of disaster in the same exposure band. In columns 2 and 4 of Table 4, I also control for newspaper-audience overlap with the disaster footprint outside the county, which captures variation in newspapers' incentives to cover the event arising from the geographic distribution of their readers (Snyder and Strömberg, 2010; Myers, 2026).[66] Appendix Table H.8 exploits this variation to instrument coverage jointly with climate interpretation, using audience overlap and newspaper chain size, respectively. The first stages show that the two instruments predict different dimensions of disaster coverage. Audience overlap predicts its volume but not its climate interpretation, whereas chain size primarily predicts its climate interpretation. The estimated effect of interpretation remains similar to the columns that instrument interpretation alone, although the joint system is weakly identified. At the outlet level, chain size leaves disaster coverage unmoved (Table H.1). Thus, the instrument generates variation in the interpretation supplied by newspapers without a corresponding change in coverage volume, conditional on these additional determinants of attention.

Results. Table 4 reports two-stage least squares estimates of the instrumental variable design. Panel A reports the first stage at the outlet and county level, Panel B the county response of Table 2, Panel C the adviser response of Table C.3 and Panel D the mutual fund manager response of Table 3.

[64] After the merger, Gannett cut nearly half of its workforce. Exploiting differences in counties' pre-merger exposure to Gannett newspapers, I find that the climate-interpreted share of disaster coverage falls more where this exposure is greater, and the green-ETF response of affected counties falls with it. See Table H.2 in the Appendix for details.

[65] Acquisitions and consolidation in the industry follow declining advertising revenue, the liquidity needs of legacy owners, and cost cutting in roll-ups (Ewens et al., 2022; Gao et al., 2020).

[66] Consider three nearby counties, A, B and C, where a disaster affects only A. Newspaper X, read in B, has 90 percent of its readers in A; newspaper Y, read in C, has none. X has more incentive than Y to cover the disaster, so B receives more coverage than C, even though neither county is affected.

Columns 1 and 2 use pre-event prices and columns 3 and 4 current prices; all columns control for coverage volume, own losses and the county's Democratic vote share, and columns 2 and 4 add the audience overlap of the county's newspapers with the disaster footprint. The coefficients remain stable in magnitude across columns. As expected, the use of 2SLS reduces statistical power, but for counties and advisers the weak-instrument-robust confidence sets exclude zero at the 10% level and the instrumented response is of the same magnitude as the local-projection estimates of Table 2.[67]

For mutual fund managers whose offices are all within 50 miles of the disaster, a 10-percentage-point increase in the supplied climate interpretation narrative raises their green tilt by 177 basis points at pre-event prices, about two and a half times the ordinary least squares estimate of Section 4 (69 basis points, Table 3). The 90% set excludes zero in columns 1, 2 and 4 and includes it in column 3. One possible reason for the larger instrumented response of managers is attenuation bias due to measurement error. The interpretation share is a classifier output and contains measurement error that can bias its coefficient (Ash and Hansen, 2023; Hausman, 2001). Since ownership changes are unrelated to the classifier's errors on a given article, the instrument removes this bias as well. Some caution is needed. While the first stage is strong at the outlet level, it is weaker once the instrument is aggregated to the county level, with an F of about 9 for counties and advisers and 11 for managers, and lower still under two-way clustering by county and disaster.[68] Inference therefore rests on the Anderson–Rubin sets, which are robust to weak instruments. They exclude zero at the 10 percent level for counties and advisers, and at the 5 percent level for advisers and, in column 2, for managers. These instrumented results are suggestive of at least some causal effect of the supplied interpretation narratives and discussion on portfolios, beyond prior beliefs and preferences.

6 Interpretation, Aggregate Flows and Relative Prices of Green Stocks

Whether climate interpretation moves aggregate flows and the relative prices of green stocks depends on how widely that interpretation is shared. When investors read the same disaster differently, they can trade against one another and therefore not necessarily affect the prices of green stocks. However, a common interpretation can shift aggregate demand and prices (van der Beck et al., 2025). I first ask whether the climate interpretation of national disaster coverage predicts aggregate flows into ESG funds, beyond the attention disasters receive. I then use my micro estimates to quantify the price implications of the demand response to interpretation.

Disasters have been found to raise flows into green ETFs and the relative returns of sustainable

[67] Per 10 percentage points of interpretation, the instrumented response is 22 to 25 basis points for counties and 19 to 23 for advisers, against 19 basis points in column 4 of Table 2, whose estimates are per standard deviation of interpretation, 15.7 percentage points.

[68] Standard errors and first-stage F statistics are clustered by county. With two-way clustering by county and disaster, the county-level first stage is weaker, with an F of about 5.8 for counties, 6.4 for advisers and 10 for managers. The Anderson–Rubin 90 percent sets for counties and advisers exclude zero under two-way clustering as well. See Appendix Table H.9 for the table with two-way clustering.

assets (Fiordelisi et al., 2023; Misev and Balles, 2024). Each month I measure national disaster attention as the number of disaster articles in national newspapers, and national interpretation as the share of those articles that read the disaster as climate change. An attention surprise is the prediction error of an autoregression of the monthly series fitted on the previous three years, in standard-deviation units, as in Ardia et al. (2023). I ask whether a surprise raises flows into ESG-labeled funds more than flows into other funds, and whether it does so more when national interpretation is high. I use my sample of ESG-labeled and other US domestic-equity mutual funds and ETFs over 2015–2024.[69]

Figure 6 shows the responses over the surprise month and the following two months. At the average level of national interpretation, the estimated three-month response of flows into ESG-labeled funds relative to other funds is about 29 basis points of fund assets, or about $288 million. The response grows with national interpretation. At the 25th percentile of national interpretation, the response is close to zero. At the 75th percentile, it is positive and about 58 basis points of assets larger, a difference of about $580 million.[70] ESG-labeled funds in the sample take in 0.7% of assets in a normal quarter, so the extra inflow associated with higher interpretation equals about 80% of their normal quarterly net inflows. This is also roughly two-thirds of the three-month inflow associated with receiving the highest Morningstar sustainability rating, about 0.9% of assets (Hartzmark and Sussman, 2019).

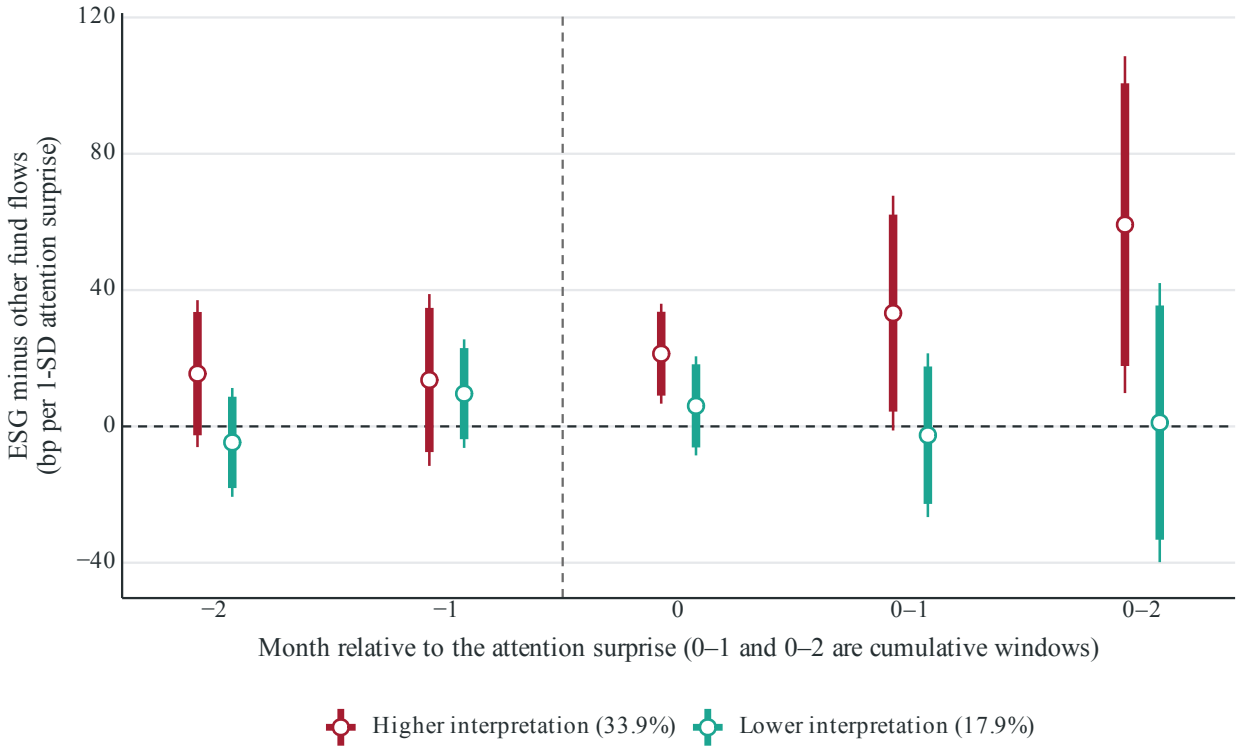
National flows, however, reflect investors' expectations about how others will respond. Moreover, the national analysis identifies variation in interpretation by comparing different disasters, which may also differ in what they reveal about climate risk. I therefore turn to my micro estimates, which compare investors exposed to the same disaster but receiving different interpretations. In a counterfactual exercise, I compute the additional ESG demand and the relative appreciation of green stocks that a stronger climate interpretation of disasters would generate. Van der Beck (2026) shows that ESG flows and, more generally, institutional ESG demand are important drivers of green-minus-nongreen stock returns. The exercise extends the response of affected advisers to investors outside the sample and prices the added demand with van der Beck's (2026) calibration of how other investors accommodate ESG flows. Appendix J derives each step. Table 5 reports the resulting demand and price responses for each activated investor base.

The first input is the allocation response. Raising local climate interpretation from its 25th to its 75th percentile in my sample, with newspaper coverage at its median and the remaining controls at their sample averages, moves interpretation by about one and a quarter standard deviations. Among affected counties, each standard deviation raises the green-ETF share by 26 basis points over the event quarter and the following quarter, so the move adds 32 basis points of ESG allocation per dollar of capital (Appendix J). I assume that affected and comparison advisers respond to the

[69]The specification, adapted from Hartzmark and Sussman (2019), compares ESG-labeled funds with other funds within the same investment category and calendar month through investment-category-by-month fixed effects. It controls for fund characteristics and weights observations by log lagged AUM.

[70]Following Hartzmark and Sussman (2019), I convert the estimated relative flow rates into dollars by multiplying each month's response by each ESG fund's assets in the previous month, summing across funds and the three response months, and averaging across the eligible starting months.

Figure 6: National attention, national interpretation and ESG fund flows



Notes. Response of flows into ESG-labeled funds relative to other funds to a one-standard-deviation surprise in national disaster attention, at the 75th and 25th percentiles of national interpretation. Flows are return-adjusted net flows over previous-month assets. The attention surprise is the standardized prediction error of an autoregression of the monthly count of disaster articles, fitted on the previous 36 months. National interpretation is the share of national disaster articles that read the disaster as climate change. The regressions include investment category × month fixed effects and control for lagged fund size, age, returns and expenses. The figure shows 95% and 90% confidence intervals, from Newey–West standard errors with 12 lags.

Table 5: Counterfactual ESG demand and green-stock appreciation by activated investor base

	ETFs (1)	Mutual funds + ETFs (2)	Institutional equity investors (3)
Reallocation ($bn)	20.12	62.24	79.21
Relative stock return (bp)	8.62	26.65	33.92
Relative valuation change ($bn)	14.43	44.64	56.81
Relative stock return as a percent of the annual green-minus-nongreen return			
Observed spread (223 bp)	3.9	11.9	15.2
Part from institutional ESG demand (186 bp)	4.6	14.3	18.2

Notes. Counterfactual additional ESG demand and relative appreciation of green stocks when local climate interpretation rises from its 25th to its 75th percentile and the estimated adviser response is extended to each investor base. Each column activates one investor base, with full activation within it. The additional reallocation is applied once to each dollar of initial capital and priced with the December 2022 multipliers of van der Beck (2026). Relative refers to green minus nongreen stocks. The return benchmarks in the bottom rows are also from van der Beck (2026). Appendix Table J.1 reports the underlying flows.

common movement in relative fund prices in the same way on average, so that this movement cancels in the comparison and the 32 basis points measure a shift in desired allocation at initial prices.

The second input is the capital that responds. Let K be the capital of an investor population, a the added ESG allocation per dollar of capital (the 32 basis points above), and α the *activated* share of that capital, whose holders respond. Assume additional ESG purchases are financed by reducing other holdings. Since the market portfolio already holds a share s of ESG funds, selling it to buy ESG funds offsets part of the purchase, and the additional ESG demand T and the reallocation X from the market portfolio to the ESG portfolio are

$$T = \alpha K a, \qquad X = \frac{T}{1-s}. \tag{11}$$

I assume that activated investors respond to stronger climate interpretation as the affected advisers in my sample do, per dollar of capital, at the same level of attention and the same national information environment, and I set $\alpha = 1$ within each population. I apply the increment to three populations in turn. The first is green-ETF investors. The second is mutual-fund and ETF investors together, since relative flows into ESG mutual funds also respond to interpretation (Section 3). The third, the main case, is institutional equity investors, since managers of funds without an ESG mandate also tilt toward greener stocks (Section 4). The manager results show that the response extends beyond household-serving advisers. The magnitude applied to institutional capital is the adviser response per dollar. For mutual-fund and ETF investors the reallocation is 0.32% of capital. Institutions held $24.7 trillion of the covered stocks in December 2022 (Appendix J).

The third input is the price response. Buying X dollars of the ESG portfolio and selling X dollars of the market portfolio generates net purchases of the stocks that ESG funds overweight and net sales of the stocks they underweight. Let τ_G be the total weight of green stocks in the ESG portfolio in excess of their weight in the market portfolio, τ_N the same difference for nongreen stocks, equal to $-\tau_G$, and V_G and V_N the market values of the two groups. The reallocation adds $X\tau_G$ dollars of demand for green stocks and removes the same amount from nongreen stocks. Scaled by each group's market value, this is the relative flow f^{rel} into green stocks, and the green-minus-nongreen return $R_G - R_N$ that it generates is the relative flow times the relative-return multiplier M_{ESG},

$$f^{\text{rel}} = \frac{X\tau_G}{V_G} - \frac{X\tau_N}{V_N}, \qquad R_G - R_N = M_{\text{ESG}}\, f^{\text{rel}}, \tag{12}$$

the counterpart for the two groups of stocks of the market multiplier in Gabaix and Koijen (2023). I take M_{ESG} from van der Beck's (2026) calibration of how other investors accommodate ESG flows, which combines the portfolio weight differences with holders' willingness to trade as prices change. With the December 2022 inputs, $M_{\text{ESG}} \simeq 1.12$.[71] I assume that other investors accommodate the reallocation as in that calibration, with their price responsiveness and ownership weights

[71] Calibrated using van der Beck's (2026) December 2022 inputs. In dollars, the same responses give $0.72 of green-minus-nongreen valuation per dollar reallocated from the market portfolio to the ESG portfolio.

unchanged as the set of activated investors grows.

To compare with annual returns, assume that over a year the disasters that occur activate the whole institutional investor base, each investor making the additional adjustment once, at unchanged attention and national news. Applying the reallocation rate to institutional capital gives $79 billion of additional ESG demand against the market portfolio over the year, counting each dollar of capital once. Under these assumptions, this demand implies 34 basis points of green-minus-nongreen appreciation (Table 5). As a reference point, van der Beck (2026) attributes 186 of the 223 basis points of the average annual green-minus-nongreen return to institutional ESG demand. The calibrated appreciation is 18% of the former and 15% of the latter (Table 5). The magnitudes are suggestive, since they extend a local response to investors who were not exposed and price it with a multiplier estimated on other flows.

7 Mechanisms

In the previous sections, I established that the interpretation of a disaster drives portfolios towards sustainable assets and that the responses reflect sustainability-related demand shocks, after ruling out mechanical changes from prices, liquidity needs and fund flows, as well as the incentives of advisers and managers toward their clients (Sections 3.1, 3.4 and 4.4).[72] Moreover, under mild assumptions on the form of return expectations,[73] I can also rule out return expectations as the key driver (Section 3.4). Household portfolios tend to be inert and therefore reflect beliefs only weakly (Giglio et al., 2021). Given the sizeable response I observe, I ask how this interpretation-induced shift in the demand for sustainable assets arises despite the inertia, and whether it comes from preferences (ethical considerations) or beliefs (climate risk and hedging demand), the two main motives for ESG investing besides return expectations (Giglio et al., 2025).

7.1 Experiences, Salience and Interpretation

A large body of work shows that personally lived outcomes leave persistent and often domain-specific marks on beliefs and financial behavior (Malmendier, 2021; Malmendier and Wachter, 2022). Extreme weather events can become disproportionately influential on beliefs and on actions of those experiencing them directly or indirectly, because they are more salient, easier to recall, more affectively charged, or more cognitively available at the moment of judgment (Deryugina, 2013; Djourelova et al., 2024; Ballew et al., 2022).

The pattern I observe in green portfolio reallocation and mutual fund manager rebalancing is consistent with salience and experiential updating more than rational belief updating. First, I observe a sizeable response to a single event, which, even if extreme, is weak evidence about

[72] These incentives could produce the same portfolio response without a shift in demand: advisers may sell their own products or rebalance to justify their fees, and managers may tilt the portfolio to show their investors a response to the disaster.

[73] The assumption is that expectations about other investors' demand follow national coverage and reading and past green returns and not the local reading of the event.

long-run climate trends, and therefore less likely to move beliefs via rational updating. Moreover, the patterns in my estimates are consistent with documented salience effects of disasters (Alok et al., 2020; Dessaint and Matray, 2017; Gallagher, 2014): both household advisers and mutual fund managers respond more strongly closer to the disaster (Tables I.1, 3, and G.7), and the response is persistent, especially among household advisers, for whom it remains positive through six quarters (Table I.2).[74]

The salience of the disaster alone would not explain the interpretation effect across investors with similar exposure to the same disaster. Theories of experience effects and memory imply that the same event can be assigned to different domains depending on prior category use, narratives and contextual cues (Malmendier and Wachter, 2022; Bordalo et al., 2025), and in the psychology of climate change, people interpret a personal experience of extreme weather through their existing mental representations and predispositions, which shape its effect on their decisions (Brügger et al., 2021; Myers et al., 2013). My results are consistent with this idea: interpretation operates through whether investors process the disaster as climate-relevant and not as an isolated local event.

In Section 5, I show suggestive causal evidence that the interpretation supplied by local outlets moves portfolios, also holding constant the salience of the disaster (Tables 4 and H.1). Here, to further isolate interpretation from salience, I run the same estimation approach on purchases of flood insurance, another active and impactful financial decision revealing beliefs about disaster or climate risk.

I compare these purchases in affected counties with those in unaffected counties of the same states, separately after floods and wildfires (Appendix Table I.6).[75] Floods make flood risk salient directly; wildfires allow me to examine whether climate attribution is associated with demand for protection against another hazard. By month three, the estimated increase relative to unaffected counties is 41 versus 15 policies per 100,000 residents at the 75th and 25th percentiles of climate attribution after wildfires, compared with 43 versus 40 after floods. As in Gallagher (2014), take-up rises strongly after floods and, as expected, regardless of how the flood is interpreted, while after wildfires it rises with the climate interpretation of the event, so that climate interpretation matters for households' demand for protection beyond disaster salience.[76]

[74] Alok et al. (2020) find that nearby mutual fund managers underweight disaster-zone stocks more than distant managers, with this aversion declining over time and distance. Gallagher (2014) finds that flood insurance take-up spikes after a flood and then declines to baseline, while take-up in nonflooded communities in the same television market rises at one third the rate.

[75] I estimate local projections of cumulative first-time voluntary NFIP issuance per 100,000 residents from the disaster month through month h. County, episode and state-by-event-year fixed effects absorb persistent county differences and shared shocks and trends, so the identifying variation comes from how insurance purchases vary with climate attribution in affected relative to unaffected counties, conditional on total disaster and climate-only coverage. Standard errors are clustered by county.

[76] Wildfires can raise subsequent flood risk in some locations, depending on their terrain. However, the outcome is the change in take-up, so county fixed effects absorb how take-up usually responds in each location, and the comparison is within the same wildfire. The objective increase in flood risk does not depend on how local coverage reads the fire.

7.2 Survey Evidence on Taste or Belief Shocks

Survey evidence supports a belief-based interpretation centered on perceived climate harm, with weaker evidence for beliefs about human causes and climate-policy attitudes. I use the Climate Change in the American Mind surveys for 2009–2019, which measure climate beliefs, perceived risks and policy attitudes. Figure 7A shows that, comparing media markets within the same year, advisers hold larger green ETF shares where more residents expect global warming to harm Americans already or within ten years. Associations with human-causation beliefs and regulatory support are positive but imprecisely estimated. Appendix Table I.3 keeps market-years with at least 30 survey responses, while Appendix Table I.5, Column 1, pools each market's answers before 2018, so the two tables use different sets of markets.

Perceived harm also responds to disaster experience. Comparing respondents interviewed in the same media market and survey year in the four weeks before and after a flood begins, moderates and conservatives become more likely after the flood to report harm occurring now or within ten years. Among conservatives, estimated changes in human-causation beliefs and regulatory support are much smaller and statistically insignificant. This contrast indicates that the perceived immediacy of climate consequences connects disaster experience to green investment, while changes in causal beliefs and policy attitudes receive less consistent support.

The evidence on flood insurance in Section 7.1 also speaks to this question. First-time voluntary flood-insurance purchases provide concrete evidence that extreme weather events affect households' financial decisions through the climate risk-perception channel, since insurance decisions are not governed by sustainability preferences.

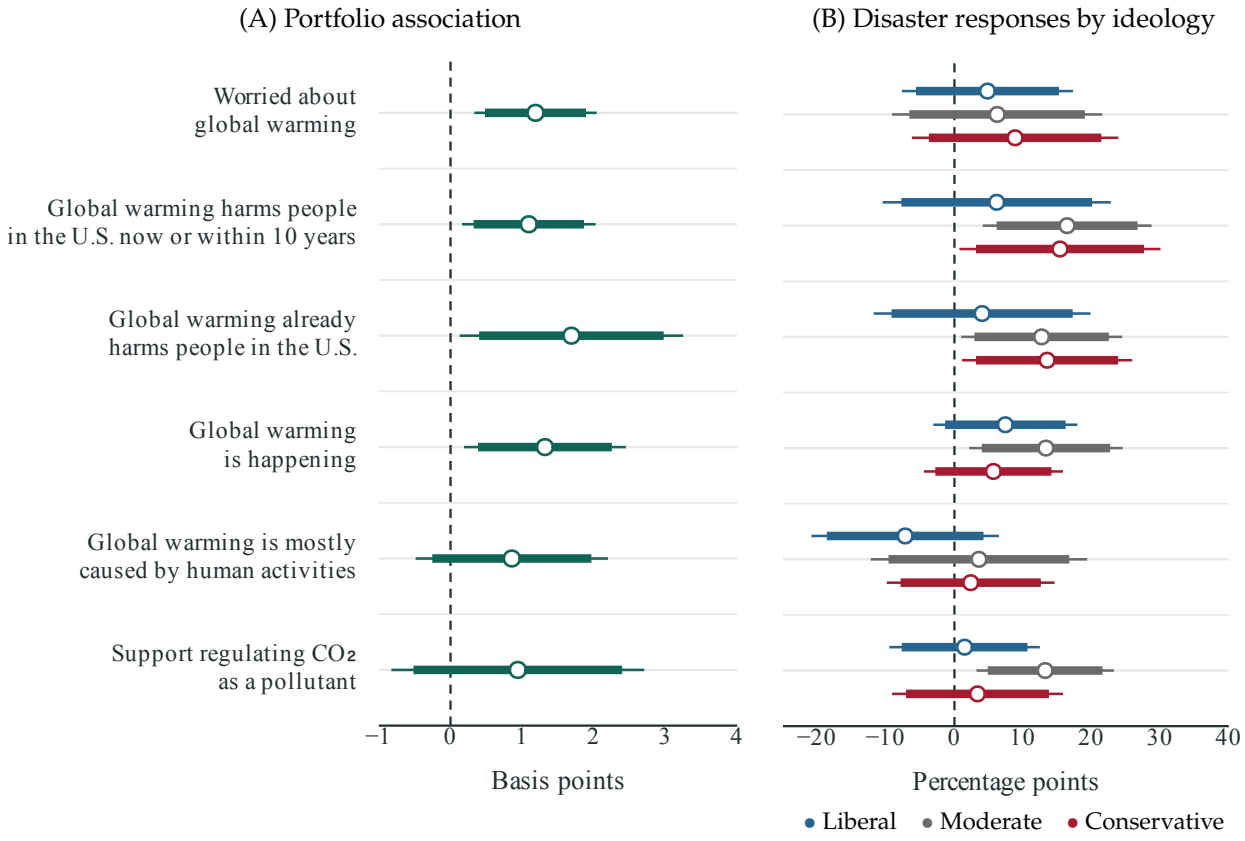
The suggestive evidence presented in this section points to at least some part played by beliefs.[77] Future work will tie the shift more tightly to one or the other. Although the origin of the shift is of academic interest, it does not change the role of interpretation, nor its implications in the aggregate.

8 Conclusion

This paper studies how the interpretation of an event shapes investors' portfolio decisions, separately from the information it reveals and the attention it receives. Using extreme weather events, I show that households and mutual fund managers reallocate toward sustainable assets when disasters are interpreted locally as evidence of climate change. This response is difficult to explain through differences in disaster attention, investors' prior political views and climate beliefs, or the direct effects of the disaster on asset fundamentals. Attention to a disaster increases trading activity without systematically shifting portfolios toward green assets, while its climate interpretation shapes the direction of reallocation. Changes in newspaper ownership further show that locally supplied interpretations can move portfolios independently of readers' prior beliefs and prefer-

[77] Harm perceptions rise after floods among moderates and even conservatives, advisers hold more green ETFs where residents expect harm sooner, and insurance take-up after wildfires rises with the climate interpretation of the event.

FIGURE 7: CLIMATE BELIEFS, GREEN INVESTMENT, AND DISASTER RESPONSES



Notes. Climate beliefs, green ETF holdings and the change in beliefs after floods, from the Climate Change in the American Mind surveys, 2009–2019. Each belief is an indicator for respondents who hold it. Panel A reports the association between the annual share of respondents holding each belief in a designated market area (DMA) and the green share of advisers' ETF holdings, per 10 percentage points of belief share. Advisers are included when they predominantly serve households and all their known US offices lie within one DMA. The Panel A regressions include year fixed effects. Panel B reports the change in each belief after a flood, separately for liberals, moderates and conservatives, using respondents in affected DMAs interviewed from 28 days before to 27 days after the start of the flood. The Panel B regressions include ideology indicators, DMA × survey-year, interview year-month and event fixed effects, and demographic and question-wording controls. The figure shows 95% and 90% confidence intervals, with standard errors clustered at the DMA level. Appendix Tables I.3 and I.4 report the estimates behind Panels A and B; Table I.5 reports them in standard deviations, with the response to the flood interacted with local interpretation.

ences. Evidence from surveys and insurance purchases is consistent with changes in perceived climate harm as a mechanism linking interpretation to financial decisions.

These responses extend beyond local portfolio choices. Climate interpretation is associated with greater inflows into ESG mutual funds, and a counterfactual exercise suggests that, if institutional investors responded as the affected advisers do, the resulting shifts in demand could have economically meaningful price effects. An interquartile increase in climate interpretation would imply 34 basis points of ESG-stock appreciation relative to other stocks, equivalent to 15% of the observed annual return spread. More broadly, the findings suggest that differences in how the same event is interpreted can have substantial consequences for capital allocation and asset prices, beyond the information the event conveys or the attention it attracts.

As climate change increases the frequency and severity of extreme weather events, understanding how their consequences propagate through financial markets becomes increasingly important. The findings suggest that the financial footprint of a disaster can extend well beyond its physical footprint. Previous research has examined how disasters affect firms exposed to physical risk and investors holding those firms (Alok et al., 2020; Dessaint and Matray, 2017; Kruttli et al., 2025). The results here highlight a different channel. When a disaster is interpreted locally as evidence of climate change, investors reallocate toward sustainable assets, even when those assets are not exposed to the event. Investors and regulators assessing the transmission of climate risk to asset prices therefore need to consider how disasters are interpreted locally, in addition to which firms are physically exposed.

The findings also speak to the ongoing debate about news deserts and the decline and consolidation of local journalism. Much of this debate concerns what communities lose when local newspapers disappear or reduce their coverage, including opportunities for local public discussion. Recent ownership changes have directly affected climate coverage, even at major national news organizations.[78] My findings highlight a further consequence. When newspaper chains acquire local outlets, the share of disaster coverage linking extreme weather to climate change declines, and the portfolio responses of local investors weaken. This suggests that the erosion of local climate interpretation may have consequences beyond public discourse, reducing demand for sustainable investments and, potentially, the financial incentives for firms to improve their environmental performance.

[78] After Skydance acquired Paramount in 2025, the new owner cut staff across the company and installed a new editor-in-chief at CBS News, which dismissed its climate unit and reduced climate coverage by 61 percent over the following year (Media Matters). The Washington Post and NPR have since dissolved their climate desks amid cost cuts following Bezos's restructuring and the rescission of federal public-media funding (Covering Climate Now, NPR Public Editor, 2026).

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A Data Construction

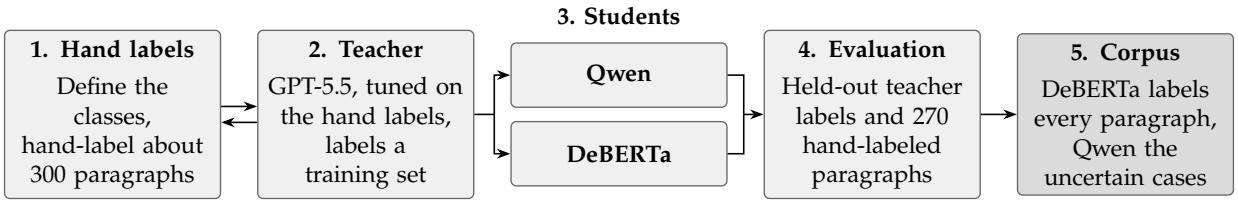
TABLE A.1: DISASTER SAMPLE: EPISODE CHARACTERISTICS

Selected flood, hurricane, wildfire, and coastal episodes, 2009–2024

Characteristic	Episodes (1)	Mean (2)	Std. dev. (3)	P25 (4)	Median (5)	P75 (6)	P90 (7)
Damage ($ millions)	1,938	167.11	1,776.55	1.33	3.37	12.26	61.38
Fatalities	1,938	1.27	5.23	0.00	0.00	1.00	3.00
Injuries	1,938	1.38	6.68	0.00	0.00	0.00	3.00
Affected counties	1,938	4.50	5.56	1.00	3.00	6.00	10.00
Duration (days)	1,938	5.04	7.13	1.00	2.00	5.00	15.00

Notes. Characteristics of the flood, hurricane, wildfire and coastal episodes used in the main analysis. Damage is in 2023 dollars. Fatalities, injuries and affected counties are measured for each episode. Affected counties are the distinct US counties linked to an episode.

FIGURE A.1: THE CLASSIFICATION PIPELINE



Notes. Steps of the paragraph-level classification of disaster articles. About 300 hand-labeled paragraphs are used to tune the prompts of a large language model, GPT-5.5, which then labels a training set. Two local models, DeBERTa and Qwen, are trained on this set and evaluated on held-out GPT-5.5 labels and on 270 hand-labeled paragraphs (Appendix Tables A.2 and A.3). DeBERTa classifies the full corpus and passes the paragraphs it classifies with low confidence to Qwen.

Table A.2: Candidate models against the reference labels

Model	Disaster (1)	Specific event (2)	Climate link (3)	Central link (4)	Skeptical (5)	Human toll (6)	Flip (7)
Qwen3.5-9B-staged	.952	.960	.947	.900	.911	.962	.015
DeBERTa-v3-large	.905	.932	.938	.869	.880	.909	.015
gpt-5.4-mini	.877	.917	.906	.838	.818	.954	.053
gpt-4.1-mini	.893	.895	.899	.605	.774	.893	.075
gpt-4o-mini	.745	.931	.739	.541	.804	.911	.063
Keyword rule	.809	.468	.856	.802	.597	.780	.215

Notes. Agreement between each candidate classification model and the reference labels. The reference labels are the GPT-5.5 labels. Columns 1 to 6 report positive-class F_1 scores on 1,399 held-out paragraphs, 639 random paragraphs and the 760 paragraphs of the hand-labeled articles. Scores range from 0 to 1, where 1 indicates perfect agreement. Climate link counts a passing or central link to climate change, and Central link counts only a central link. Flip is the share of paragraphs with an affirming or denying stance to which the model assigns the opposite stance. The keyword rule labels paragraphs from lists of hazard, climate, skeptic, casualty and event terms. It has no central-link label, so its climate-link label is used in Column 4.

Table A.3: Candidate models against hand labels on the held-out paragraphs

Model	Disaster (1)	Climate link (2)	Central link (3)	Skeptical (4)	Flip (5)
Qwen3.5-9B-staged	.888	.876	.727	.918	.009
DeBERTa-v3-large	.876	.868	.682	.871	.027
gpt-5.4-mini	.804	.768	.667	.830	.029
gpt-4.1-mini	.869	.846	.636	.800	.059
gpt-4o-mini	.667	.638	.526	.844	.077
Keyword rule	.803	.887	.684	.565	.196

Notes. Agreement between each candidate classification model and hand labels on 270 held-out paragraphs. Columns 1 to 4 report positive-class F_1 scores, which range from 0 to 1, where 1 indicates perfect agreement. Climate link counts a passing or central link to climate change, and Central link counts only a central link. Flip is the share of paragraphs with an affirming or denying stance to which the model assigns the opposite stance. The keyword rule labels paragraphs from lists of hazard, climate and skeptic terms. It has no central-link label, so its climate-link label is used in Column 3.

Table A.4: Example paragraphs and their classification

Climate link (1) Hurricane Helene, Associated Press, October 9, 2024	**Human toll and personal story** (2) Hurricane Katrina, *Wall Street Journal*, August 31, 2005
"The scientists warned that **continued burning of fossil fuels will lead to more hurricanes like Helene**, with 'unimaginable' floods well inland, not just on coasts." *Classification.* Specific disaster event; affirming climate link, central to the paragraph. The paragraph never mentions "climate change."	"After climbing out of one boat, Judy Martin took a few steps and then **collapsed onto the highway** [. . .] Ms. Martin said that **her 95-year-old mother had drowned in their house** as the floodwaters rose around them." *Classification.* Specific disaster event; human toll, told as one person's story; no climate link.

Notes. Two paragraphs from the coverage of disaster events and the labels the classifier assigns to them. Bold text marks the passages that determine the label.

TABLE A.5: AGREEMENT BETWEEN THE COUNTY NEWS CLASSES AND PUBLISHED NATIONAL CLIMATE-NEWS INDICES

News class	EGKLS WSJ (monthly)		MCCC (weekly)		NYT (monthly)	
	Level (1)	Innov. (2)	Level (3)	Innov. (4)	Level (5)	Innov. (6)
Panel A. Climate-topic classes						
Climate, no disaster, plus climate policy and green energy	.565	.333	−.011	.313	.159	.126
Climate coverage, no disaster	.564	.411	.227	.291	.305	.202
Climate policy and green energy	.550	.282	−.027	.309	.142	.106
Climate or peripheral (disaster-contaminated)	.318	.253	−.462	.299	−.580	.064
Panel B. Disaster classes						
Disaster coverage with a climate attribution	.475	.333	.647	.278	.709	.237
All disaster coverage	.088	.037	−.516	.019	−.553	−.059
Disaster policy, preparedness, insurance	−.067	.020	−.592	.046	−.683	−.132
Panel C. Pooled series, denominator and placebo						
All scored coverage except irrelevant	.207	.099	−.534	.149	−.583	−.034
All scored coverage	.140	.070	−.571	.127	−.628	−.045
Irrelevant coverage (placebo)	−.086	−.054	−.633	−.002	−.709	−.098
Periods (levels / innovations)	210 / 209		1,074 / 916		288 / 287	

Notes. Correlation between the county news classes and three published national climate-news indices. Each class is aggregated to a county panel, standardized within county and reduced to a national series by its first principal component across counties. Level columns report the correlation of this series with the published index in levels, and Innov. columns the correlation of their innovations. MCCC is published daily and aggregated to weeks, EGKLS is monthly and ends in June 2017, and the NYT index is published daily and aggregated to months. Innovations are AR(1) forecast errors, from the prior 156 weeks in the weekly comparison and from the full sample in the monthly comparisons, except for EGKLS, whose innovations are those published by the authors. The placebo row is coverage the classifier marks as unrelated to climate.

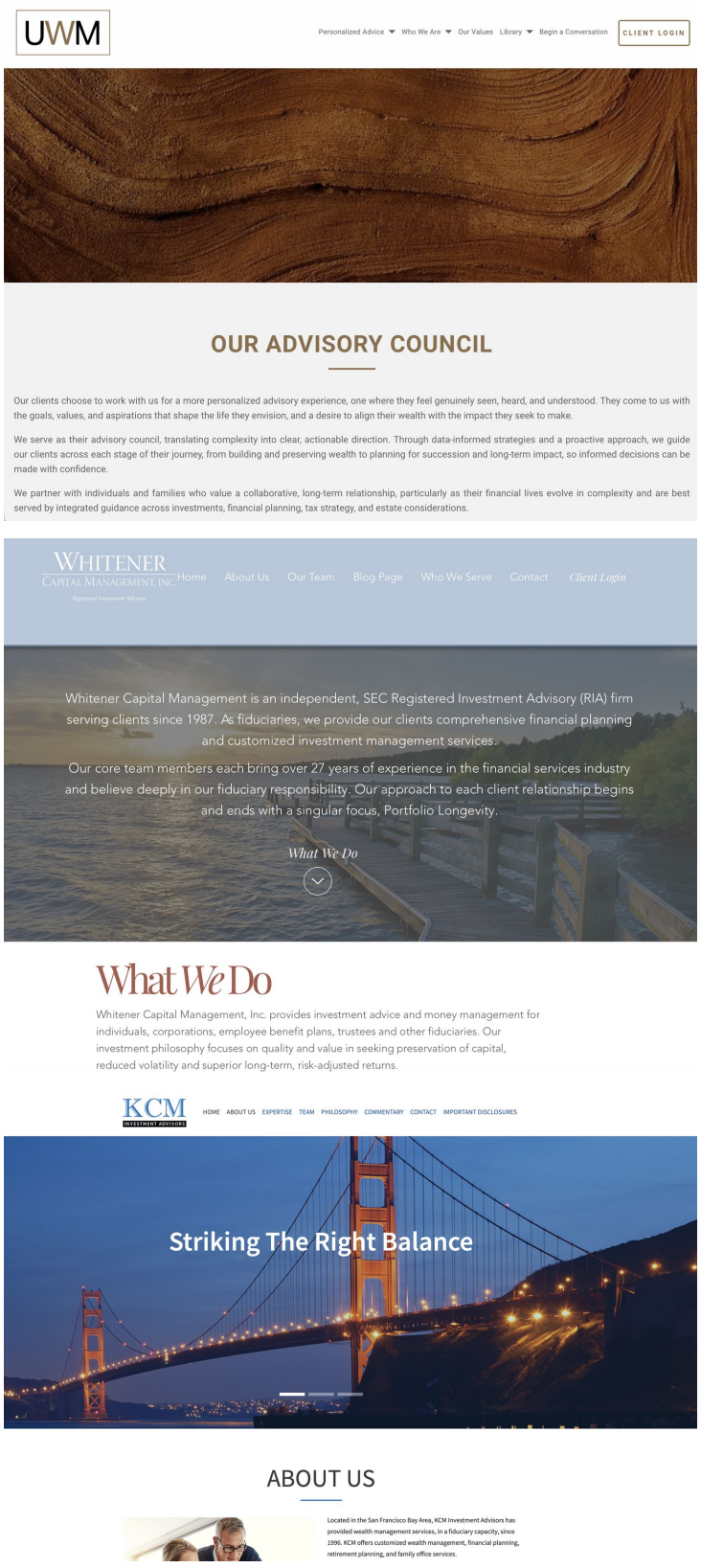
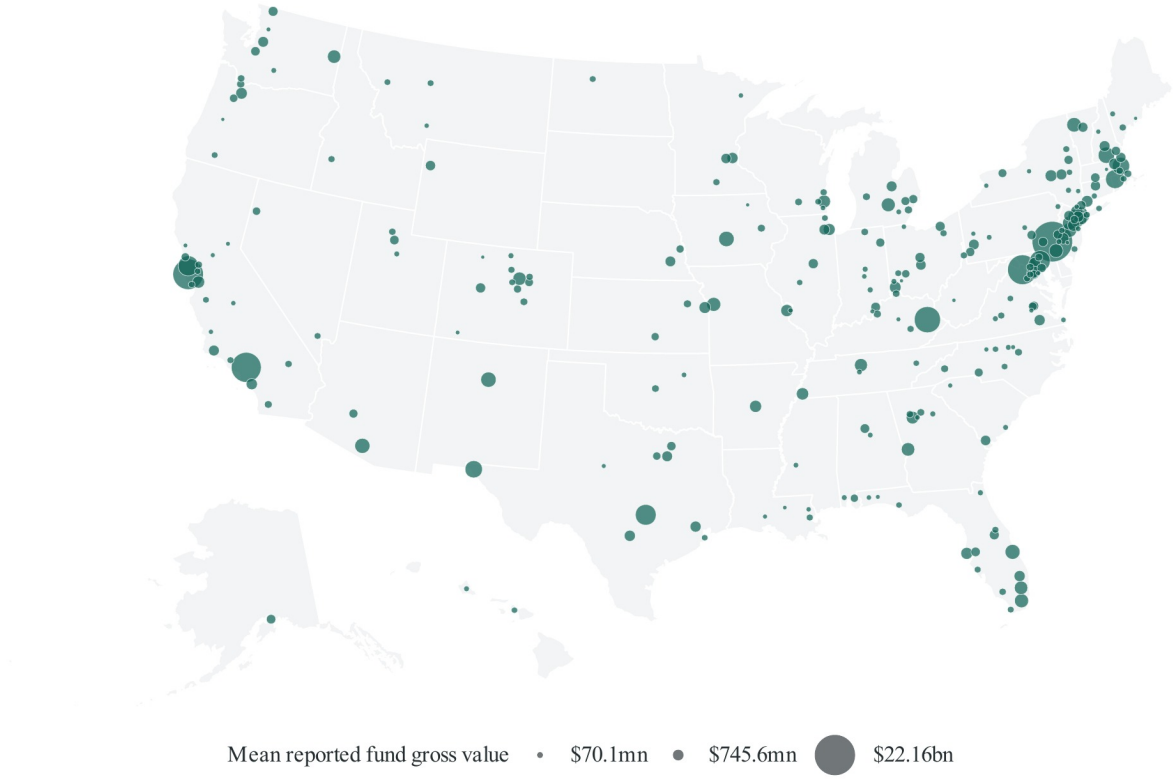


FIGURE A.2: THREE ILLUSTRATIVE LOCAL REGISTERED INVESTMENT ADVISERS

Notes. Public web pages of three advisers in the household-serving sample, chosen across its size range. Urban Wealth Management is near the bottom of the range, Whitener Capital at the median and KCM Investment Advisors near the top.

FIGURE A.3: MUTUAL-FUND MANAGEMENT GEOGRAPHY, 2009–2024



Notes. Counties from which mutual funds are managed, 2009–2024. Point area is the mean reported gross value of the funds managed from each county. Funds whose managers or managing firms span several counties are assigned to each county with proportional weights.

B Conceptual Framework and Empirical Strategy

I use a portfolio-choice model to describe how interpreting a disaster as evidence of climate change affects demand for ESG funds. The model links the local allocation response to investors' preferences and belief updating. It then provides the additional allocation for the exercise in Appendix J, holding attention and the wider information environment fixed.

B.1 Portfolio choice and beliefs

Consider an investor choosing the share $q \in [0, 1]$ of eligible wealth invested in a representative ESG portfolio. The remaining share, $1 - q$, is invested in an other-fund portfolio. Let $P > 0$ be the price of the ESG portfolio relative to the other-fund portfolio, whose price is normalized to one. Initial eligible capital is normalized to one. If q_0 is the inherited ESG share at relative price P^0, wealth before rebalancing is $w(P) = q_0 P/P^0 + 1 - q_0$. The chosen shares purchase $qw(P)/P$ units of the ESG portfolio and $(1 - q)w(P)$ units of the other portfolio, so the budget is satisfied without external deposits or withdrawals.

There are two future climate states, adverse h and benign l. In state k, the ESG and other portfolios pay $X_{Ek} > 0$ and $X_{Ok} > 0$ per unit, respectively. The investor incurs background loss L_k and receives a nonfinancial benefit ψg_k per ESG unit in consumption units: ψ measures preference strength and g_k the state-specific benefit. Let

$$r_k(P) = \frac{X_{Ek} + \psi g_k}{P} - X_{Ok}, \qquad k \in \{h, l\}, \tag{B.1}$$

be the payoff, including the holdings benefit, from shifting one dollar from the other-fund portfolio to the ESG portfolio. I assume $r_h(P) > 0 > r_l(P)$ over the relevant price range. The ESG tilt provides insurance in the adverse climate state at a cost in the benign state.

The other-fund portfolio costs one, so X_{Ok} is its return per dollar in state k, the benchmark return. The ESG portfolio costs P, so $(X_{Ek} + \psi g_k)/P$ is its return per dollar, the economic payoff plus the nonfinancial benefit, and $r_k(P)$ in equation (B.1) is the difference between the two. For perceived probability π of the adverse state, the investor has exponential utility of end-of-period consumption with risk aversion $\rho > 0$ and solves

$$\begin{aligned} \max_{0 \le q \le 1} \quad & -\pi \exp\left\{-\rho\left[w(P)\left((1-q)X_{Oh} + q\,\frac{X_{Eh} + \psi g_h}{P}\right) - L_h\right]\right\} \\ & -(1-\pi)\exp\left\{-\rho\left[w(P)\left((1-q)X_{Ol} + q\,\frac{X_{El} + \psi g_l}{P}\right) - L_l\right]\right\}, \end{aligned} \tag{B.2}$$

which, collecting the terms in q and using $r_k(P)$, is

$$\begin{aligned} \max_{0 \le q \le 1} \quad & -\pi \exp\{-\rho\left[w(P)X_{Oh} - L_h + w(P)q r_h(P)\right]\} \\ & -(1-\pi)\exp\{-\rho\left[w(P)X_{Ol} - L_l + w(P)q r_l(P)\right]\}. \end{aligned} \tag{B.3}$$

The news changes the perceived probability of each climate state, while asset payoffs and losses within each state, as well as investors' preferences, remain unchanged. The following derivation considers interior portfolios.

For episode e, let $f_i(z_e \mid k)$ be investor i's subjective likelihood of disaster news z_e in state k. Define the likelihood ratio $\mathrm{LR}_{i,e} = f_i(z_e \mid h)/f_i(z_e \mid l)$ and its logarithm $\ell_{i,e} = \log \mathrm{LR}_{i,e}$.

The event indicator η_e is zero before disaster news and one afterward. Let $\pi_{0i} \in (0,1)$ and π_{1i} be the prior and posterior probabilities of the adverse state, with odds $\omega_{0i} = \pi_{0i}/(1-\pi_{0i})$ and $\omega_{1i} = \pi_{1i}/(1-\pi_{1i})$. Bayes' rule gives

$$\omega_{1i} = \omega_{0i}\mathrm{LR}_{i,e}^{\eta_e}, \qquad \log \omega_{1i} = \log \omega_{0i} + \eta_e \ell_{i,e}. \tag{B.4}$$

Positive $\ell_{i,e}$ raises perceived adverse-climate risk. Interpretation may reflect investors' own models or supplied narratives. The benchmark shares preferences, prior odds $\omega_{0i} = \omega_0$, and initial normalized portfolios; investors do not infer additional information from prices.

B.2 The predicted portfolio response

Dividing expected utility by $1-\pi$ leaves the optimal portfolio unchanged. Beliefs then enter through the odds of the adverse state relative to the benign state, $\omega = \pi/(1-\pi)$. Differentiating with respect to q and dividing by $\rho w(P)$ gives the optimality condition

$$\begin{aligned} &\omega r_h(P) e^{-\rho[w(P)X_{Oh} - L_h + w(P)q r_h(P)]} \\ &\quad = [-r_l(P)] e^{-\rho[w(P)X_{Ol} - L_l + w(P)q r_l(P)]}. \end{aligned} \tag{B.5}$$

Denote the optimal ESG share by $q^*(P,\omega)$. Taking logarithms gives a linear equation in this share. Because news changes log odds by $\eta_e \ell_{i,e}$, the solution implies

$$q^*(P,\omega_{1i}) - q^*(P,\omega_0) = \eta_e \chi(P)\ell_{i,e}, \qquad \chi(P) = \frac{1}{\rho w(P)[r_h(P) - r_l(P)]} > 0. \tag{B.6}$$

Here $\chi(P)$ is the change in the ESG share per unit increase in log odds, holding the price fixed. The formula applies to finite belief updates on the interior support.

Let $q_0 = q^*(P^0,\omega_0)$ be the initial optimal share. At initial prices, the event changes desired allocation by

$$\begin{aligned} &u_{i,e} \equiv q^*(P^0,\omega_{1i}) - q_0 = \eta_e \chi(P^0)\ell_{i,e} = \eta_e \gamma_{i,e}, \\ &\gamma_{i,e} \equiv \chi(P^0)\ell_{i,e}. \end{aligned} \tag{B.7}$$

Thus $u_{i,e} = 0$ before news ($\eta_e = 0$) and $u_{i,e} = \gamma_{i,e}$ after news ($\eta_e = 1$). The event response $\gamma_{i,e}$ combines portfolio responsiveness and the belief update at initial prices.

At post-news relative price P_e, the observed share change is $\Delta q_{i,e} = q^*(P_e,\omega_{1i}) - q_0$. Adding

and subtracting the post-news allocation at initial prices gives

$$\Delta q_{i,e} = u_{i,e} + \underbrace{q^*(P_e, \omega_{1i}) - q^*(P^0, \omega_{1i})}_{\text{response to the price change after news}} . \tag{B.8}$$

The ratio P_e/P^0 is the gross relative-price return, and $(P_e - P^0)/P^0$ is the corresponding net return. Thus $\Delta p_e = \log(P_e/P^0) = \log(1 + (P_e - P^0)/P^0) \approx (P_e - P^0)/P^0$. No relative-price change means gross return one, net return zero, and $\Delta p_e = 0$. The expansion around $\Delta p_e = 0$ therefore concerns small relative-price returns. Holding updated beliefs fixed gives

$$\begin{aligned} \Delta q_{i,e} &= u_{i,e} - \zeta^q_{i,e} \Delta p_e + o(|\Delta p_e|), \\ \zeta^q_{i,e} &= - \left. \frac{\partial q^*(P, \omega_{1i})}{\partial \log P} \right|_{P=P^0} . \end{aligned} \tag{B.9}$$

The coefficient $\zeta^q_{i,e}$ measures the response of the portfolio share to prices. Its independence from the news is an additional local restriction.

Assumption: price responsiveness. Disaster exposure and stronger climate interpretation shift desired allocations but do not change investors' responsiveness to prices. Conditional on the controls, average price responsiveness does not systematically differ with disaster exposure or interpretation.[79]

I impose this assumption on the local price-response term in (B.9). The common price movement then contributes an episode component to the conditional mean, while differences associated with disaster exposure and interpretation reflect $u_{i,e}$. For holdings valued at initial prices, I impose the corresponding conditional-average restriction on the price response of that measured share.[80]

B.3 From the model to the estimating equation

Let $A_{i,e}$ denote attention to disaster news, $I_{i,e}$ its climate interpretation, and Z_e the wider information environment. Write the belief update as $\ell_{i,e} = \ell_i(A_{i,e}, I_{i,e}, Z_e)$ and the allocation response as $u_{i,e}(A, I, Z) = \eta_e \chi(P^0) \ell_i(A, I, Z)$.

For county c, the impact outcome $\Delta q_{c,e} = q_{c,0} - q_{c,-1}$ is the ESG-share change from the pre-event quarter -1 to the event quarter 0. Let $I_{c,e}$ be the circulation-weighted average of outlets' shares of disaster articles linking the event to climate change. Write $I^*_{c,e} = (I_{c,e} - \bar{I})/\sigma_I$, where $\bar{I}$ and σ_I are its sample mean and standard deviation. Let $A_{c,e}$ be local disaster-news coverage and $A^*_{c,e}$ its standardized $\log(1 + A_{c,e})$. Set $H_{c,e} = 1$ for affected counties and zero for clean comparison counties in the same episode. All these counties are observed around a disaster, so $\eta_e = 1$.

[79] A related benchmark in van der Beck et al. (2025), Assumption 1, allows heterogeneous price elasticities that are independent of the process generating demand shifts across investors.

[80] Let $q_i = q^*(P, \omega_{1i})$. The share of these holdings valued at P^0 is $q_i^{\text{FP}} = (P^0/P)q_i/[1 - q_i + (P^0/P)q_i]$. At $P = P^0$, it equals q_i, so its initial-price information shift is also $u_{i,e}$. Its price response is obtained by expanding this measured share; its coefficient generally differs from $\zeta^q_{i,e}$.

Let $\ell_{c,e}$ be the conditional average belief update and $\ell^0_{c,e}$ its value at mean interpretation. Holding attention and controls fixed, I assume a unit increase in I^* changes the belief update by $\gamma^\ell_{1,e}$ among affected investors and $\gamma^\ell_{0,e}$ among comparison investors:

$$\ell_{c,e} = \ell^0_{c,e} + \gamma^\ell_{H_{c,e},e} I^*_{c,e}. \tag{B.10}$$

In the common-response benchmark, $u_{c,e} = \chi(P^0)\ell_{c,e}$. Write $\overline{\Delta q}_{c,e}$ for the predicted share change conditional on exposure, interpretation, attention, controls, and episode. Under the price-response assumption, comparing counties c and c' at the same controls within an episode gives

$$\overline{\Delta q}_{c,e} - \overline{\Delta q}_{c',e} \simeq u_{c,e} - u_{c',e} = \chi(P^0)\big(\ell_{c,e} - \ell_{c',e}\big). \tag{B.11}$$

The approximation inherits the price remainder in (B.9). Individual price responses may differ; the assumption concerns their conditional average in the comparison.

Let $b_e = -\bar{\zeta}^q_e \Delta p_e$ denote the common conditional price contribution, where $\bar{\zeta}^q_e$ is average price responsiveness. Substituting the interpretation rule into the allocation response gives

$$\begin{aligned} \overline{\Delta q}_{c,e} \simeq b_e + \chi(P^0)\ell^0_{c,e} + \chi(P^0)\gamma^\ell_{0,e} I^*_{c,e} \\ + \chi(P^0)(\gamma^\ell_{1,e} - \gamma^\ell_{0,e}) H_{c,e} I^*_{c,e}. \end{aligned} \tag{B.12}$$

Assume a linear baseline response. Let λ_e denote episode effects, δ_H the exposure coefficient, β_A the comparison-county attention slope, and δ_A its affected-county increment. Remaining controls and other fixed effects $\mathbf{W}_{c,e}$ have coefficients θ:

$$\begin{aligned} b_e + \chi(P^0)\ell^0_{c,e} = \lambda_e + \delta_H H_{c,e} + \beta_A A^*_{c,e} \\ + \delta_A H_{c,e} A^*_{c,e} + \mathbf{W}'_{c,e}\theta. \end{aligned} \tag{B.13}$$

Episode effects absorb b_e; portfolio responsiveness $\chi(P^0)$ remains in the interpretation response.

With interpretation slope β_I in comparison counties, affected-county increment δ_I, and regression residual $\varepsilon_{c,e}$, the estimating equation is

$$\begin{aligned} \Delta q_{c,e} = \lambda_e + \delta_H H_{c,e} + \beta_A A^*_{c,e} + \beta_I I^*_{c,e} \\ + \delta_A H_{c,e} A^*_{c,e} + \delta_I H_{c,e} I^*_{c,e} + \mathbf{W}'_{c,e}\theta + \varepsilon_{c,e}. \end{aligned} \tag{B.14}$$

The residual includes individual deviations from the conditional price response and has zero conditional mean in the maintained first-order representation. Matching the interpretation terms gives

$$\beta_I = \chi(P^0)\gamma^\ell_{0,e}, \qquad \delta_I = \chi(P^0)(\gamma^\ell_{1,e} - \gamma^\ell_{0,e}). \tag{B.15}$$

This coefficient mapping assumes that the response products are common across episodes. Otherwise, the pooled coefficients summarize the heterogeneous products using the county–episode variation remaining after controls and fixed effects; they are not generally arithmetic averages.

The mapping therefore uses the portfolio model, the local price approximation and price-response assumption, the linear interpretation and baseline relations, and common response products across episodes. Under these assumptions, the interpretation effect among affected investors is

$$\beta_I + \delta_I = \underbrace{\chi(P^0)}_{\substack{\text{portfolio response} \\ \text{to a belief update}}} \underbrace{\gamma^{\ell}_{1,e}}_{\substack{\text{belief response} \\ \text{to interpretation}}} = \frac{\gamma^{\ell}_{1,e}}{\rho[r_h(P^0) - r_l(P^0)]}. \tag{B.16}$$

It measures the additional desired ESG share at initial prices from one standard deviation more climate interpretation, holding attention and controls fixed. Here $w(P^0) = 1$ by the initial wealth normalization.

For stronger interpretation I^1 relative to baseline I^0 in the same county and event, define $a^I_{i,e} = u_{i,e}(A, I^1, Z) - u_{i,e}(A, I^0, Z)$. Appendix J aggregates its estimated counterpart,

$$\widehat{a}^I = (\widehat{\beta}_I + \widehat{\delta}_I)\frac{I^1 - I^0}{\sigma_I}. \tag{B.17}$$

B.4 County and adviser portfolio aggregation

For a common set of advisers observed at both endpoints, let $\omega_{ac,t}$ denote adviser a's share of county ETF holdings and g_{at} its green ETF share. The change in the county green share satisfies

$$\Delta g_c = \underbrace{\sum_{a \in c} \omega_{ac,0} \Delta g_a}_{\text{within-adviser changes at pre-disaster weights}} + \underbrace{\sum_{a \in c} (\omega_{ac,1} - \omega_{ac,0}) g_{a,1}}_{\text{changes in advisers' relative ETF holdings}}. \tag{B.18}$$

Both components can reflect household investment decisions. The county outcome captures their combined contribution, whereas the pre-disaster-weighted average of adviser changes captures the first component. The two changes coincide when the second component is zero; unchanged adviser weights are a sufficient condition. Holding ETF prices fixed does not itself hold advisers' relative ETF holdings fixed, since purchases and sales can change those holdings.

Regression equivalence additionally requires the same estimation support and outcome window, regressors common to advisers within each county-event observation, and compatible regression weights. If the county-event regression weight is q_{ce}, the corresponding adviser weight is $q_{ce}\omega_{ac,0}$, with adviser shares summing to one on the estimation sample. County-event regressors and fixed effects must be repeated identically across its advisers. Under these conditions, the weighted adviser regression has the same coefficient estimates as the county regression using $\sum_a \omega_{ac,0}\Delta g_a$ as its outcome. The coefficients also equal those from the actual county outcome when the second component is zero. More generally, the difference in a particular coefficient equals the coefficient from regressing that second component on the same regressors with the same county-event weights. Standard-error equivalence requires compatible clustering and finite-sample adjustments as well.

The reported regressions are complementary specifications. The county outcome compares the average green share in quarters 0 through 2 with its average in quarters −2 and −1, while the adviser outcome compares quarters +1 and −1. Adviser financial controls and, in one column, adviser fixed effects also distinguish the specifications. Their similar magnitudes are therefore an empirical comparison rather than an exact regression identity.

C Appendix to Section 2

Table C.1: Scale and household relevance of the adviser ETF channel

	All registered advisers (1)	Household-serving advisers (2)
Panel A. ETF adoption among registered investment advisers, 2009–2024		
Registered investment advisers	8,489	4,439
Adviser-quarters holding any ETF (%)	72.1	87.4
Advisers ever holding any ETF (%)	87.1	97.3
Adviser-quarters holding a green ETF (%)	16.4	19.8
Advisers ever holding a green ETF (%)	36.3	45.6
	All single-county advisers (1)	Household-serving single-county advisers (2)
Panel B. Portfolio allocation among single-county ETF holders, 2009–2024		
ETF value / observed 13F value (%)	8.1	17.7
ETF value / (ETF + directly held stocks) (%)	8.4	18.3
Median adviser-quarter ETF value / observed 13F value (%)	19.1	28.1
Adviser-quarters with ETF value above directly held stocks (%)	34.8	39.6
Green-ETF value / ETF value (%)	0.9	1.1
Green-ETF value / observed 13F value (%)	0.07	0.19
	Share of total market (%)	Share of observed Form 13F value (%)
Panel C. Share of the U.S. ETF market by reporting sector, 2024Q4 ($10,294.1 billion)		
All registered advisers	41.1	67.0
Household-serving single-county advisers	8.1	13.1
Other registered advisers	33.1	53.8
Other Form 13F institutions	20.3	33.0
Households and other non-13F holders, residual	38.6	—
Panel D. Share of the U.S. green-ETF market by reporting sector, 2024Q4 ($91.7 billion)		
All registered advisers	45.2	71.6
Household-serving single-county advisers	12.8	20.3
Other registered advisers	32.4	51.3
Other Form 13F institutions	17.9	28.4
Households and other non-13F holders, residual	36.9	—

Notes. ETF holdings of registered investment advisers and their share of the U.S. ETF market. Panel A includes relying advisers. Panel B covers adviser-quarters with positive ETF holdings. Its ratios pool market values across adviser-quarters, except for the median, which is taken across adviser-quarters. The first column divides by total CRSP ETF market capitalization and the second by the CRSP-matched ETF value reported on Form 13F. The residual row is the market value not reported on Form 13F.

Table C.2: Scale of the registered-adviser sample at the end of 2024

	All registered advisers (1)	Household-serving, single-county (2)
Regulatory assets under management ($ billions)	73,545.3	5,319.3
Share of all registered advisers' regulatory assets (%)	100.0	7.2
Client accounts (millions)	49.75	12.25
ETF holdings ($ billions)	3,957.5	828.7
Green-ETF holdings ($ billions)	38.2	11.7

Notes. Aggregate size of all registered investment advisers and of household-serving, single-county advisers in the fourth quarter of 2024. Regulatory assets under management cover all client types. ETF holdings are Form 13F ETF positions valued at the last December CRSP price of the year.

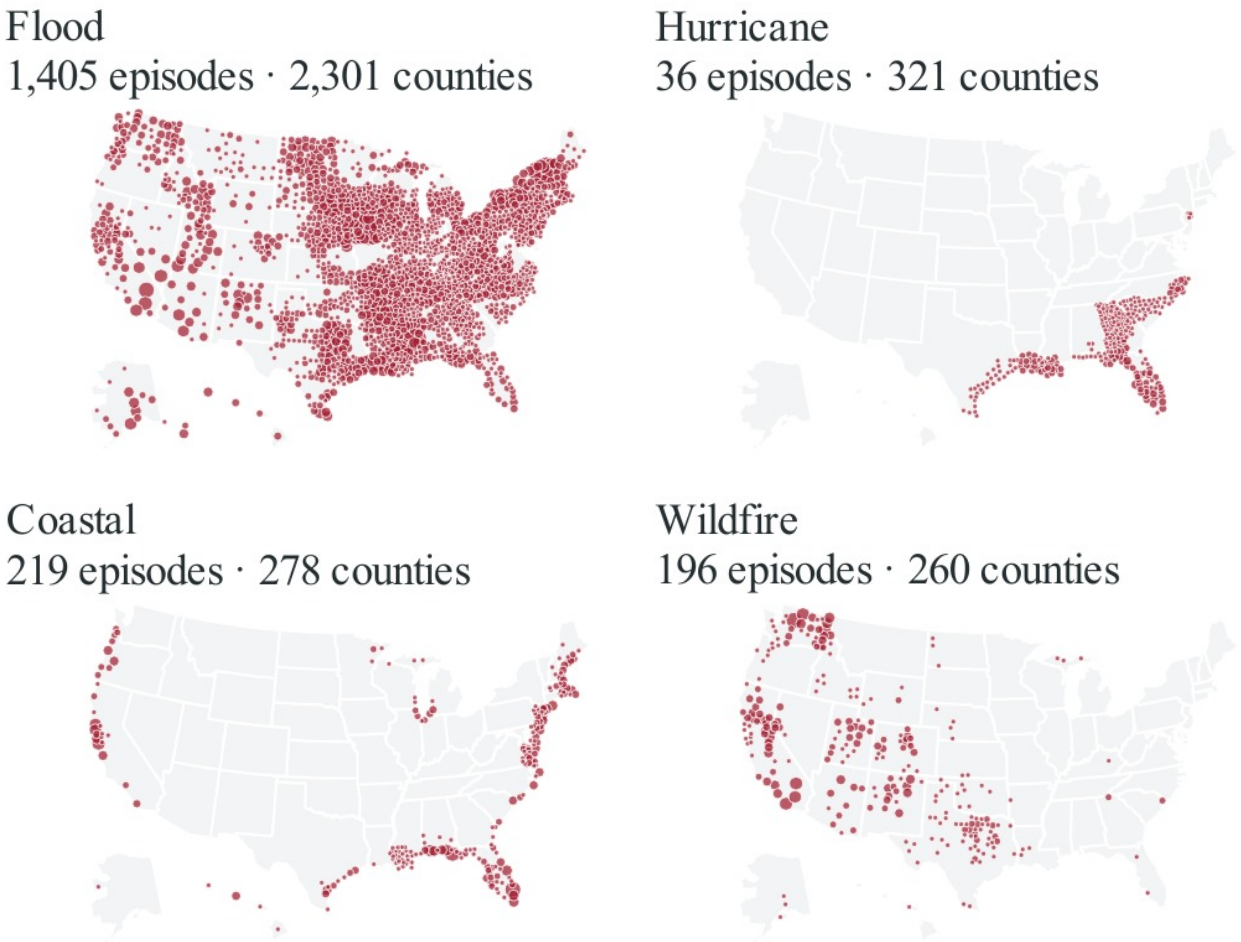


Figure C.1: Geographic distribution of within-hazard top-salience episodes

Notes. U.S. counties affected by flood, hurricane, coastal and wildfire episodes that begin between 2009 and 2024, one map per hazard. Each map keeps the episodes in the top 15 percent of the salience index within their hazard type. Point area is the number of episodes in the county. The panel headers report the number of episodes and of affected counties.

TABLE C.3: ADVISER GREEN-ETF PORTFOLIO RESPONSE

	Dependent variable:					
	Green-ETF share response (bp)			Entry into green ETFs (pp)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Advisers weighted by their share of the county's ETF holdings						
Affected × Interpretation	23.21***	27.19***	26.81***	5.20**	5.06**	6.07**
	(7.76)	(8.25)	(8.94)	(2.23)	(2.53)	(2.41)
Affected × Attention	10.68**	11.02*	12.53*	−.42	.84	1.15
	(5.18)	(5.98)	(6.94)	(1.11)	(1.14)	(1.17)
Total Interpretation effect among affected advisers	22.81***	26.78***	26.57***	5.27**	5.13**	6.20**
	(7.73)	(8.24)	(9.00)	(2.20)	(2.50)	(2.40)
Observations	465,701	465,701	465,641	350,373	350,373	350,322
R^2	.090	.090	.132	.196	.196	.375
Affected adviser-episodes	1,156	1,156	1,096	857	857	806
Panel B. Advisers weighted equally						
Affected × Interpretation	14.55**	14.12**	15.06**	2.52*	3.32**	4.00**
	(6.97)	(6.83)	(7.52)	(1.30)	(1.43)	(1.61)
Affected × Attention	15.30***	16.71***	20.55***	−.58	.27	.64
	(3.76)	(4.02)	(4.83)	(.95)	(1.07)	(1.24)
Total Interpretation effect among affected advisers	14.37**	13.95**	14.65*	2.45*	3.24**	3.94**
	(6.90)	(6.77)	(7.46)	(1.31)	(1.44)	(1.61)
Observations	465,701	465,701	465,641	350,373	350,373	350,322
R^2	.018	.018	.155	.075	.075	.346
Affected adviser-episodes	1,156	1,156	1,096	857	857	806
Episode and quarter FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓		✓	✓	
Adviser FE			✓			✓
Affected × hazard × year FE	✓	✓	✓	✓	✓	✓
Financial and demographic controls	✓	✓	✓	✓	✓	✓
County damages, fatalities and injuries	✓	✓	✓	✓	✓	✓
Political and belief controls	✓	✓	✓	✓	✓	✓
Lagged climate attention	✓	✓	✓	✓	✓	✓
Affected × controls		✓	✓		✓	✓

Notes. Effect of local climate interpretation on the green-ETF portfolio of registered investment advisers after disasters. In Columns 1 to 3, the outcome is the change in the adviser's green-ETF share from the quarter before the episode to the quarter after it. In Columns 4 to 6, the sample includes only advisers with no green ETF in the quarter before the episode, and the outcome is 100 times an indicator for holding a green ETF in the quarter after it. Panel A weights use ETF holdings in the quarter before the episode. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage, both measured over the first four weeks of the episode and standardized. Financial controls are the logs of the adviser's ETF holdings and of its total Form 13F holdings in the quarter before the episode. Demographic controls are county income, college share, white share, population and population density. Political and belief controls are the prior county Democratic vote share and the county share worried about global warming. Lagged climate attention is the share of local coverage on climate policy and green topics in the quarter before the episode. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

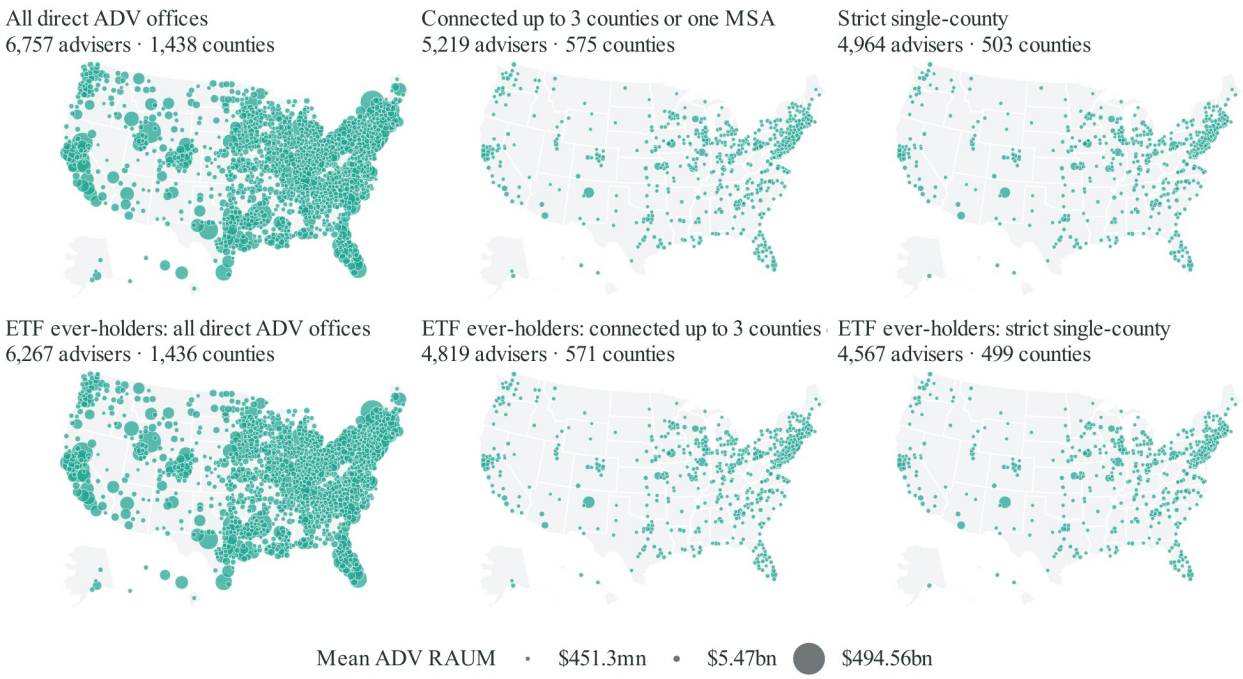
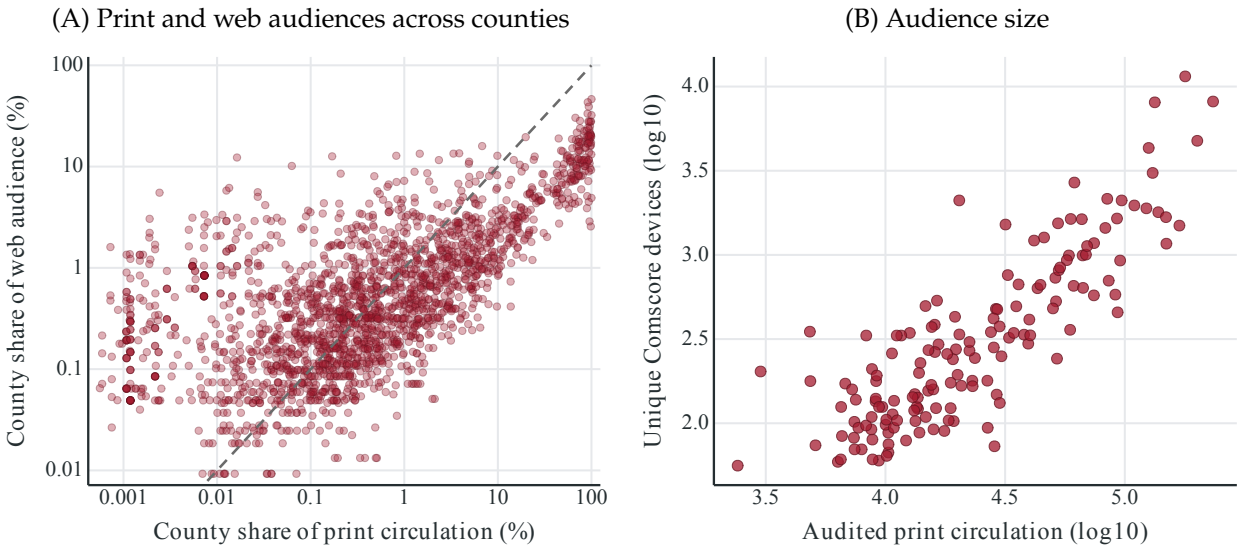


FIGURE C.2: REGISTERED INVESTMENT-ADVISER GEOGRAPHY AND ETF PARTICIPATION

Notes. Location of the principal and branch offices that registered investment advisers report on Form ADV, 2009–2024. Hedge-fund managers and exempt reporting advisers are excluded. The top row shows, from left to right, all offices, advisers whose offices lie in at most three connected counties or one metropolitan statistical area, and advisers whose offices all lie in one county. The bottom row repeats these maps for advisers that held an ETF at least once during 2009–2024. Point area is the mean regulatory assets under management of the advisers in the county.

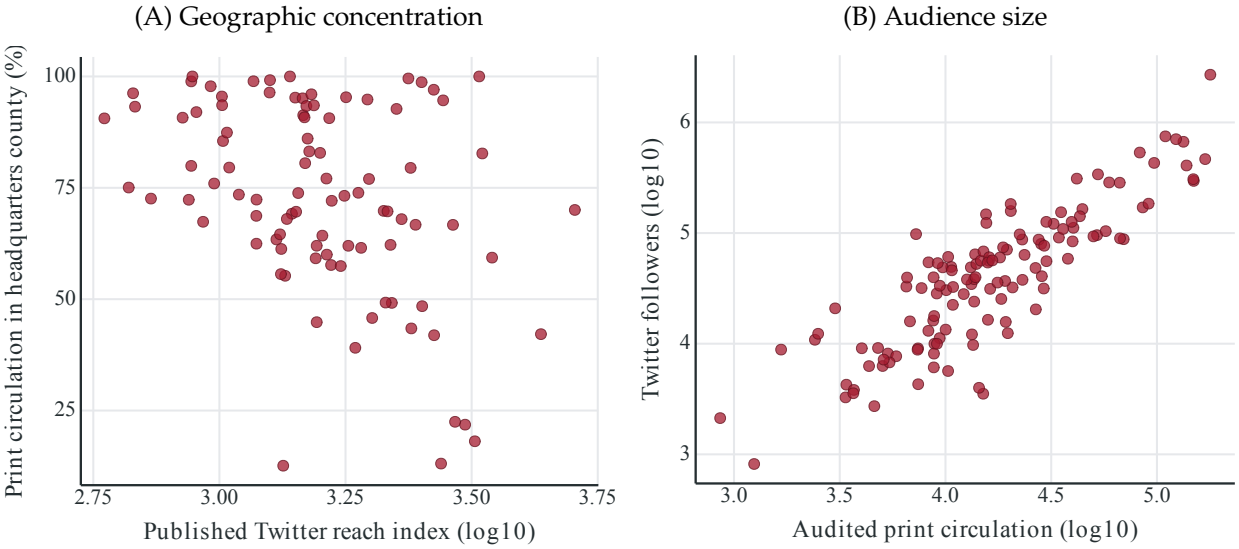
D Appendix to Section 2.2

FIGURE D.1: PRINT CIRCULATION AND OBSERVED WEB AUDIENCES



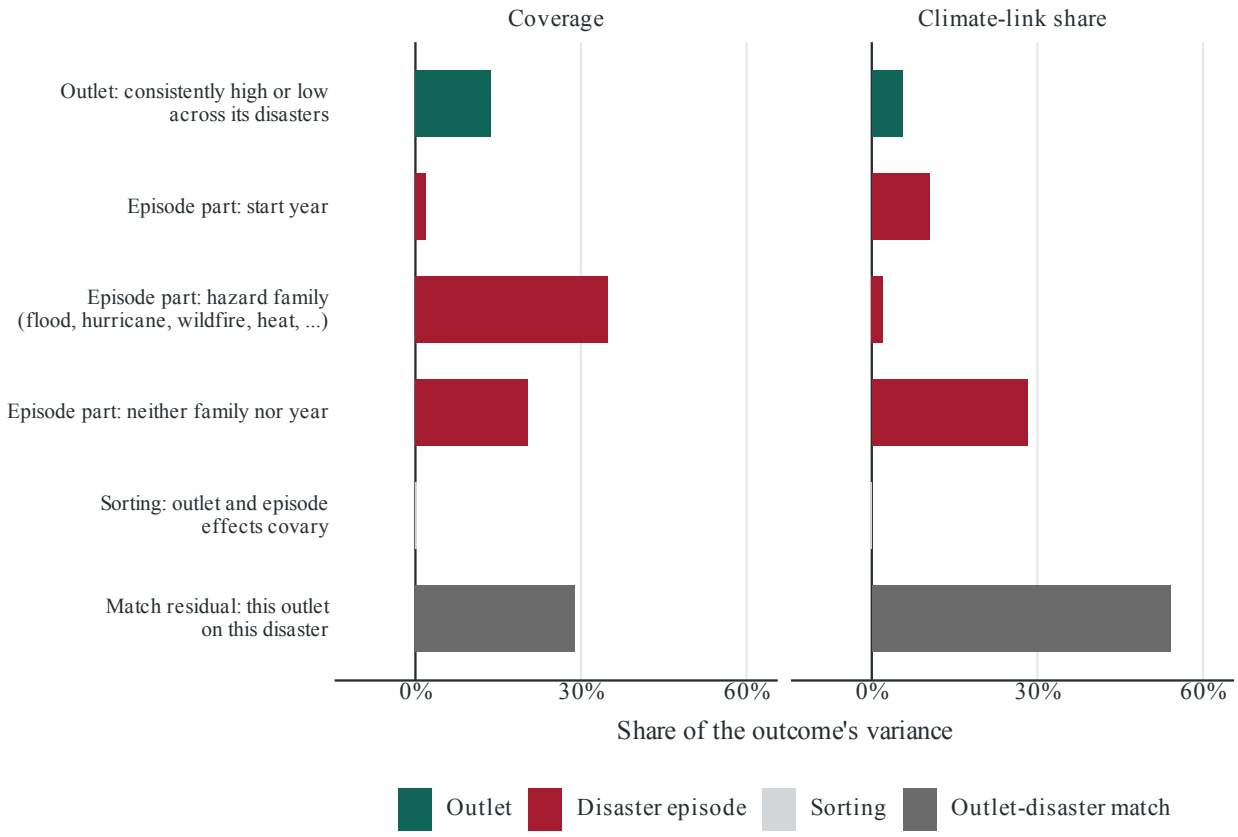
Notes. Comscore web audiences and audited print circulation of 153 local newspapers. Panel A plots, for 2,114 newspaper and county pairs observed in both sources, the share of the newspaper's web audience in the county against the share of its print circulation in the county, on logarithmic axes. The dashed line marks equal shares. The Pearson correlation of the shares is 0.822 and the Spearman correlation is 0.628. Panel B plots the number of distinct Comscore devices reaching each newspaper against its audited print circulation, both in logs (Spearman correlation 0.823). Web audiences are measured in 2020 and print circulation averages the audits available for 2015–2025. Newspapers with fewer than 50 unique web devices are excluded.

FIGURE D.2: PRINT CIRCULATION AND TWITTER AUDIENCES



Notes. Twitter audiences and audited print circulation of local newspapers. Panel A plots the share of each newspaper's audited circulation in its headquarters county against the population-reach index of Le Quéré et al. (2022), for 93 newspapers (Spearman correlation −0.360). Higher index values indicate a geographically broader Twitter audience. Panel B plots total Twitter followers against total audited print circulation, both in logs, for 127 newspapers. Each newspaper receives equal weight. Twitter counts are recorded in 2020 or 2022, and print circulation averages the audits available for 2015–2025.

FIGURE D.3: VARIANCE DECOMPOSITION OF COVERAGE AND CLIMATE INTERPRETATION



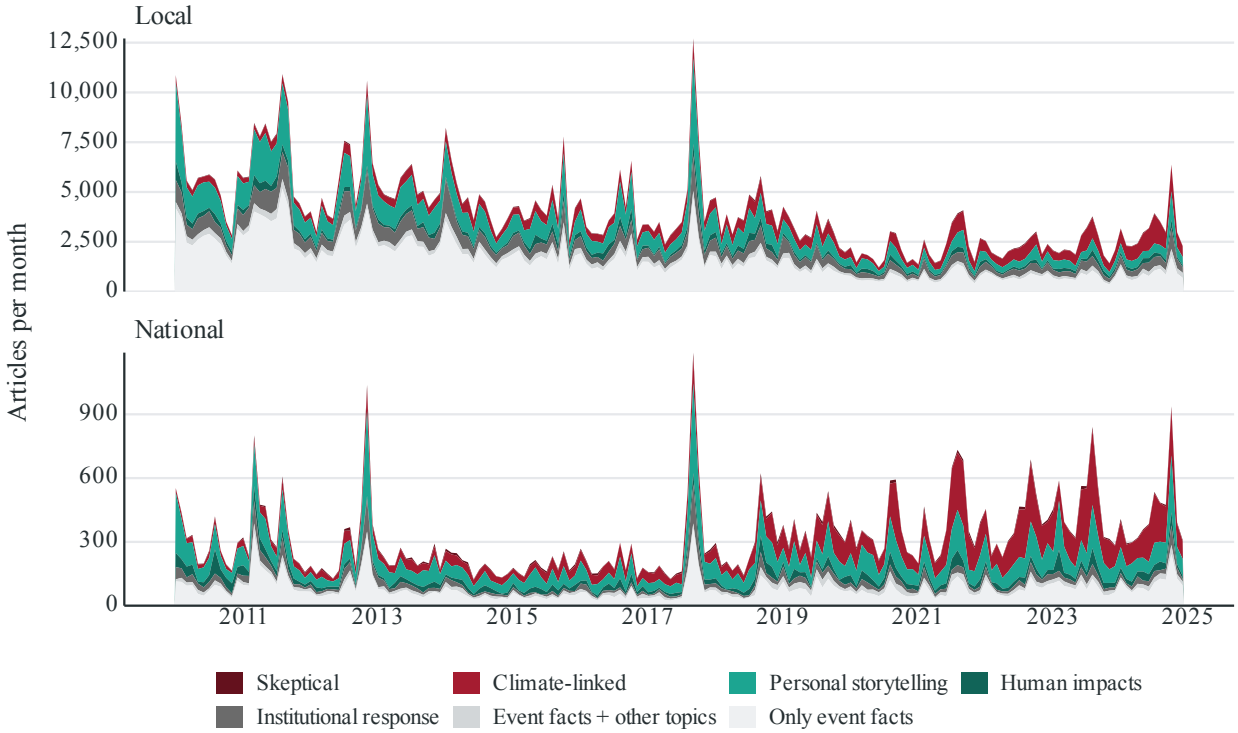
Notes. Decomposition of the variance of disaster coverage (left panel) and of the climate-link share (right panel) across outlets and disasters, in weeks 0 to 3 from the start of the disaster. Coverage is the log of one plus the number of articles on the disaster, including outlets with no article. The climate-link share is the share of these articles that link the disaster to climate change, among outlets with at least one article. Bars report the share of total variance due to the outlet, to the parts of the disaster episode, to the covariance of outlet and episode effects (sorting), and to the residual specific to each outlet and disaster.

TABLE D.1: COMPOSITION OF DISASTER COVERAGE: CHAIN-OWNED AND INDEPENDENT LOCAL OUTLETS

	Dependent variable: article belongs to the category (percent)						
	Skeptical (1)	Climate-linked (2)	Personal storytelling (3)	Human impacts (4)	Institutional response (5)	Event facts + other topics (6)	Only event facts (7)
Panel A. No fixed effects							
Local, chain-owned	−0.66***	−4.22**	0.31	1.01*	0.24	−0.85	4.16*
	(0.24)	(2.10)	(2.00)	(0.57)	(0.91)	(1.52)	(2.15)
Constant	1.54	21.15	20.64	4.90	12.86	6.55	32.36
	(0.23)	(2.07)	(1.98)	(0.54)	(0.86)	(1.51)	(1.97)
Observations	383,872	383,872	383,872	383,872	383,872	383,872	383,872
R^2	.0003	.0009	.0000	.0001	.0000	.0001	.0005
Panel B. Calendar-quarter fixed effects							
Local, chain-owned	−0.67***	−3.83**	0.30	1.02*	0.26	−0.90	3.81*
	(0.23)	(1.66)	(1.76)	(0.58)	(0.90)	(1.51)	(2.14)
Observations	383,872	383,872	383,872	383,872	383,872	383,872	383,872
R^2	.0016	.0333	.0103	.0046	.0021	.0019	.0093
Calendar-quarter FEs	✓	✓	✓	✓	✓	✓	✓

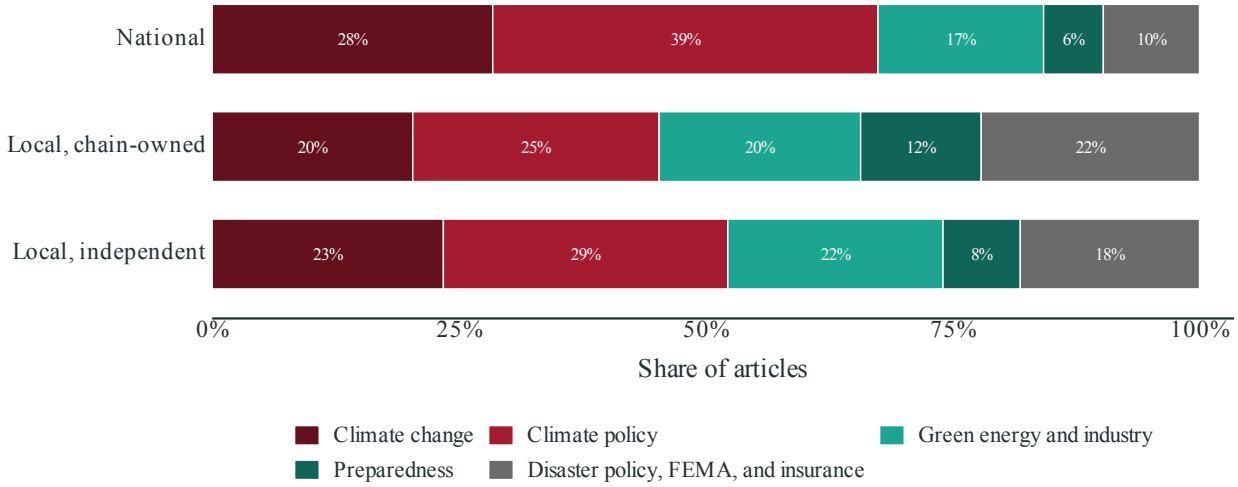
Notes. Differences in the composition of disaster coverage between chain-owned and independent local outlets. Observations are disaster articles published by 370 local outlets from 2015 to 2024. The outcome equals 100 when the article belongs to the category named in the column header and 0 otherwise. Categories are mutually exclusive. Local, chain-owned equals one when the owner of the outlet holds two or more newspaper titles in the quarter of publication and zero when it holds one. Panel A includes no fixed effects, so the constant is the share of the category among independent outlets. Panel B adds calendar-quarter fixed effects. Stars are reported for the Local, chain-owned coefficient only. Standard errors in parentheses are clustered at the outlet level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

FIGURE D.4: MONTHLY COMPOSITION OF DISASTER COVERAGE



Notes. Monthly number of disaster articles by category in local outlets (top panel) and national outlets (bottom panel), 2010–2024. An article is counted once for each outlet that publishes it. Climate-linked articles link the disaster to climate change, and skeptical articles question that link. Only event facts are articles that report only the specific event. Event facts + other topics are articles that also discuss hazards as a class, trends, projections, green products, sustainability or climate regulation. The two panels use different vertical scales.

Figure D.5: Climate and disaster-related coverage beyond individual events by outlet ownership



Notes. Composition of climate- and disaster-related articles that are not centered on a disaster event, by outlet type, 2015–2024. A local outlet is chain-owned when its owner holds two or more newspaper titles in the quarter of publication, and independent when its owner holds one. Disaster policy, FEMA and insurance are combined in one category.

E Appendix to Section 3

TABLE E.1: COUNTY GREEN-ETF PORTFOLIO RESPONSE

	Dependent variable:									
	Green-ETF share response (basis points)									
	Pre-event prices					Current prices				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Affected × Interpretation	25.48**	25.86**	22.46*	30.31**	22.76*	25.87**	25.58**	22.53*	29.50**	22.55*
	(10.13)	(12.33)	(12.18)	(12.58)	(12.44)	(10.46)	(12.50)	(12.25)	(12.62)	(12.28)
Affected × Attention	.86	4.91	3.64	1.69	−9.36	.46	4.55	3.40	1.79	−9.16
	(10.93)	(10.92)	(10.30)	(10.06)	(10.01)	(11.17)	(10.84)	(10.24)	(10.08)	(10.11)
Total Interpretation effect among affected counties	26.70**	27.08**	23.47*	31.32**	22.73*	27.02**	26.73**	23.43*	30.43**	22.54*
	(10.45)	(12.44)	(12.26)	(12.53)	(12.31)	(10.75)	(12.61)	(12.32)	(12.58)	(12.16)
Observations	105,662	105,662	105,662	105,662	105,662	105,662	105,662	105,662	105,662	105,662
R^2	.028	.029	.031	.032	.102	.030	.030	.033	.033	.106
Affected county-episodes	244	244	244	244	244	244	244	244	244	244
Episode and quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓		✓	✓	✓	✓	
County FE					✓					✓
Affected × hazard × year FE		✓	✓	✓	✓		✓	✓	✓	✓
Financial and demographic controls			✓	✓	✓			✓	✓	✓
County damages, fatalities and injuries			✓	✓	✓			✓	✓	✓
Political and belief controls				✓	✓				✓	✓
Lagged climate attention				✓	✓				✓	✓
Affected × controls				✓	✓				✓	✓

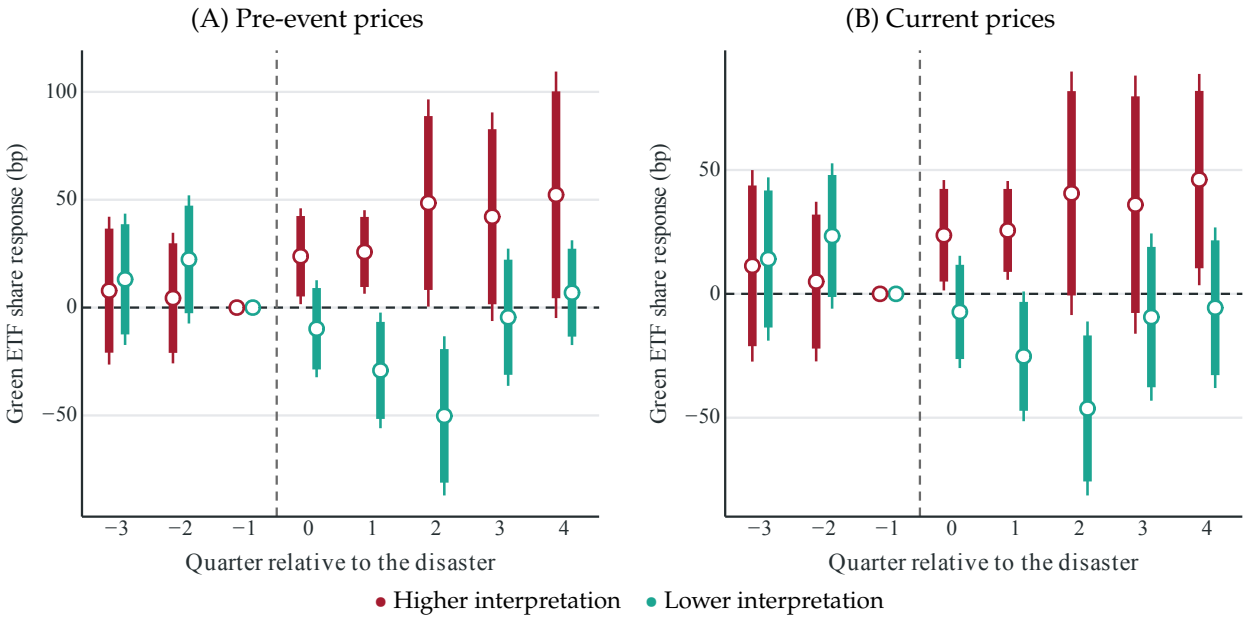
Notes. Effect of local climate interpretation on the county green-ETF share after disasters. The outcome is the mean county green-ETF share over the quarter of the episode and the two following quarters minus its mean over the two quarters before. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage, both measured over the first four weeks of the episode and standardized. Each regression also includes Interpretation and Attention, and Columns 1 and 6 include Affected. Financial controls are lagged log portfolio assets. Demographic controls are income, college share, white share, population and population density. Political and belief controls are the prior Democratic vote share and the county share worried about global warming. Lagged climate attention is the share of local coverage on climate policy and green topics in the quarter before the episode. A bootstrap that resamples counties (999 draws) gives $p = 0.036$ for Affected × Interpretation in Column 4 and $p = 0.032$ in Column 9. Standard errors in parentheses are clustered at the county level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table E.2: County green-ETF portfolio response, standard errors clustered by county and episode

Dependent variable: Green-ETF share response (basis points, pre-event prices)					
	(1)	(2)	(3)	(4)	(5)
Affected × Interpretation	25.48**	25.86**	22.46*	30.31**	22.76*
	(10.23)	(12.77)	(12.49)	(13.11)	(12.57)
Affected × Attention	.86	4.91	3.64	1.69	−9.36
	(10.90)	(11.05)	(10.47)	(10.32)	(10.09)
Total Interpretation effect among affected counties	26.70**	27.08**	23.47*	31.32**	22.73*
	(10.51)	(12.85)	(12.53)	(13.01)	(12.42)
Observations	105,662	105,662	105,662	105,662	105,662
R^2	.028	.029	.031	.032	.102
Affected county-episodes	244	244	244	244	244
Episode and quarter FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	
County FE					✓
Affected × hazard × year FE		✓	✓	✓	✓
Financial and demographic controls			✓	✓	✓
County damages, fatalities and injuries			✓	✓	✓
Political and belief controls				✓	✓
Lagged climate attention				✓	✓
Affected × controls				✓	✓

Notes. See notes to Table 2. Standard errors in parentheses are clustered two-way by county and episode. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE E.1: DISASTER RESPONSE OF COUNTY GREEN ETF SHARES BY LOCAL INTERPRETATION, BY QUARTER



Notes. Response of the county green-ETF share to disasters by quarter relative to the disaster, for counties with local interpretation above and below the median. The outcome at each quarter is the change in the county green-ETF share from the quarter before the disaster to that quarter, so the paths are cumulative. The regressions include calendar-quarter and episode fixed effects and Affected × year terms. Controls are lagged portfolio assets, prior political lean, demographic characteristics, Attention, and Interpretation as a continuous variable. The joint test that the gap between the two groups is zero in quarters −4 to −2 gives $p = 0.463$ in Panel A and $p = 0.397$ in Panel B. The figure shows 95% and 90% confidence intervals, with standard errors clustered by county and episode.

TABLE E.3: LOCAL CLIMATE INTERPRETATION AND GREEN ETF DEMAND AFTER DISASTERS, CALENDAR-QUARTER TIMING

	(1)	(2)	(3)	(4)	(5)
Panel A. Green ETF share change at pre-event prices (basis points)					
Affected × Interpretation (1 SD)	42.07**	43.89**	46.76**	46.76**	47.92**
	(18.14)	(18.76)	(20.51)	(20.50)	(20.67)
Interpretation (1 SD)	−6.71	−6.87	−7.47	−7.46	−7.20
	(4.23)	(4.25)	(4.38)	(4.39)	(4.34)
Affected	13.63	15.61	9.04	9.04	12.86
	(27.20)	(26.65)	(27.05)	(27.06)	(28.18)
R^2	.094	.103	.105	.105	.106
Mean dependent variable (bp)	1.06	1.06	1.06	1.06	1.06
Panel B. Green ETF share change at current prices (basis points)					
Affected × Interpretation (1 SD)	42.62**	44.47**	47.43**	47.41**	48.92**
	(18.19)	(18.78)	(20.58)	(20.56)	(20.84)
Interpretation (1 SD)	−6.74	−6.89	−7.51	−7.45	−7.19
	(4.20)	(4.21)	(4.34)	(4.35)	(4.30)
Affected	13.51	15.53	8.85	8.86	12.55
	(27.84)	(27.29)	(27.60)	(27.54)	(28.55)
R^2	.098	.107	.109	.109	.111
Mean dependent variable (bp)	1.21	1.21	1.21	1.21	1.21
Share observations	77,571	77,571	77,571	77,571	77,571
Counties	319	319	319	319	319
Disaster episodes	632	632	632	632	632
County fixed effects	✓	✓	✓	✓	✓
Calendar-quarter fixed effects	✓	✓	✓	✓	✓
Disaster-episode fixed effects	✓	✓	✓	✓	✓
Affected × year effects	✓	✓	✓	✓	✓
Prior green-share change		✓	✓	✓	✓
Lagged portfolio assets			✓	✓	✓
Predetermined political controls				✓	✓
Predetermined demographic controls					✓

Notes. Effect of local climate interpretation on the county green-ETF share after disasters, with interpretation measured over the calendar quarter of the event. The outcome is the change in the county green-ETF share from quarter $t-1$ to quarter $t+1$. The sample covers high-salience flood, hurricane and coastal episodes, 2018–2024. Interpretation is the climate-interpreted share of local disaster coverage in the calendar quarter of the event, standardized. All columns include county, calendar-quarter and disaster-episode fixed effects and Affected × year effects. Column 2 adds the prior green-share change. Column 3 adds lagged portfolio assets. Column 4 adds predetermined political controls. Column 5 adds predetermined demographic controls. Political controls are the county's Democratic vote share at the last presidential election. Demographic controls are county income, college share, share of white residents and population. Standard errors in parentheses are clustered by county and episode. $^{*}\,p<0.1$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

TABLE E.4: COUNTY GREEN-ETF PORTFOLIO RESPONSE, 2018–2024 SAMPLE

	(1)	(2)	(3)	(4)	(5)
Panel A. Pre-event prices					
Affected × Interpretation	36.01*** (13.20)	38.71*** (13.06)	38.73*** (13.05)	38.80*** (12.99)	43.05*** (13.26)
Affected	-8.88 (48.92)	-6.11 (47.97)	-13.74 (48.64)	-14.04 (48.10)	-16.39 (50.19)
Interpretation	-4.50* (2.44)	-4.62* (2.50)	-4.66* (2.47)	-4.59* (2.47)	-4.08* (2.44)
Attention	-12.72** (5.48)	-13.26** (5.58)	-12.66** (5.57)	-12.68** (5.58)	-12.78** (5.85)
Affected × Attention	33.21* (17.64)	34.13* (18.58)	33.94* (19.16)	34.16* (19.11)	34.82* (20.09)
Observations	59,330	59,330	59,330	59,330	59,330
Panel B. Current prices					
Affected × Interpretation	34.78*** (13.12)	37.46*** (12.97)	37.48*** (12.96)	37.62*** (12.85)	42.56*** (13.39)
Affected	-10.64 (51.07)	-7.89 (50.11)	-15.61 (50.71)	-16.16 (50.04)	-17.83 (51.66)
Interpretation	-4.81** (2.43)	-4.93** (2.48)	-4.97** (2.46)	-4.85* (2.46)	-4.34* (2.41)
Attention	-13.39** (5.55)	-13.92** (5.65)	-13.31** (5.64)	-13.35** (5.65)	-13.52** (5.91)
Affected × Attention	34.30* (18.55)	35.22* (19.46)	35.02* (20.05)	35.43* (20.01)	35.76* (20.93)
Observations	59,330	59,330	59,330	59,330	59,330
County fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter and episode fixed effects	Yes	Yes	Yes	Yes	Yes
Affected × year effects	Yes	Yes	Yes	Yes	Yes
Prior green-share change		Yes	Yes	Yes	Yes
Lagged log portfolio assets			Yes	Yes	Yes
Political controls				Yes	Yes
Demographic controls					Yes

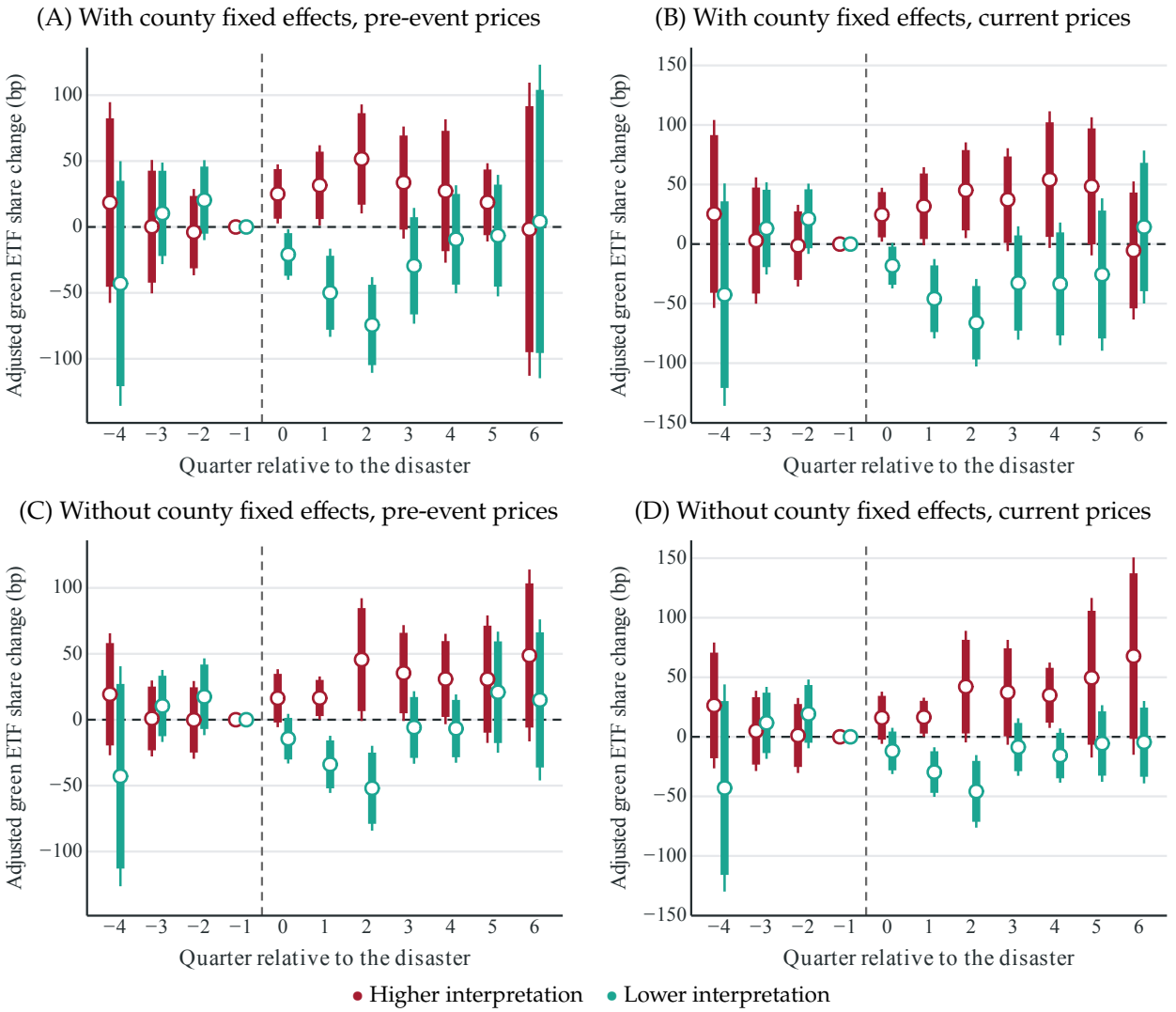
Notes. Effect of local climate interpretation on the county green-ETF share after disasters, 2018–2024. The outcome is the change in the county green-ETF share from quarter $t-1$ to quarter $t+1$. The sample covers high-salience flood, hurricane and coastal episodes from 2018Q1 to 2024Q4. Interpretation is the climate-interpreted share of local disaster coverage and Attention the log of total disaster-news coverage, both measured over weeks 0 to 3 of the event and standardized. All columns include county, quarter and episode fixed effects and Affected × year effects. Column 2 adds the prior green-share change. Column 3 adds lagged log portfolio assets. Column 4 adds political controls. Column 5 adds demographic controls. Political controls are the county's Democratic vote share at the last presidential election. Demographic controls are county income, college share, share of white residents and population. Standard errors in parentheses are clustered by county and episode. $^{*}\,p<0.1$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

TABLE E.5: ADVISER-LEVEL LOCAL CLIMATE INTERPRETATION AND GREEN ETF DEMAND AFTER DISASTERS, CALENDAR-QUARTER TIMING

	(1)	(2)	(3)	(4)
Panel A. Green ETF share change at pre-event prices (basis points)				
Affected × Interpretation (1 SD)	10.41*	10.11*	10.05*	10.07*
	(5.39)	(5.68)	(5.69)	(5.67)
Interpretation (1 SD)	−1.05	−1.19	−1.17	−1.32
	(1.52)	(1.53)	(1.54)	(1.55)
Affected	1.95	2.27	2.23	.77
	(4.24)	(4.71)	(4.69)	(4.88)
R^2	.069	.144	.144	.144
Mean dependent variable (bp)	−.62	−.62	−.62	−.62
Panel B. Green ETF share change at current prices (basis points)				
Affected × Interpretation (1 SD)	10.48**	10.19*	10.13*	10.15*
	(5.29)	(5.55)	(5.56)	(5.55)
Interpretation (1 SD)	−.84	−.97	−.95	−1.11
	(1.73)	(1.74)	(1.75)	(1.74)
Affected	1.16	1.46	1.42	−.15
	(4.47)	(4.90)	(4.89)	(5.15)
R^2	.067	.133	.133	.133
Mean dependent variable (bp)	−.58	−.58	−.58	−.58
Share observations	621,761	621,761	621,761	621,761
Advisers	2,765	2,765	2,765	2,765
Disaster episodes	632	632	632	632
Adviser fixed effects	✓	✓	✓	✓
Calendar-quarter fixed effects	✓	✓	✓	✓
Disaster-episode fixed effects	✓	✓	✓	✓
Affected × year effects	✓	✓	✓	✓
Prior green-share change		✓	✓	✓
Lagged portfolio assets			✓	✓
Predetermined political controls				✓

Notes. Effect of local climate interpretation on the green-ETF share of registered investment advisers after flood, hurricane and coastal episodes. The outcome is the change in the adviser's green-ETF share from quarter $t-1$ to quarter $t+1$. Interpretation is the circulation-weighted mean, across local outlets, of the share of disaster articles in the quarter that link the disaster to climate change, standardized. The Interpretation row is the slope among unaffected advisers. The Affected row is the difference between affected and unaffected advisers in the reference year, at mean interpretation and coverage. All columns include coverage, its interaction with Affected, adviser, calendar-quarter and disaster-episode fixed effects, and Affected × year effects. Column 2 adds the prior green-share change. Column 3 adds lagged log portfolio assets. Column 4 adds predetermined political controls. Political controls are the county's Democratic vote share at the last presidential election. Standard errors in parentheses are clustered by adviser location. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE E.2: FLOODS, HURRICANES AND COASTAL EPISODES: HIGH- AND LOW-INTERPRETATION AFFECTED COUNTIES



Notes. Response of the green-ETF share of affected counties to flood, hurricane and coastal episodes, for counties with interpretation above and below the median. The median is held fixed across quarters. All regressions include calendar-quarter and episode fixed effects, Affected × year terms, interpretation, attention, Affected × Attention and the remaining controls, without the previous green-share change. The number of observations varies across quarters. The joint test that the gap between the two groups is zero in quarters −4 to −2 gives $p = 0.368$ in Panel A, 0.327 in Panel B, 0.468 in Panel C and 0.439 in Panel D. The figure shows 95% and 90% confidence intervals, with standard errors clustered by county and episode.

Table E.6: County green-holding margins

	(1)	(2)	(3)	(4)	(5)
Share of advisers holding green, all advisers (percentage points)					
Affected × Interpretation	5.76*** (1.40)	5.77*** (1.40)	5.76*** (1.41)	5.74*** (1.44)	5.96*** (1.53)
Affected	3.27 (3.25)	3.27 (3.23)	2.87 (3.18)	2.99 (3.24)	2.95 (3.02)
Interpretation	-0.51* (0.29)	-0.51* (0.29)	-0.51* (0.29)	-0.53* (0.29)	-0.56* (0.29)
Attention	-0.54 (0.58)	-0.54 (0.58)	-0.51 (0.59)	-0.50 (0.59)	-0.58 (0.59)
Affected × Attention	-0.51 (1.28)	-0.50 (1.29)	-0.51 (1.31)	-0.60 (1.31)	-0.81 (1.23)
Observations	59,326	59,326	59,326	59,326	59,326
Share holding green, continuing in the same county (percentage points)					
Affected × Interpretation	5.94*** (1.75)	5.94*** (1.74)	5.94*** (1.74)	5.91*** (1.75)	5.89*** (1.86)
Affected	2.75 (3.29)	2.75 (3.26)	2.50 (3.21)	2.51 (3.29)	2.22 (3.06)
Interpretation	-0.37 (0.28)	-0.37 (0.28)	-0.37 (0.28)	-0.40 (0.28)	-0.42 (0.28)
Attention	0.16 (0.52)	0.16 (0.52)	0.18 (0.52)	0.19 (0.52)	0.10 (0.53)
Affected × Attention	0.11 (1.14)	0.11 (1.15)	0.10 (1.17)	0.03 (1.16)	-0.14 (1.09)
Observations	56,693	56,693	56,693	56,693	56,693
County entry (percentage points)					
Affected × Interpretation	1.64 (2.15)	1.55 (2.27)	1.46 (2.28)	1.42 (2.28)	0.99 (1.95)
Affected	4.22 (9.66)	4.38 (9.67)	4.83 (10.02)	5.52 (10.37)	3.66 (9.68)
Interpretation	0.53 (0.48)	0.54 (0.49)	0.54 (0.49)	0.51 (0.48)	0.52 (0.49)
Attention	0.54 (1.40)	0.54 (1.40)	0.52 (1.39)	0.51 (1.38)	0.60 (1.38)
Affected × Attention	-1.24 (2.76)	-1.40 (2.96)	-1.46 (2.95)	-1.71 (2.93)	-2.02 (2.80)
Observations	34,389	34,389	34,389	34,389	34,389
County incumbent share (basis points)					
Affected × Interpretation	41.51** (16.00)	42.35*** (15.80)	32.62** (13.48)	32.26** (13.66)	44.82** (17.77)
Affected	-66.71 (59.78)	-57.57 (58.65)	-75.47** (37.51)	-86.67** (41.88)	-102.07* (56.50)
Interpretation	-10.26** (4.73)	-10.27** (4.97)	-11.06** (5.00)	-11.41** (5.03)	-10.52** (5.08)
Attention	-26.04** (10.28)	-27.23** (10.86)	-26.75** (11.39)	-26.32** (11.44)	-22.14* (12.43)
Affected × Attention	55.87*** (17.57)	53.63*** (18.19)	45.54** (18.89)	46.44** (19.12)	43.79** (21.09)
Observations	24,934	24,934	24,934	24,934	24,934
County fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter and episode fixed effects	Yes	Yes	Yes	Yes	Yes
Affected × year effects	Yes	Yes	Yes	Yes	Yes
Prior green-share change		Yes	Yes	Yes	Yes
Lagged log portfolio assets			Yes	Yes	Yes
Political controls				Yes	Yes
Demographic controls					Yes

Notes. Effect of local climate interpretation on the margins of county green holdings after disasters. Each block reports a different outcome, measured as the change from quarter $t-1$ to quarter $t+1$. Share-of-adviser outcomes use only the advisers observed at both $t-1$ and $t+1$. County entry includes only counties with no green holdings before the event. The county incumbent share includes only counties with positive green holdings before the event. The sample covers high-salience flood, hurricane and coastal episodes from 2018Q1 to 2024Q4. Interpretation and Attention, the log of total disaster-news coverage, are measured over weeks 0 to 3 of the event. All columns include county, quarter and episode fixed effects and Affected × year effects. Column 2 adds the prior green-share change. Column 3 adds lagged log portfolio assets. Column 4 adds political controls. Column 5 adds demographic controls. Political controls are the county's Democratic vote share at the last presidential election. Demographic controls are county income, college share, share of white residents and population. Standard errors in parentheses are clustered by county and episode. $^{*}\,p<0.1$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

TABLE E.7: EVENT TIMING AND THE PORTFOLIO RESPONSE

	Green-ETF share response (basis points)							
	Without affected × hazard × year FE				Table 2, column 4			
	0–30 days		31–91 days		0–30 days		31–91 days	
	Episode quarter (1)	Next quarter (2)	Episode quarter (3)	Next quarter (4)	Episode quarter (5)	Next quarter (6)	Episode quarter (7)	Next quarter (8)
Panel A. Pre-event prices								
Affected × Interpretation	13.87	27.23	28.18*	38.92**	8.74	22.31*	25.85**	48.17**
	(8.73)	(16.59)	(14.38)	(19.10)	(6.35)	(13.18)	(12.17)	(20.02)
Affected × Attention	7.30	7.48	−5.01	−15.36	10.33	6.84	−3.48	−16.51
	(7.65)	(12.49)	(10.02)	(10.27)	(6.53)	(11.16)	(12.41)	(10.33)
Total Interpretation effect among affected counties	16.22*	30.17*	27.35*	38.57**	11.08*	25.24**	25.02**	47.80**
	(8.49)	(15.61)	(14.42)	(19.21)	(5.96)	(11.99)	(12.21)	(19.73)
Panel B. Current prices								
Affected × Interpretation	13.15	25.55	27.78*	38.85**	8.23	21.48*	25.36**	47.81**
	(8.72)	(16.23)	(14.13)	(18.73)	(6.43)	(12.69)	(11.87)	(19.18)
Affected × Attention	6.76	6.07	−4.20	−14.53	9.65	5.01	−2.95	−15.52
	(7.45)	(11.66)	(9.68)	(10.19)	(6.44)	(10.40)	(12.23)	(10.06)
Total Interpretation effect among affected counties	15.35*	28.52*	27.05*	38.31**	10.42*	24.44**	24.63**	47.25**
	(8.44)	(15.27)	(14.17)	(18.91)	(6.01)	(11.53)	(11.92)	(18.94)
Observations	37,714	34,765	67,853	62,759	37,712	34,764	67,853	62,758
R^2	.024	.032	.018	.027	.024	.032	.018	.028
Affected county-episodes	100	95	144	129	98	94	144	128
Affected × hazard × year FE					✓	✓	✓	✓
Episode and quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Financial and demographic controls	✓	✓	✓	✓	✓	✓	✓	✓
County damages, fatalities and injuries	✓	✓	✓	✓	✓	✓	✓	✓
Political and belief controls	✓	✓	✓	✓	✓	✓	✓	✓
Lagged climate attention	✓	✓	✓	✓	✓	✓	✓	✓
Affected × controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes. Effect of local climate interpretation on the county green-ETF share after disasters, by the day on which the episode starts within its calendar quarter. Columns 1, 2, 5 and 6 include episodes that start in the last 30 days of the quarter. Columns 3, 4, 7 and 8 include episodes that start 31 to 91 days before its end. The outcome is the change in the county green-ETF share from the quarter before the episode to the quarter of the episode (Columns 1, 3, 5 and 7) or to the following quarter (Columns 2, 4, 6 and 8). Both panels use the same observations. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage, both measured over the first four weeks of the episode and standardized. All columns include episode, quarter and state fixed effects. Columns 5 to 8 add Affected × hazard × year fixed effects, which replace the Affected indicator of Columns 1 to 4. Controls are lagged log portfolio assets, income, college share, white share, population, population density, county damages, fatalities and injuries, the prior Democratic vote share, the county share worried about global warming, and the share of local coverage on climate policy and green topics in the quarter before the episode, all also interacted with Affected. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Appendix to Section 3.4

Table F.1: Who responds to climate interpretation: heterogeneity of the interpretation effect

Characteristic	Interactions with:			At the mean		N
	Affected (1)	Interpretation (2)	Affected × Interpretation (3)	Affected × Interpretation (4)	Affected (5)	
Panel A. Beliefs and ambient coverage						
Share worried about global warming	-13.9 (23.4)	-1.8 (2.7)	22.4* (13.3)	36.7*** (10.1)	-14.2 (45.8)	59,330
Perceived scientific consensus	-0.7 (23.5)	-0.0 (2.8)	9.9 (16.4)	42.8*** (12.8)	-16.6 (46.9)	59,330
Climate-policy news share (same quarter)	34.5** (17.1)	-5.3* (2.8)	4.3 (14.5)	32.6*** (12.1)	0.5 (54.3)	59,330
Climate-policy news share (previous quarter)	28.6* (16.9)	-1.1 (2.5)	10.8 (15.0)	43.3*** (15.6)	-4.5 (53.3)	59,330
News circulation per resident	18.7 (14.3)	-3.1 (3.0)	-0.2 (18.6)	43.1*** (13.5)	-21.5 (48.5)	59,330
Panel B. Politics and socioeconomic characteristics						
County Democratic vote	-8.2 (27.1)	-3.6 (2.8)	0.9 (11.0)	45.2*** (11.5)	-13.9 (44.9)	59,330
Median income	-29.0 (25.0)	0.6 (2.3)	17.5 (14.1)	47.2*** (15.0)	-28.7 (48.6)	59,330
College share	-28.2 (19.1)	0.6 (2.2)	4.6 (10.4)	39.3*** (12.7)	-19.9 (51.3)	59,330
Panel C. Exposure and experience						
Episode damages	-24.9* (13.5)	-0.1 (1.4)	10.1 (11.9)	41.1*** (12.7)	-12.7 (49.3)	59,330
County damages	-28.3 (17.6)	—	13.1 (12.6)	41.0*** (12.2)	-9.2 (50.7)	59,330
ETF turnover before 2018 (high vs low)	100.4* (56.1)	-5.4 (6.8)	31.8 (53.2)	49.1*** (18.3)	45.8 (53.6)	43,558
History of the same disaster type (previous 60 months)	4.3 (16.3)	-7.1 (5.2)	2.9 (11.0)	42.2** (18.6)	-27.4 (47.8)	59,330
No history of the same disaster type (previous 60 months)	-7.5 (56.6)	-6.8 (8.1)	124.8** (63.3)	42.2** (18.6)	-27.4 (47.8)	59,330
History of other disaster types (previous 60 months)	-13.2 (13.0)	-4.4 (3.0)	-0.3 (10.1)	44.0*** (13.8)	-7.8 (50.3)	59,330
History of climate-related disasters (previous 60 months)	-9.5 (12.4)	-5.3* (3.1)	-4.6 (10.4)	48.5*** (15.6)	-10.0 (49.6)	59,330
Prior climate episodes	-24.9 (23.9)	-6.7 (5.1)	-2.0 (13.7)	42.3** (16.5)	-1.1 (53.7)	59,330
Panel D. Population and density						
Population	2.3 (15.9)	1.4 (3.6)	-16.5 (10.3)	39.9*** (13.7)	-16.1 (46.3)	59,330
Population density	-10.1 (19.1)	0.2 (4.0)	-10.9 (12.7)	31.1** (15.6)	-9.1 (43.9)	59,330

Notes. Heterogeneity of the effect of local climate interpretation on the county green-ETF share by county characteristics. Each row is a separate regression that interacts one characteristic with Affected, Interpretation and their interaction. The outcome is the change in the county green-ETF share. The sample covers flood, hurricane and coastal episodes from 2018Q1 to 2024Q4. The coefficients at the mean are evaluated at the sample mean of the characteristic. Continuous characteristics are centered and divided by their standard deviation. Indicators are not rescaled. The no-history indicator is not centered, so its Affected × Interpretation estimate at the mean refers to counties with a history of the same disaster type. ETF turnover before 2018 enters as terciles, with the low tercile omitted. County damages are zero in unaffected counties, so their interaction with Interpretation is not estimated. Interpretation and Attention, the log of total disaster-news coverage, are measured over weeks 0 to 3 of the event. All regressions include the baseline controls and county, quarter and episode fixed effects. The baseline controls are the prior green-share change, lagged log portfolio assets, the county's Democratic vote share at the last presidential election and county income, college share, share of white residents and population. Standard errors in parentheses are clustered by county and episode. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table F.2: Earthquake placebo: local green-ETF share and climate interpretation

	Dependent variable:	
	Green-ETF share change at pre-event prices (bp)	
Interpretation	Event quarter	Mean through $q-1$
	(1)	(2)
Affected × Interpretation (bp per SD)	1.01	−.86
	(4.53)	(7.26)
Affected	10.00	10.42
	(6.27)	(7.12)
Interpretation	−1.56	5.01
	(2.66)	(15.42)
Coverage	3.64	3.59
	(6.33)	(5.26)
Affected × Coverage	3.11	3.51
	(7.83)	(6.68)
p-value: Affected × Interpretation	.824	.906
Observations	180,934	195,425
Treated counties	17	18
Treated county–quarters	32	34
Treated episodes	52	54
County, quarter and episode FE	✓	✓

Notes. Effect of local climate interpretation on the county green-ETF share after earthquakes. Earthquakes are from the USGS ComCat catalog. The outcome is the change in the county green-ETF share from the quarter before to the quarter after the earthquake. Interpretation is the county's climate interpretation of other disasters, measured in the event quarter (Column 1) or averaged over the quarters up to $q-1$ (Column 2), standardized. Column 2 includes counties with at least four earlier observations. Coverage is disaster coverage in the event quarter, standardized. Episodes with a large climate disaster in an affected county from $q-1$ to $q+1$ are excluded. All columns include county, calendar-quarter and earthquake-episode fixed effects. Standard errors in parentheses are clustered at the county level. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

TABLE F.3: DISASTER NEWS AND TURNOVER OF ETF AND TOTAL REPORTED PORTFOLIOS

	Outcome: log(1 + turnover in bp), quarter $t+1$	
	(1) ETFs	(2) All reported securities
Affected × Interpretation	0.050	-0.003
	(0.065)	(0.055)
Unaffected × Interpretation	0.028	0.032**
	(0.018)	(0.014)
Affected × Attention	0.121*	0.107**
	(0.062)	(0.054)
Unaffected × Attention	0.091***	0.081***
	(0.030)	(0.022)
Interpretation: affected minus unaffected	0.023	-0.035
	(0.067)	(0.055)
Attention: affected minus unaffected	0.031	0.026
	(0.062)	(0.053)
Observations	101,785	101,785
R^2	0.135	0.188
Affected county-episodes	236	236
Episode and quarter FE	✓	✓
State FE	✓	✓
Affected × hazard × year FE	✓	✓
Financial and demographic controls	✓	✓
County damages, fatalities and injuries	✓	✓
Political and belief controls	✓	✓
Lagged climate attention	✓	✓
Affected × controls	✓	✓

Notes. Effect of local climate interpretation and attention on the portfolio turnover of registered investment advisers after disasters. Turnover is the sum of the absolute changes in the quantities of the securities held at the end of quarter t, valued at current prices, divided by their starting value, following Calvet et al. (2009). It is computed for each adviser and averaged within the county with weights equal to starting values. The outcome is the log of one plus turnover, from the end of event quarter t to the end of quarter $t+1$. Both columns use the same advisers and county-episodes. The slopes for affected and unaffected counties are estimated jointly in each column. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage, both measured over the first four weeks of the episode and standardized. All columns include episode, quarter and state fixed effects and Affected × hazard × year fixed effects. Controls are lagged log portfolio assets, income, college share, white share, population, population density, county damages, fatalities and injuries, the prior Democratic vote share, the county share worried about global warming, and the share of local coverage on climate policy and green topics in the quarter before the episode, all also interacted with Affected. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE F.4: LOCAL CLIMATE INTERPRETATION AND ADVISER PORTFOLIOS NEAR DISASTERS

	Dependent variable:				
	Green-ETF share response (bp) Pre-event prices				
	(1)	(2)	(3)	(4)	(5)
Panel A. $h = 0$					
Interpretation effect among:					
Affected or nearby advisers, 0–50 miles	7.97***	8.21**	6.69***	6.64***	7.32**
	(2.75)	(3.18)	(2.44)	(2.53)	(3.09)
Observations	6,481	6,481	6,481	6,481	6,481
R^2	.069	.074	.100	.101	.272
Advisers	1,030	1,030	1,030	1,030	1,030
ZIP codes	431	431	431	431	431
Counties	124	124	124	124	124
Episodes	303	303	303	303	303
Panel B. $h = 1$					
Interpretation effect among:					
Affected or nearby advisers, 0–50 miles	11.75**	11.60**	11.59**	10.70**	13.12*
	(4.57)	(5.79)	(5.42)	(4.99)	(7.85)
Observations	5,889	5,889	5,889	5,889	5,889
R^2	.181	.185	.215	.218	.454
Advisers	992	992	992	992	992
ZIP codes	416	416	416	416	416
Counties	123	123	123	123	123
Episodes	295	295	295	295	295
Episode × state FE	✓	✓	✓		
Episode × band FE			✓		
Episode × state × band FE				✓	✓
County FE	✓	✓	✓	✓	
Adviser FE					✓
Attention controls	✓	✓	✓	✓	✓
Financial and demographic controls	✓	✓	✓	✓	✓
County damages, fatalities and injuries	✓	✓	✓	✓	✓
Political controls	✓	✓	✓	✓	✓
Lagged climate attention	✓	✓	✓	✓	✓
Group × controls		✓	✓	✓	✓

Notes. Effect of local climate interpretation on the green-ETF share of advisers in affected counties and of nearby advisers within 50 miles of the affected area. The outcome is the change in the green-ETF share from the quarter before the episode to the disaster quarter (Panel A, $h = 0$) or to the following quarter (Panel B, $h = 1$). Interpretation is the share of disaster coverage at the adviser's ZIP code that links the disaster to climate change over the first four weeks of the episode. Coefficients are per 10 percentage points of Interpretation and are common to affected and nearby advisers. Columns 1 to 3 include episode × state fixed effects, and Column 3 adds episode × band fixed effects. Columns 4 and 5 include episode × state × band fixed effects. Columns 1 to 4 include county fixed effects, and Column 5 adviser fixed effects. All columns control for attention, the log volume of disaster coverage, and its interaction with Affected. Financial controls are lagged log ETF holdings and lagged log total Form 13F holdings. Demographic controls are county income, college share, white share, population and population density. Political controls are the prior county Democratic vote share. All columns also control for county damages, fatalities and injuries and for lagged climate attention, the share of local coverage on climate policy and green topics in the quarter before the episode. Group × controls lets the financial, demographic and political controls differ across affected advisers and nearby advisers at 0–25 and 25–50 miles. Observations are weighted by the adviser's share of the pre-event ETF holdings of the advisers in the same ZIP code and episode. Standard errors in parentheses are clustered by physical event and by the ZIP code of the adviser's office. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

TABLE F.5: LOCAL CLIMATE INTERPRETATION AND ADVISER PORTFOLIOS NEAR DISASTERS, BY DISTANCE BAND

	Dependent variable:							
	Green-ETF share response (bp)							
	Pre-event prices				Current prices			
	$h = 0$		$h = 1$		$h = 0$		$h = 1$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Advisers weighted by their share of the ZIP code's ETF holdings								
Interpretation effect among:								
Affected advisers	11.00**	9.91**	11.25	10.63	9.04*	8.35*	11.68	11.21
	(5.50)	(4.94)	(8.21)	(8.21)	(4.61)	(4.24)	(8.47)	(8.19)
Nearby advisers, 0–25 miles	8.95***	7.03***	14.37**	11.86*	8.38***	6.33**	16.05**	13.38
	(2.64)	(2.59)	(5.59)	(6.61)	(2.73)	(2.60)	(7.13)	(8.30)
Nearby advisers, 25–50 miles	6.40**	8.85**	9.41*	11.62**	5.78**	8.33**	11.10*	12.96**
	(2.80)	(3.45)	(4.97)	(5.49)	(2.81)	(3.45)	(5.86)	(6.00)
Observations	6,481	6,481	5,889	5,889	6,481	6,481	5,889	5,889
R^2	.069	.074	.181	.185	.067	.072	.176	.180
Advisers	1,030	1,030	992	992	1,030	1,030	992	992
ZIP codes	431	431	416	416	431	431	416	416
Counties	124	124	123	123	124	124	123	123
Episodes	303	303	295	295	303	303	295	295
Panel B. Advisers weighted equally								
Interpretation effect among:								
Affected advisers	9.15**	9.79*	9.78	11.88	8.42*	8.89*	11.07	13.43*
	(4.45)	(5.44)	(6.89)	(7.56)	(4.59)	(4.98)	(7.61)	(7.89)
Nearby advisers, 0–25 miles	8.19**	7.41	10.58**	8.17	8.23*	7.44	13.31*	10.97
	(3.62)	(4.84)	(4.52)	(5.80)	(4.24)	(5.15)	(7.07)	(7.82)
Nearby advisers, 25–50 miles	7.02**	8.68**	10.47**	12.66**	6.81*	8.40*	12.68**	14.55**
	(3.40)	(4.27)	(4.12)	(5.01)	(3.70)	(4.38)	(5.85)	(5.99)
Observations	6,481	6,481	5,889	5,889	6,481	6,481	5,889	5,889
R^2	.045	.049	.084	.089	.048	.052	.087	.091
Advisers	1,030	1,030	992	992	1,030	1,030	992	992
ZIP codes	431	431	416	416	431	431	416	416
Counties	124	124	123	123	124	124	123	123
Episodes	303	303	295	295	303	303	295	295
Episode × state FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Attention controls	✓	✓	✓	✓	✓	✓	✓	✓
Financial and demographic controls	✓	✓	✓	✓	✓	✓	✓	✓
County damages, fatalities and injuries	✓	✓	✓	✓	✓	✓	✓	✓
Political controls	✓	✓	✓	✓	✓	✓	✓	✓
Lagged climate attention	✓	✓	✓	✓	✓	✓	✓	✓
Group × controls		✓		✓		✓		✓

Notes. Effect of local climate interpretation on the green-ETF share of affected advisers and of nearby advisers outside the disaster footprint, by distance band. The outcome is the change in the green-ETF share from the quarter before the episode to the disaster quarter ($h = 0$) or to the following quarter ($h = 1$). Interpretation is the share of disaster coverage at the adviser's ZIP code that links the disaster to climate change, per 10 percentage points. Each regression estimates the three group effects jointly and controls for Attention, the log volume of disaster coverage at the same ZIP code, and for Affected × Attention. Financial controls are lagged log ETF holdings and lagged log total Form 13F holdings. Demographic controls are county income, college share, white share, population and population density. Political controls are the prior county Democratic vote share. All columns also control for county damages, fatalities and injuries and for lagged climate attention, the share of local coverage on climate policy and green topics in the quarter before the episode. Even-numbered columns interact the financial, demographic and political controls with the three groups. All columns include episode × state and county fixed effects. Panel A weights each adviser by its share of the pre-event ETF holdings of the advisers in the same ZIP code and episode. Standard errors in parentheses are clustered by physical event and by the ZIP code of the adviser's office. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table F.6: Local climate interpretation and adviser portfolios: two-quarter average

	Dependent variable:			
	Green-ETF share response (bp)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. Advisers weighted by their share of the ZIP code's ETF holdings				
Interpretation effect among:				
Affected advisers	11.49*	10.42*	10.64*	9.85*
	(5.91)	(5.75)	(6.10)	(5.79)
Nearby advisers, 0–25 miles	11.93***	9.49**	12.46**	9.85*
	(4.19)	(4.39)	(4.93)	(5.24)
Nearby advisers, 25–50 miles	8.08**	10.41**	8.54*	10.75**
	(3.96)	(4.25)	(4.35)	(4.57)
Observations	5,889	5,889	5,889	5,889
R^2	.124	.128	.124	.128
Advisers	992	992	992	992
ZIP codes	416	416	416	416
Counties	123	123	123	123
Episodes	295	295	295	295
Panel B. Advisers weighted equally				
Interpretation effect among:				
Affected advisers	9.64*	10.60*	10.09*	11.24*
	(5.54)	(6.05)	(6.08)	(6.62)
Nearby advisers, 0–25 miles	9.93**	8.33*	11.50**	9.95
	(3.85)	(4.94)	(5.69)	(6.63)
Nearby advisers, 25–50 miles	9.70***	11.59**	10.81**	12.49**
	(3.63)	(4.50)	(4.77)	(5.32)
Observations	5,889	5,889	5,889	5,889
R^2	.064	.069	.067	.072
Advisers	992	992	992	992
ZIP codes	416	416	416	416
Counties	123	123	123	123
Episodes	295	295	295	295
Episode × state FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Attention controls	✓	✓	✓	✓
Financial and demographic controls	✓	✓	✓	✓
County damages, fatalities and injuries	✓	✓	✓	✓
Political controls	✓	✓	✓	✓
Lagged climate attention	✓	✓	✓	✓
Group × controls		✓		✓

Notes. Effect of local climate interpretation on the two-quarter average green-ETF share of affected advisers and of nearby advisers outside the disaster footprint, by distance band. The outcome is the mean green-ETF share in the disaster quarter and the following quarter minus the share in the quarter before the episode. The sample keeps advisers observed in both quarters after the episode. Interpretation is the share of disaster coverage at the adviser's ZIP code that links the disaster to climate change, per 10 percentage points. Each regression estimates the three group effects jointly and controls for Attention, the log volume of disaster coverage at the same ZIP code, and for Affected × Attention. Financial controls are lagged log ETF holdings and lagged log total Form 13F holdings. Demographic controls are county income, college share, white share, population and population density. Political controls are the prior county Democratic vote share. All columns also control for county damages, fatalities and injuries and for lagged climate attention, the share of local coverage on climate policy and green topics in the quarter before the episode. Columns 2 and 4 interact the financial, demographic and political controls with the three groups. All columns include episode × state and county fixed effects. Panel A weights each adviser by its share of the pre-event ETF holdings of the advisers in the same ZIP code and episode. Standard errors in parentheses are clustered by physical event and by the ZIP code of the adviser's office. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE F.7: WHOSE VIEWS: COUNTY VIEWS AGAINST THE ADVISERS' OWN LEAN

	Dependent variable: ETF green-share response, $h = 1$ (bp)					
	ETF-holdings weights				Equal weights	
	Adviser lean	County vote	Both	Both, giving	Both	Both, giving
	(1)	(2)	(3)	(4)	(5)	(6)
Interpretation response, at affected means	19.40***	21.55***	21.65***	21.34***	5.44	5.25
	(7.43)	(7.96)	(8.03)	(7.98)	(6.54)	(5.97)
Disaster response, at affected means	5.91	13.24**	13.77**	8.12*	0.43	−2.58
	(4.74)	(5.57)	(5.92)	(4.71)	(5.67)	(5.00)
Interpretation response × County Rep. vote		6.90*	10.64*		10.52**	
		(3.96)	(5.48)		(5.15)	
Interpretation response × Adviser Rep. lean	−8.37		−13.84	−5.08	−7.82	−6.34
	(8.33)		(10.31)	(9.56)	(8.62)	(8.09)
Disaster response × County Rep. vote		7.54	6.56		3.41	
		(5.88)	(5.97)		(3.85)	
Disaster response × Adviser Rep. lean	1.52		0.79	−3.01	−9.83*	−10.71**
	(5.17)		(5.33)	(5.12)	(5.20)	(4.88)
Interpretation: adviser minus county			−24.48*	−2.49	−18.34	−12.58
			(14.83)	(12.73)	(12.92)	(10.66)
Interpretation response × County Rep. giving				−2.60		6.25*
				(5.01)		(3.29)
Disaster response × County Rep. giving				11.49*		5.45**
				(6.40)		(2.69)
Observations			465,705			
Affected adviser-episodes (with an adviser lean)			1158 (723)			
Advisers			2130			

Interpretation response by county political group (slope within group, group-specific disaster response removed)

	ETF-holdings weights			Equal weights		
	Rep. share < .33	.33–.50	≥ .50	Rep. share < .33	.33–.50	≥ .50
Interpretation response	9.21	41.29**	21.47**	−4.42	17.24	5.35
	(6.51)	(16.71)	(8.36)	(5.33)	(14.08)	(5.17)

Notes. Response of advisers to local climate interpretation and to the disaster by the political lean of the county and of the adviser. The outcome is the change in the adviser's green-ETF share from the quarter before the episode to the quarter after it ($h = 1$). Columns 1 to 4 weight each adviser by its share of the county's ETF holdings, and Columns 5 and 6 weight advisers equally. Columns 4 and 6 use the county giving tilt in place of the county vote share. The county giving tilt is Republican minus Democratic donations from the county over 2015 to 2024, divided by their sum. The adviser's Republican lean comes from the political donations of the individuals on the adviser's roster or, without a match, of the firm's investment-decision staff. Zero is a politically neutral firm. County Republican vote is the two-party presidential vote share, averaged over the sample elections. County Republican vote, the county giving tilt, Interpretation and attention are per standard deviation. The response rows are evaluated at the means of all county and adviser characteristics among affected advisers. The interpretation rows report differences in slopes between affected and comparison advisers. The lower panel reports interpretation slopes specific to three county groups by Republican vote share, each with its own disaster response. The p-value of the test that the three slopes are equal is 0.145 with ETF-holdings weights and 0.117 with equal weights. All columns include episode and calendar-quarter fixed effects, Affected × year effects, attention and its interactions, the previous green-share change, lagged portfolio size and an indicator for advisers with no measured lean. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F.7 reports the estimates for the disaster response at reference levels of interpretation and attention and for the response to interpretation among affected counties. The disaster response does not move significantly with either county politics or the adviser's own lean. The interpretation effect is estimated to be stronger in less Democratic counties. A one-standard-deviation higher Republican vote share moves a county from the average of 47 percent to 62 percent. Such counties respond to interpretation by 11 basis points per standard deviation more. This is about half the base response.

I divide the counties into three political groups, with a Republican vote share below one third, between one third and one half, and at least one half, and net out each group's own direct disaster response. Within groups, the response to interpretation is estimated to be largest in counties with a Republican vote share between one third and one half, at 41 basis points per standard deviation of interpretation, and is statistically significant. It is also present among stronger Republican-majority counties, at about half that size, while the estimate in the strongly Democratic group is positive but not statistically distinguishable from zero. The point estimates suggest that the combination of a disaster and a climate narrative is most persuasive where the population is politically mixed, although the differences across groups are not jointly statistically significant. This is consistent with the survey evidence of Section 7.2.

Table F.8: Interpretation, predetermined activity, and flows during the event, county level, 2015Q1–2024Q4

Outcome	Affected × Interpretation (1)	Affected × Coverage (2)	Affected (3)	Mean	N
Panel A. Predetermined quantities					
Predetermined ETF turnover, per quarter	-44.7 (229.1)	170 (694)	-2,288 (1,393)	3,699.5	79,683
Predetermined total-book turnover, per quarter	42.0 (91.1)	-281 (179)	734 (341)	2,171.5	79,712
Predetermined ETF net flow, per quarter	-61.4 (211.6)	612 (634)	-3,100 (1,419)	1,594.4	79,683
Predetermined total-book net flow, per quarter	-56.1 (44.0)	163 (130)	53.9 (134.4)	288.2	79,712
Panel B. Event-window quantities					
ETF net flow, $t..t+1$	277.7 (375.1)	285 (302)	-1,896 (558)	1,098.8	79,737
Total-book net flow, $t..t+1$	32.0 (158.9)	172 (210)	-1,550 (346)	364.9	79,674
ETF asset growth, $t..t+1$ (percent)	4.2 (3.1)	5.0 (2.4)	-23.1 (7.0)	11.8	79,737
Total-book asset growth, $t..t+1$ (percent)	1.4 (1.7)	2.3 (1.8)	-14.4 (3.5)	7.5	79,674
Green-ETF net purchases, $t..t+1$	14.6* (7.4)	13.8 (7.8)	2.6 (3.9)	4.5	79,737
Total-book turnover, $t..t+1$, per quarter	166.8 (123.5)	-13.1 (139.7)	1,653 (670)	1,949.4	79,674

Notes. Effect of disasters and of local climate interpretation on predetermined adviser activity and on adviser flows during the event, at the county level. Each row reports one regression with a different outcome. Each outcome is the mean of an adviser-level quantity over the county's advisers, weighted by lagged ETF assets and winsorized at the 1st and 99th percentiles. Panel A reports predetermined quantities, per-quarter means over quarters $t-5$ to $t-2$. Panel B reports quantities cumulated over quarters t to $t+1$, with turnover as a per-quarter mean. Turnover and net flow are in basis points of lagged assets, over the ETF positions or the whole Form 13F report. Green-ETF net purchases are net green-ETF position changes over lagged ETF assets. The Affected coefficient is the reference-year effect for affected counties. All rows control for the county's prior Democratic vote share, share of residents worried about global warming, income, college share, white share, population, population density, lagged advised portfolio size, lagged share of local coverage on climate policy and green topics, and damage, fatalities and injuries. All rows include county, quarter and episode fixed effects. Standard errors in parentheses are clustered by county and episode. Stars are reported for Affected × Interpretation only. $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.

TABLE F.9: COUNTY HOLDINGS BY ASSET CLASS, IN LOGS

	Affected	Affected × Interpretation
	(1)	(2)
log(1 + green ETF assets)	0.125	0.769**
	(0.181)	(0.384)
log(1 + non-green ETF assets)	0.043	0.043**
	(0.033)	(0.021)
log ETF assets	0.039	0.047**
	(0.032)	(0.020)
log total observed holdings	-0.008	0.010
	(0.021)	(0.019)
log stock holdings	-0.037*	0.003
	(0.021)	(0.027)

Notes. Effect of disasters and of local climate interpretation on county holdings by asset class one quarter after the episode ($h = 1$). The sample covers all eligible disasters. The Affected column includes county, quarter and episode fixed effects. The Affected × Interpretation column includes county, quarter, episode and hazard type × exposure group fixed effects. The regressions include no county controls. The first column reports the Affected coefficient from the specification without Interpretation. The second column reports the Affected × Interpretation coefficient from the specification with Interpretation. Total observed holdings are the total Form 13F holdings in FactSet. Standard errors in parentheses are clustered by county. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table F.10: Direct trades in constituent stocks and implied purchases through green ETFs

	All constituents		Constituents held at $t-1$	
	Dollars	Basis points of book	Dollars	Basis points of book
	(1)	(2)	(3)	(4)
Panel A. Trades from $t-1$ to t				
Implied indirect purchase	4.450***	1.724***	4.536**	2.389**
	(1.408)	(0.310)	(1.961)	(1.165)
Implied indirect purchase, with lagged position control	6.405***	1.712***	7.235***	2.368**
	(2.443)	(0.310)	(1.775)	(1.166)
Observations	6,037,448	6,037,448	937,024	937,024
Adviser-quarters	11,516	11,516	9,601	9,601
Advisers	1,610	1,610	1,449	1,449
Panel B. Trades from $t-1$ to $t+1$				
Implied indirect purchase	5.032***	1.845***	4.633	1.751***
	(1.812)	(0.265)	(3.003)	(0.673)
Implied indirect purchase, with lagged position control	8.260***	1.822***	8.906***	1.706**
	(2.253)	(0.269)	(1.473)	(0.679)
Observations	7,011,653	7,011,653	1,080,221	1,080,221
Adviser-quarters	12,875	12,875	10,823	10,823
Advisers	1,601	1,601	1,441	1,441
Adviser × quarter FE	X	X	X	X
Stock × quarter FE	X	X	X	X

Notes. Direct trades of advisers in the constituent stocks of the green ETFs they buy, regressed on the purchases of those stocks implied by their green-ETF purchases. Each observation is an adviser, stock and quarter. The sample covers household-serving single-county advisers from 2018Q1 to 2024Q4, in quarters with positive net purchases of green ETFs. Advisers that sponsor a green ETF are excluded. The dependent variable is the adviser's direct trade in the stock, valued at the price of quarter $t-1$. The regressor is the purchase of the stock implied by the adviser's green-ETF purchases and the stock's weight in each ETF one quarter earlier. Columns 2 and 4 divide both sides by the adviser's total holdings at $t-1$. Columns 1 and 2 assign a zero trade to constituents the adviser does not hold directly. All columns include adviser × quarter and stock × quarter fixed effects. Standard errors in parentheses are clustered by adviser and stock. $^{*}\,p<0.1$, $^{**}\,p<0.05$, $^{***}\,p<0.01$.

TABLE F.11: PRIOR TURNOVER AND THE INTERPRETATION RESPONSE, 2015–2024

	Outcome: fixed-price change in green-ETF share (bp)			
	ETF turnover		Whole-portfolio turnover	
Prior window	4 quarters	8 quarters	4 quarters	8 quarters
	(1)	(2)	(3)	(4)
Prior turnover	-0.22	-0.47	1.12	-0.59
	(2.00)	(3.12)	(1.96)	(3.21)
Affected × Prior turnover	25.59	23.18	9.70*	8.28*
	(17.85)	(17.50)	(5.32)	(4.41)
Interpretation × Prior turnover	-3.11**	-3.33**	-2.39*	-2.00*
	(1.42)	(1.33)	(1.27)	(1.10)
Affected × Interpretation × Prior turnover	-8.40	-9.58	6.55	4.44
	(6.95)	(9.30)	(5.40)	(4.27)
Affected × Interpretation, at mean turnover	4.13	3.56	3.90	4.18
	(7.58)	(7.57)	(7.22)	(7.36)
Affected, at mean turnover	2.17	2.28	-4.12	-3.63
	(6.62)	(6.40)	(5.42)	(5.38)
Observations	464,020	464,629	464,528	464,950
Advisers	2,061	2,065	2,063	2,064
County clusters	291	292	292	292
Episodes	974	974	974	974
Adviser, quarter and episode FE	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓
Affected × year effects	✓	✓	✓	✓

Notes. Effect of local climate interpretation on the green-ETF share of advisers by prior portfolio turnover. The outcome is the change in the adviser's green-ETF share from quarter $t-1$ to quarter $t+1$. Prior turnover is mean quarterly gross turnover, in basis points of lagged assets. It is measured over quarters $t-5$ to $t-2$ in Columns 1 and 3 and over quarters $t-9$ to $t-2$ in Columns 2 and 4. Prior turnover enters as the log of one plus prior turnover, standardized. Interpretation is standardized. The Affected row is the reference-year effect. All columns control for Interpretation, disaster coverage and its interaction with Affected, Affected × year effects, the previous green-share change, lagged log assets and the county Democratic vote share. All columns include adviser, quarter and episode fixed effects. Standard errors in parentheses are clustered at the level of the county of the adviser's location. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F.12: National news and local interpretation among affected counties and advisers

	Dependent variable: Green-ETF share response (bp)		
	County	Advisers, −1 to +1	
	Pooled	ETF-holdings weights	Equal weights
	(1)	(2)	(3)
Baseline local interpretation	31.32**	26.78***	13.95**
	(12.53)	(8.24)	(6.77)
With national coverage	27.28**	22.44***	11.53**
	(12.26)	(6.27)	(4.91)
× national coverage	26.85*	22.88**	15.35
	(15.66)	(10.41)	(12.06)
With national interpretation	22.41*	23.64***	13.00*
	(12.82)	(8.38)	(6.61)
× national interpretation	18.89	−1.47	1.11
	(12.48)	(5.61)	(4.67)
Observations	105,662	465,701	465,701

Notes. Effect of local climate interpretation among affected counties and advisers, and its change with national news. The first row reports the effect of a one-standard-deviation increase in local interpretation. The rows "With national coverage" and "With national interpretation" report the same effect evaluated at mean national news. The rows marked × report its change per standard deviation of national news. National coverage and national interpretation enter separate regressions. National coverage is the log of one plus national disaster coverage, and national interpretation is the share of that coverage that links the disaster centrally to climate change. Both are measured over weeks 0 to 3 across nine national outlets. Both are interacted with Affected, local interpretation and local coverage, and with the interactions of the last two with Affected. In Column 1 the outcome is the county's mean green-ETF share in quarters 0 to 2 minus its mean in quarters −2 and −1. In Columns 2 and 3 the outcome is the change in the adviser's green-ETF share from quarter −1 to quarter +1. Column 2 weights advisers by their pre-event share of the county's ETF holdings. Within each column the sample is the same in every row. All columns control for the county's prior Democratic vote share, share of residents worried about global warming, income, college share, white share, population, population density, lagged advised portfolio size, lagged share of local coverage on climate policy and green topics, and damage, fatalities and injuries. All columns include episode, quarter, Affected × hazard × year and geographic fixed effects, by state for counties and by county for advisers. Standard errors in parentheses are clustered at the county level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

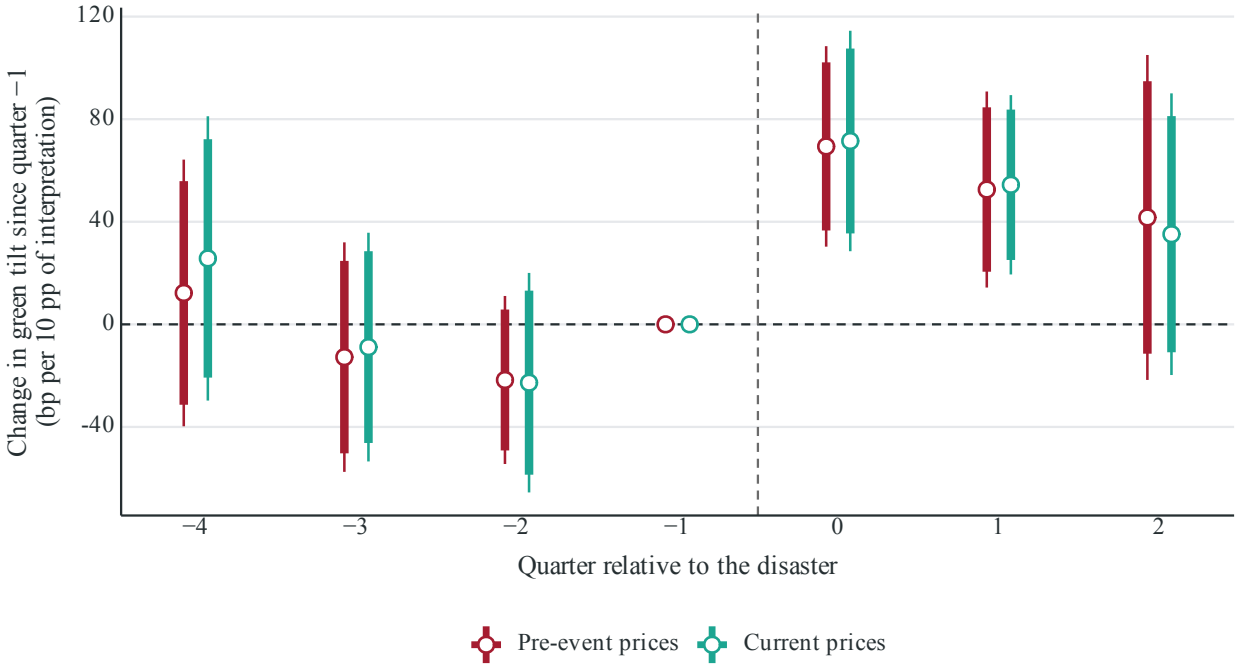
G Appendix to Section 4

TABLE G.1: MUTUAL FUND PORTFOLIO RESPONSE

	Dependent variable: response in basis points							
	Pre-event prices				Current prices			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Fund level: change in the fund's green tilt								
Interpretation	69.34***	69.38***	66.25***	67.58***	71.03***	71.49***	68.74***	65.75***
	(20.11)	(19.87)	(18.99)	(19.86)	(20.85)	(21.85)	(21.08)	(21.56)
Attention	−2.05	−.85	−1.09	−1.95	−4.52	−3.79	−4.01	−4.43
	(2.84)	(3.12)	(3.09)	(3.36)	(2.98)	(3.36)	(3.28)	(3.58)
Observations (fund-episodes)	37,047	37,047	37,047	36,964	37,047	37,047	37,047	36,964
Nearby fund-episodes	1,712	1,712	1,712	1,710	1,712	1,712	1,712	1,710
R^2	.031	.032	.033	.093	.044	.045	.045	.102
Exposure × episode FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓	✓	✓	✓	✓
Fund FE				✓				✓
Fund controls	✓	✓	✓	✓	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓	✓	✓	✓	✓
Exposure × county controls		✓	✓	✓		✓	✓	✓
Exposure × political controls			✓	✓			✓	✓
Panel B. Stock level: change in the fund's weight in a stock, top minus bottom tercile								
Interpretation		3.57***	3.56***			3.66***	3.71***	
		(1.28)	(1.28)			(1.33)	(1.29)	
Attention		.04	.03			−.09	−.13	
		(.27)	(.28)			(.29)	(.30)	
Observations (fund-episode-stocks)		5,426,327	5,426,327			5,426,327	5,426,327	
Fund-episodes		53,028	53,028			53,028	53,028	
R^2		.577	.577			.586	.586	
Fund × episode FE		✓	✓			✓	✓	
Fund style × stock × episode FE		✓	✓			✓	✓	
Exposure × episode FE		✓	✓			✓	✓	
Damage and coverage controls		✓	✓			✓	✓	
Exposure × political controls			✓				✓	

Notes. Effect of local climate interpretation on the green tilt of mutual funds managed near the disaster. The disasters are floods, hurricanes, storms and wildfires. The change in the fund's green tilt over the episode quarter is the change in its weight in stocks in the top tercile of the Environmental Pillar score minus the change in its weight in bottom-tercile stocks. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. County and political controls enter separately for each exposure group. In Panel A, all columns include exposure group × episode, county and fund style fixed effects, and Columns 4 and 8 add fund fixed effects. In Panel B, all columns include fund × episode, fund style × stock × episode and exposure group × episode fixed effects. Standard errors in parentheses are clustered at the episode level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Figure G.1: Interpretation effect among nearby managers, by quarter



Notes. Effect of local climate interpretation on the green tilt of mutual funds with managers within 50 miles of the disaster, by quarter relative to the disaster. The green tilt is the weight of stocks in the top tercile of the Environmental Pillar score minus the weight of bottom-tercile stocks. The regressions include exposure group × episode, county and fund style fixed effects and control for fund size, age and turnover, for damage and local coverage volume, and for county controls by exposure group. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. The figure shows 95% and 90% confidence intervals, with standard errors clustered at the episode level.

TABLE G.2: LOCAL HEAT AND THE ENVIRONMENTAL-PILLAR TILT OF MUTUAL FUNDS

	Dependent variable:	
	Environmental-Pillar tilt response (basis points)	
	Pre-event prices	Current prices
	(1)	(2)
Heat exposure	65.39*	71.40**
	(37.74)	(34.46)
Observations (fund-quarters)	53,802	53,802
Funds	2,335	2,335
Location-weighted county effects	✓	✓
Fund style × quarter FE	✓	✓
Fund controls	✓	✓
Heat severity controls	✓	✓

Notes. Effect of local heat waves on the Environmental Pillar tilt of mutual funds. Heat exposure is the share of the fund's offices in counties with a heat wave that caused injuries or fatalities in the quarter, from SHELDUS. The outcome is the quarterly change in the fund's tilt, the weight of top-tercile minus bottom-tercile stocks by Environmental Pillar score. The sample covers fund-quarter observations from 2010 to 2023. Fund controls are the past-year return and flow, expense ratio, turnover, log assets and log age. Heat severity controls are the fatalities, injuries and damages of the heat events. Both columns include location-weighted county effects and fund style × quarter fixed effects. Standard errors in parentheses are clustered by fund and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE G.3: MUTUAL FUND PORTFOLIO RESPONSE: ALL FUND-EPISODES AND FUND-EPISODES WITH POLITICAL MEASURES

	Dependent variable: response in basis points									
	Pre-event prices					Current prices				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Fund level: change in the fund's Environmental-Pillar tilt										
Interpretation	50.25***	48.15***	69.34***	69.38***	52.03**	42.47***	39.76**	71.03***	71.49***	53.39**
	(12.80)	(12.51)	(20.11)	(19.87)	(20.69)	(15.46)	(15.37)	(20.85)	(21.85)	(22.64)
Attention	−1.06	−1.06	−2.05	−.85	−.15	−2.27	−2.32	−4.52	−3.79	−1.91
	(2.39)	(2.54)	(2.84)	(3.12)	(2.27)	(2.34)	(2.44)	(2.98)	(3.36)	(2.32)
Observations (fund-episodes)	51,226	51,226	37,047	37,047	37,051	51,226	51,226	37,047	37,047	37,051
Nearby fund-episodes	2,280	2,280	1,712	1,712	1,712	2,280	2,280	1,712	1,712	1,712
R^2	.025	.025	.031	.032	.025	.039	.039	.044	.045	.037
Exposure × episode FE	✓	✓	✓	✓		✓	✓	✓	✓	
Episode FE					✓					✓
Exposure × hazard × quarter FE					✓					✓
County FE	✓	✓	✓	✓		✓	✓	✓	✓	
Fund style FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fund controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Exposure × county controls		✓		✓	✓		✓		✓	✓
Sample with political measures			✓	✓	✓			✓	✓	✓
Panel B. Stock level: change in the fund's weight in a stock, High-E minus Low-E										
Interpretation		4.44***		3.57***			4.51***		3.66***	
		(1.28)		(1.28)			(1.21)		(1.33)	
Attention		−.09		.04			−.16		−.09	
		(.18)		(.27)			(.19)		(.29)	
Observations (fund-episode-stocks)		7,125,159		5,426,327			7,125,159		5,426,327	
Fund-episodes		72,461		53,028			72,461		53,028	
R^2		.539		.577			.550		.586	
Fund × episode FE		✓		✓			✓		✓	
Fund style × stock × episode FE		✓		✓			✓		✓	
Exposure × episode FE		✓		✓			✓		✓	
Damage and coverage controls		✓		✓			✓		✓	
Sample with political measures				✓					✓	

Notes. Effect of local climate interpretation on the green tilt of mutual funds managed near the disaster, in the full sample and in the sample with political measures. The change in the fund's green tilt over the episode quarter is the change in its weight in stocks in the top tercile of the Environmental Pillar score minus the change in its weight in bottom-tercile stocks. Columns 1, 2, 6 and 7 use all fund-episode observations, including managers and management companies without matched political donations. The other columns use the observations for which the political controls are observed. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. County controls enter separately for each exposure group. In Panel A, Columns 1 to 4 and 6 to 9 include exposure group × episode and county fixed effects. Columns 5 and 10 replace them with episode fixed effects and exposure group × hazard × calendar quarter fixed effects. All columns of Panel A include fund style fixed effects. In Panel B, all columns include fund × episode, fund style × stock × episode and exposure group × episode fixed effects. Standard errors in parentheses are clustered at the episode level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table G.4: Mutual fund portfolio response: manager location and continuous score

	Dependent variable: response in basis points									
	Pre-event prices					Current prices				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Funds with all offices in one county										
Interpretation	57.75***	53.93***	81.00***	79.28***	74.74***	55.02***	50.86***	76.93***	75.17***	70.43***
	(15.51)	(15.89)	(22.60)	(22.77)	(21.80)	(15.81)	(16.93)	(22.04)	(23.18)	(22.37)
Attention	−1.61	−1.59	−2.58	−1.52	−2.41	−2.99	−3.05	−4.27	−3.69	−4.64
	(2.79)	(2.82)	(3.26)	(3.49)	(3.43)	(2.83)	(2.83)	(3.40)	(3.73)	(3.56)
Observations (fund-episodes)	37,590	37,590	25,559	25,559	25,559	37,590	37,590	25,559	25,559	25,559
Nearby fund-episodes	2,061	2,061	1,404	1,404	1,404	2,061	2,061	1,404	1,404	1,404
Panel B. Fund located at all its offices										
Interpretation	53.10***	49.74***	72.30***	71.79***	68.23***	47.75***	43.91***	72.26***	71.63***	68.45***
	(13.81)	(14.01)	(20.06)	(19.75)	(19.01)	(14.25)	(14.63)	(21.16)	(21.84)	(21.23)
Attention	−2.77	−2.70	−4.42	−3.23	−3.58	−3.93	−3.83	−6.30*	−5.46	−5.77
	(2.90)	(3.03)	(3.13)	(3.46)	(3.46)	(2.98)	(3.01)	(3.34)	(3.64)	(3.58)
Observations (fund-episodes)	51,252	51,252	37,080	37,080	37,080	51,252	51,252	37,080	37,080	37,080
Nearby fund-episodes	2,531	2,531	1,884	1,884	1,884	2,531	2,531	1,884	1,884	1,884
Panel C. Fund located at its office closest to the disaster										
Interpretation	43.29***	38.62***	62.29***	63.50***	57.90***	45.16***	41.10***	65.08***	67.20***	61.61***
	(14.02)	(13.95)	(17.88)	(17.39)	(16.69)	(14.01)	(13.83)	(18.70)	(19.15)	(18.48)
Attention	−2.42	−2.03	−2.54	−1.21	−1.86	−3.99	−3.44	−4.79*	−3.44	−4.10
	(2.43)	(2.58)	(2.70)	(3.10)	(3.04)	(2.48)	(2.56)	(2.82)	(3.13)	(3.03)
Observations (fund-episodes)	51,257	51,257	37,084	37,084	37,084	51,257	51,257	37,084	37,084	37,084
Nearby fund-episodes	2,389	2,389	1,784	1,784	1,784	2,389	2,389	1,784	1,784	1,784
Panel D. Continuous Environmental-Pillar score										
Interpretation	14.64***	13.47***	18.54**	19.37**	17.66**	13.55**	12.03**	20.48**	21.30**	19.54**
	(4.65)	(4.73)	(7.73)	(8.16)	(8.19)	(5.91)	(5.82)	(8.92)	(9.33)	(9.44)
Attention	−.18	−.24	−.28	.09	−.12	−.35	−.39	−.92	−.60	−.79
	(.86)	(1.04)	(1.12)	(1.40)	(1.49)	(.91)	(1.07)	(1.17)	(1.47)	(1.54)
Observations (fund-episodes)	51,226	51,226	37,047	37,047	37,047	51,226	51,226	37,047	37,047	37,047
Nearby fund-episodes	2,280	2,280	1,712	1,712	1,712	2,280	2,280	1,712	1,712	1,712
Exposure × episode FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fund controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Exposure × county controls		✓		✓	✓		✓		✓	✓
Exposure × political controls					✓					✓
Sample with political measures			✓	✓	✓			✓	✓	✓

Notes. Effect of local climate interpretation on the green tilt of mutual funds managed near the disaster, by fund location and with a continuous score. The outcome is the change in the fund's green tilt over the episode quarter, the change in its weight in stocks in the top tercile of the Environmental Pillar score minus the change in its weight in bottom-tercile stocks. Panel B places the fund at all its offices, with equal weight. In Panel D the outcome sums, over the fund's scored stocks, the change in each stock's weight times the difference between its Environmental Pillar score, from 0 to 1, and the fund's pre-event average score. Columns 1, 2, 6 and 7 use all fund-episode observations, and the other columns the observations for which the political controls are observed. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. County and political controls enter separately for each exposure group. All columns include exposure group × episode, county and fund style fixed effects. Standard errors in parentheses are clustered at the episode level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

TABLE G.5: MUTUAL FUND PORTFOLIO RESPONSE: TOP- AND BOTTOM-TERCILE WEIGHTS

	Dependent variable: change in the fund's weight, basis points			
	Pre-event prices		Current prices	
	Top tercile (1)	Bottom tercile (2)	Top tercile (3)	Bottom tercile (4)
Interpretation	45.72***	−23.66***	42.47***	−29.02***
	(13.37)	(9.13)	(14.12)	(9.97)
Attention	−.63	.23	−2.06	1.73
	(1.97)	(1.79)	(2.02)	(1.94)
Observations (fund-episodes)	37,047	37,047	37,047	37,047
Nearby fund-episodes	1,712	1,712	1,712	1,712
R^2	.029	.034	.038	.045
Exposure × episode FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓
Fund controls	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × county controls	✓	✓	✓	✓

Notes. Effect of local climate interpretation on the weights of mutual funds managed near the disaster in top-tercile and bottom-tercile stocks by Environmental Pillar score. The outcome is measured over the episode quarter. The two outcomes are scaled so that their difference equals the fund's green tilt. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share, and enter separately for each exposure group. All columns include exposure group × episode, county and fund style fixed effects. Standard errors in parentheses are clustered at the episode level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE G.6: MUTUAL FUND PORTFOLIO RESPONSE BEFORE AND AFTER THE EPISODE

	Dependent variable:					
	Environmental-Pillar tilt response (basis points)					
	Pre-event prices			Current prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Interpretation × Pre (−4, −3)	3.04	13.86	11.83	15.38	22.21	19.82
	(16.93)	(19.28)	(19.43)	(15.00)	(18.93)	(18.71)
Interpretation × Post (0 to 2)	70.28***	71.03***	67.50***	61.26***	69.56***	68.29***
	(20.04)	(20.56)	(19.72)	(20.25)	(21.88)	(21.35)
Observations (fund-episode quarters)	251,856	251,856	251,856	251,856	251,856	251,856
Fund-episodes	37,066	37,066	37,066	37,066	37,066	37,066
R^2	.375	.375	.376	.384	.384	.384
Fund-episode FE	✓	✓	✓	✓	✓	✓
Exposure × episode FE, by bin	✓	✓	✓	✓	✓	✓
County and fund style FE, by bin	✓	✓	✓	✓	✓	✓
Fund controls, by bin	✓	✓	✓	✓	✓	✓
Exposure × county controls, by bin		✓	✓		✓	✓
Exposure × political controls, by bin			✓			✓

Notes. Effect of local climate interpretation on the green tilt of mutual funds managed near the disaster, before and after the episode. The outcome is the change in the fund's green tilt since the end of quarter −1, in quarters −4 to 2 around each episode. The green tilt is the weight of stocks in the top tercile of the Environmental Pillar score minus the weight of bottom-tercile stocks. Every regressor is interacted with Pre (quarters −4 and −3) and Post (quarters 0 to 2), with quarters −2 and −1 as the base. Coefficients are the effects among managers within 50 miles of the affected counties, per 10 percentage points of Interpretation. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are. Fund controls are lagged log total net assets, log age and turnover. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. Columns 2, 3, 5 and 6 add county controls by exposure group, and Columns 3 and 6 add political controls by exposure group. All columns include fund-episode fixed effects and, by bin, exposure group × episode, county and fund style fixed effects and fund controls. Standard errors in parentheses are clustered at the episode level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE G.7: MUTUAL FUND PORTFOLIO RESPONSE BY DISTANCE BAND

	Dependent variable:					
	Environmental-Pillar tilt response (basis points)					
	Pre-event prices			Current prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Nearby managers (offices within 50 miles of the affected counties)						
Interpretation	69.38***	66.25***	67.58***	71.49***	68.74***	65.75***
	(19.87)	(18.99)	(19.86)	(21.85)	(21.08)	(21.56)
Fund-episodes in the band	1,712	1,712	1,710	1,712	1,712	1,710
Panel B. Affected managers (offices in the affected counties)						
Interpretation	75.15**	73.98**	81.18***	70.18**	70.47**	77.54**
	(30.54)	(31.05)	(31.23)	(30.06)	(30.45)	(31.32)
Fund-episodes in the band	1,973	1,973	1,961	1,973	1,973	1,961
Panel C. Managers more than 100 miles away						
Interpretation	3.70**	3.70**	3.34**	3.43**	3.45**	3.16*
	(1.52)	(1.52)	(1.65)	(1.71)	(1.70)	(1.83)
Observations	37,047	37,047	36,964	37,047	37,047	36,964
R^2	.032	.033	.093	.045	.045	.102
Exposure × episode FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓	✓	✓
Fund FE			✓			✓
Fund controls	✓	✓	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓	✓	✓
Exposure × county controls	✓	✓	✓	✓	✓	✓
Exposure × political controls		✓	✓		✓	✓

Notes. Effect of local climate interpretation on the green tilt of mutual funds, by distance of the managers from the disaster. The outcome is the change in the fund's green tilt over the episode quarter, the change in its weight in stocks in the top tercile of the Environmental Pillar score minus the change in its weight in bottom-tercile stocks. Each column is one regression. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. County and political controls enter separately for each exposure group. All columns include exposure group × episode, county and fund style fixed effects, and Columns 3 and 6 add fund fixed effects. Standard errors in parentheses are clustered at the episode level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE G.8: LOCAL FIRMS IN THE PORTFOLIOS OF MANAGERS NEAR THE DISASTER

	Dependent variable: stock weight response (basis points)		
	Pre-event prices (1)	Current prices (2)	Active trading (3)
Panel A. Stocks of firms in the disaster zone or within 50 miles of it			
Affected or nearby managers	−2.93***	−2.75***	−0.90**
	(1.01)	(0.98)	(0.43)
× Interpretation	−0.20	−0.08	−0.25
	(0.58)	(0.57)	(0.28)
× Attention	0.28***	0.24**	0.02
	(0.11)	(0.10)	(0.04)
Affected managers	−2.09	−2.22	−0.99**
	(1.44)	(1.49)	(0.49)
× Interpretation	−0.64	−0.41	−0.44
	(0.91)	(0.99)	(0.38)
× Attention	0.32*	0.29*	0.04
	(0.18)	(0.17)	(0.06)
Nearby managers	−4.34***	−3.90***	−0.71
	(1.24)	(1.39)	(0.63)
× Interpretation	−0.25	−0.07	−0.02
	(0.75)	(0.76)	(0.30)
× Attention	0.27*	0.20	−0.00
	(0.16)	(0.16)	(0.06)
Panel B. Stocks of firms in the disaster zone or within 100 miles of it			
Affected or nearby managers	−1.90**	−1.52**	−0.71**
	(0.76)	(0.74)	(0.34)
× Interpretation	−0.01	−0.04	−0.13
	(0.43)	(0.43)	(0.16)
× Attention	0.13	0.11	0.03
	(0.09)	(0.08)	(0.04)
Affected managers	−1.91*	−1.78*	−0.89**
	(1.06)	(1.03)	(0.37)
× Interpretation	0.18	0.18	−0.12
	(0.69)	(0.68)	(0.27)
× Attention	0.10	0.12	0.03
	(0.14)	(0.13)	(0.04)
Nearby managers	−2.39**	−1.82*	−0.44
	(0.95)	(1.00)	(0.53)
× Interpretation	−0.26	−0.21	−0.07
	(0.60)	(0.61)	(0.22)
× Attention	0.16	0.11	0.03
	(0.13)	(0.13)	(0.07)
Observations (fund-episode-stocks)	7,125,159	7,125,159	7,161,660
R^2	.100	.113	.136
Fund-episodes	72,461	72,461	74,676
Stocks	3,426	3,426	3,427
Fund × episode FE	✓	✓	✓
Stock × episode FE	✓	✓	✓

Notes. Response of the weight of a stock in a fund, at pre-event and at current prices, and of the fund's net active purchases of it, in basis points, for stocks of firms headquartered in the affected counties (the disaster zone) or within 50 miles of them, and in the zone or within 100 miles of it. Each row compares the managers in the group with managers more than 100 miles from the disaster who hold the same stock in the same episode. Affected managers have an office in an affected county and nearby managers an office within 50 miles of one. The first group of each panel treats the two as one, in a separate regression from the two groups below it. Interpretation is per 10 percentage points and Attention per 10 log points of local coverage, each centered at the mean of the group, so the group rows are the response at the average coverage and interpretation of the group. All columns include fund *imes* episode and stock *imes* episode fixed effects. Standard errors in parentheses are clustered at the episode level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE G.9: MUTUAL FUND ACTIVE TRADING

	Dependent variable:			
	Response (basis points of fund assets)			
	(1)	(2)	(3)	(4)
Interpretation	30.37***	30.14***	28.81***	29.80***
	(8.36)	(7.43)	(6.50)	(6.90)
Attention	.21	1.32	1.14	.68
	(1.36)	(1.52)	(1.48)	(1.63)
Nearby fund-episodes	1,806	1,806	1,806	1,804
Observations	38,177	38,177	38,177	38,091
R^2	.025	.026	.026	.087
Exposure × episode FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓
Fund FE				✓
Fund controls	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × county controls		✓	✓	✓
Exposure × political controls			✓	✓

Notes. Effect of local climate interpretation on the active trading of mutual funds managed near the disaster. The outcome is net active purchases of top-tercile minus bottom-tercile stocks by Environmental Pillar score in the episode quarter, in basis points of lagged fund assets. As in Sammon and Shim (2023), the change in a continuing position is net of its proportional scaling with the fund's flow, and the whole change in a position opened or closed in the quarter counts as active. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. Column 2 adds county controls by exposure group, and Column 3 adds political controls by exposure group. Column 4 adds fund fixed effects. All columns include exposure group × episode, county and fund style fixed effects. Standard errors in parentheses are clustered at the episode level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE G.10: DECOMPOSITION OF THE PORTFOLIO RESPONSE

	Dependent variable:							
	Environmental-Pillar tilt response component (basis points)							
	Within distance band		Across distance bands		Within sector		Across sectors	
	Pre-event	Current	Pre-event	Current	Pre-event	Current	Pre-event	Current
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Without political controls								
Interpretation	69.90***	71.60***	−.52	−.11	34.48*	31.73	34.90**	39.76**
	(19.49)	(22.06)	(4.74)	(4.53)	(17.66)	(20.02)	(14.98)	(15.86)
Attention	−1.62	−3.77	.77	−.02	−2.30	−3.61	1.45	−.18
	(3.21)	(3.34)	(.83)	(.82)	(2.78)	(3.00)	(2.12)	(2.25)
Nearby fund-episodes	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712
Observations	37,047	37,047	37,047	37,047	37,047	37,047	37,047	37,047
R^2	.033	.043	.027	.029	.030	.038	.026	.030
Panel B. With political controls								
Interpretation	66.33***	68.76***	−.07	−.02	31.65**	28.54	34.60**	40.19**
	(18.44)	(21.20)	(4.65)	(4.74)	(15.97)	(18.30)	(14.85)	(15.81)
Attention	−1.88	−3.99	.78	−.02	−2.64	−4.01	1.55	.00
	(3.13)	(3.24)	(.80)	(.81)	(2.72)	(2.89)	(2.15)	(2.27)
Nearby fund-episodes	1,712	1,712	1,712	1,712	1,712	1,712	1,712	1,712
Observations	37,047	37,047	37,047	37,047	37,047	37,047	37,047	37,047
R^2	.033	.044	.027	.029	.031	.039	.027	.030
Exposure × episode FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓	✓	✓	✓	✓
Fund controls	✓	✓	✓	✓	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓	✓	✓	✓	✓
Exposure × county controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes. Decomposition of the effect of local climate interpretation on the green tilt of mutual funds managed near the disaster. The outcome is a component of the change in the fund's green tilt over the episode quarter. The green tilt is the weight of stocks in the top tercile of the Environmental Pillar score minus the weight of bottom-tercile stocks. Firm-distance bands group firms by their distance from the disaster, and sectors are GICS sectors. Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Political controls are the county Democratic two-party vote share and the managers' political score. County and political controls enter separately for each exposure group. All columns include exposure group × episode, county and fund style fixed effects. Standard errors in parentheses are clustered at the episode level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE G.11: MUTUAL FUND RESPONSE ACROSS STOCKS: FIRM LOCATION

	Dependent variable:			
	Stock weight response, High-E minus Low-E (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. Baseline				
Interpretation	3.57***	3.56***	3.66***	3.71***
	(1.28)	(1.28)	(1.33)	(1.29)
Observations	5,426,327	5,426,327	5,426,327	5,426,327
Fund-episodes	53,028	53,028	53,028	53,028
Fund × episode FE	✓	✓	✓	✓
Fund style × stock × episode FE	✓	✓	✓	✓
Exposure group × episode FE	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × political controls		✓		✓
Panel B. Firm in the disaster zone				
Interpretation, firms outside the zone	3.57***	3.54***	3.66***	3.69***
	(1.11)	(1.09)	(1.12)	(1.07)
Interpretation, firms in the zone	18.61**	18.52**	17.47**	17.34**
	(7.48)	(7.50)	(7.50)	(7.50)
Observations	5,272,599	5,272,599	5,272,599	5,272,599
Fund-episodes	53,028	53,028	53,028	53,028
Fund × episode FE	✓	✓	✓	✓
Fund style × stock × episode FE	✓	✓	✓	✓
Exposure group × episode FE	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × political controls		✓		✓
Panel C. Firm within 100 miles of the disaster zone				
Interpretation, firms more than 100 miles away	3.50***	3.46***	3.55***	3.57***
	(1.16)	(1.13)	(1.15)	(1.08)
Interpretation, firms within 100 miles	6.44**	6.48**	6.48**	6.62**
	(2.60)	(2.64)	(3.25)	(3.32)
Observations	5,272,599	5,272,599	5,272,599	5,272,599
Fund-episodes	53,028	53,028	53,028	53,028
Fund × episode FE	✓	✓	✓	✓
Fund style × stock × episode FE	✓	✓	✓	✓
Exposure group × episode FE	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × political controls		✓		✓

Notes. Effect of local climate interpretation on the stock weights of mutual funds managed near the disaster, by the location of the firm. The outcome is the change in the fund's weight in each stock over the episode quarter, and the rows report the response of top-tercile relative to bottom-tercile stocks by Environmental Pillar score. In Panels B and C every term is interacted with an indicator for the location of the firm's headquarters, in the disaster zone (Panel B) or within 100 miles of it (Panel C). Coefficients are the effects among managers within 50 miles of the affected counties. Interpretation is the share of local coverage that interprets the disaster as climate change where the fund's managers are, per 10 percentage points. Political controls are the county Democratic two-party vote share and the managers' political score. Columns 2 and 4 add political controls by exposure group. All columns include fund × episode and fund style × stock × episode fixed effects. Standard errors in parentheses are clustered at the episode level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE G.12: MANAGERS OR HEADQUARTERS: WHO RESPONDS

	Dependent variable:	
	Environmental-Pillar tilt response, pre-event prices (basis points)	
	(1)	(2)
Panel A. Nearby managers, headquarters within 100 miles		
Interpretation	66.21***	65.87***
	(21.00)	(20.72)
Attention	−2.64	−1.52
	(3.06)	(3.24)
Fund-episodes (episodes)	1,245 (50)	1,245 (50)
Panel B. Nearby managers, headquarters more than 100 miles away		
Interpretation	71.19***	69.07***
	(20.73)	(21.62)
Attention	−.07	1.54
	(3.60)	(4.02)
Fund-episodes (episodes)	418 (46)	418 (46)
Panel C. Headquarters within 50 miles, managers more than 100 miles away		
Interpretation	18.74	21.04
	(32.42)	(33.06)
Attention	−11.87*	−11.97*
	(6.19)	(6.26)
Fund-episodes (episodes)	482 (75)	482 (75)
Panel D. Panel B minus Panel C		
Interpretation	52.45*	48.04
	(30.64)	(33.80)
Observations	36,165	36,165
Exposure × episode FE	✓	✓
County FE	✓	✓
Fund style FE	✓	✓
Fund controls	✓	✓
Damage and coverage controls	✓	✓
Exposure × county controls		✓

Notes. Effect of local climate interpretation on the green tilt of mutual funds by the location of their managers and headquarters. The outcome is the change in the fund's green tilt over the episode quarter, the change in its weight in stocks in the top tercile of the Environmental Pillar score minus the change in its weight in bottom-tercile stocks. Each column is one regression. Panels A and B report the effect among managers within 50 miles of the affected counties, for funds whose headquarters county is within 100 miles of the affected counties, an affected county included (Panel A), or more than 100 miles away (Panel B). Panel C reports the effect of the headquarters county's interpretation and attention for funds with no office within 100 miles and the headquarters county within 50 miles, an affected county included. The rows report slopes. Nearby managers share the level of their distance band in each episode, with an additional level common to all episodes when the headquarters is more than 100 miles away. The funds of Panel C have their own level in each episode. The sample is the fund-episode observations with political controls and a known headquarters location. Interpretation is the share of local coverage that interprets the disaster as climate change, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Column 2 adds county controls by exposure group. Both columns include exposure group × episode, county and fund style fixed effects. Standard errors in parentheses are clustered at the episode level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE G.13: MANAGERS OR HEADQUARTERS: WHO RESPONDS, ALL FUND-EPISODES

	Dependent variable:			
	Environmental-Pillar tilt response, pre-event prices (basis points)			
	All funds		Funds below median size	
	(1)	(2)	(3)	(4)
Panel A. Nearby managers, headquarters within 100 miles				
Interpretation	47.36***	45.22***	48.55***	53.73***
	(13.03)	(12.56)	(12.37)	(13.52)
Attention	−1.52	−1.52	.09	.85
	(2.39)	(2.50)	(2.98)	(3.15)
Fund-episodes (episodes)	1,707 (63)	1,707 (63)	765 (62)	765 (62)
Panel B. Nearby managers, headquarters more than 100 miles away				
Interpretation	55.64***	52.08***	66.85***	75.34***
	(16.18)	(16.87)	(22.52)	(25.43)
Attention	.75	.98	−1.85	−1.05
	(3.63)	(3.86)	(5.12)	(5.33)
Fund-episodes (episodes)	510 (51)	510 (51)	252 (49)	252 (49)
Panel C. Headquarters within 50 miles, managers more than 100 miles away				
Interpretation	−22.06	−20.41	−38.77	−37.00
	(23.68)	(23.89)	(29.41)	(30.36)
Attention	−6.29	−6.25	−5.97	−5.97
	(5.80)	(5.85)	(5.45)	(5.50)
Fund-episodes (episodes)	653 (83)	653 (83)	345 (75)	345 (75)
Panel D. Panel B minus Panel C				
Interpretation	77.69***	72.49***	105.62***	112.35***
	(26.44)	(27.40)	(35.14)	(36.44)
Observations	50,046	50,046	25,008	25,008
Exposure × episode FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Fund style FE	✓	✓	✓	✓
Fund controls	✓	✓	✓	✓
Damage and coverage controls	✓	✓	✓	✓
Exposure × county controls		✓		✓

Notes. Effect of local climate interpretation on the green tilt of mutual funds by the location of their managers and headquarters, in the full sample. The outcome is the change in the fund's green tilt over the episode quarter, the change in its weight in stocks in the top tercile of the Environmental Pillar score minus the change in its weight in bottom-tercile stocks. Each column is one regression. Panels A and B report the effect among managers within 50 miles of the affected counties, for funds whose headquarters county is within 100 miles of the affected counties, an affected county included (Panel A), or more than 100 miles away (Panel B). Panel C reports the effect of the headquarters county's interpretation and attention for funds with no office within 100 miles and the headquarters county within 50 miles, an affected county included. The rows report slopes. Nearby managers share the level of their distance band in each episode, with an additional level common to all episodes when the headquarters is more than 100 miles away. The funds of Panel C have their own level in each episode. The sample is all fund-episode observations with a known headquarters location, including those without political controls. Interpretation is the share of local coverage that interprets the disaster as climate change, per 10 percentage points. Attention is the log volume of that coverage, per 10 log points. Fund controls are lagged log total net assets, log age and turnover. Damage and coverage controls are the damage in the affected counties and the volume of local coverage at the fund's offices. County controls are the county's interpretation of its other episodes, log fatalities, log population, log population density, log income, college share, unemployment rate and urban share. Columns 2 and 4 add county controls by exposure group. All columns include exposure group × episode, county and fund style fixed effects. Standard errors in parentheses are clustered at the episode level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G.14: Tropical Storm Isaias: tilt of nearby funds

Offices of the fund	Funds	Change in the tilt (basis points)	
		Median	Mean
	(1)	(2)	(3)
Somerset and Morris, New Jersey	7	0	+210
Essex, New Jersey, and Westchester, New York	14	−40	−162
Essex, New Jersey	11	−99	−220
More than 100 miles away	102	−11	−40

Notes. Change in the Environmental Pillar tilt of mutual funds over the quarter of Tropical Storm Isaias, which hit New York City and Long Island in August 2020. The tilt is the weight of stocks in the top tercile of the Environmental Pillar score minus the weight of bottom-tercile stocks. The first three rows group the funds with offices within 50 miles of the storm footprint by the counties of their offices. In Somerset and Morris counties, a share of 0.16 of local articles on the storm interpreted it as climate change. In Essex and Westchester counties, the shares were 0.08 and 0.02. The last row reports the funds with all their offices more than 100 miles away. The funds are those in the estimation sample of the main fund-level regression with county controls.

H Appendix to Section 5

Table H.1: Outlet-level first stage of newspaper-chain size

	Dependent variable:	
	Disaster coverage (1)	Interpretation share (2)
Log chain size	−0.061	−0.023***
	(0.041)	(0.005)
Observations	6,711	6,711
R^2	.650	.362
First-stage F	2.20	20.85
Newspaper and quarter FE	✓	✓
Disaster coverage control		✓

Notes. Effect of newspaper-chain size on the disaster coverage of each newspaper and on its climate interpretation, by quarter. The sample covers 263 chained newspapers with positive disaster coverage over 40 quarters, 2015–2024. In Column 1 the outcome is disaster coverage, the log of one plus the number of disaster articles in the quarter. In Column 2 the outcome is the interpretation share, the share of those articles that link the disaster to climate change. Log chain size is the log of one plus the number of other newspapers held by the same owner, measured under the owner in place before the quarter. Column 2 controls for disaster coverage. All columns include newspaper and quarter fixed effects. Standard errors in parentheses are clustered at the newspaper level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table H.2 replaces the chain-size instrument with the 2019 Gannett–GateHouse merger, which formed the largest owner of US dailies (Table H.3). The specification is that of Table 2, with the county's pre-merger Gannett circulation share interacted with an indicator for quarters after 2019 and with the affected and nearby indicators; nearby counties enter as in the instrumental-variable sample. After the merger the response of affected or nearby counties is 6 to 7 basis points lower per 10 percentage points of Gannett share, unchanged with the political triple interaction; the difference is in affected and nearby counties, with none further away.

TABLE H.2: NEWSPAPER OWNERSHIP, INTERPRETATION AND THE COUNTY GREEN-ETF RESPONSE

	Floods, hurricanes and coastal episodes				Flood episodes			
Dependent variable:	Interpretation share (pp)	Green-ETF share response (basis points)			Interpretation share (pp)	Green-ETF share response (basis points)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gannett share × Post	−2.15**				−2.30**			
	(.94)				(.96)			
Affected or Nearby ×		−6.05**	−5.79**			−6.97**	−6.83**	
Gannett share × Post		(2.75)	(2.67)			(2.80)	(2.77)	
Affected ×				−6.44				−7.91
Gannett share × Post				(4.82)				(5.17)
Nearby (0–50 miles) ×				−5.91*				−6.75**
Gannett share × Post				(3.27)				(3.26)
Further (50–100 miles) ×				.11				−.79
Gannett share × Post				(3.23)				(3.06)
Observations	239	77,571	77,571	77,571	222	64,938	64,938	64,938
R^2	.770	.093	.093	.093	.708	.100	.100	.100
Affected or nearby county-episodes	239	599	599	599	222	484	484	484
Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Episode FE		✓	✓	✓		✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Hazard × distance band FE	✓				✓			
Affected or Nearby × Republican share × Post			✓				✓	

Notes. Effect of the 2019 Gannett–GateHouse merger on the climate interpretation of local disaster coverage and on the county green-ETF share response to disasters. In Columns 1 and 5 the outcome is the interpretation share, the share of the county's local coverage of the event that links it to climate change. These columns use the exposed county-episodes with local coverage of the event. In the other columns the outcome is the change in the county green-ETF share, the mean over the quarter of the episode and the two following quarters minus the mean over the two quarters before. Gannett share is the share of the county's audited newspaper circulation held by Gannett before the merger, per 10 percentage points. Post is one from the first quarter of 2020. Nearby is one for counties within 50 miles of the episode footprint, and Further for counties 50 to 100 miles from it. Columns 2, 3, 6 and 7 pool affected and nearby counties. Columns 3 and 7 add the interaction of Affected or Nearby with the county Republican share and Post. The Republican share is the county's two-party Republican vote share in the latest presidential election up to the quarter's year, per 10 percentage points. Each regression also includes the lower-order interactions of its terms, which are not reported. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE H.3: LARGEST OWNERS OF US DAILY NEWSPAPERS

Parent owner	Daily newspapers (1)
Gannett	250
Lee Enterprises	90
Alden Global Capital / Digital First Media	56
Chatham Asset Management / McClatchy	30
Hearst	23
Advance Local	22
Tribune	10

Notes. Number of major US daily newspapers held by each of the seven largest parent owners. The News Media Alliance counts 672 major US dailies, of which 382 are held by these seven owners. Data from the Harvard Future of Media Project, Index of Seven Big Owners of Dailies (2021).

Table H.4: Chain size and predetermined characteristics

	Dependent variable: chain size (1)
Politics and beliefs	
Democratic two-party share, latest presidential election	0.057
	(0.257)
Share worried about global warming	-0.214
	(0.159)
Investors	
Green-ETF share change, two pre-event quarters	0.001
	(0.005)
Portfolio assets (log)	-0.033
	(0.028)
County	
Population growth, four years	0.024
	(0.052)
Income growth, four years	0.066
	(0.056)
Disaster	
Fatalities in the county (log)	0.013
	(0.013)
Damage in the county (log)	-0.022
	(0.030)
Fatalities outside the county (log)	-0.002
	(0.013)
Damage outside the county (log)	0.003
	(0.017)
Counties in the footprint (log)	0.007
	(0.014)
Distance to the disaster (miles)	0.022
	(0.017)
Local disaster coverage (log)	-0.035
	(0.025)
Audience overlap with the footprint	0.005
	(0.017)
Joint test, p-value	0.66
County-events	694
Counties	184

Notes. Balance of newspaper-chain size on predetermined county, investor and disaster characteristics. Each row reports the coefficient from a separate regression of chain size on the characteristic, both standardized. All regressions include county, calendar-quarter and hazard-by-distance-band fixed effects. The joint test is from a regression of chain size on all characteristics. Standard errors in parentheses are clustered at the county level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

TABLE H.5: INSTRUMENTED INTERPRETATION, DROPPING PURCHASES OF INDEPENDENT NEWSPAPERS

	Portfolio response (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. County ETF holdings				
Interpretation (IV)	26.98*	26.71*	29.19*	28.89*
	(15.62)	(15.48)	(15.80)	(15.65)
Observations	642	642	642	642
First-stage F	9.94	9.89	9.94	9.89
Anderson–Rubin p	.030	.030	.022	.022
Anderson–Rubin 90% set	[6.1, 71.0]	[6.0, 70.4]	[7.9, 73.3]	[7.7, 72.6]
Panel B. Adviser ETF holdings				
Interpretation (IV)	20.65*	20.58*	23.76**	23.69**
	(11.05)	(11.03)	(11.51)	(11.50)
Observations	3,974	3,974	3,974	3,974
County-events	608	608	608	608
First-stage F	10.05	10.03	10.05	10.03
Anderson–Rubin p	.022	.022	.017	.017
Anderson–Rubin 90% set	[5.6, 51.2]	[5.6, 51.0]	[7.6, 54.5]	[7.5, 54.4]
Panel C. Mutual fund managers				
Interpretation (IV)	109.24	100.34	119.20	104.81
	(79.46)	(84.99)	(88.92)	(99.26)
Observations	1,716	1,716	1,716	1,716
County-events	113	113	113	113
First-stage F	6.11	5.85	6.11	5.85
Anderson–Rubin p	.138	.198	.100	.214
Anderson–Rubin 90% set	[−13.7, 373.9]	[−31.9, 392.4]	[0.2, 461.4]	[−33.4, 485.9]
Coverage, county fatalities and damages	✓	✓	✓	✓
Democratic vote share	✓	✓	✓	✓
Audience reach		✓		✓
Fund size, age and turnover (Panel C)	✓	✓	✓	✓
County, quarter and hazard × distance-band FE	✓	✓	✓	✓

Notes. Two-stage least squares estimates of the effect of local climate interpretation on portfolios, excluding purchases of independent newspapers by chains. The sample drops the county-events at which a newspaper serving the county passed, since the county's previous event, from an owner with no other newspaper in the sample to an owner with at least one. For managers, the newspapers are those serving the counties of the manager's offices, and the previous event is the previous disaster of the manager's county. In Panel A the outcome is the change in the county green-ETF share, the mean over the quarter of the episode and the two following quarters minus the mean over the two quarters before. In Panel B the outcome is the change in the adviser green-ETF share from the quarter before the episode to the quarter after it. In Panel C the outcome is the change in the green tilt of mutual funds whose managers' offices are all within 50 miles of the disaster, the change in the weight of stocks in the top tercile of the Environmental Pillar score minus the change in the weight of bottom-tercile stocks over the episode quarter. Interpretation effects are per 10-percentage-point increase. All columns control for log local disaster coverage, the logs of one plus county fatalities and damages, and the county Democratic two-party vote share. Columns 2 and 4 add audience reach, the overlap of the audience of the county's newspapers with the disaster footprint. Panel C also controls for fund size, age and turnover. All columns include county, calendar-quarter and hazard-by-distance-band fixed effects. Standard errors in parentheses and first-stage F statistics are clustered at the county level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table H.6: Instrumented interpretation, chain size at the owner before the purchase

	Portfolio response (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. County ETF holdings				
Interpretation (IV)	25.08*	24.89*	27.52*	27.29*
	(14.79)	(14.72)	(15.18)	(15.11)
Observations	694	694	694	694
First-stage F	11.34	11.33	11.34	11.33
Anderson–Rubin p	.038	.039	.029	.030
Anderson–Rubin 90% set	[4.8, 64.0]	[4.7, 63.6]	[6.5, 67.0]	[6.3, 66.5]
Panel B. Adviser ETF holdings				
Interpretation (IV)	21.36**	21.27*	25.12**	25.02**
	(10.80)	(10.80)	(11.49)	(11.49)
Observations	4,342	4,342	4,342	4,342
County-events	660	660	660	660
First-stage F	11.79	11.79	11.79	11.79
Anderson–Rubin p	.016	.017	.012	.012
Anderson–Rubin 90% set	[6.5, 49.3]	[6.4, 49.2]	[8.8, 53.9]	[8.7, 53.8]
Panel C. Mutual fund managers				
Interpretation (IV)	94.03	108.38	69.64	102.65
	(78.18)	(80.93)	(90.86)	(98.58)
Observations	2,052	2,052	2,052	2,052
County-events	136	136	136	136
First-stage F	9.34	9.25	9.34	9.25
Anderson–Rubin p	.275	.212	.438	.278
Anderson–Rubin 90% set	[−66.9, 245.2]	[−45.4, 278.5]	[−89.6, 275.9]	[−58.3, 343.9]
Coverage, county fatalities and damages	✓	✓	✓	✓
Democratic vote share	✓	✓	✓	✓
Audience reach		✓		✓
Fund size, age and turnover (Panel C)	✓	✓	✓	✓
County, quarter and hazard × distance-band FE	✓	✓	✓	✓

Notes. Two-stage least squares estimates of the effect of local climate interpretation on portfolios, instrumented with newspaper-chain size measured at the owner before the purchase. Chain size keeps each newspaper bought from an owner with no other newspaper in the sample at that previous owner, from the county's first event after the purchase on. For managers, the newspapers are those serving the counties of the manager's offices. In Panel A the outcome is the change in the county green-ETF share, the mean over the quarter of the episode and the two following quarters minus the mean over the two quarters before. In Panel B the outcome is the change in the adviser green-ETF share from the quarter before the episode to the quarter after it. In Panel C the outcome is the change in the green tilt of mutual funds whose managers' offices are all within 50 miles of the disaster, the change in the weight of stocks in the top tercile of the Environmental Pillar score minus the change in the weight of bottom-tercile stocks over the episode quarter. Interpretation effects are per 10-percentage-point increase. All columns control for log local disaster coverage, the logs of one plus county fatalities and damages, and the county Democratic two-party vote share. Columns 2 and 4 add audience reach, the overlap of the audience of the county's newspapers with the disaster footprint. Panel C also controls for fund size, age and turnover. All columns include county, calendar-quarter and hazard-by-distance-band fixed effects. Standard errors in parentheses and first-stage F statistics are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE H.7: INSTRUMENTED INTERPRETATION WITH AUDIENCE REACH AND SOCIAL CONNECTEDNESS

	Portfolio response (basis points)					
	Pre-event prices			Current prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. County ETF holdings						
Interpretation (IV)	22.47	21.95	21.18	24.60*	24.20*	23.36*
	(14.21)	(13.97)	(13.65)	(14.59)	(14.39)	(14.09)
Observations	694	694	694	694	694	694
First-stage F	9.33	9.55	9.69	9.33	9.55	9.69
Anderson–Rubin p	.067	.070	.077	.054	.056	.063
Anderson–Rubin 90% set	[2.3, 61.2]	[2.0, 59.4]	[1.5, 57.2]	[3.6, 63.9]	[3.4, 62.4]	[2.8, 60.1]
Panel B. Adviser ETF holdings						
Interpretation (IV)	19.18*	19.27*	19.02*	22.38**	22.51**	22.24**
	(10.53)	(10.33)	(10.30)	(11.31)	(11.13)	(11.10)
Observations	4,342	4,342	4,342	4,342	4,342	4,342
County-events	660	660	660	660	660	660
First-stage F	9.44	9.67	9.80	9.44	9.67	9.80
Anderson–Rubin p	.032	.026	.029	.027	.022	.024
Anderson–Rubin 90% set	[4.5, 48.2]	[5.0, 47.7]	[4.6, 47.0]	[6.0, 52.5]	[6.6, 52.2]	[6.3, 51.5]
Panel C. Mutual fund managers						
Interpretation (IV)	209.87**	170.49**	202.72**	164.27*	97.54	153.58
	(97.94)	(84.94)	(100.68)	(97.44)	(82.27)	(97.13)
Observations	2,052	2,052	2,052	2,052	2,052	2,052
County-events	136	136	136	136	136	136
First-stage F	11.13	10.78	9.69	11.13	10.78	9.69
Anderson–Rubin p	.043	.062	.037	.073	.223	.074
Anderson–Rubin 90% set	[47.1, 429.3]	[25.1, 357.3]	[48.6, 460.5]	[14.5, 400.3]	[−37.7, 286.0]	[12.3, 415.3]
Coverage, county fatalities and damages	✓	✓	✓	✓	✓	✓
Democratic vote share	✓	✓	✓	✓	✓	✓
Audience reach	✓		✓	✓		✓
SCI-reach		✓	✓		✓	✓
Fund controls (Panel C)	✓	✓	✓	✓	✓	✓
County, quarter, hazard×band FE	✓	✓	✓	✓	✓	✓

Notes. Two-stage least squares estimates of the effect of local climate interpretation on portfolios, controlling for audience reach and social connectedness with the affected counties. In Panel A the outcome is the change in the county green-ETF share, the mean over the quarter of the episode and the two following quarters minus the mean over the two quarters before. In Panel B the outcome is the change in the adviser green-ETF share from the quarter before the episode to the quarter after it. In Panel C the outcome is the change in the green tilt of mutual funds whose managers' offices are all within 50 miles of the disaster, the change in the weight of stocks in the top tercile of the Environmental Pillar score minus the change in the weight of bottom-tercile stocks over the episode quarter. Interpretation effects are per 10-percentage-point increase. All columns control for log local disaster coverage, the logs of one plus county fatalities and damages, and the county Democratic two-party vote share. Columns 1, 3, 4 and 6 control for audience reach, the overlap of the audience of the county's newspapers with the disaster footprint. Columns 2, 3, 5 and 6 control for SCI-reach, the share of the county's Facebook social connectedness that falls in the affected counties, excluding the county itself. For managers, SCI-reach is weighted by the manager's offices within 50 miles. Panel C also controls for fund size, age and turnover. All columns include county, calendar-quarter and hazard-by-distance-band fixed effects. Standard errors in parentheses and first-stage F statistics are clustered at the county level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

TABLE H.8: INTERPRETATION AND COVERAGE JOINTLY INSTRUMENTED

	Portfolio response (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. First stages				
Interpretation on chain size	−8.81***	−8.51***	−8.81***	−8.51***
	(2.89)	(2.83)	(2.89)	(2.83)
Interpretation on audience reach		−.05		−.05
		(1.05)		(1.05)
Coverage on chain size		−.21*		−.21*
		(.12)		(.12)
Coverage on audience reach		.13***		.13***
		(.04)		(.04)
Panel B. County ETF holdings				
Interpretation (IV)	22.75	28.47	24.96*	32.02*
	(14.30)	(17.57)	(14.69)	(18.60)
Coverage (IV)		−17.46		−23.82
		(39.15)		(42.12)
Observations	694	694	694	694
First-stage F	9.32	2.50	9.32	2.50
Anderson–Rubin p	.064	.121	.051	.097
Anderson–Rubin 90% set	[2.5, 61.9]	[−5.0, 570.0]	[3.9, 64.7]	[0.0, 675.0]
Panel C. Adviser ETF holdings				
Interpretation (IV)	19.34*	22.89*	22.54**	26.41**
	(10.51)	(11.73)	(11.30)	(13.09)
Coverage (IV)		−12.06		−14.61
		(37.90)		(39.20)
Observations	4,342	4,342	4,342	4,342
County-events	660	660	660	660
First-stage F	9.43		9.43	
Anderson–Rubin p	.029		.025	
Anderson–Rubin 90% set	[4.7, 48.4]		[6.3, 52.8]	
Coverage as a control	✓		✓	
Coverage instrumented by audience reach		✓		✓
County fatalities and damages, Democratic vote share	✓	✓	✓	✓
County, quarter, hazard×band FE	✓	✓	✓	✓

Notes. Two-stage least squares estimates of the effects of local climate interpretation and disaster coverage on portfolios, instrumented jointly with newspaper-chain size and audience reach. Audience reach is the overlap of the audience of the county's newspapers with the disaster footprint. In Columns 1 and 3 chain size instruments interpretation and disaster coverage is a control. In Columns 2 and 4 chain size and audience reach instrument interpretation and coverage jointly. Panel A reports the county-level first stages per standard deviation of each instrument, in percentage points of the interpretation share and in log points of coverage. In Panel B the outcome is the change in the county green-ETF share, the mean over the quarter of the episode and the two following quarters minus the mean over the two quarters before. In Panel C the outcome is the change in the adviser green-ETF share from the quarter before the episode to the quarter after it. Interpretation effects are per 10-percentage-point increase, and coverage effects are per log point. All columns control for the logs of one plus county fatalities and damages and the county Democratic two-party vote share. All columns include county, calendar-quarter and hazard-by-distance-band fixed effects. In Columns 2 and 4 the Anderson–Rubin test is of the joint zero of both coefficients, and the 90% set is its projection on interpretation. Standard errors in parentheses are clustered at the county level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table H.9: Portfolio response to instrumented interpretation, standard errors clustered by county and disaster

	Portfolio response (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Panel A. First stage				
Outlet level	−2.29***	−2.29***	−2.29***	−2.29***
	(.50)	(.50)	(.50)	(.50)
County level	−8.81**	−8.82**	−8.81**	−8.82**
	(3.66)	(3.65)	(3.66)	(3.65)
Newspaper-quarters	6,711	6,711	6,711	6,711
County-events	694	694	694	694
First-stage F, outlet level	20.85	20.85	20.85	20.85
First-stage F, county level	5.79	5.84	5.79	5.84
Panel B. County ETF holdings				
Interpretation (IV)	22.75	22.47	24.96	24.60
	(15.90)	(15.79)	(16.41)	(16.26)
Observations	694	694	694	694
Anderson–Rubin p	.075	.078	.061	.064
Anderson–Rubin 90% set	[1.7, 85.0]	[1.4, 83.4]	[3.1, 88.7]	[2.8, 86.8]
Panel C. Adviser ETF holdings				
Interpretation (IV)	19.34*	19.18*	22.54**	22.38*
	(10.45)	(10.45)	(11.37)	(11.35)
Observations	4,342	4,342	4,342	4,342
County-events	660	660	660	660
First-stage F	6.42	6.46	6.42	6.46
Anderson–Rubin p	.028	.032	.026	.028
Anderson–Rubin 90% set	[5.1, 55.9]	[4.8, 55.2]	[6.6, 61.3]	[6.4, 60.5]
Panel D. Mutual fund managers				
Interpretation (IV)	176.56**	209.87*	107.27	164.27
	(87.29)	(107.23)	(86.80)	(119.68)
Observations	2,052	2,052	2,052	2,052
County-events	136	136	136	136
First-stage F	10.96	9.98	10.96	9.98
Anderson–Rubin p	.035	.014	.185	.087
Anderson–Rubin 90% set	[42.9, 390.6]	[66.2, 520.6]	[−26.3, 320.5]	[5.5, 515.8]
Coverage, county fatalities and damages	✓	✓	✓	✓
Democratic vote share	✓	✓	✓	✓
Audience reach		✓		✓
Fund size, age and turnover (Panel D)	✓	✓	✓	✓
County, quarter and hazard × distance-band FE	✓	✓	✓	✓

Notes. See notes to Table 4. Standard errors in parentheses, first-stage F statistics and Anderson–Rubin sets are clustered two-way by county and disaster episode; the outlet-level first stage keeps its newspaper clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I Appendix to Section 7

Table I.1: County green-ETF portfolio response by exposure band

	Dependent variable:			
	Green-ETF share response (basis points)			
	Pre-event prices		Current prices	
	(1)	(2)	(3)	(4)
Affected × Interpretation		37.27***		37.93***
		(13.64)		(13.56)
Band × Interpretation	4.34	−9.54	4.30	−9.87
	(6.52)	(7.38)	(6.57)	(7.53)
Affected × Attention		−3.51		−4.70
		(14.10)		(13.99)
Band × Attention	−10.13*	−9.47	−9.31*	−8.09
	(5.55)	(7.81)	(5.27)	(7.41)
Total Interpretation effect among affected and nearby counties	4.35		4.32	
	(6.51)		(6.57)	
Total Interpretation effect among nearby counties		−9.52		−9.84
		(7.27)		(7.45)
Total Interpretation effect among affected counties		27.74**		28.08**
		(11.88)		(11.80)
Observations	105,662	105,662	105,662	105,662
R^2	.101	.102	.106	.106
Affected county-episodes	244	244	244	244
Nearby county-episodes	569	569	569	569
Affected and its interactions		✓		✓
Episode and quarter FE	✓	✓	✓	✓
Band × hazard × year FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Controls and their band interactions	✓	✓	✓	✓

Notes. Effect of local climate interpretation on the county green-ETF share response to disasters, by exposure to the disaster. The outcome is the mean county green-ETF share over the quarter of the episode and the two following quarters minus its mean over the two quarters before. Band is one for counties in the episode footprint or within 50 miles of it, and distant counties form the comparison group. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage, both over the first four weeks of the episode and standardized. Columns 1 and 3 include the band indicator and its interactions with Interpretation and Attention. Columns 2 and 4 add Affected and its interactions. Each regression also includes Interpretation, Attention, the band indicator and, in Columns 2 and 4, Affected, whose coefficients are not reported. All columns include episode, quarter, county and band × hazard × year fixed effects. Controls are lagged log portfolio assets, income, college share, white share, population, population density, county damages, fatalities and injuries, the prior Democratic vote share, the county share worried about global warming, and the share of local coverage on climate policy and green topics in the quarter before the episode, each also interacted with the band indicator. Standard errors in parentheses are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE I.2: PERSISTENCE OF THE COUNTY GREEN-ETF PORTFOLIO RESPONSE

	Dependent variable: Green-ETF share response (basis points)						
Quarter	$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Pre-event prices							
Affected × Interpretation	19.64**	29.56**	16.30	48.33**	52.37*	140.54***	162.69**
	(8.57)	(11.67)	(42.41)	(23.15)	(31.08)	(46.06)	(64.59)
Total Interpretation effect among affected counties	20.29**	30.64***	18.05	48.45**	52.34*	139.52***	159.43**
	(8.62)	(11.34)	(41.68)	(23.30)	(31.31)	(46.35)	(64.63)
Observations	105,567	97,524	89,450	81,682	75,123	69,407	62,850
Affected county-episodes	244	224	195	179	151	139	121
County clusters	301	297	286	276	267	262	248
Panel B. Current prices							
Affected × Interpretation	19.39**	28.35**	15.20	48.79**	50.62*	132.18***	145.47**
	(8.68)	(11.55)	(42.81)	(23.56)	(28.88)	(43.58)	(57.78)
Total Interpretation effect among affected counties	20.04**	29.29***	16.77	48.61**	50.19*	130.60***	141.67**
	(8.73)	(11.24)	(42.14)	(23.68)	(29.05)	(43.87)	(57.91)
Observations	105,567	97,524	89,450	81,682	75,123	69,407	62,850
Affected county-episodes	244	224	195	179	151	139	121
County clusters	301	297	286	276	267	262	248

Notes. Effect of local climate interpretation on the county green-ETF share response to disasters, by quarter after the episode. Each column is a separate regression. The outcome is the county green-ETF share at the end of quarter h minus its mean over quarters -2 and -1, where quarter 0 is the disaster quarter. Panel A values holdings at the prices and green classifications of the quarter before the episode. Panel B uses current prices and classifications. Both panels use the same observations. It excludes counties with another sample episode in quarters -2 and -1 or between the episode and quarter h, so it varies across horizons. Interpretation is the climate-interpreted share of local coverage of the episode, and Attention is the log volume of that coverage, both over the first four weeks of the episode and standardized. Entries are responses to a one-standard-deviation increase in Interpretation, conditional on Attention. All columns include episode, quarter, state and Affected × hazard × year fixed effects. Controls are lagged log portfolio assets, income, college share, white share, population, population density, county damages, fatalities and injuries, the prior Democratic vote share, the county share worried about global warming, and the share of local coverage on climate policy and green topics in the quarter before the episode, each also interacted with Affected. Standard errors in parentheses are clustered at the county level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table I.3: Climate beliefs and green ETF holdings

	Dependent variable: Green share of ETF holdings (basis points)					
	Worried	U.S. harm now/within 10 years	U.S. harm already happening	Warming happening	Mostly human caused	Support CO_2 regulation
	(1)	(2)	(3)	(4)	(5)	(6)
Belief share	1.19***	1.09**	1.69**	1.32**	0.86	0.94
	(0.41)	(0.44)	(0.74)	(0.54)	(0.64)	(0.84)
DMA-years	128	128	128	135	135	126
Media markets	20	20	20	21	21	19
Advisers	1,227	1,227	1,227	1,251	1,251	1,210
Survey respondents	7,047	7,017	7,017	7,547	7,542	6,851
Mean green share (bp)	5.61	5.61	5.61	5.32	5.32	5.66
Year fixed effects	✓	✓	✓	✓	✓	✓

Notes. Relationship between climate beliefs and the green share of adviser ETF holdings across designated market areas (DMAs), 2009–2019. Each column regresses the annual green share of adviser ETF holdings in the DMA on the share of DMA residents who hold the belief named in the column header. Coefficients are basis points per 10-percentage-point higher belief share. Advisers are those that predominantly serve households and whose known US offices all lie within one DMA. Belief shares come from the Climate Change in the American Mind surveys and require at least 30 valid responses per DMA and year. Column 1 measures worry about global warming. Columns 2 and 3 measure the expectation that global warming harms people in the United States now or within 10 years, and now. Column 4 measures the belief that global warming is happening, Column 5 that it is mostly caused by human activities, and Column 6 support for regulating carbon dioxide as a pollutant. All columns include year fixed effects. Standard errors in parentheses are clustered at the DMA level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table I.4: Climate beliefs after floods

	Dependent variable: Binary survey answer (percentage points)					
	Worried	U.S. harm now/within 10 years	U.S. harm already happening	Warming happening	Mostly human caused	Support CO_2 regulation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average response						
Post-disaster	6.83	13.44**	11.41**	10.42**	0.69	6.09
	(5.99)	(5.19)	(4.78)	(4.32)	(5.87)	(4.15)
Respondents	1,172	1,157	1,157	1,204	1,203	1,131
Media markets	62	61	61	63	63	60
Panel B: Responses by ideology						
Post × Liberal	4.82	6.17	4.04	7.43	-7.18	1.48
	(6.24)	(8.32)	(7.90)	(5.26)	(6.84)	(5.49)
Post × Moderate	6.23	16.43***	12.72**	13.34**	3.57	13.23**
	(7.66)	(6.15)	(5.87)	(5.60)	(7.90)	(5.01)
Post × Conservative	8.85	15.39**	13.51**	5.68	2.38	3.36
	(7.53)	(7.33)	(6.20)	(5.07)	(6.12)	(6.23)
Respondents	1,145	1,131	1,131	1,177	1,176	1,112
Media markets	62	61	61	63	63	60
Liberal respondents	319	318	318	328	328	310
Moderate respondents	434	427	427	441	441	422
Conservative respondents	392	386	386	408	407	380
DMA × survey-year FE	✓	✓	✓	✓	✓	✓
Interview year-month FE	✓	✓	✓	✓	✓	✓
Event fixed effects	✓	✓	✓	✓	✓	✓
Demographic/wording controls	✓	✓	✓	✓	✓	✓

Notes. Change in climate beliefs after floods among respondents to the Climate Change in the American Mind surveys, 2009–2019. The sample covers respondents in affected designated market areas (DMAs) interviewed from 28 days before to 27 days after the start of the flood. The outcome is an indicator for the answer named in the column header. Column 1 measures worry about global warming. Columns 2 and 3 measure the expectation that global warming harms people in the United States now or within 10 years, and now. Column 4 measures the belief that global warming is happening, Column 5 that it is mostly caused by human activities, and Column 6 support for regulating carbon dioxide as a pollutant. Panel B includes ideology indicators and separate post-disaster coefficients for liberals, moderates and conservatives. All columns include DMA × survey-year, interview year-month and event fixed effects. Controls are age, college education, gender, income and question wording. Standard errors in parentheses are clustered at the DMA level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE I.5: GREEN SHARES, FLOODS AND CLIMATE BELIEFS

	Green share	Answer	
	Belief	Post	Post × Interpretation
	(1)	(2)	(3)
Worry	.731*	.135	.137*
	(.319)	(.089)	(.055)
	[.058]	[.398]	[.059]
Observations	117	1,671	1,635
Media markets	117	76	71
Harm sooner	1.122***	.294***	.151**
	(.341)	(.082)	(.054)
	[.007]	[.003]	[.034]
Observations	117	1,654	1,618
Media markets	117	76	71
Happening	.912*	.181	.061
	(.384)	(.085)	(.088)
	[.058]	[.147]	[.493]
Observations	117	1,316	1,280
Media markets	117	70	66
Human causation	.841*	−.016	.088
	(.467)	(.104)	(.062)
	[.074]	[.881]	[.475]
Observations	117	1,702	1,666
Media markets	117	77	73
CO_2 regulation	.706**	.114	.081
	(.271)	(.081)	(.059)
	[.041]	[.398]	[.475]
Observations	117	1,516	1,480
Media markets	117	68	63
Media market × survey-year FE		✓	✓
Interview year-month FE		✓	✓
Episode FE		✓	✓
Age, college, gender, income, wording		✓	✓

Notes. Relationship between climate beliefs, adviser green shares and floods, for five questions of the Yale–George Mason Climate Change in the American Mind surveys. The questions measure worry about global warming (Worry), how soon it will harm people in the United States (Harm sooner), whether it is happening (Happening), whether it is mostly caused by human activities (Human causation), and support for regulating carbon dioxide as a pollutant (CO2 regulation). Harm sooner enters here as the standardized answer and in Tables I.3 and I.4 as two indicators. Column 1 regresses the mean 2010–2017 green share of adviser holdings in each media market on the market's mean answer before 2018, with one observation per market. Its coefficient is in basis points of green share per between-market standard deviation of the mean answer. Columns 2 and 3 use respondents in affected media markets interviewed from 28 days before to 27 days after the start of a flood, with answers standardized within survey wave. Post is one on or after the start day. Column 3 interacts Post with the climate interpretation of local coverage of the flood from its start through the interview day. Interpretation is the share of articles that link the event centrally to climate change, averaged across the covering outlets with circulation weights. Column 3 drops post-event interviews with no coverage. Columns 2 and 3 keep media markets with interviews both before and after the flood in the same survey year. They include media market × survey-year, interview year-month and episode fixed effects, and control for age, college education, gender, income and question wording. Regressions are unweighted. Standard errors in parentheses are clustered at the media-market level. Holm-adjusted p-values in brackets are computed over the five questions within each column, and stars use these adjusted values. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE I.6: WILDFIRE AND FLOOD NEWS ATTRIBUTION AND FLOOD INSURANCE TAKE-UP: FIRST-LAG DIFFERENCE

	Dependent variable: $CNew_{c,t_e+h} - CNew_{c,t_e-1}$			
	Wildfire		Flood	
	$h = 2$	$h = 3$	$h = 2$	$h = 3$
	(1)	(2)	(3)	(4)
Hazard-affected	14.48**	21.71**	32.04***	40.88***
	(7.15)	(10.48)	(8.06)	(10.35)
Total hazard-news volume	6.32	10.02	4.38	5.21
	(12.57)	(15.59)	(5.79)	(7.14)
Climate-attributed hazard-news volume	−8.49	−13.97	−1.58	−1.13
	(9.85)	(12.12)	(4.36)	(5.68)
Strict climate-only news volume	4.76**	6.07*	3.35*	3.39
	(2.40)	(3.50)	(1.85)	(2.15)
Hazard-affected × Total hazard-news volume	−17.26*	−15.14	−10.71	−17.47
	(9.79)	(13.61)	(11.11)	(13.62)
Hazard-affected × Climate-attributed hazard-news volume	17.82**	18.18*	−.15	2.11
	(8.07)	(10.02)	(8.14)	(9.80)
Hazard-affected × Strict climate-only news volume	−1.27	−8.78	−2.36	−2.70
	(5.94)	(9.90)	(4.60)	(5.82)
Observations	881	881	4,206	4,206
Counties	190	190	904	904
Hazard episodes	50	50	227	227
R^2	.846	.835	.662	.676
County FE	✓	✓	✓	✓
Hazard-episode FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓

Notes. Effect of wildfire and flood news and its climate attribution on first-time flood-insurance take-up. The outcome is the change in cumulative first-time voluntary NFIP flood-insurance policies per 100,000 residents from the month before the hazard to month h after it. The wildfire and flood columns are estimated separately. Observations are counties by hazard episode, from 2010. Hazard-affected is one for counties affected by the hazard. News volumes are local articles weighted by county circulation over days 0 to 13 after the start of the hazard. Each news volume enters as the log of one plus the volume, standardized within the hazard sample. Strict climate-only news volume counts articles with climate content and no disaster content in the same window. The wildfire sample excludes counties with a flood from six months before to three months after the wildfire and with any other large disaster from four months before to three months after. The flood sample excludes counties with any other large disaster from six months before to three months after the flood. All columns include county, hazard-episode and state × year fixed effects. Standard errors in parentheses are clustered at the county level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table I.7: Past green returns and the adviser response

	Dependent variable: ETF green-share response, $h = 1$ (bp)		
	Base	Prior green return added	Prior green return × interpretation
	(1)	(2)	(3)
Interpretation response	19.34***	19.33***	20.70***
	(7.14)	(7.10)	(7.21)
Disaster response × prior green return		0.23	
		(6.03)	
Interpretation response × prior green return			−1.45
			(4.79)
Interpretation response, prior green return −1 SD			22.15***
			(8.38)
Interpretation response, prior green return +1 SD			19.25**
			(8.92)
Observations		465,705	
Affected adviser-episodes		1,158	

Notes. Effect of local climate interpretation on adviser green-ETF shares, by the return of green ETFs before the disaster. The outcome is the change in the adviser green-ETF share from the quarter before the episode to the quarter after it. Interpretation response is per standard deviation of Interpretation. The prior green return is the return of green ETFs minus all non-green ETFs over the 52 weeks before the event week, equal-weighted across funds, with one value per episode, per standard deviation (6.1 percentage points). Column 2 adds the prior green return interacted with the disaster. Column 3 interacts the prior green return with interpretation, the disaster and attention, and reports the interpretation response at one standard deviation below and above the mean prior green return. Lower-order terms are not reported. All columns control for attention and its interaction with the disaster, affected-by-year terms, lagged log portfolio size and the county Democratic vote share. All columns include episode and calendar-quarter fixed effects. Advisers are weighted by their share of the county's ETF holdings in the quarter before the episode. Standard errors in parentheses are clustered at the county level. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

J Aggregation: Framework and Calibration

1. Aggregate ESG flows

The additional allocations $a^I_{i,e}$ derived in Appendix B generate demand for ESG funds and their underlying stocks. Consider the resulting purchase of X dollars of the ESG portfolio, financed by selling X dollars of the broad market portfolio, at initial prices.

First, I establish how much additional ESG investment this transaction generates. Let K be the fixed capital of the investor population considered and s its initial share in ESG funds. The other-fund portfolio in the individual problem is the non-ESG component of this broad portfolio. Because the broad market portfolio includes ESG funds with share s, selling it offsets sX of the ESG purchase. The net dollar addition to ESG holdings is therefore $T = (1-s)X$. Relative to initial ESG assets $G_0 = sK$, the corresponding proportional flow is

$$f = \frac{T}{G_0}. \tag{J.1}$$

2. Induced relative demand for green stocks

To trace the consequences for stock prices, I now look through the fund portfolios to the stocks they hold. The ESG purchase and broad-portfolio sale generate different stock demands because the two portfolios assign different weights to each stock.

Following van der Beck (2026), I define green stocks as those overweighted by ESG-labeled funds relative to the aggregate fund portfolio. In particular, the representative ESG portfolio pools the holdings of ESG-labeled funds: w_n^{ESG} equals their total dollar holdings of stock n divided by their aggregate assets. The benchmark weight w_n^{all} is constructed in the same way across all funds, including ESG funds. Defining $\tau_n = w_n^{\text{ESG}} - w_n^{\text{all}}$, green stocks ($\tau_n > 0$) form group G and the remaining stocks form group N.

I assume that the reallocation is implemented through purchases and sales of the underlying stocks in these portfolio proportions. Buying X dollars of the ESG portfolio therefore means demanding Xw_n^{ESG} of each stock n, while financing the purchase by selling the broad market portfolio generates sales of Xw_n^{all}. Writing w_n^O for the stock weight in the other-fund portfolio gives $w_n^{\text{all}} = sw_n^{\text{ESG}} + (1-s)w_n^O$. The individual-model reallocation of T dollars from other funds into ESG funds therefore induces the same stock demand as the $X = T/(1-s)$ broad-market-financed purchase:

$$T\left(w_n^{\text{ESG}} - w_n^O\right) = X\left(w_n^{\text{ESG}} - w_n^{\text{all}}\right) = X\tau_n. \tag{J.2}$$

The reallocation thus generates net purchases of green stocks and net sales of underweighted stocks.

Let τ_G and τ_N denote the sums of the weight differences within each group. Aggregating the stock demands gives total net demand for green and nongreen stocks of $X\tau_G$ and $X\tau_N$, respectively. Dividing each by its initial total market capitalization, V_G or V_N, gives the corresponding

proportional flow. Their difference is the relative flow into green versus nongreen stocks induced by the initial reallocation of X dollars from the broad market portfolio into the ESG portfolio:

$$f^{\text{rel}} = \frac{X\tau_G}{V_G} - \frac{X\tau_N}{V_N}. \tag{J.3}$$

3. Valuation and price response

Finally, the relative prices of green and nongreen stocks adjust as other investors accommodate the reallocation. Van der Beck's (2026) *ESG flow multiplier*, denoted here by κ_{ESG}, measures the equilibrium difference in green and nongreen stocks' dollar valuation changes per dollar reallocated from the broad market portfolio into the ESG portfolio. It combines the weight differences τ_n defined above with holders' willingness to trade as prices change, captured by ownership-weighted demand elasticities estimated using other institutions' dividend-induced trading as an instrument for price changes.[81]

Let ΔV_G and ΔV_N denote the resulting changes in the total market values of green and nongreen stocks. Holding fundamentals and other demand drivers fixed, the calibrated first-order valuation response to this X-dollar reallocation, accounting for other investors' accommodation, is

$$\Delta V_G - \Delta V_N = \kappa_{\text{ESG}} X. \tag{J.4}$$

To express the same response in terms of relative returns, I define the *relative-return multiplier*, M_{ESG}, as the change in the return difference between value-weighted green and nongreen portfolios, $R_G - R_N$, per unit of relative flow f^{rel}. It is obtained from the same stock-price responses by dividing each portfolio's dollar valuation change by its initial market capitalization and the resulting return difference by f^{rel}:

$$\Delta(R_G - R_N) = \frac{\Delta V_G}{V_G} - \frac{\Delta V_N}{V_N} = M_{\text{ESG}} f^{\text{rel}}. \tag{J.5}$$

For the calibration, I use van der Beck's (2026) approach with his December 2022 replication inputs, including the portfolio weights used above to define green and nongreen stocks and their induced demand. These inputs give $\kappa_{\text{ESG}} \simeq 0.72$ and imply $M_{\text{ESG}} \simeq 1.12$.

4. From the local allocation response to aggregate ESG demand

The calculation in Parts 1–3 takes the aggregate reallocation X as given. I now use the local allocation estimates to determine the additional reallocation generated by stronger climate interpretation, holding disaster attention fixed. The comparison keeps other demand drivers unchanged, so baseline allocations may differ across investors while interpretation contributes an additional component to aggregate demand.

[81] Van der Beck (2026, Sections 5.A, 5.C and 6.A, and Appendix A.3).

4.1. The additional allocation The event-induced demand shift derived in (B.7) is $u_{i,e} = \eta_e \gamma_{i,e}$. Allow the portfolio parameters to differ across investors, and denote investor i's responsiveness to log odds at initial prices by $\chi_i(P^0)$. The same solution gives $\gamma_{i,e} = \gamma_i(A_{i,e}, I_{i,e}, Z_e) = \chi_i(P^0)\ell_i(A_{i,e}, I_{i,e}, Z_e)$. Superscripts 0 and 1 denote the baseline and counterfactual information configurations. Relative to $(A^0_{i,e}, I^0_{i,e}, Z^0_e)$, the additional desired share at (A, I, Z) is

$$\begin{aligned} a_{i,e}(A, I, Z) &\equiv u_{i,e}(A, I, Z) - u_{i,e}(A^0_{i,e}, I^0_{i,e}, Z^0_e) \\ &= \eta_e \left[\gamma_i(A, I, Z) - \gamma_i(A^0_{i,e}, I^0_{i,e}, Z^0_e)\right]. \end{aligned} \tag{J.6}$$

The calibration changes interpretation while holding attention and the wider information environment fixed. Its individual allocation increment is therefore

$$\begin{aligned} a^I_{i,e} &= u_{i,e}(A_{i,e}, I^1_{i,e}, Z_e) - u_{i,e}(A_{i,e}, I^0_{i,e}, Z_e) \\ &= \eta_e \chi_i(P^0) \left[\ell_i(A_{i,e}, I^1_{i,e}, Z_e) - \ell_i(A_{i,e}, I^0_{i,e}, Z_e)\right]. \end{aligned} \tag{J.7}$$

This is the individual counterpart of the estimated additional allocation $\widehat{a}^I$ in (B.17).

4.2. Aggregation Let K_i be investor i's initial eligible capital, with total capital $K = \sum_i K_i$. Denote ESG-fund units by Q_i. At initial prices, a portfolio share q_i purchases $Q_i = K_i q_i / P^0$ units. Write $Q^0_{i,e}$ and $Q^1_{i,e}$ for baseline and counterfactual units, and $a_{i,e}$ for the corresponding share increment. They satisfy

$$P^0\left(Q^1_{i,e} - Q^0_{i,e}\right) = K_i a_{i,e}. \tag{J.8}$$

This converts the derived share increment into desired dollar demand at initial prices. Summing across investors gives

$$T = \sum_i P^0\left(Q^1_{i,e} - Q^0_{i,e}\right) = \sum_i K_i \, a_{i,e}(A^1_{i,e}, I^1_{i,e}, Z^1_e). \tag{J.9}$$

Additional ESG purchases are financed by reducing other holdings, keeping each investor's capital fixed.

For the interpretation calibration, let $\mathcal{A}$ contain the investors activated by the counterfactual. Their combined capital represents a share α of total eligible capital:

$$\alpha = \frac{\sum_{i \in \mathcal{A}} K_i}{K}. \tag{J.10}$$

The central assumption is that investors "activated" in my counterfactual analyses would respond to stronger climate interpretation as the disaster-exposed investors in my sample do, at the specified level of attention and information environment. I use $\widehat{a}^I$ to estimate their capital-weighted average additional allocation a^I per dollar of initial capital, while allowing individual responses, initial portfolios and baseline responses to differ. I apply this increment once to each

investor's initial capital, treating it as the cumulative allocation adjustment over the event quarter and the following quarter.

The resulting additional ESG investment is

$$T^I = \sum_{i \in \mathcal{A}} K_i a^I_{i,e} = \alpha K a^I. \tag{J.11}$$

Using the accounting in Part 1, its proportional ESG flow and equivalent broad-market-to-ESG reallocation are

$$f^I = \frac{T^I}{G_0}, \qquad X^I = \frac{T^I}{1-s}, \qquad G_0 = sK, \tag{J.12}$$

where s is the target population's initial ESG share.

Setting $\alpha = 1$ extends the estimated interpretation increment to all eligible capital, at the specified attention and information environment. Interpreting this calculation as the complete response to a national change additionally requires that any demand generated by a change in Z_e be negligible or separately included.

To obtain the associated price response, I assume that the reallocation translates fully into underlying stock demand in the portfolio proportions defined above. **Assumption: market accommodation.** I hold the estimated stock-demand elasticities and initial ownership weights fixed as the set of activated investors changes. Activation shifts desired allocations, while both activated and nonactivated investors retain their price responsiveness. These are the stock-quantity elasticities entering van der Beck's multiplier. Substituting X^I for X in Parts 2 and 3 gives the additional relative stock flow, denoted $f^{\text{rel},I}$, and the associated valuation changes and returns.

4.3. The national information environment In the calibration, I abstract from changes in the national information environment, holding Z_e fixed as I extend the estimated interpretation response to the selected population.

A nationally covered event can also change Z_e. Public coverage and framing can shape expectations about other investors' responses (Morris and Shin, 2002). Investors might consequently buy green assets to profit from the price increases they expect others' purchases to generate (Schmidt-Engelbertz and Vasudevan, 2025).[82] This speculative motive lies outside the climate-belief channel modeled here. Within the model, Z_e changes $\gamma_i(A, I, Z)$ through its effect on the climate-belief update $\ell_i(A, I, Z)$.

Let $T^{\text{fixed } Z}$ be the sum of investors' demand changes when attention and interpretation take their counterfactual values but the national information environment remains at Z_e^0. For the interpretation-only exercise, this is the calibrated T^I. National publicity can additionally change the climate-belief update through Z_e.

Denote by T^Z the additional aggregate demand generated through climate-belief updating when that environment changes to Z_e^1, holding the same attention and interpretation profiles

[82] See Schmidt-Engelbertz and Vasudevan (2025). Using investor surveys, they document that beliefs about others' beliefs can motivate positions that conflict with investors' own market valuations.

fixed:

$$T^Z = \sum_i K_i \left[\gamma_i(A^1_{i,e}, I^1_{i,e}, Z^1_e) - \gamma_i(A^1_{i,e}, I^1_{i,e}, Z^0_e)\right] \eta_e,$$
$$T^{\text{national}} = T^{\text{fixed } Z} + T^Z. \tag{J.13}$$

The term T^Z, which is not included in my calibration, captures what the change in national coverage and framing adds beyond the specified changes in individual attention and interpretation. It can include both a response shared across investors and changes in how strongly they respond to attention or interpretation. When $T^Z > 0$, the national climate-belief response exceeds the sum of local responses evaluated at the baseline national information environment.

5. Calibration exercise

For this calibration exercise, I measure attention and interpretation using newspaper coverage of the event, assuming that coverage captures its broader local salience and interpretation captures the local discussion and narratives attributing it to climate change. I control for other important determinants of attention and interpretation, such as whether the county was affected and local political views, which can also influence interpretation and thus portfolio choices. By holding these factors at their average levels in the calibration sample, I focus on the additional event-specific portfolio response induced by variation in interpretation captured by local climate narratives.

5.1. Applying the estimated allocation response The numerical calibration uses the same interpretation contrast as (B.17), evaluated among affected counties. Its outcome is the cumulative change in the green-ETF share from the pre-event quarter through the following quarter, valuing holdings at pre-event prices. I apply the price-response assumption of Appendix B to this measured share and horizon. The impact response in that section and the following-quarter response used here are separate estimates of the corresponding allocation adjustments.

Let $\widehat{\beta}^{\text{cal}}_I + \widehat{\delta}^{\text{cal}}_I$ be the estimated interpretation effect among affected counties for this calibration outcome, reported in basis points per standard deviation. Holding coverage and the other covariates fixed, the additional allocation in decimal share units is

$$\widehat{a}^I = \frac{\widehat{\beta}^{\text{cal}}_I + \widehat{\delta}^{\text{cal}}_I}{10{,}000} \frac{I^1 - I^0}{\sigma_I}. \tag{J.14}$$

This is the allocation increment used in $T^I = \alpha K \widehat{a}^I$.

For coverage, let $\widehat{\beta}^{\text{cal}}_A + \widehat{\delta}^{\text{cal}}_A$ be the affected-county response in basis points per standard deviation of $\log(1 + A)$, and σ_A that standard deviation. For a joint change in coverage and interpretation, the estimated additional share $\widehat{a}$ is

$$\widehat{a} = \frac{1}{10{,}000} \left[(\widehat{\beta}^{\text{cal}}_A + \widehat{\delta}^{\text{cal}}_A) \frac{\log(1 + A^1) - \log(1 + A^0)}{\sigma_A} + (\widehat{\beta}^{\text{cal}}_I + \widehat{\delta}^{\text{cal}}_I) \frac{I^1 - I^0}{\sigma_I} \right], \tag{J.15}$$

Here A^0, A^1 and I^0, I^1 are the baseline and counterfactual news measures.

5.2. A stronger climate interpretation Consider an increase in climate interpretation from its 25th to its 75th percentile, holding coverage at its median. In the calibration sample, this raises the share of coverage attributing the event to climate change from 8.07% to 27.51%, a change of approximately 1.24 standard deviations.

The estimated interpretation response is 26 allocation basis points per standard deviation. The implied additional reallocation is

$$\widehat{a}^I = \frac{25.5665 \times 1.23782}{10{,}000} \simeq 0.003165. \tag{J.16}$$

Thus, stronger interpretation increases the ESG allocation share by 32 basis points, or approximately 32 cents per 100 dollars of initial capital, over the event quarter and the following quarter. The 95% confidence interval is 7–56 basis points.

5.3. Aggregate demand and the stock-price response I consider three scenarios, depending on which investors are activated: ETF investors, mutual-fund and ETF investors together, and institutional equity investors. The institutional scenario is the main counterfactual. Table J.1 collects the calculations using the formulas in Parts 1–4, with full activation ($\alpha = 1$) within each investor base and the additional reallocation applied once to each investor's initial capital.

Table J.1: Additional ESG demand and stock-price responses by activated investor base

	ETFs	Mutual funds + ETFs	Institutional equity investors
	(1)	(2)	(3)
Additional ESG investment T^I ($bn)	19.91	61.51	—
Proportional ESG flow f^I (%)	30.47	26.95	—
Reallocation X^I ($bn)	20.12	62.24	79.21
Relative stock flow $f^{\text{rel},I}$ (bp)	7.73	23.90	30.41
Relative stock return (bp)	8.62	26.65	33.92
Relative valuation change ($bn)	14.43	44.64	56.81

Notes. Additional ESG demand and stock-price responses implied by the calibration, by activated investor base. Each column activates one investor base, with full activation within it. The additional reallocation is applied once to each dollar of initial capital. All scenarios use the December 2022 price multipliers. The fund-flow measures T^I and f^I apply to the first two scenarios only. Stock flows, returns and valuation changes compare green with nongreen stocks. For the institutional scenario, the 95% confidence intervals are 7–60 basis points for the relative stock return and $12.5–101.1 billion for the relative valuation change. These intervals reflect only the uncertainty in the estimated local response.

In November 2024, US domestic-equity ETFs managed approximately K = $6.29 trillion, including G_0 = $65.35 billion in ESG ETFs, corresponding to an initial ESG share of $s \simeq 1.039\%$. The first scenario applies the estimated interpretation increment to this capital.

The evidence that mutual-fund flows respond to climate interpretation supports extending the calculation from ETFs to mutual funds and ETFs together. I assume that investors in both types of

fund make the same additional ESG allocation per dollar of capital as the investors represented in the local estimate.

In November 2024, US domestic-equity mutual funds and ETFs managed approximately $K =$ \$19.44 trillion, including $G_0 =$ \$228.20 billion in ESG funds, corresponding to an initial ESG share of $s \simeq 1.174\%$.

The evidence on mutual-fund managers' rebalancing in response to interpretation motivates extending the exercise to institutional investors' stock demand. In this main counterfactual, I assume that institutional investors make the same additional ESG-versus-benchmark reallocation per dollar of capital. The fund-sector calculation implies a reallocation rate of

$$\frac{X^I}{K} = \frac{\$62.24 \text{ billion}}{\$19.44 \text{ trillion}} \simeq 0.320\%. \tag{J.17}$$

In December 2022, institutions held $K_{\text{inst}} =$ \$24.74 trillion of the stocks covered by the calibration, or 73.8% of their total market value. Applying the same reallocation rate gives

$$X^I_{\text{inst}} = K_{\text{inst}} \frac{X^I}{K} \simeq \$79.21 \text{ billion}. \tag{J.18}$$

Institutional holdings include stocks held by fund managers on behalf of their investors, so the underlying equity capital is counted once. The price multipliers retain accommodation by all investors, with the additional demand generated by institutions.

As a broader counterfactual, I extend the same reallocation rate to all investors in the covered equity market. Applying it to the \$33.53 trillion of equity capital covered by the December 2022 calibration, $K_{\text{all}} = V_G + V_N$, gives

$$X^I_{\text{all}} = K_{\text{all}} \frac{X^I}{K} \simeq \$107.36 \text{ billion}. \tag{J.19}$$

This implies 46 basis points of green-minus-nongreen appreciation and \$76.99 billion in relative valuation change. This broader scenario includes institutional and non-13F owners, counting the underlying equity capital once.

5.4. Comparison with annual ESG returns Consider a year in which stronger climate interpretation induces additional reallocations equivalent to every institutional investor making the estimated adjustment once, at unchanged attention. These adjustments are completed during the year, holding the national information environment and other conditions unchanged.[83]

In dollar terms, this is the difference in annual ESG-versus-benchmark demand between the

[83] I measure the allocation adjustment from the quarter before the disaster through the following quarter, allowing for events occurring late in the quarter and for delayed portfolio adjustment. In the annual counterfactual, each investor's additional adjustment is counted once.

stronger- and weaker-interpretation scenarios:

$$\underbrace{X_{\text{year}}^{\text{stronger } I} - X_{\text{year}}^{\text{weaker } I}}_{X_{\text{inst}}^{I}} \simeq \$79.21 \text{ billion.} \tag{J.20}$$

Applying the calibrated price response gives 34 basis points more green-minus-nongreen appreciation in the stronger-interpretation scenario.

In van der Beck's (2026) decomposition, the average annual return spread is 223 basis points, with 186 basis points attributed to institutional ESG demand. Table J.2 expresses each calibrated effect as a percentage of these benchmarks.

Table J.2: Calibrated appreciation relative to annual ESG-return benchmarks

Activated investor base	Percent of observed annual ESG return spread (1)	Percent of annual institutional ESG-demand contribution (2)
ETFs	3.9	4.6
Mutual funds + ETFs	11.9	14.3
Institutional equity investors	15.2	18.2

Notes. Calibrated green-minus-nongreen appreciation in each scenario as a percentage of annual ESG-return benchmarks. Both benchmarks are from van der Beck (2026).

This additional appreciation is equivalent in magnitude to 18.2% of the annual contribution attributed to institutional ESG demand and 15.2% of the observed annual return spread.[84]

For the broader all-equity counterfactual, the corresponding ESG-demand benchmark includes both institutional and non-13F demand and equals 155 basis points annually. The calibrated 46-basis-point effect is equivalent to 29.7% of that contribution and 20.6% of the observed annual spread.

[84]These comparisons measure the size of the calibrated effect. Estimating interpretation's contribution to historical returns would require actual activation and interpretation changes over that sample. The calibration uses December 2022 portfolio weights and price responses; the historical returns reflect changing portfolios and market conditions and include dividends.