Disaster as Catalyst: How Natural Disasters Shape Fund Managers' ESG Commitment *

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Abstract

This paper explores whether the exposure of fund managers to negative events affects their investment behavior with regard to sustainability. I use climatic disasters as a shock to a manager's attention to climate change. I find that managers located in counties neighboring major disaster areas significantly improve the ESG score of their overall holdings in periods following disasters by over 2.5%, and the E-component score by up to 6%. I propose social interactions with affected areas, beliefs about climate change, and increased attention to climate-related news as possible amplification mechanisms. Alternative explanations such as performance and divestment from disaster stocks do not explain the results.

JEL Classification: G11, G14, Q51

Keywords: ESG, Salience, Natural Disasters, Social Connectedness, Beliefs, Attention

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1. Introduction

The United Nations Principles for Responsible Investment (PRI) define ESG integration as "the systematic and explicit inclusion of material ESG factors into investment analysis and investment decisions" [1]. In this paper, I study how and through which mechanisms mutual fund managers increase their commitment to environmental, social, and governance (ESG) issues. I use climatic disasters as a shock to a fund manager's attention to climate risk, and test whether this translates into increased ESG integration. ESG investing represents a growing portion of overall capital market transactions (e.g Matos [2020], Hartzmark and Sussman [2019], Kim and Yoon [2022]) as well as an important concern for institutional investors (e.g. Krueger et al. [2020], Stroebel and Wurgler [2021]). The Global Sustainable Investment Alliance reports that in 2018, over US$30 trillion was managed according to ESG principles. However, scholars and practitioners alike argue that climate risks (which are defined as risks stemming from exposure to climate change) have adverse effects on the valuations of assets managed by institutional investors, especially those who are long-term- and ESG-oriented. Many recent papers have looked at the asset pricing implications of climate risk (eg. Engle et al. [2020], Giglio et al. [2021], Alok et al. [2020], Choi et al. [2020]). Moreover, at the firm level, Huang et al. [2022] find that increased climate risk pushes corporate ESG disclosure to improve in the periods following the event. However, the impact of this risk on ESG integration by mutual funds is yet to be established.

Several factors can influence ESG integration at the fund level. Managers may engage in ESG investing to maximize returns and attract flows (Bolton and Kacperczyk [2021]), to capture nonpecuniary benefits (Oehmke and Opp [2020], Riedl and Smeets [2017] and Pástor et al. [2021]), to cater to investors (Kim and Yoon [2022]), to improve the ESG performance of target firms (Gantchev et al. [2022] and Gibson Brandon et al. [2021]) or simply to emulate a growing trend (Dumitrescu et al. [2022]). In this paper, I study whether life experiences of mutual fund managers, such as exposure to catastrophic circumstances, also play a part in their transition to ESG investing, beyond the considerations cited above. This assumption is based on prior

[1] PRI ESG Integration Techniques

research that suggests that an individual manager's life experiences influence their decision-making and behavior (eg. Bernile et al. [2017], Benmelech and Frydman [2015], Malmendier and Nagel [2011]). This motive is an important one to study because if presumably rational money managers make unreasoned investment decisions following a natural disaster, this could reflect negatively on the returns of their fund shareholders, and ultimately on the informational efficiency of stock prices. This follows from Pástor et al. [2021], who theoretically show that ESG preferences move asset prices.

A natural disaster can prompt a fund manager to integrate ESG considerations into their investment process by highlighting the potential financial and material risks associated with environmental and social issues, specifically the impact of natural disasters on companies and communities. The events of a natural disaster can draw attention to the potential negative consequences of companies' operations on the environment and society and can be an opportunity for fund managers to evaluate the potential impact of these risks on the companies in which they invest. I focus on natural disasters because they represent salient unexpected events for mutual fund managers. Previous research suggests that investors are more likely to pay attention to uncommon, striking events rather than to frequent and gradual changes, such as rising temperatures (Da et al. [2014]).

How might a personal experience, such as exposure to major climatic events, affect a fund manager's investment decision? I make use of the extensive finance and behavioral psychology literatures to posit that the fund-level ESG and climate risk relation is attention-triggered and can be in part attributed to the salience hypothesis (eg. Bordalo et al. [2012], Tversky and Kahneman [1974]). For instance, Hirshleifer and Teoh [2003] find that information presented in a more salient manner is more easily absorbed than information that is present in the public information set. This precedes an increasingly prevalent literature in finance and economics which shows that exposure to extreme negative shocks does affect financial decisions, as well as risk-taking, through changes in beliefs and emotions (see Guiso et al. [2018], Malmendier and Nagel [2011], Bernile et al. [2017] and Liu et al. [2022]). For instance, Dessaint and Matray [2017] document an irrationally excessive hoarding of liquidity by corporations following hurricane strikes. Similarly, Bernile et al. [2021] find that fund managers become more risk averse after experiencing a natural disaster, resulting in a reduction of the fund's volatility. This study contributes to the existing body of literature by examining the impact of negative events, specifically natural disasters, on mutual fund managers' investment decisions and their overall perception of sustainability investing. By exploring this relationship, I provide a deeper understanding of the factors that drive mutual fund managers to transition to ESG investing.

Using a difference-in-differences approach [2], I explore whether fund managers located in counties neighboring disaster areas increase the ESG score of their overall holdings in the periods following the event, thus signaling an increased commitment to sustainable investing. I exploit natural disasters as an exogenous shock to mutual fund managers' attention to climate risk. This setting is also exogenous to a fund's characteristics, meaning that variations in ESG commitment following a major climatic event cannot directly be attributed to reverse causality or unobserved heterogeneity. I find that managers located close to disaster areas exhibit an increased commitment to ESG by improving their overall fund-level score by over 2.5%. The effect is more pronounced when only examining the environmental score, where the increase post-disaster is around 6%. I conduct a placebo test and use a fund's social score as the dependent variable and find that the effect is not present. This essentially means that following a natural disaster, the transition to a (more) sustainable way of investing happens for the most part through the improvement of fund-level environmental scores.

I also explore the temporal dynamics and investigate whether the observed effects persist beyond a period of four quarters, and I extend the analysis to five and six quarters following the natural disaster. Upon examining the five quarters, I observe a diminishing significance and magnitude of the coefficients associated with portfolio-level ESG. Moreover, the coefficient of interest experiences further reduction after six quarters. This potentially suggests a reversion in the fund score as the salient event becomes gradually distant in time, and highlights the possibility of a decaying effect.

[2] For similar settings see e.g Alok et al. [2020], Dessaint and Matray [2017], Frydman and Wang [2020]

Mutual fund managers can increase their commitment to ESG by buying (selling) high (low) ESG performers. I find that managers generally implement an exit strategy by selling stocks with lower scores. I do not find evidence that managers implement an entry strategy whereby they buy high ESG performers. This is consistent with the fact that divestment is a prevalent strategy to implement ESG integration (see Atta-Darkua and Dimson [2020], Becht et al. [2019], Berk and van Binsbergen [2021] and Gantchev et al. [2022]). I also find that the transition towards ESG is more pronounced among bottom ESG performers, meaning those that fall in the bottom 25% of the sample. This highlights the importance of personal experiences in shaping the investment decisions of fund managers and driving the integration of ESG considerations into their portfolios.

A fitting question to ask is: what are the underlying mechanisms that prompt a manager to react to climatic events happening nearby? I look into three amplification mechanisms that could possibly enable a manager to consider the effects of the nearby climatic disaster in the subsequent investment decisions. First, I look into social interactions with peers who reside in affected areas. This channel serves as an informational source that facilitates indirect learning about the salient event (Hu [2022]). In other terms, I conjecture that the manager will learn about the disaster through social connections in the affected area, be it from friends, family or acquaintances. In the wake of recent developments in the finance and economics literature, where many studies suggest a strong link between social leaning and economic outcomes (e.g Hirshleifer [2020], Han et al. [2022], Kuchler and Stroebel [2021]), I hypothesize and find in the data that mutual fund managers who are socially connected to major disaster areas increase their commitment to ESG by improving the score of their overall portfolio. This result is consistent with a growing literature on the effects of social interactions on economic outcomes (e.g Bailey et al. [2018a], Bailey et al. [2018b], Kuchler et al. [2022]). For instance, Hu [2022] finds that households increase their flood insurance purchase by up to 5% when they are socially connected to areas where a major flooding event happened. To establish this link, I leverage endogenously formed links from a social network and exploit random climatic shocks. Essentially, these exogenous shocks should only influence a fund manager's investment decision through social interactions. Following a natural disaster, managers who are socially connected to the affected areas increase the environmental score of their portfolio by over 10% following the event.

The second mechanism I explore is a manager's prior climate change awareness. I conjecture that managers located in counties that are more receptive to scientific evidence on climate change (and that collectively believe that climate change is happening) are more likely to react to salient climatic events. Through high-resolution opinion estimates, Howe et al. [2015] find that belief in climate change and its consequences widely varies at the county level, ranging from 43% to 80%. I exploit this publicly available data and surprisingly find that mutual fund managers who are supposedly less perceptive of climate change, react to the salient event in a more pronounced way. The results, along with the personal views of fund managers towards climate change, suggest that raising awareness among the general public and fund managers specifically about the adversities of climate change can greatly influence investment behavior. Following a natural disaster, managers who had weak prior belief in climate change increase the environmental score of their portfolio by 5.6% following the event, compared to an increase of only 2% for the high belief group.

The third proposed mechanism explains the change in the commitment to ESG through increased attention. Fund managers can become aware of the risks associated with natural disasters through media coverage of the event. This can include news reports, social media, and other online sources, which can provide information on the extent of the disaster, the impact on companies and communities, and the response of government and other organizations. I use the Climate Policy Uncertainty (CPU) index introduced by Gavriilidis [2021] which serves as a proxy for increased discussion about climate change in the news. The index, which builds on the widely used Wall Street Journal (WSJ) Climate Change Index by Engle et al. [2020], assumes that reporting on climate news increases when climate risk is high, as well as when there is an impending change in climate policy. I find that in times of high media attention, managers increase their portfolio ESG score following a salient disaster by over 9%. Comparably, in times of limited attention, managers don't seem to increase their fund-level ESG scores even after being exposed to a nearby climatic event. These findings are consistent with growing evidence that attention is a relevant catalyst for climate-related action (e.g Engle et al. [2020], Choi et al. [2020] and Hu [2022]).

I explore a number of alternative explanations for the findings and conclude that the evidence for them is not convincing. First, I look at whether managerial skill, as measured by fund returns and flows, can explain the increase in portfolio ESG following a natural disaster. Essentially, fund managers may use their stock selection or market timing abilities to maximize returns or attract more flows following the natural disaster. I find that net returns and flows remain unchanged in the four quarters that follow a natural disaster Huang et al. [2011].

The second alternative explanation is related to catering to investors. Similar to Alok et al. [2020], I investigate whether funds underweight disaster zone stocks merely because they have to cater to the preferences of their investor clientele. Mutual fund managers may reduce their investments in stocks from disaster zones, not due to their own preferences or biases, but instead to align with their clients' desire to limit their exposure to such investments. Another interpretation of this setting is that fund managers could be increasing or reducing their investments in disaster zone stocks to capture a time-sensitive investment opportunity. However, the analysis did not yield convincing evidence to support this explanation. The weights of disaster stocks following the event remain unchanged in the subsequent quarters.

This study builds upon existing literature that examines the increasing concern among institutional investors for environmental and climate risk (e.g., Ilhan et al. [2021], Krueger et al. [2020]). While it is known that more institutional investors are paying attention to climate risk, the factors that contribute to raising awareness on the matter are not yet fully understood. This research presents new insights into the role of personal experiences in increasing climate awareness.

This paper also contributes to the existing literature on the effects of personal experiences on financial decisions. I find that indirect exposure to climatic disasters renders fund managers more committed to ESG issues. Moreover, unlike contemporaneous studies that tackle a similar hypothesis (e.g Venkat et al. [2022], Fich and Xu [2022], Di Giuli et al. [2022]) the setting of this study evidently addresses the endogeneity concern because the events in question affect variables which are unlikely to be related to investment decisions. The results outlined in this paper provide empirical evidence that life experiences influence capital allocation decisions and the perception of sustainable investments especially.

The rest of this paper is organized as follows. Section 2 presents the data and descriptive statistics. Section 3 presents the empirical design, Section 4 outlines the results and Section 5 concludes.

2. Data and Descriptive Statistics

2.1 Fund Data

I obtain mutual fund data, such as monthly returns, fund fees, and turnover ratio from the Center for Research in Security Prices (CRSP) SurvivorBias-Free Mutual Fund Database. Since CRSP provides data at the share class level, I aggregate by value-weight to avoid multiple-counting of funds with more than one share class. I use Thomson Financial to obtain quarter-end holdings of funds and focus only on actively managed U.S. equity mutual funds. I exclude funds with total net assets (TNA) less than $5 million. I then use MFLINKS (initially developed by Wermers [2000] and available through Wharton Research Data Services (WRDS)) to link the holdings data to CRSP.

For the exact location of managers, I use ADV filings. Form ADV is mandatory for investment advisers who are required to register with the Securities and Exchange Commission (SEC). It contains information about an investment adviser and its business operations. Using ADV filings instead of fund headquarters is more advantageous because it includes the location of the manager(s) making the day-to-day decisions. For instance, while Vanguard is headquartered in Pennsylvania, a number of their funds are overseen by Wellington Management Company in Boston [3]. Essentially, the ADV filings allow me to locate the advisors and sub-advisors responsible for the investment decisions. I then use fuzzy matching to match holdings data and the ADV filings. I keep the names that match perfectly and check the remaining matches manually. I impose a number of restrictions to minimize potential errors in locating the advisors. Following Chang [2021], I exclude funds with advisors located outside the United States and observations where a fund is located in multiple counties. The final sample includes 1739 funds between 2009 and 2018.

2.2 ESG Scores

To obtain company-level ESG scores, I use Sustainalytics. It identifies key ESG issues based on analysis of a company's peer group and its broader value chain, review of the business model, and the key activities associated with environmental and/or social impacts. It then weights a comprehensive set of core and sector-specific metrics to determine a company's overall ESG performance ranging from 0 (most negative) to 100 (most positive). It also assesses data related to major controversies related to business ethics, supply chain, products, employees, etc. Sustainalytics data are available from 2009. I first fuzzy-match Sustainalytics with Compustat to get the PERMNO identifier before matching with the fund-holding data. I construct fund-level ESG scores as follows:

$$ESG_{ft} = \sum_{i} w_{fit} \times ESG_{it}^{Stock} \tag{1}$$

where w_{fit} is the weight of stock i in fund f at time t. ESG_{it}^{Stock} is the ESG score for stock i at time t. I also use an alternative definition of ESG by adjusting the score for investment style. Since exposures to ESG-sensitive assets is, according to the literature, inherent in several classic investment styles such as those based on "value" and "size", style-adjusted fund-level scores are key to the conducted analyses (see. Bauer et al. [2005], Borgers et al. [2015]). To attribute style to each fund, I use the 3 x 3 grid of investment styles reported in CRSP.

[3]A similar distinction is made in Chang [2021] and Hong et al. [2005]

2.3 Natural Disasters

I identify natural disasters using the Federal Emergency Management Agency (FEMA) Disaster Declarations Summary. This database lists all official FEMA disaster declarations and provides information on disaster ID numbers, declaration dates, incident start and end dates, declared states and counties, and incident types. Under the Stafford Act of 1988, a disaster is declared by FEMA when federal assistance is necessary after the damage is assessed to be beyond the capabilities of a local government.

Disaster types include biological incidents, storms, hurricanes, fires, terrorist attacks, droughts, earthquakes, floods, tornadoes and volcanic eruptions. I limit my sample of declarations to fires, floods and hurricanes because of their apparent link to climate change. Human emissions of greenhouse gases affect temperature and rainfall patterns, which in turn impact the intensity as well as the frequency of extreme environmental events, such as fires, hurricanes, heat waves, floods, and storms (Van Aalst [2006]). I identify 102 declarations over my sample period. One declaration typically includes multiple affected counties.

2.4 Social Connectedness

Data on the strength of connectedness between two geographic areas is obtained through social network friendship ties. Facebook's Social Connectedness Index (SCI) is constructed based on the friendship links between anonymized Facebook users in different U.S. counties. Facebook is the world's most popular social network, with more than 2.7 billion active global users monthly as of September 30, 2020. It covers approximately 70% of the U.S. population, with 231 million active users. A survey of the social network users reports that usage rates among adults were similar, and well as constant, across income groups, education levels, race, urban, rural, and suburban groups (Greenwood et al. [2016]). I argue, following the literature, that the SCI is a sensible proxy for real-world US social networks and for both online and offline social interactions. This is a result of Facebook's enormous scale, its comprehensive market penetration, and the fact that on Facebook, connections require the consent of both individuals, making it a more accurate reflection of real-world social networks compared to other online platforms where connections to non-acquaintances are common.

$$SCI_{i,j} = \frac{\#FriendshipLinks_{ij}}{\#FB\ \ Users_i \times \#FB\ \ Users_j} \tag{2}$$

The SCI is calculated as the likelihood that a Facebook user in county i is friends with a user in county j. It is determined by dividing the number of cross-county friendship links by the product of the number of Facebook users in both counties for each county pair (i, j), with adjustments made for an unknown random noise factor and rounded to the nearest whole number. This index reflects the relative probability that a Facebook user in one county is friends with another user in another county (e.g. Kuchler et al. [2022], Bailey et al. [2018a])

2.5 Climate Change Beliefs and Attention

To proxy for county-level climate change awareness, I use data from the Yale Program on Climate Change Communication [4] (YPCCC). Using national surveys, YPCCC reports variations in climate change beliefs and awareness at local levels, and shows that American opinion varies widely depending on where people live. For instance, estimates show that only 48% of people living in Emery County, Utah agree that climate change is happening. However, in the neighboring Grand County, 71% of the population agrees. Overall, the survey and opinion estimates show that public concern about global warming and climate change has generally increased since 2014, with the percentage of American adults who think global warming is happening reaching 72% as of 2021.

To account for attention through news, I use the Climate Policy Uncertainty (CPU) index introduced by Gavriilidis [2021]. The measure of uncertainty related to climate policy as well as increased attention to climate change through mentions in the news. The index demonstrates notable spikes during key events related to climate policy, such as the implementation of new legislation on emissions, worldwide climate change strikes, and presidential declarations on climate

[4] Yale Climate Opinion Maps

policy, among other significant events. It is constructed using the scaled frequency of articles from eight major newspapers in the United States (Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal) to capture significant events related to climate policy. The research conducted by the authors is largely influenced by the work of Engle et al. [2020], who utilized textual analysis to develop a climate change news index using articles from the Wall Street Journal (WSJ). However, Gavriilidis [2021] improves the measure by increasing the breadth of news sources and incorporating articles from eight major newspapers instead of just one, and by including mentions of climate policy rather than just climate-related events. The index primarily captures changes in climate policy, but can also serve as a proxy for increased attention to climate change and climate-related events.

2.6 Descriptive Statistics

Table 1 presents descriptive statistics for the sample. Panel A reports summary statistics for all fund-quarter observations. The average fund size in the full sample is $1.18 billion. The annual expense ratio is 0.90% and turnover is 56%. This reflects that the sample consists mainly of actively managed funds. The average ESG score for funds in the sample is 56.40 (the average score for the Sustainalytics universe is around 58) and the average style-adjusted ESG score is -0.004 with a standard deviation of 4.18. Funds in this sample hold around 54 stocks per quarter with a minimum of 4 and a maximum of 278. Moreover, the portfolio of the average fund is composed of 32.6% of high ESG stocks (based on the highest percentile of ESG scores) and 29.5% of low ESG stocks (based on the lowst percentile of ESG scores).

In Panel B, I compare funds that are close to a disaster area (i.e. within 100 miles) (treatment) to funds in distant counties (control). Funds in both groups are virtually similar with slight differences in returns and size. Accordingly, I control for these characteristics in my specification.

Panel C of Table 1 reports the weights of different types of natural disasters. Hurricanes are more frequent in the sample, followed by floods and fires.

3. Change in fund-level ESG following a climatic disaster

3.1 Empirical Methodology

In this section, I lay out my empirical strategy to test how fund managers become more ESG-conscious. My identification strategy relies on exogenous shocks to a manager's awareness or attention to climate risk. This setting is optimal because the natural disasters studied should only affect the manager's investment decision through the salience effect. This is possible to establish because counties neighboring the location of the managers are the ones essentially being hit by natural disasters.

I compare a treatment group of close yet unaffected funds to a control group of unaffected and relatively far away funds. This identification relies on exogenous shocks, which should affect a fund's investment decision only through variation in the salience of the disaster. This setup also mitigates the concern of changes in local conditions and how they could affect a manager's decision if directly exposed to the shock. Figure 2 presents an example of this setting. The full map including all the affected counties and the fund manager locations is reported in Figure 1.

To implement the difference-in-differences approach, I use county location of fund managers and their distance from disaster zones. I classify a fund as being close to a disaster area if the distance is within 100 miles. The unit of observation in this analysis is at the fund-quarter level. Formally, the specification is as follows:

$$\begin{aligned} ESG_{fq} = \beta_0 + \beta_1 Close_{fc} + \beta_2 Post_q + \beta_3 (Post_q \times Close_{fc}) \\ + X_{ft-1} + \sigma_{ft} + \delta_q + \gamma_c + \epsilon_{ftqc} \end{aligned} \tag{3}$$

where ESG_{fq} is the ESG score of fund f at quarter q (or the style-adjusted score in some specifications). $Close_{fc}$ is a county-level dummy that takes the value of one if the manager is located in a county neighboring a disaster area and zero otherwise. $Post_q$ is a time-level dummy that takes the value of 1 for a disaster quarter and the four following quarters. β_3 is the coefficient of interest, and it measures the variation in ESG investing by close funds following a climatic disaster, relative to distant funds.

X_{fq-1} is a vector of lagged fund-level covariates and characteristics (including size, fee, turnover ratio, expense ratio, flows and returns). I control for unobserved time-varying managerial heterogeneity through the inclusion of high-dimensional fund-by-year fixed effects σ_{ft}. This approach addresses the possibility that confounding variables at the fund-time level could distort the results. For example, a change in a fund's overall mission over the years to cater to socially responsible investors could bias the estimates. As reported by Morningstar, the inflows into U.S. mutual funds with an ESG focus saw a significant boost in recent year. In 2020, the amount reached $51.1 billion, which was double the amount from 2019 and nine times more than the inflow from 2018. Additionally, Morningstar also noted that by the end of 2020, the number of U.S. ESG funds had increased to 369, representing a 23% growth from the previous year (Hale [2021]).

Disaster quarter fixed effects δ_q are included to control for aggregate macroeconomic shocks and county fixed effects γ_c are used to control for local economic conditions. A positive β_3 indicates that funds close to disaster zones increase their commitment to ESG (by increasing the overall score of their portfolio) more than funds that are far away.

3.2 Results

I begin my empirical analysis by exploring whether fund managers exposed to salience disasters nearby transition to ESG investing by altering the composition of their portfolios. The results of this section are based on specifications (3) and (4) and are reported in Figure 3, Table 2 and Table 34.

Figure 3 documents the dynamic effects and there is a noticeable persistence of the effect once an increase happens after two quarters. To conduct this analysis I use the methodology by De Chaisemartin and d'Haultfoeuille [2020]. In the field of applied econometrics, it has become widely recognized that employing two-way fixed-effects (TWFE) estimations for difference-in-differences coefficients may result in significant biases, particularly when dealing with staggered treatment timing and varied or time-dependent treatment effects. This observation has been discussed and highlighted in various studies such as Borusyak et al. [2021], Callaway and Sant'Anna [2021], De Chaisemartin and d'Haultfoeuille [2020] and Sun and Abraham [2021]. The use of a TWFE estimator with heterogeneous treatment effects guarantees the absence of bias in my estimations.

Columns 1 of Table 2 report results for a fund's total ESG score as the dependent variable. The positive and significant coefficient on the variable of interest essentially means that when managers are close to an area where a major salient disaster took place, they increase their commitment to ESG by increasing the overall score of their portfolio in the four subsequent quarters. In terms of magnitude, the effect is economically sizeable since in this baseline case, managers increase the ESG score of their portfolio by over 2.5%, when compared to the mean of the overall sample. Column 2 reports results that use an alternative definition of ESG by looking at the style-adjusted score. The coefficient is positive, significant, and close in magnitude to the specification reported in column 1. This essentially means that a fund's investment style is not driving the results. In column 3, I repeat the same analysis using only a fund's environmental score and find similar results. The magnitude when only looking at the environmental score is greater and more than doubles. In column 4, I use a different set of more restrictive fixed effects (Fund, County and Quarter-Year) and find positive and significant results, albeit lower in magnitude.

In Table 3, I look at fund heterogeneity to discern which kind of funds engages in ESG integration following the exposure to a nearby disaster. I find that, maybe surprisingly, bottom ESG performers are more prone to increase their fund-level score when compared to top performers. This means that investors who prioritize climate concerns are less likely to perceive natural disasters as a sudden shock that brings attention to environmental issues. This result also means that personal experience is a relevant factor that partially explains the transition to ESG investing.

Funds in my sample experience 1.4 natural disasters on average. I look at the intensive margin and compare fund managers that experienced only one natural disaster versus managers that experienced multiple. In results reported in Table A5 columns 1 and 2, I find that both types of managers exhibit a significant increase in the E-component of ESG. However, when looking at returns as reported in columns 3 and 4, fund managers who have experienced more than one natural disaster do not leave returns on the table, compared to managers affected for the first time. This suggests that managers learn from previous experiences (e.g. Alok et al. [2020] and Bernile et al. [2017]). An alternative way to interpret these results is that managers invest with other incentives in mind when disasters become more frequent, and ultimately capitalize on maximizing returns rather than investing sustainably.

I exploit temporal dynamics and examine whether the effect persists beyond four quarters. In Table A1, I report results for specification (2) but $Post_q$ takes a value of one for the five and six subsequent quarters instead of four. When looking at five quarters following a disaster, the coefficients of the style-adjusted score and the environmental score both decrease in significance and magnitude. The coefficient of interest shrinks even more after six quarters. This could potentially mean that fund managers cease to invest sustainably and actively increase their ESG scores when the salient event becomes distant in time. However, there is no apparent reversion in the time frame studied.

In Table A2, I examine whether the effect is persistent when looking at a different definition of $Close_{fc}$. For funds situated within 500 miles of the disaster (instead of 100 miles) The variable of interest $Post_q \times Close_{fc}$ is no longer significant and decreases in magnitude to become negative. This is the case when using the standard level-terms ESG score, the style-adjusted score or the environmental score. This potentially means that the climatic event is not salient when it is too geographically distant from the fund manager, and thus does not affect the manager's investment decision.

In Table A3, I conduct a placebo test and use only the social component of the fund-level score. In column (1), which is the baseline specification, I find no effect following the natural disaster. In the results reported in columns (2) and (3), I repeat the analysis using different definitions of $Post_q$ and $Close_{fc}$ and still find no significant effect. These results reinforce the idea that the salient climatic event is the main catalyst behind the documented increase in fund-level ESG and environmental scores.

As a robustness check, I look at non-major natural disasters such as heavy snowfall, heavy rainfall, ice storms and droughts. In results reported in Table A4, I find no significant effect using three different definitions of the dependent variable. The effect is absent even with the use of a different set of fixed effects in column 4. This reinforces the idea that the salience and severity of the disaster are what induce managers to react and alter their investments.

3.3 Entry and Exit as ESG Commitment Strategies

In this section, I explore how mutual funds managers implement ESG integration following exposure to a climatic disaster. I propose exit (selling low ESG performers) and entry (buying high ESG performers) as possible strategies to increase commitment to ESG investing. To measure this, I use the following specification:

$$\begin{aligned} \#Stocks_{fq} = \beta_0 + \beta_1 Close_{fc} + \beta_2 Post_q + \beta_3 (Post_q \times Close_{fc}) \\ + X_{ft-1} + \sigma_{ft} + \delta_q + \gamma_c + \epsilon_{ftqc} \end{aligned} \tag{4}$$

where $\#Stocks_{fq}$ is the number of high (low) ESG stocks held by fund f in quarter q, which is calculated as the number of stocks in the 75th (25th) percentile ESG score over the total number of stocks in a given portfolio-quarter, following the method in Kim and Yoon [2022].

In Table 4, I report results that document what are the potential ESG integration strategies of fund managers. I find that in order to increase their portfolio-level ESG score following exposure to a natural disaster, fund managers engage in exit strategies where they sell low ESG stocks. As reported in column (1), I do not find evidence that managers engage in an entry strategy.

In Table A6, I look into whether the weights of high and low ESG stocks change in response to the disasters. I re-estimate equation (4) using a different dependent variable: the dollar amount of stocks in the highest (and lowest) quartile of ESG divided by assets under management (or the total dollar amount of stocks in the portfolio) for each quarter q. Column (1) shows that there is no increase in the weight of high ESG stocks. However, the results in column (2) show a sizeable change of -14.7% in the weight of low ESG stocks. This reinforces the findings of Table 4, where funds engage in exit strategies, by selling low ESG stocks.

4. Amplification Mechanisms

4.1 Social connectedness as a mechanism

In the previous section, I present a specification that captures the variation in ESG investing at the fund-level following secondhand exposure to a natural disaster. In this section, I explore social connectedness as a mechanism that potentially explains the fund managers' actions. I posit that fund managers learn about the magnitudes and consequences of climatic disasters via social interactions with friends and family which leads them to update their beliefs. In a given state, two counties are socially connected if the SCI for the pair is higher than the state average. The first two columns of Table 5 present the findings for counties that exhibit a high level of social connectedness with disaster areas. Notably, the coefficient assigned to the variable of interest, denoted as $Post_q \times Close_{fc}$, emerges as statistically significant and positively associated with the level of ESG commitment. This result suggests that funds that engage in extensive social interactions with disaster-affected areas, owing to their robust social connections (be it through friends, family or acquaintances in the affected county), display higher levels of ESG commitment following climatic disasters. The results also holds when using the style- adjusted measure. Moreover, the economic magnitude is substantial, with a sizeable 10.3% increase observed in the environmental component of ESG. In columns 3 and 4, I repeat the same analysis for fund managers who reside locations that are not socially connected to disaster areas. The effect is lower in magnitude and not significant. In essence, the findings suggest that the relationship between climatic disasters and fund-level ESG investing follows a monotonic pattern determined by the strength of social ties.

4.2 Prior Beliefs and Climate Change Awareness

In this section, I present an alternative mechanism that plausibly plays a role in capturing a fund manager's attention. I hypothesize that managers who are located in areas where awareness of climate change is prevalent are more prone to increase their commitment to ESG following a salient climatic event nearby. Myers et al. [2013] study this mechanism and find that through 'motivated reasoning', prior belief in climate change influences people's perceptions of impacts and perceptions of personal experiences. The coefficient of interest $Post_q \times Close_{fc}$ captures whether fund managers who are exposed to climatic disasters, change their commitment to ESG when they have prior beliefs that climate change is real, and are aware of its consequences. The same set of fixed effects and controls as in the previous sections applies.

The results for this specification are reported in columns (1) and (2) of Table 6. The interaction is positive and significant, which means that a fund increases ESG commitment following a nearby disaster when the manager has prior beliefs that climate change is happening. The magnitudes are economically sizeable, since managers who are a priori aware of climate change increase the environmental score of their respective portfolios by 2% following the natural disaster.

To ensure the robustness of the analysis, I replicate the same analysis for the bottom quartile, which provides interesting insights. Contrary to initial expectations, the coefficient of interest remains statistically significant and exhibits a considerably larger magnitude in both columns (3) and (4). This finding implies that fund managers located in regions with relatively high climate change awareness do not react as strongly as their counterparts in areas with lower awareness. In essence, managers in these highly aware regions demonstrate a diminished response to climatic events compared to those in regions with lower awareness.

One plausible interpretation of these results is that fund managers who already hold strong beliefs about climate change are less likely to be surprised or significantly impacted by their exposure to climate-related events. The presence of strong beliefs may act as a filter that impacts their perception of the event. Consequently, their reactions and subsequent learning from these experiences may be attenuated compared to individuals who do not possess such pre-existing beliefs.

4.3 Attention to news as an alternative mechanism

The change in investment decisions following the exposure to a climatic disaster could also logically be attributed to learning through news, as opposed to social connections or prior beliefs. I test this hypothesis using the Climate Policy Uncertainty index developed by Gavriilidis [2021]. The results are reported in Table 7. Columns (1) and (2) report a positive and significant interaction for the style-adjusted score and the environment component only. This means that when attention to climate change is high (through increased media mentions), managers who are exposed to climatic disasters are more prone to increase their commitment to ESG.

In the results reported in columns (3) and (4), I repeat the same analysis using low attention to climate change. In this specification, the coefficient of interest is positive but lower in magnitude (and insignificant in column 4) when looking at both specifications. This essentially illustrates that attention to news is an important factor that determines the understanding of climate risk.

5. Alternative Explanations

5.1 Managerial Skill

The main claim or forecast of this explanation is that funds that are exposed to a nearby disaster are expected to have better performance in subsequent quarters. In other words, experiencing a nearby disaster may provide managers with an advantage in terms of information. This advantage, when combined with their abilities in selecting stocks or timing the market, may enable them to perform better than others. This in turn could be an alternative explanation to the increase in fund-level ESG. I test this hypothesis using the following specification:

$$Returns_{fq} = \beta_0 + \beta_1 Close_{fc} + \beta_2 Post_q + \beta_3 (Post_q \times Close_{fc}) \\ + \sigma_{ft} + \delta_q + \gamma_c + \epsilon_{ftqc} \tag{5}$$

where $Returns_{fq}$ is the quarterly fund-level net returns, and it is used as the primary measure of managerial skill. The results of this specification are reported in Table 8. I look at different definitions of $Post_q$ and find that in the two and four quarters following the natural disaster, there is no sizeable or significant change in return. One interpretation of these results is that managers leave returns on the table in order to invest more responsibly. In column 3, after six quarters, a significant increase in returns is captured, but that is not necessarily in relation to the event.

Alternatively, I look at flows as a measure of managerial skills. In Table 9, there are no significant changes to fund flows following the salient event. In column 3, after six quarters, a significant decrease in flows is captured, but similar to the previous specification, it is not necessarily in relation to the event.

5.2 Divestment from Local Stocks

Another explanation for the increase in fund-level ESG is that managers are reducing their investments in disaster zone stocks. This could be done in order to satisfy investor preferences and reduce outflows. This indicates that even if fund managers themselves are rational, they may still trade in a biased way due to flow-driven trading pressures created by the behavioral biases of their investors. An alternative way of looking at this could simply be that managers disinvest because they expect a lower performance from the affected firms. To rule out this explanation as a driver of the increase in ESG, I test the following specification:

$$Weight_{fiq} = \beta_0 + \beta_1 Close_{fc} + \beta_2 Post_q + \beta_3(Post_q \times Close_{fc}) \quad (6)$$
$$+ \sigma_{ft} + \delta_q + \gamma_c + \zeta_i + \epsilon_{ftqc}$$

where $Weight_{fiq}$ is the weight of firm i that is in or close to a disaster area, in the portfolio of fund f at quarter q. The same set of fixed effects applies, with the addition of firm fixed effects ζ_i to control for unobserved heterogeneity and time-invariant characteristics at the firm level.

The results of this specification are reported in Table 10. I look at different definitions of $Post_q$ and find that in the two, four and six quarters following the natural disaster, there is no sizeable or significant change in the weights of firms located in or near disaster area, thus ruling out the divestment (or catering) alternative explanation.

6. Conclusion

I empirically study how fund managers become more conscious about climate risk, leading them to integrate ESG issues into their investment decisions. To do so, I use natural disasters in neighboring counties as an exogenous shock to their attention to climate risk. More broadly, these shocks serve as a learning factor that partially drive a mutual fund manager's ESG adoption. The evidence in this paper indicates that managers exposed to acute climatic events are more prone to increase their commitment to ESG issues, and I attribute these results to the salient nature of the events. Consistent with the idea that exposure to negative shocks does in fact affect decision-making through changes in beliefs, emotions, and information sets. Funds that are bottom performers in term of past ESG performance are more likely to alter their investment decisions compared to top ESG performers. This makes sense since the striking nature of the disaster would have a more drastic influence on managers who were not previously receptive to climate risk. Fund managers implement ESG integration through an exit strategy (divestment) rather than an entry strategy.

Following the exogenous shock, there are a number of mechanisms that lead fund managers to increase their commitment to sustainable investing. I first propose social interactions with individuals living in affected states. Fund managers are more likely to become aware of the disaster if they are socially connected to the area through friends, family and acquaintances. I find that fund managers exposed to a salient event react even more when they have considerable social ties in the affected area.

The alternative mechanisms that potentially explain the change in investment decisions are prior beliefs about climate change and increased attention to climate risk through mainstream media. I find that the impact of climatic disasters on fund-level ESG is monotonic in the strength of both mechanisms. First, I find that a fund is more committed to ESG following a nearby disaster when the manager has prior beliefs that climate change is happening. Second, when mainstream media increase mentions of climate change, and thus capture a fund manager's attention, commitment to ESG increases at the fund level following the exposure to a natural disaster.

Lastly, alternative explanations, including managerial skill assessed through returns and flows, as well as the possibility of divestment from disaster stocks, are examined to assess whether they drive the variations observed in ESG investment following the onset of natural disasters. However, the results indicate that these factors do not account for the observed changes.

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Figure 1: Map Representing Counties and Funds in the Sample

This figure shows a map of all disasters (in red) and mutual fund manager locations (in blue).

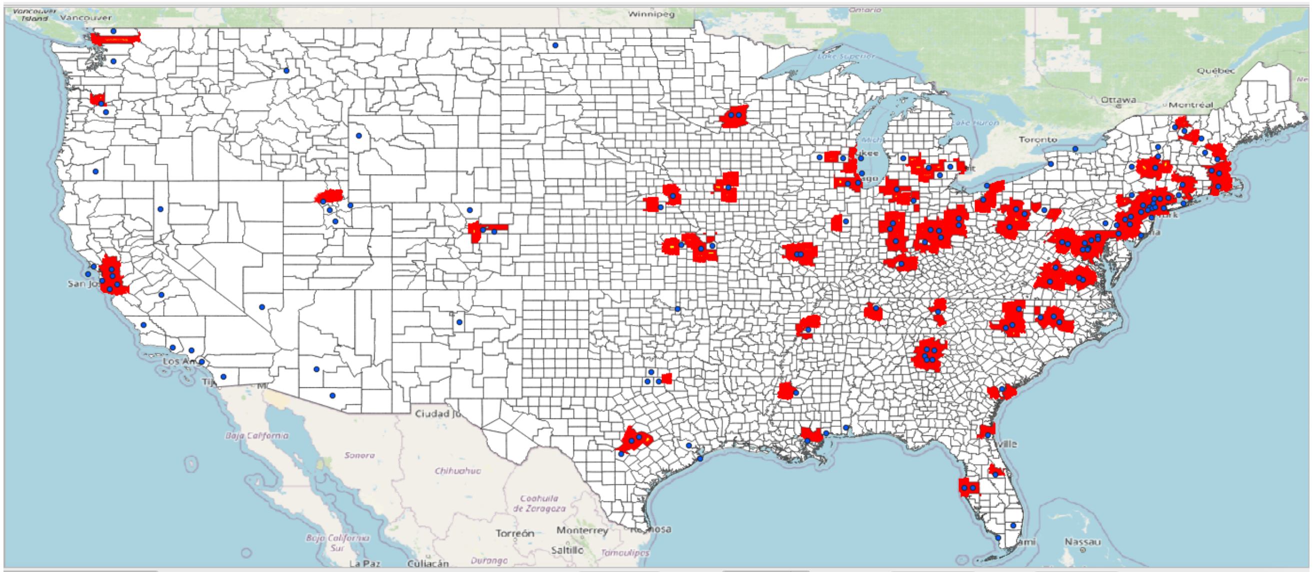

FIGURE 2: Empirical Design (Example)

This figure shows an example of how I structure my empirical design. The dots in blue represent funds and counties in yellow represent counties that are hit by a natural disaster.

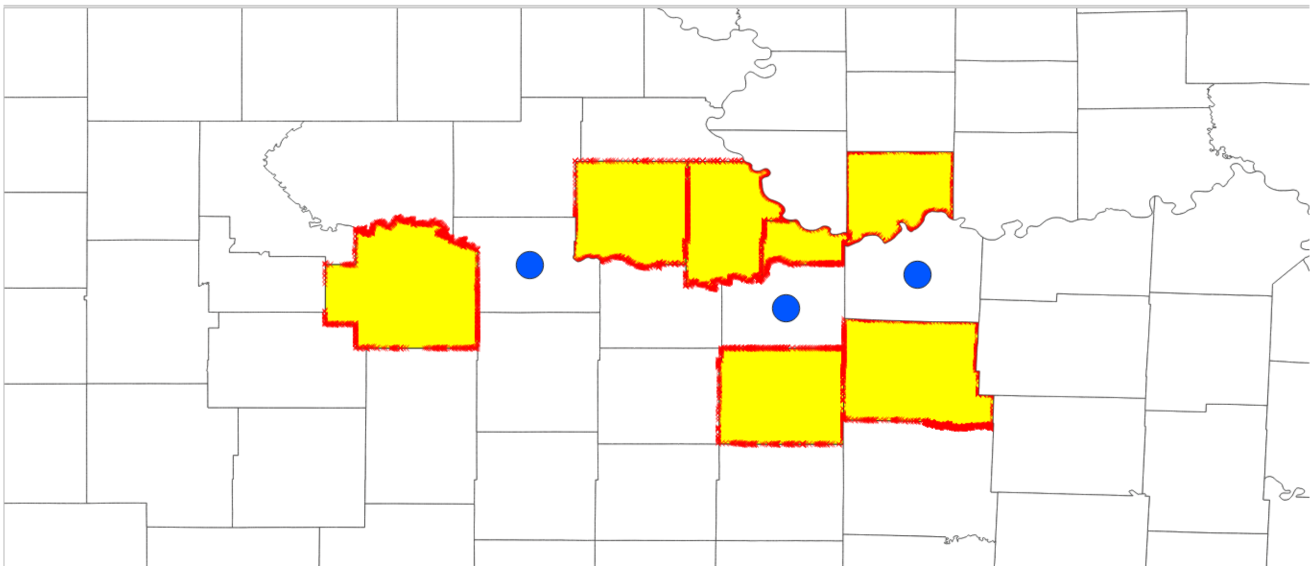

FIGURE 3: Fund-level ESG change following the exposure of managers to natural disasters

This figure presents the results using the approach proposed by De Chaisemartin and d'Haultfoeuille [2020] to correct the biases of two-way fixed effects estimations of difference-in-differences coefficients. Standard errors are clustered at the fund level. The bands around the coefficient estimates show the 95% confidence intervals.

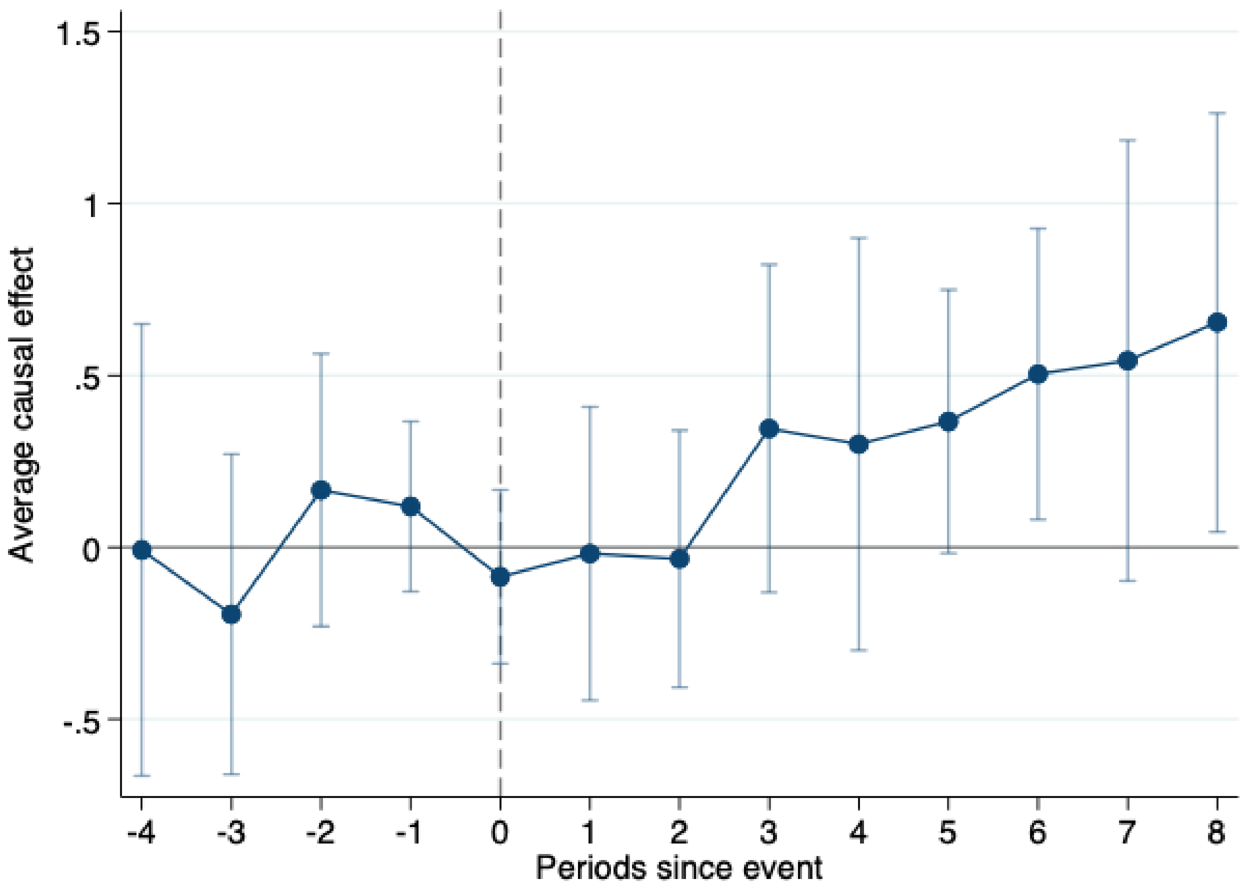

TABLE 1: Fund-level and Disaster Summary Statistics
Panel A reports summary statistics over the full sample of fund-quarters. Panel B reports characteristics of treatment and control group funds separately, as well as a test of their differences. Panel C reports summary statistics for the natural disasters in the sample. All variables are winsorized at the 1st and 99th percentiles.

A: Fund-quarters (Full Sample)					
Variables	N	Mean	SD	Min	Max
Total ESG	32,336	56.40	4.758	45.02	66.67
Env. Score	32,336	52.73	7.654	36.86	69.72
Soc. Score	32,336	55.41	5.488	40.59	67.40
Gov. Score	32,336	63.89	3.433	53.45	72.52
Style-adj Score	32,336	0	4.182	-10.35	9.364
Size	32,336	1,184	2,527	5	15,964
Size (log)	32,033	5.610	1.821	1.856	9.686
Flows	32,032	0.965	0.108	0.272	1.262
Return	32,336	0.0342	0.0718	-0.200	0.185
Turnover	32,336	0.559	0.547	0	2.910
Expense	32,336	0.00954	0.00493	0	0.0206
Fee	32,336	0.611	0.364	-0.427	1.387
# Stocks Held	33,768	54.03	58.35	4	278
High ESG Stocks (%)	26,926	0.326	0.201	0.027	0.847
Low ESG Stocks (%)	28,257	0.295	0.208	0.02	1

B: Treatment versus control funds			
Variables	Treatment	Control	Difference
Size	1162.816	1190.237	-27.421
Expense	0.009	0.009	0.000
Turnover	0.565	0.559	0.006
Fee	0.611	0.585	0.026
Return	-0.022	0.167	-0.189
Total ESG	56.012	56.401	-0.389
Env. Score	52.010	52.736	-0.726
Soc. Score	54.981	55.388	-0.407
Gov. Score	64.091	63.826	0.265

C: Weights of disasters in the sample	
Incident Type	Percentage
Fire	15.69%
Flood	24.82%
Hurricane	59.49%

TABLE 2: Fund-level ESG change following disasters
This table reports the coefficients for equation (3), where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable Total ESG is the fund-level overall ESG score, Env. Score captures only the environmental component and style-adjusted ESG is the fund score minus the style average. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Total ESG	(2) Style-Ajd ESG	(3) Env. Score	(4) Env. Sore
$Post_q \times Close_{fc}$	1.475***	1.453***	3.197**	2.142*
	(0.552)	(0.550)	(1.312)	(1.119)
$Post_q$	-1.186**	-1.189**	-2.823**	-2.240**
	(0.548)	(0.547)	(1.309)	(1.118)
$Close_{fc}$	0.00225	0.0122	-0.294	-2.329**
	(0.467)	(0.468)	(1.171)	(1.126)
$Return_{t-1}$	-1.886***	-1.847***	-4.298***	0.464
	(0.438)	(0.416)	(0.655)	(1.081)
$Expense_{t-1}$	-24.75	-15.22	-7.338	28.93
	(25.25)	(25.39)	(41.51)	(22.52)
$Turnover_{t-1}$	-0.0718	-0.0845	0.0283	-0.252**
	(0.142)	(0.142)	(0.223)	(0.110)
$Size_{t-1}$	-0.154*	-0.132	-0.375***	0.290***
	(0.0841)	(0.0876)	(0.125)	(0.0605)
$Flows_{t-1}$	2.331***	2.277***	2.245***	0.294
	(0.383)	(0.357)	(0.561)	(0.440)
Fee_{t-1}	0.592*	0.520	0.352	-0.412
	(0.334)	(0.327)	(0.552)	(0.285)
Observations	26,025	26,025	26,025	27,402
R-squared	0.918	0.890	0.930	0.769
Fund x Year FE	Yes	Yes	Yes	No
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	No
Fund FE	No	No	No	Yes
Quarter-Year FE	No	No	No	Yes

TABLE 3: Trend in Top and Bottom ESG performers
The variable of interest is $Post_q \times Close_{fc}$. The dependent variable Total ESG is the fund-level overall ESG score and Style-Ajd. ESG captures the score adjusted to fund style. Columns (1) and (2) refer to top ESG performers as measured by quartiles, and columns (3) and (4) refer to bottom performers. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Style-Adj ESG *Top ESG*	(2) Env. Score *Top ESG*	(3) Style-Adj ESG *Bottom ESG*	(4) Env. Score *Bottom ESG*
$Post_q \times Close_{fc}$	-0.867	-3.915	3.512***	0.638***
	(0.558)	(2.550)	(0.158)	(0.175)
$Post_q$	0.736	3.916	-2.744***	0.149
	(0.550)	(2.545)	(0.0485)	(0.209)
$Close_{fc}$	1.604**	4.156***	-0.466***	
	(0.730)	(0.223)	(0.131)	
$Return_{t-1}$	-0.192***	-0.220**	-0.113	0.0863
	(0.0584)	(0.0952)	(0.0825)	(0.131)
$Expense_{t-1}$	63.06*	34.18	5.874	-18.86
	(36.97)	(74.23)	(40.09)	(76.98)
$Turnover_{t-1}$	-0.0932	-0.0594	-0.593**	0.224
	(0.193)	(0.343)	(0.246)	(0.419)
$Size_{t-1}$	0.118	0.224	-0.125	-0.670***
	(0.164)	(0.274)	(0.169)	(0.219)
$Flows_{t-1}$	-0.0628	-0.137*	0.0218	0.113
	(0.0501)	(0.0815)	(0.0766)	(0.109)
Fee_{t-1}	-0.338	0.552	0.226	0.754
	(0.519)	(1.120)	(0.476)	(0.804)
Observations	5,073	5,487	3,845	4,649
R-squared	0.795	0.793	0.762	0.728
Fund x Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	Yes

TABLE 4: Entry vs. Exit as ESG commitment strategies

This table reports the coefficients for equation (4), where the variable of interest is $Post_q \times Close_{fc}$. # High ESG Stocks in column (1) indicates the percentage of stocks in the highest quartile of ESG scores. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) # High ESG Stocks	(2) # Low ESG Stocks
$Post_q \times Close_{fc}$	0.00551	-0.0153***
	(0.00410)	(0.00504)
$Post_q$	-0.00623*	-0.00332
	(0.00361)	(0.00442)
$Close_{fc}$	-0.0224***	0.00944*
	(0.00422)	(0.00513)
$Return_{t-1}$	0.00201	0.00498**
	(0.00148)	(0.00208)
$Expense_{t-1}$	0.0123	1.630
	(1.063)	(1.279)
$Turnover_{t-1}$	-0.00767	0.000781
	(0.00565)	(0.00668)
$Size_{t-1}$	-0.00893***	0.0147***
	(0.00337)	(0.00418)
$Flows_{t-1}$	0.00477***	-0.00801***
	(0.00129)	(0.00189)
Fee_{t-1}	0.00467	-0.0264
	(0.0128)	(0.0163)
Observations	28,659	28,659
R-squared	0.897	0.827
Fund x Year FE	Yes	Yes
County FE	Yes	Yes
Disaster Quarter FE	Yes	Yes

TABLE 5: Social connectedness as an explanatory mechanism
This table reports the impact of natural disasters on fund-level ESG, using social connectedness as an explanatory mechanism, where the variable of interest is $Post_q \times Close_{fc} \times Connected_{fc}$. The dependent variable, Env. Score captures only the environmental component of ESG and style-adjusted ESG is the fund score minus the style average. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Style-Adj ESG *High Connectedness*	(2) Env. Score *High Connectedness*	(3) Style-Adj ESG *Low Connectedness*	(4) Env. Score *Low Connectedness*
$Post_q \times Close_{fc}$	2.319***	5.454***	0.171	-2.385
	(0.475)	(1.118)	(0)	(0)
$Post_q$	-2.209***	-5.189***	0.215	2.764
	(0.467)	(1.109)	(0)	(0)
$Close_{fc}$	-0.193	-1.798	1.930	4.746
	(0.449)	(1.326)	(0)	(0)
$Return_{t-1}$	-1.619***	-3.885***	-1.473	-4.287
	(0.529)	(0.790)	(0)	(0)
$Expense_{t-1}$	16.87	37.54	-35.55	7.451
	(36.17)	(59.50)	(0)	(0)
$Turnover_{t-1}$	-0.441*	-0.540	-0.0478	-0.0573
	(0.260)	(0.429)	(0)	(0)
$Size_{t-1}$	-0.201*	-0.419***	-0.157	-0.485
	(0.105)	(0.126)	(0)	(0)
$Flows_{t-1}$	2.662***	2.793***	2.586	2.496
	(0.412)	(0.604)	(0)	(0)
Fee_{t-1}	0.518	0.903	0.456	-0.153
	(0.493)	(0.724)	(0)	(0)
Observations	434,650	434,650	449,438	449,438
R-squared	0.902	0.936	0.899	0.934
Fund x Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	Yes

TABLE 6: Belief in Climate Change and ESG Commitment

This table reports the impact of natural disasters on fund-level ESG, using prior beliefs about climate change as an amplification mechanism, where the variable of interest is $Post_q \times Close_{fc} \times Connected_{fc}$. The dependent variable, Env. Score captures only the environmental component of ESG and style-adjusted ESG is the fund score minus the style average. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Style-Adj ESG	Env. Score	Style-Adj ESG	Env. Score
	High Belief	*High Belief*	*Low Belief*	*Low Belief*
$Post_q \times Close_{fc}$	1.079***	1.097***	1.145**	2.971**
	(0.119)	(0.195)	(0.552)	(1.327)
$Post_q$			-1.167**	-2.816**
			(0.537)	(1.313)
$Close_{fc}$			0.257	-0.178
			(0.470)	(1.178)
$Return_{t-1}$	-1.015	-3.246**	-2.988***	-5.624***
	(1.007)	(1.569)	(0.615)	(1.025)
$Expense_{t-1}$	-25.62	-24.61	-5.189	37.37
	(48.72)	(77.58)	(41.92)	(72.74)
$Turnover_{t-1}$	-0.255	-0.00748	0.112	0.151
	(0.271)	(0.401)	(0.189)	(0.378)
$Size_{t-1}$	0.0812	-0.174	-0.113	-0.276
	(0.159)	(0.224)	(0.138)	(0.194)
$Flows_{t-1}$	2.411***	2.591*	1.617***	1.642**
	(0.917)	(1.451)	(0.507)	(0.831)
Fee_{t-1}	0.457	0.00509	0.822	0.738
	(0.506)	(0.988)	(0.591)	(0.991)
Observations	8,719	8,719	8,706	8,706
R-squared	0.889	0.930	0.889	0.925
Fund x Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	Yes

TABLE 7: Attention to Climate Change Through News

This table reports the impact of natural disasters on fund-level ESG, using attention to climate change through news as an amplification mechanism, where the variable of interest is $Post_q \times Close_{fc} \times Connected_{fc}$. The dependent variable, Env. Score captures only the environmental component of ESG and style-adjusted ESG is the fund score minus the style average. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

	(1) Style Adj-ESG *High Attention*	(2) Env. Score *High Attention*	(3) Style Adj-ESG *Low Attention*	(4) Env. Score *Low Attention*
$Post_q \times Close_{fc}$	2.523***	4.767***	0.299*	0.555
	(0.322)	(1.271)	(0.181)	(0.421)
$Post_q$	-2.065***	-4.057***	-0.389**	-0.627
	(0.286)	(1.253)	(0.158)	(0.396)
$Close_{fc}$	-0.139	-2.992***	0.261	0.450
	(0.252)	(0.967)	(0.331)	(0.808)
$Return_{t-1}$	-6.088***	-7.355***	0.772	-0.986
	(1.352)	(2.171)	(0.684)	(1.173)
$Expense_{t-1}$	-36.55	-136.9	89.18	228.0*
	(69.24)	(111.1)	(65.73)	(116.9)
$Turnover_{t-1}$	-0.326	-0.457	-0.0392	0.212
	(0.282)	(0.472)	(0.214)	(0.443)
$Size_{t-1}$	-0.000631	0.203	0.0874	0.234
	(0.169)	(0.258)	(0.216)	(0.334)
$Flows_{t-1}$	0.453	0.907	-0.190	-0.376
	(1.259)	(2.044)	(0.557)	(0.991)
Fee_{t-1}	1.212	2.164	-0.810	-2.297
	(1.111)	(1.765)	(0.776)	(1.485)
Observations	5,201	5,201	5,017	5,017
R-squared	0.876	0.924	0.913	0.949
Fund x Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	Yes

TABLE 8: The effect of natural disasters on fund performance (returns)
This table reports the effect of natural disasters on the net returns of mutual funds, where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable is $NetReturns$. f refers to a fund, c to a county and t to a quarter. Columns (1), (2) and (3) report results for the same equation but with a different definition of the dummy $Post_q$. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Net Returns After 2 Quarters	(2) Net Returns After 4 Quarters	(3) Net Returns After 6 Quarters
$Post_q \times Close_{fc}$	0.035	0.025	0.056**
	(0.023)	(0.025)	(0.027)
$Post_q$	-0.001	-0.010	-0.042
	(0.023)	(0.025)	(0.027)
$Close_{fc}$	0.075***	0.076***	0.059***
	(0.025)	(0.025)	(0.022)
Observations	31,492	31,492	31,492
R-squared	0.286	0.277	0.277
Fund x Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes

TABLE 9: The effect of natural disasters on fund flows
This table reports the effect of natural disasters on the flows of mutual funds, where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable is $Flows$. f refers to a fund, c to a county and t to a quarter. Columns (1), (2) and (3) report results for the same equation but with a different definition of the dummy $Post_q$. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Flows After 2 Quarters	(2) Flows After 4 Quarters	(3) Flows After 6 Quarters
$Post_q \times Close_{fc}$	-0.035	-0.030	-0.061*
	(0.027)	(0.031)	(0.034)
$Post_q$	0.0072	0.024	0.054
	(0.028)	(0.031)	(0.034)
$Close_{fc}$	-0.099**	-0.099***	-0.082**
	(0.036)	(0.033)	(0.031)
Observations	31,165	31,165	31,165
R-squared	0.359	0.356	0.356
Fund x Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes

TABLE 10: Investment in firms located in disaster zones

This table reports the effect of natural disasters on the weights of affected firms in the portfolios of mutual funds, where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable $StockWeight$ is the weight of firms close to disaster areas in the portfolio of fund f. f refers to a fund, c to a county and t to a quarter. Columns (1), (2) and (3) report results for the same equation but with a different definition of the dummy $Post_q$. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

	(1) Stock Weight After 2 Quarters	(2) Stock Weight After 4 Quarters	(3) Stock Weight After 6 Quarters
$Post_q \times Close_{fc}$	0.0001	0.0001	0.0002
	(0.002)	(0.002)	(0.002)
$Post_q$	0.001**	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
$Close_{fc}$	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Observations	668,870	668,870	668,870
R-squared	0.580	0.580	0.580
Quarter-Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Appendix A1: Definition of the Main Variables

Name	Explanation
Size	Natural logarithm of total net assets (TNA) under management. *Source: CRSP*
Expense Ratio	Total annual expenses and fees divided by year-end TNA. *Source: CRSP*
Turnover	Minimum of aggregate purchases and sales of securities divided by average TNA *Source: CRSP*
Flows	The change in log TNA not attributable to the portfolio return of the fund *Source: CRSP*
Return	The percentage change in an investment over a one-quarter period *Source: CRSP*
Total ESG	Fund-level ESG score, which is the weighted average of holdings ESG score. *Source: Sustainalytics*
Style-Adjusted ESG	Alternative definition of ESG by adjusting the score for investment style *Source: Sustainalytics and CRSP*
Post	Dummy variable that takes a value of one for four quarters following a disaster *Source: FEMA*
Close	Dummy variable that takes a value of one when a fund manager is within 100 miles of a natural disaster *Source: NBER County Distance Database*

TABLE A1: Fund-level ESG change following disasters - Temporal dynamics
This table reports the coefficients for equation (3), where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable Total ESG is the fund-level overall ESG score, Env. Score captures only the environmental component and style-adjusted ESG is the fund score minus the style average. f refers to a fund, c to a county and t to a quarter. $Post_q$ takes a value of one for five and six quarters (instead of four) following a disaster. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Style Adj-ESG *5 quarters*	(2) Env. Score *5 quarters*	(3) Style Adj-ESG *6 quarters*	(4) Env. Score *6 quarters*
$Post_q \times Close_{fc}$	0.876	2.185**	0.429	0.884
	(0.594)	(0.996)	(0.460)	(0.791)
$Post_q$	-0.594	-1.844*	-0.0685	-0.503
	(0.591)	(0.992)	(0.456)	(0.786)
$Close_{fc}$	0.293	0.210	0.492	0.838
	(0.466)	(1.067)	(0.402)	(0.936)
$Return_{t-1}$	-1.857***	-4.309***	-1.825***	-4.271***
	(0.416)	(0.656)	(0.416)	(0.656)
$Expense_{t-1}$	-15.37	-7.702	-14.81	-7.075
	(25.38)	(41.50)	(25.35)	(41.46)
$Turnover_{t-1}$	-0.0815	0.0347	-0.0851	0.0327
	(0.142)	(0.223)	(0.142)	(0.223)
$Size_{t-1}$	-0.129	-0.373***	-0.128	-0.373***
	(0.0876)	(0.125)	(0.0876)	(0.125)
$Flows_{t-1}$	2.272***	2.251***	2.263***	2.255***
	(0.357)	(0.561)	(0.357)	(0.561)
Fee_{t-1}	0.523	0.358	0.501	0.332
	(0.326)	(0.552)	(0.326)	(0.552)
Observations	26,027	26,027	26,027	26,027
R-squared	0.886	0.919	0.887	0.919
Fund x Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	Yes

TABLE A2: Fund-level ESG change following disasters - Alternative $Close_{fc}$ Definition

This table reports the coefficients for equation (3), where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable Total ESG is the fund-level overall ESG score and style-adjusted ESG is the fund score minus the style average.. f refers to a fund, c to a county and t to a quarter. Columns (1), (2) and (3) report results for the same equation but with a different definition of the dummy $Close_{fc}$. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) ESG Score *500 miles*	(2) Style-Adj ESG *500 miles*	(3) Env. Score *500 miles*
$Post_q \times Close_{fc}$	-0.535	-0.564	-1.608
	(0.968)	(0.966)	(1.004)
$Post_q$	0.901	0.895	2.107**
	(0.966)	(0.964)	(0.999)
$Close_{fc}$	0.0397	0.0731	0.960
	(0.391)	(0.391)	(0.765)
$Return_{t-1}$	-0.0815	-0.0714	0.0143
	(0.0520)	(0.0487)	(0.0717)
$Expense_{t-1}$	-39.88	-32.29	-25.30
	(26.00)	(25.53)	(42.77)
$Turnover_{t-1}$	-0.0685	-0.0808	0.0609
	(0.144)	(0.144)	(0.228)
$Size_{t-1}$	-0.355***	-0.344***	-0.778***
	(0.0869)	(0.0879)	(0.134)
$Flows_{t-1}$	0.125***	0.129***	0.207***
	(0.0474)	(0.0443)	(0.0676)
Fee_{t-1}	0.827**	0.757**	0.592
	(0.346)	(0.334)	(0.566)
Observations	26,022	26,022	26,022
R-squared	0.912	0.886	0.919
Fund x Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes

TABLE A3: Placebo test using only fund-level Social score

This table reports the coefficients for equation (3), where the variable of interest is $Post_q \times Close_{fc}$. The dependent variable Soc. Score is the fund-level Social component score. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

	(1) Soc. Score	(2) Soc. Score *6 quarters*	(3) Soc. Score *500 miles*
$Post_q \times Close_{fc}$	0.218	0.410	-0.898
	(0.394)	(0.656)	(0.752)
$Post_q$	0.138	0.0487	1.325*
	(0.384)	(0.650)	(0.747)
$Close_{fc}$	0.223	0.0991	-0.705
	(0.406)	(0.466)	(0.597)
$Return_{t-1}$	-0.664	-0.638	-0.138**
	(0.516)	(0.517)	(0.0676)
$Expense_{t-1}$	-73.35**	-72.90**	-82.68**
	(32.61)	(32.66)	(34.12)
$Return_{t-1}$	-0.208	-0.214	-0.204
	(0.167)	(0.168)	(0.176)
$Size_{t-1}$	-0.0579	-0.0520	-0.191*
	(0.108)	(0.108)	(0.110)
$Flows_{t-1}$	3.279***	3.264***	0.134**
	(0.448)	(0.447)	(0.0632)
Fee_{t-1}	1.207***	1.191***	1.412***
	(0.431)	(0.432)	(0.457)
Observations	26,027	26,025	26,026
R-squared	0.879	0.879	0.879
Fund x Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes

TABLE A4: Fund-level ESG change following disasters (non-major events)
This table reports the impact of natural disasters on fund-level ESG, using only non-major disasters. The variable of interest is $Post_q \times Close_{fc}$. The dependent variable Total ESG is the fund-level overall ESG score, Env. Score captures only the environmental component and style-adjusted ESG is the fund score minus the style average. f refers to a fund, c to a county and t to a quarter. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Total ESG	Style-Ajd ESG	Env. Score	Env. Sore
$Post_q \times Close_{fc}$	0.613	0.640	0.713	1.142
	(1.192)	(1.192)	(1.642)	(1.628)
$Post_q$	-0.549	-0.553	-0.987	-1.283
	(1.190)	(1.189)	(1.637)	(1.624)
$Close_{fc}$	-3.445**	-3.463**	-5.241***	-1.082
	(1.435)	(1.434)	(1.801)	(1.632)
$Return_{t-1}$	-0.0650	-0.0546	0.0274	-0.0403
	(0.0496)	(0.0466)	(0.0674)	(0.0735)
$Expense_{t-1}$	-39.42	-33.12	-37.09	6.081
	(26.61)	(26.34)	(40.91)	(40.70)
$Turnover_{t-1}$	-0.229	-0.238	-0.179	-0.298
	(0.145)	(0.145)	(0.222)	(0.196)
$Size_{t-1}$	-0.173*	-0.184**	-0.548***	0.287*
	(0.0894)	(0.0890)	(0.135)	(0.151)
$Flows_{t-1}$	0.0839*	0.0889**	0.129**	-0.0609
	(0.0453)	(0.0425)	(0.0634)	(0.0561)
Fee_{t-1}	0.835**	0.810**	0.707	-0.0167
	(0.353)	(0.343)	(0.522)	(0.550)
Observations	25,235	25,235	25,235	26,605
R-squared	0.917	0.894	0.924	0.762
Fund x Year FE	Yes	Yes	Yes	No
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	No
Fund FE	No	No	No	Yes
Quarter-Year FE	No	No	No	Yes

TABLE A5: Do Managers Lean? Fund-level ESG change following disasters (One vs. Multiple disasters)

This table reports the impact of natural disasters on fund-level ESG. The coefficient of interest is $Post_q \times Close_{fc}$. in columns (1) and (3) Env. Score captures the environmental component of ESG. In columns (2) and (4) are the quarterly net returns. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) Env. Score 1 Disaster	(2) Env. Score Multiple Disasters	(3) Returns 1 Disaster	(4) Returns Multiple Disasters
$Post_q \times Close_{fc}$	2.349**	3.171**	-0.0234	0.0955***
	(0.916)	(1.529)	(0.0246)	(0.0135)
$Post_q$	-2.235**	-2.408	0.0233	-0.0783***
	(0.900)	(1.524)	(0.0244)	(0.0132)
$Close_{fc}$	-1.300	-0.440	0.0764**	0.0306
	(1.174)	(1.913)	(0.0327)	(0.0189)
Observations	7,056	14,869	7,056	14,869
R-squared	0.923	0.926	0.254	0.306
Fund x Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Disaster Quarter FE	Yes	Yes	Yes	Yes

TABLE A6: Variation in the weights of high and low ESG stocks
This table reports the coefficients for equation (3), where the dependent variable is the dollar amount of high (or low) ESG stocks over the dollar amount of assets under management. The variable of interest is $Post_q \times Close_{fc}$. % High ESG Stocks in column (1) indicates the weight of high ESG stocks in a given fund f in a given quarter q. Estimates are reported for the period 2009-2018. Standard errors are robust to heteroscedasticity, clustered at the fund level and are presented in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

	(1) % High ESG Stocks	(2) % Low ESG Stocks
$Post_q \times Close_{fc}$	-0.0264	-0.0434**
	(0.0164)	(0.0215)
$Post_q$	0.0204	0.00833
	(0.0161)	(0.0212)
$Close_{fc}$	0.00636	-0.0412
	(0.0373)	(0.0340)
$Return_{t-1}$	0.0204***	0.0587***
	(0.00652)	(0.0103)
$Expense_{t-1}$	-0.812	1.844
	(0.977)	(1.423)
$Turnover_{t-1}$	-0.00758	0.00137
	(0.00572)	(0.00773)
$Size_{t-1}$	-0.00292	0.00514
	(0.00403)	(0.00491)
$Flows_{t-1}$	-9.19e-05	0.0581***
	(0.00548)	(0.00920)
Fee_{t-1}	0.0131	-0.0279
	(0.0157)	(0.0194)
Observations	25,665	21,534
R-squared	0.890	0.854
Fund x Year FE	Yes	Yes
County FE	Yes	Yes
DisasterQuarter FE	Yes	Yes