When Disaster Strikes: How Climate Events Influence Employment Preferences

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Abstract:

This paper examines how experiences with climate disasters shape workers' employment preferences. We find that, in disaster-affected areas, firms with worse environmental performance fill vacancies more slowly and hire lower quality employees than better environmentally performing firms, compared to unaffected areas. The job vacancy effect is more pronounced in regions with stronger belief in climate change and emerges within accounting firms. After disasters, local employees at environmentally worse-performing firms leave more negative employer reviews about environmental issues and are more likely to move to greener employers, relative to other-location employees. Overall, our evidence suggests that climate disasters increase workers' climate awareness and their preference for environmentally responsible employers.

Keywords: Climate Disaster; Salient Climate Events; Employment Preferences; Environmental Performance; Employee Turnover

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1. Introduction

Extreme climate events, such as tornadoes, heat waves, wildfires, and floods, have become increasingly frequent and severe in recent decades (IPCC 2021), imposing significant costs on society (e.g., Deloitte 2022; Bittle 2023).[1] Most empirical studies investigating the consequences of extreme weather on firms focus on the direct effect on their physical assets and operations (e.g., Barrot and Sauvagnat 2016; Hsu et al. 2018; Pankratz et al. 2023; Tran 2023) and not their employees, a group of critical stakeholders who help drive firm value. Although these events can impact individuals and their views on climate change (Myers et al. 2013; Zaval et al. 2014; Konisky et al. 2016), whether that effect influences firms through their workforces has not been explored. This paper fills this void by examining how experiencing climate disasters shapes workers' preferences for employers.

Specifically, we test whether recent experiences with climate disasters heighten individuals' sensitivity to employers' environmental performance when making employment decisions. Studies suggest that experiencing extreme weather can increase awareness of climate change and amplify perceptions of its social and economic impacts (Egan and Mullin 2012; Myers et al. 2012; Zaval et al. 2014; Sisco et al. 2017; Hazlett and Mildenberger 2020). As individuals' environmental concerns grow, they are more likely to scrutinize potential employers' environmental records. Consequently, experiences with climate disasters can increase their disapproval of corporate environmental irresponsibility, reducing their willingness to work for firms with poor environmental records.

Nevertheless, if workers always prioritize environmental considerations and avoid firms with poor environmental records, experiences with extreme climate events may not have any discernible

[1] We use the terms "extreme climate events," "salient climate events," and "climate disasters" interchangeably in the paper.

effect on their preferences (Wappenhans et al. 2024). At the same time, other factors that influence workers' career choices, such as compensation, benefits, and firms' financial conditions and culture, could have a more direct impact (e.g., Brown and Matsa 2016; Al-Sabah and Ouimet 2021; Choi et al 2023a; Huang et al. 2024), and thus experiencing climate disasters may not substantially change job preferences. As a result, whether climate disasters affect workers' employment decisions is an unresolved empirical question.

Our main analyses focus on job seekers for two reasons. First, current employees may have already considered their employers' environmental performance, and additional environmental concerns due to climate disasters may not change their preferences. Second, even if employees have heightened environmental concerns, they face costs, such as time spent searching for new positions and financial barriers to mobility, when transitioning to another job, making their employment decisions less sensitive than those of job seekers (e.g., Edwards 2022).

Our empirical analyses leverage comprehensive climate hazards data in the Spatial Hazard Events and Losses Database for the United States (SHELDUS). To identify disasters most salient to workers, we focus on the ones causing the most damage (county-level loss exceeding 90th percentile of all hazards). We infer job seekers' locations based on the geographic location of job postings, assuming that firms primarily hire locally.[2] To measure job seekers' preferences toward employers, we use job vacancy duration, sourced from LinkUP. When job seekers perceive a firm negatively, they are less likely to apply for its openings, leading to lower labor supply and longer vacancy durations. We use the LSEG environmental score, which benchmarks a firm's

[2] Studies document that various labor market frictions, such as information asymmetry and moving costs, deter workers from searching for jobs beyond their local area (Marinescu and Rathelot 2018; Edwards 2022). In robustness tests, we focus on jobs that are more likely recruit locally and find similar results (see details in Section 4.3).

environmental practices relative to its industry peers, to capture job seekers' perceptions of a firm's environmental performance.

In our main analysis, we find that the difference in job vacancy durations between firms with low and high environmental performance (which we'll refer to as "low environmental performers" and "high environmental performers") is more pronounced in counties that experienced a climate disaster within the past six months than in unaffected counties. Economically, in counties impacted by a climate disaster, low environmental performers' job vacancy durations increase by 1.3% relative to those at high environmental performers, compared to these firms' hiring in areas free of disaster. This effect accounts for 13.1% of the average vacancy duration gap between the two groups of firms. This pattern supports our hypothesis that exposure to climate disasters heightens job seekers' preference for environmentally responsible firms.

Dynamic effects analyses reveal no pre-treatment trends, mitigating the concern that confounding factors may bias our estimation. Our results are also robust across various fixed effects and clustering choices, excluding job postings likely to be filled by out-of-area job seekers, in stacked regressions designed to account for potential biases due to heterogeneous dynamic treatment effects, and using alternative measures of the main variables. In addition, given the accounting profession's role as a gatekeeper of corporate reporting and ESG matters, we focus specifically on accounting firms and find significant impact of climate disasters on job seekers' preferences for these firms.

Next, we provide evidence explaining the documented effects. Besides job seekers' environmental preferences, if climate disasters cause worse disruptions to the operations of low environmental performers, these firms may experience delays in recruiting, and their job offerings may become less attractive. Moreover, disasters may change the labor demand, hiring strategies, or workplace safety of low and high environmental performers differently, affecting their hiring outcomes.

We conduct four sets of analyses to explore these potential mechanisms. First, if job seekers' environmental concerns drive our results, we expect this effect to be larger for job seekers with a stronger belief in climate change because they are more likely to attribute climate disasters to human activities (Sloggy et al. 2021). Consistent with this mechanism, we find a stronger effect of climate disasters on job vacancy durations in counties where people have a stronger belief in climate change, measured using survey data from the Yale Climate Opinion Maps.

Second, we examine whether climate disasters disrupt the operations of environmental underperformers to a greater extent. We find no significant relationship between firms' environmental performance and their climate-related physical shock exposure (developed by Sautner et al. 2023). We also observe no significant post-disaster changes in employees' perceptions of the business outlook for worse environmental performers compared to those for other firms. In addition, we analyze whether climate disasters affect the durations of job vacancies in counties neighboring but outside the disaster zone, which report much less damage than those within the zone. We argue that firms' operations in these neighboring counties are largely unaffected by the disasters, yet their job seekers likely experience the extreme climate events due to the proximity, for example, through personal encounters, friends, and local news coverage (e.g., Gallagher, 2014). We find results similar to our main analyses.

Third, we explore whether differences in labor demand or hiring strategies between low and high environmental performers explain our main findings. We observe no significant differences between low and high performers in their changes in the number of job postings and their salary levels following disasters. To further test whether firms' changes in job characteristics after a disaster explain our main findings, we restrict the sample to positions posted prior to the treatment and find similar results. Moreover, we find no evidence that low environmental performers change hiring practices to improve their environmental performance following climate disasters. Fourth, we compare the disaster's effect on vacancy durations between low and high climate-exposure jobs and find no significant difference, suggesting that concerns about workplace safety are not the primary driver of the decreased attractiveness of low environmental performers.

Taken together, these additional analyses support that the prolonged job vacancies observed for low environmental performers after climate disasters are driven by job seekers' environmental preferences rather than the disasters' effect on firm operations, hiring strategies, or workplace safety.

In our final set of tests, we explore how climate disasters affect employees joining firms and incumbent employees to more comprehensively measure these disasters' impact on firms and to further corroborate the mechanism of environmental awareness. First, using job profile data from Revelio Labs, we find that worse environmental performers hire lower-quality employees in counties experiencing climate disasters relative to better environmental performers, compared to their hiring in counties not experiencing climate disasters. Second, we examine employees' perceptions of employers, measured by their quantitative and qualitative feedback on Glassdoor.com. Our analyses reveal that, following climate disasters, employees at poor environmental performers give their employers lower overall ratings and, more importantly, express greater concerns about environmental issues in their comments.

Third, we analyze employees' departure decisions and find that climate disasters increase the likelihood that employees at low environmental performers moving to high environmental performers while reducing the likelihood that these employees move to firms with even worse environmental performance. Collectively, our findings suggest that climate disasters reduce both job seekers' and current employees' willingness to work for low environmental performers and that this change is likely due to workers' heightened environmental concerns.

Our study contributes to several strands of literature. First, we provide additional evidence on the consequences of climate risks on firms. Studies have shown that extreme weather hurts firms' operations by disrupting supply chains, increasing cooling costs, and suppressing retail sales (e.g., Barrot and Sauvagnat 2016; Hsu et al. 2018; Pankratz et al. 2023; Tran 2023; Pankratz and Schiller 2024). Others show that investor demand for climate-related information changes firms' disclosure and carbon emissions (Cohen et al. 2023), and that such disclosure can further influence firms' climate-related investments (Xue 2025). Our study is the first to document the impact of climate events on firms from the perspective of workers' employment decisions. Considering the importance of human capital for firms, changes in workers' preferences can have significant implications for firms' long-term competitiveness.

Second, this paper deepens our understanding of the factors that shape workers' preferences for employers. Research has shown that various firm characteristics influence employer attractiveness, including earnings (Choi et al. 2023a, deHaan et al. 2023), fraudulent financial reporting (Choi and Gipper 2024), equity compensation (Balsam and Miharjo 2007), financial distress (Brown and Matsa 2016), workforce diversity (Choi et al. 2023b), performance-potential assessment systems (Deller, 2023), firm-specific human capital (Gao et al. 2024a), and organizational structure (Gao et al. 2024b). Particularly relevant to our study, research underscores the role of corporate environmental performance in attracting job seekers (Turban and Greening 1997; Aiman-Smith et al. 2001). Our results demonstrate that these preferences are not static and that personal experiences with climate disasters can accentuate individuals' desire to work for employers with better environmental records.

Last, we contribute to research on how salient events influence individual decision-making related to firms. Studies have examined how analysts, managers directors, and investors, respond to such events (Dessaint and Matray 2017; Alok et al. 2020; Chen et al. 2020; Bourveau and Law 2021; Kong et al. 2021; Lins et al. 2024; Kim et al. 2025). Our study shifts the focus to employees, a crucial stakeholder group with direct impact on firm operations, and explores how climate disasters shape their preferences for firms. Our findings demonstrate that salient climate events affect low environmental performers' ability to attract and retain human capital, underscoring the broader impact of environmental factors on labor market dynamics.

2. Literature Review and Hypothesis Development

2.1 Literature Review

Firms are facing escalated concerns related to climate change, which exposes them to physical, reputational, and regulatory risks (Mbanyele and Muchenje 2022). Research has recognized the effects of climate risks on firms' operation and capital markets. For example, Addoum et al. (2023), Huang et al. (2018), Pankratz et al. (2023), and Pankratz and Schiller (2024) document that climate risks significantly affect firms' revenues and earnings. Unsurprisingly, studies show that investors consider climate risks in their investment decisions (Sharfman and Fernando 2008; Chava 2014; Krueger et al. 2020; Javadi and Masum 2021; Huang et al. 2022a; Cohen et al. 2023; Li et al. 2024a; Li et al. 2024b; Giglio et al. 2025; Xue 2025). More generally, Bolton and Kacperczyk (2021, 2023) and Ilhan et al. (2021) examine how carbon emissions are priced in equity and option markets. Nevertheless, there is scarce evidence on how climate change influences firms' human capital.

The labor and corporate finance literature identifies various determinants of individuals' preferences for employers. For instance, studies find that job seekers avoid firms in financial distress (Brown and Matsa 2016; Baghai et al. 2021; Choi et al 2023a). Other studies document that workers consider nonmonetary aspects, such as firms' financial reporting fraud (Choi and Gipper 2024), company culture (Huang et al. 2024), CEO activism (Mkrtchyan et al. 2024), and corporate organizational forms (Gao et al. 2024). Related to our study, one stream of research examines the role of corporate environmental performance in shaping job seekers' preferences. For example, Turban and Greening (1997) find that firms' environmental performance is positively associated with their attractiveness to prospective employees. Jones et al. (2014) and Jones et al. (2016) further attribute job seekers' preferences for environmentally responsible firms to perceived pride, aligned values, and expected favorable employee treatment. Krueger et al. (2023) find that workers are willing to accept lower pay to work for greener employers, and Cen et al (2023) document that employer-employee values alignment in CSR enhances employee retention.

Climate disasters are salient events that cause significant damage to society. Salience bias can lead to individuals who have experienced these disasters to overestimate their risks due to vividness, proximity, or emotional impact (Tversky and Kahneman 1973).[3] Recent studies have shown that capital market participants affected by such events overestimate the adverse impact of disasters on firms (Alok et al. 2020; Bourveau and Law 2021; Kong et al. 2021; Huynh and Xia 2023; Han et al. 2024; Ru et al. 2025). Turning to the general public, surveys indicate that personal

[3] Specific to the capital market, research finds that terrorist attacks, which induce negative emotions and increased risk aversion, are associated with worse IPO underpricing (Chen et al. 2020), outflows from equity funds into safer government bonds (Wang and Young 2020), and more pessimistic managers' and analysts' forecasts (Cuculiza et al. 2020; Chen et al. 2021).

encounters with extreme weather lead to a heightened perception of climate risk (Joireman et al. 2010; Myers et al. 2013; Akerlof et al. 2013; Howe et al. 2013; Borick and Rabe 2014; Zaval et al. 2014; Broomell et al. 2015; Konisky et al. 2016). Notably, Li et al. (2011) document that perceived deviations from normal temperature not only influence beliefs about climate change but also prompt actions: individuals become more inclined to donate to environmental charities.

Recent studies use large-sample archival data to explore how climate disasters affect managers' and investors' personal environmental beliefs and decision-making. For example, O'Sullivan et al. (2021), Choi et al. (2023b), and Kim et al. (2025) find that CEOs and directors' experience of natural disasters is associated with stronger firm CSR commitment. Choi et al. (2020) document that, in the month when the local temperature is abnormally high, retail investors sell shares of carbon-intense firms, consistent with people revising their beliefs about global warming upward when experiencing attention-grabbing weather events. Fich and Xu (2025) and Giuli et al. (2025) show that institutional investors who have experienced extreme climate events are more likely to endorse an environmental proposal.

2.2 Hypothesis Development

When evaluating potential employers, job seekers consider organizational mission and values and seek employers whose values align with their own (Ashraf and Bandiera 2018; Cassar and Meier 2018). A salient climate event causes considerable property losses, injuries, and casualties and drastically disrupts the local community (e.g., Fan et al. 2024). Exposure to the tangible consequences of climate disasters can heighten individuals' awareness of and concern about climate change (Egan and Mullin 2012; Myers et al. 2013; Zaval et al. 2014; Sisco et al. 2017). As environmental consciousness grows, individuals are more likely to scrutinize employers' environmental profiles (Turban and Greening 1997; Jones et al. 2014). Therefore, we posit that, after climate disasters, job seekers will be less interested in firms with poor environmental performance.

Nevertheless, for job seekers who already prioritize environmental considerations in their career choices, personal experiences with climate events may not meaningfully change their preferences (Wappenhans et al. 2024). Meanwhile, given the variety of factors that influence career choices, experiencing a single climate disaster may not substantially impact individuals' decisions about employers (e.g., Brown and Matsa 2016; Al-Sabah and Ouimet 2021; Hacamo and Kleiner 2022; Gao et al. 2024). As a result, whether climate disasters on average affect workers' employment decisions is ultimately an empirical question. We formally state our hypothesis directionally as follows:

Hypothesis 1: Following a climate disaster, firms with poor environmental performance become less attractive to affected workers relative to firms with good environmental performance, compared to firms in unaffected areas.

3. Data and Sample

Following the literature on the effects of climate disasters (e.g., Alok et al. 2020; Bourveau and Law 2021; Huynh and Xia 2023), we use data from the SHELDUS, which maintains a county-level hazard dataset for the United States and covers natural hazards since 1960. For each hazard, SHELDUS records the hazard type, the month, the affected location (county and state), and the direct losses caused. Of the 18 types of hazards reported by SHELDUS, we focus on the 13 climate-related ones, i.e., flooding, hurricane/tropical storm, tornado, wildfire, hail, drought, wind, winter weather, severe storm/thunderstorm, landslide, lightning, coastal, and heat, in our main test.[4]

[4] The list of 13 climate-related disasters is from the U.S. National Centers for Environmental Information (Billion-Dollar Weather and Climate Disasters, available at https://www.ncei.noaa.gov/access/billions/events). The five nonclimate-related hazards tracked by SHELDUS are avalanche, earthquake, fog, tsunami/seiche, and volcano. Our

Table 1 Panel A summarizes the total amount of damage and the number of county-months affected of each of the 13 types of climate disasters during our sample period between July 2009 and December 2022.[5] We adjust the amounts of the losses to 2015 U.S. dollars to facilitate time-series comparison. Among the types of disasters, flooding causes the highest total damage ($137 billion), followed by hurricane/tropical storm ($63 billion), consistent with the statistics reported in the literature (e.g., Huang et al. 2022b). These two combined account for 64.3% of the total damage caused by all climate disasters. The three most frequent disasters are wind (63,867 county-months), severe storm/thunderstorm (49,375 county-months), and flooding (18,535 county-months), affecting 12.8%, 9.9%, and 3.7% of all county-months, respectively. Untabulated statistics show that 19.4% of all county-months are affected by climate disasters and that almost all counties (99.1%) experience at least one climate disaster during the sample period.

Table 1 Panel B reports the statistics of the aggregated damage amount at the county-month level for all climate disasters. The average (median) damage amount is $3,207,600 ($13,719), with a standard deviation of $95.6 million. We classify county-months with damage exceeding the 90th percentile ($464,549) as experiencing salient disasters.[6] Note that the damage amounts in SHELDUS include only direct losses in crops and property but not indirect ones, such as cleanup and recovery expenses and economic losses resulting from infrastructure and utility outages.

We obtained online job posting data of U.S. headquartered firms between 2010 and 2022, including employer identities, job posting creation and deletion dates, the zip code of the position, detailed job descriptions including salary information if it is disclosed, and the occupation code

results are robust to using either all types of hazards in SHELDUS or five types of disasters including drought, flooding, heat, hurricane/tropical storm, and wildfire, following Huang et al. (2022b) (discussed in detail in Section 4.3).

[5] Our job posting sample period begins in 2010, the year the LSEG ESG performance score was introduced, and ends in 2022, the year that our LinkUp data ends. We include disasters from July 2009 onward to account for a six-month persistence of disaster effect on individual preferences.

[6] For robustness checks, we use the 95th percentile of damage amount ($1,648,826) to define salient disasters. We find robust results, as discussed in Section 4.3.

(O*NET code) of the job from the LinkUP database.[7] By 2022, LinkUp covered approximately 76% of US public firms, which accounted for 81% of the total market value. It obtains job postings directly from employer websites, which offers two advantages over databases that collect job postings from third-party online job boards. First, firms update their own websites more promptly than third-party job boards, which are often paid for fixed-term listings, ensuring that job postings' deletion dates are accurately recorded by LinkUp. Second, firms typically list each job only once on their own sites but may post the same job multiple times across different job boards, resulting in duplicate postings in databases using third-party job boards (Campello et al. 2024). Due to these advantages, most of the recent studies on corporate hiring use LinkUp as the primary data source (e.g., Chen and Li 2023; Campello et al. 2024; Hann et al. 2024).[8]

We use job vacancy duration to infer job seekers' preferences. Conceptually, job vacancy duration is driven by the equilibrium of labor supply (i.e., the number of applicants) and demand (i.e., the number of vacancies) (e.g., Davis et al. 2013; Hall and Schulhofer-Wohl 2018). Given the same level of labor demand, less labor supply means a firm will have to spend more time to find a qualified candidate (Moen 1997).[9] Firms perceived less favorably by job seekers attract fewer applications and thus have longer job vacancy durations.[10]

We measure job vacancy duration as the number of days between a job's creation and deletion dates. To validate this measure, Chen and Li (2023) show that the patterns of univariate variations

[7] The results are robust when we include firms headquartered outside the United States (untabulated).
[8] Another widely used database for job postings is Lightcast (formerly BurningGlass). However, Lightcast only started to collect job vacancy postings' addition and deletion dates information from 2022.
[9] In an untabulated validation test, we use labor force data (the number of employees and unemployed persons) between 2010 and 2022 from the Bureau of Labor Statistics, and find a negative correlation (-0.02, significant at the 1% level) between the labor force and average posting duration at the county-month level, indicating that lower labor supply is associated with longer vacancy durations.
[10] Ideally, we could also infer job seekers' preferences based on job application data, including the number of applications for each position and the backgrounds of the applicants. However, such data are not publicly available. In Section 6.1, we conduct additional analyses based on the quality of newly hired employees to provide corroborating evidence.

of vacancy duration across job skill requirements, employee turnover, and unemployment rate are consistent with those patterns from Job Openings and Labor Turnover Survey data. Following Chen and Li (2023), we exclude job postings with vacancy durations exceeding 180 days to avoid "evergreen" postings that are rarely removed from a company's website to fill multiple positions and postings with durations shorter than one day to filter out jobs that bypass standard hiring procedures.[11]

Environmental ratings are from the LSEG (formerly Refinitiv) ESG (Environmental, Social and Governance) database, which assesses firms' environmental performance relative to firms in the same industry.[12] The LSEG database has been widely used in studies to capture firms' environmental performance (e.g., Hawn and Ioannou 2016; Dyck et al. 2019; Wang 2023). Its environmental ratings align with individuals' perceptions of firms' relative environmental performance because these ratings are based on publicly reported data, including the media, corporate annual reports, ESG or CSR (corporate social responsibility) reports, stock exchange filings, nonprofit organizations, and government documents.[13] Accounting and stock return data are from Compustat and CRSP, respectively. After merging the datasets, we obtain a final sample of 51,406,413 job postings in 1,261,864 zip-months by 17,492 firm-years. On average, each firm has 15,578 job postings across 192 zip code areas, and 604 disaster-affected zip-months.

[11] Our main results are robust if we include job postings with durations shorter than one day or longer than 180 days (untabulated).

[12] The firm-year level mean value of *Worse E* is 0.822, much higher than 0.5, which is because we define worse E performance based on the posting-level sample median to ensure a balanced panel in the baseline analysis. The results remain robust when using the firm-year median instead.

[13] We use an alternative measurement of environmental performance based on negative environmental issues and find similar results (discussed in Section 4.3).

4. Climate Disasters and Job Vacancy Duration

4.1 Empirical Model and Summary Statistics

To test the effect of climate disasters on job seekers' preferences, we run the following regression at the job posting level:

$$ln(Duration_{j,i,l,t}) = \beta_1 \, Disaster_{l,t} \times Worse\ E_{i,t} + \beta_2 \, Disaster_{l,t} + \beta_3 \, Disaster_{l,t} \times Size_{i,t} + \tau_{i,y} + \theta_{o,t} + \gamma_{i,l,o} + \varepsilon_{j,i,l,t}, \quad (1)$$

where $ln(Duration_{j,i,l,t})$ is the natural logarithm of the number of days to fill the vacancy for job posting j from firm i in zip code l during month t.[14] We define job postings as impacted by climate disasters ($Disaster_{l,t}$) if zip code l is mapped to at least one county with climate disaster losses exceeding the 90th percentile in a given month between months t-6 and t.[15] We use a six-month window based on the assumption that individuals' preferences persist over a certain period.[16] *Worse E*, which denotes firms with bad environmental performance, equals one if a firm's LSEG E-score is below the sample median. Our main variable of interest is $Disaster_{l,t} \times Worse\ E_{i,t}$ (β_1), which captures the changes in job seekers' preferences for worse E-performance firms relative to better E-performance firms following climate disasters. H1 predicts a negative coefficient of β_1.

Since firm size and firm environmental performance are highly correlated (shown in Table 2), we control for $Disaster_{l,t} \times Size_{i,t}$ to alleviate the concerns that the effects are driven by changes in job seekers' preferences for firms of different sizes after climate disasters. We add various fixed effects to control for unobserved heterogeneity that influence job posting vacancy duration,

[14] The posting-level analysis allows us to remove effects arising from changes in the occupation mix inside a firm by controlling for firm-location-occupation fixed effects. In untabulated robustness tests, we aggregate the job posting sample to the firm-zip-month level and find similar results.
[15] We match zip codes to counties because SHELDUS reports disasters at the county level. To reduce noise, we include only postings from zip codes linked to no more than two counties. Our results remain robust when defining disaster exposure at the commuting-zone level, where we classify postings as affected if climate disaster losses in the commuting zone-month exceed the 90th percentile in any month between month t-6 and t.
[16] Our results are robust to using a one-month or a three-month event window, as discussed in Section 4.3.

including firm-year fixed effects ($\tau_{i,y}$) for time-varying firm characteristics, such as firm performance and growth opportunity, and occupation-month fixed effects ($\theta_{o,t}$) for job seekers' time-varying preferences of occupations. We also include firm-state-occupation fixed effects ($\gamma_{i,l,o}$) for time-invariant unobserved heterogeneity at the firm × state × occupation level, such as firms' location-specific compensation policies and hiring practices and local labor supply with certain skills. Occupation is defined by Standard Occupational Classification (SOC) code, i.e., the first six digits of the O*NET code. We cluster standard errors at the state level in the main analyses, but our results are robust to clustering standard errors by firm, or double-clustering by firm and zip (untabulated).

Table 2 Panel A presents descriptive statistics for the main variables.[17] The average (median) job vacancy duration is 37 (24) days, which implies that most of the posted positions are filled in a month. While there is substantial variation in vacancy duration (the standard deviation is 38 days), the vast majority (90%) are filled within a quarter (92 days). Approximately 19.2% of zip-months are affected by salient disasters. We include firm control variables, such as size, profitability, leverage, book-to-market, firm age, and returns, in specifications without firm-year fixed effects. (Definitions of these variables are in the appendix.) We winsorize all accounting and stock return variables at the top and bottom 1% of the distribution to minimize the influence of outliers. The descriptive statistics of control variables are consistent with the firm characteristics in the literature (e.g., Li et al. 2022; Moss et al. 2023; Briscoe-Tran 2024; Fich and Xu 2025). Table 2 Panel B reports Pearson correlations among the main variables. Job posting vacancy duration exhibits a weak positive correlation with the disaster indicator (0.00) and a moderate negative correlation with the environmental performance (-0.06). While firms' environmental performance shows

[17] The descriptive statistics of variables used in robustness and additional analyses are presented in Online Appendix Table OA-1.

moderate correlations with firm leverage (0.20) and firm age (0.25), it has a high correlation with firm size (0.62), consistent with the observations in the literature (e.g., Darendeli et al. 2022).

In developing our hypothesis, we argue, based on survey evidence (Turban and Greening 1997; Deloitte, 2025), that job seekers consider firms' environmental performance when selecting positions. We confirm this premise using large-sample regression analysis. Results in Online Appendix Table OA-2 show that, ceteris paribus, a one standard-deviation increase in E-performance is associated with a 3.08% ($= 1 - e^{-0.112\times 0.279}$) shorter vacancy duration, consistent with our expectation that, on average, job seekers prefer working for firms with better environmental performance.

4.2 Main Results

Table 3 displays the results from estimating Equation (1). Column (1) presents a baseline specification with firm controls without fixed effects, while Columns (2) to (4) progressively add occupation-month, firm-occupation-state, and firm-year fixed effects. Across all specifications, the coefficients of the interaction term *Disaster* × *Worse E* are positive and statistically significant. This finding is consistent with H1 that, in counties affected by a climate disaster, job vacancy durations of firms with poor environmental performance increase relative to those of firms with better environmental performance, compared to unaffected areas. The coefficient of 0.013 in the most stringent specification with all fixed effects (Column (4)) indicates that, in counties affected by a climate disaster, job vacancy durations increase by 1.31% ($= e^{0.013} - 1$) for *Worse E* firms relative to those for other firms, compared to their hiring in unaffected areas. This magnitude is equivalent to 13.09% of the mean duration difference between low and high environmental performers (3.702 days $= 38.867 - 35.165$).

This estimated effect is economically meaningful for several reasons. First, with a mean vacancy duration of 37 days and an average of 286 postings per firm-month, a 1.3% increase in vacancy duration translates into roughly 138 ($= 0.013 \times 37 \times 286$) additional vacancy-days per firm-month, representing a sizable increase in firms' overall hiring frictions. Second, firms that become less attractive after disasters may respond by relaxing hiring standards to speed up the delayed hiring process, which implies that the observed changes in vacancy duration underestimates the effect of disasters. In Section 6.1, we provide evidence consistent with such adjustments in recruitment quality. Third, our specifications include highly granular fixed effects including firm-occupation-state, firm-year, and occupation-year, which tend to exacerbate measurement error in independent variables such as firms' environmental performance and attenuate coefficients (Angrist and Pischke 2009). As a result, our estimates are likely conservative, and the true impact of disasters on firms' hiring frictions may be even larger.

A necessary condition for the validity of our identification strategy is that, absent climate disasters, the difference in job seekers' preferences for low versus high environmental performers remains stable over time between affected and unaffected counties. Scientific research has shown that global warming has exacerbated the unpredictability of climate disasters, making these events plausibly exogenous (Hope and Friedman 2018). Nevertheless, to confirm this parallel trends assumption, we examine the temporal dynamics of vacancy duration surrounding the months of climate disasters. Accordingly, we re-estimate Equation (1) replacing $Disaster_{l,t}$ with $Disaster_{l,t+n}$, where n ranges between -3 and +6, representing the months between three months before and six months after the disaster. We exclude job postings in counties experiencing salient disasters in more than one month during this window. We tabulate the regression results in Online Appendix Table OA-3 and plot the dynamic treatment effects in Figure 1. We find that the timing of observed effects lines up with the disaster's strike time. That is, significant changes in vacancy duration emerge only in the months following the disaster but not beforehand. This pattern mitigates the concerns that other differences between disaster-affected and unaffected groups confound the observed effect on job vacancy duration.

4.3 Robustness Tests

We conduct a battery of tests to ensure that our results are robust to choices in empirical designs. First, an assumption underlying our analyses is that job vacancies are primarily filled by local residents, because we use the location of the job to identify whether job seekers are affected by the climate disasters. However, some positions can attract nonlocal applicants, which could create a discrepancy between the locations of the job and the applicants. To mitigate this measurement error, we exclude job postings with O*NET codes identified as remote work applicable, based on Dingel and Neiman (2020). Our results are robust to using this filtered sample (Table 4 Column (1)). We also exclude counties with population inflows higher than the sample median (based on geographic mobility data from the Census Bureau) and find similar results (Table 4 Column (2)).

Second, we address concerns related to potential biases introduced by time-varying effects in staggered difference-in-differences regressions. Specifically, we estimate stacked difference-in-differences regressions, following Cengiz et al. (2019) and Baker et al. (2022). To construct the stacked sample, we match each treated zip code to zip codes that were never exposed to disasters during our sample period. Treated postings associated with the same disaster month, along with their matched controls, form a cohort. We then stack all such cohorts to create the estimation sample. Following Duchin et al. (2025), we control for all the fixed effects specified in Equation (1) interacted with cohort indicators, enabling within-cohort comparisons between treated units and their matched controls. Our findings remain robust under this approach (Table 4 Column (3)).

In our main analyses, we use a six-month block as our event window and identify salient climate disasters based on a 90th percentile cutoff in total damages. We examine whether our results are sensitive to alternative empirical choices. We use a one-month event window (Table 4 Column (4)), a three-month event window (Table 4 Column (5)), and a 95th percentile cutoff to define salient climate disasters (Table 4 Column (6)), and our results continue to hold. Furthermore, we use an alternative definition of climate disasters and restrict our analysis to the five types of disasters, including drought, flooding, heat, hurricanes, and wildfire, following Huang et al. (2022b), and find consistent results (Table 4 Column (7)).

Our primary measure of environmental performance, i.e., the E-rating from LSEG, is designed to transparently and objectively measure a firm's relative environmental performance based on publicly available data. However, one may argue that this rating does not represent job seekers' perceptions of firms' environmental performance, either because job seekers do not have access to this rating or because they rely on other sources for information. To mitigate this concern, we use the number of negative environmental issues (from the RepRisk database) as an alternative environmental performance measure. RepRisk screens over 100,000 public sources, including print media, online media, state, national, and global government bodies, international NGOs, newsletters, and other online sources, for negative ESG-related issues and classifies each issue into one of 28 predefined ESG categories. We define *E_Issues* as one if the firm-year level environmental issue count is at or above the sample median and zero otherwise. We find consistent results using this alternative measure (Table 4 Column (8)).

Another concern with the E-performance measures is the positive correlation among environmental, social (S), and governance (G) scores, which may lead to a worse environmental performance indicator also reflecting poorer social or governance performance.[18] To address this issue, we regress environmental scores on social and governance scores and use the residuals as the orthogonal component to isolate environmental performance. Our findings remain robust when we orthogonalize environmental on both social and governance, social alone, or governance alone (Online Appendix Table OA-4 Columns (1)-(3)).

Finally, we restrict the sample to job postings from accounting firms, which serve as key gatekeepers of corporate reporting and play an increasingly central role in sustainability and ESG matters. Shocks to their ability to attract and retain talent can have important implications for audit quality and the credibility of environmental disclosures (Johnstone and Bedard 2003; Griffin et al. 2017; Blankespoor et al. 2025). Specifically, we identify accounting firms by the four-digit NAICS code 5412 (Blankespoor et al. 2025). Results in Table 5 show that the coefficient on Disaster × Worse E is positive and statistically significant, indicating that climate disasters reduce the attractiveness of worse E performance accounting firms to their potential employees. These findings provide accounting-specific evidence that climate risk can influence the composition of the accounting labor force and, in turn, the human capital underpinning financial and sustainability reporting.

5. Climate Disasters and Job Vacancy Duration: Investigating the Mechanism

When developing our hypothesis, we argue that personal exposure to climate disasters heightens individuals' awareness of and concern about climate change, consequently influencing their preferences for firms' environmental performance. While we use difference-in-differences analysis and include high-dimensional fixed effects in our model specification in Equation (1) to

[18] In our sample, the Pearson correlation coefficient is 0.83 between E-score and S-score and 0.46 between E-score and G-score.

mitigate potential confounding effects and strengthen our causal interpretation, our findings could be driven by climate disasters causing different levels of disruption to the operations or hiring strategies of firms with high versus low environmental performance, resulting in changes in vacancy duration that are not driven by job seekers' environmental awareness. Therefore, we conduct four sets of analyses to support the hypothesized mechanism and address alternative explanations.

5.1 Subsample Test: Belief in Climate Change

First, we perform a subsample test based on public belief in climate change. If environmental awareness is driving our results, we anticipate seeing stronger effects in regions where people's belief in climate change is greater. Specifically, individuals who have a stronger belief in climate change tend to attribute climate disasters to human activities and show stronger disapproval of environmental underperformers after experiencing these disasters (Sloggy et al. 2021). In contrast, those with a weaker belief may view these disasters as purely natural events. We obtain data on public opinions related to climate change from the Yale Climate Opinion Maps (Howe et al. 2015; Marlon et al. 2022). This dataset provides county-year level estimates of U.S. public beliefs, risk perceptions, and policy preferences related to climate change, derived from a large, nationally representative survey of over 32,000 respondents from 50 states and 2,379 of 3,144 U.S. counties. The dataset includes 11 variables between 2014 and 2022 that estimate the proportion of the respondents who (1) believe that climate change is happening, (2) believe that climate change is human-caused, (3) think they will be personally affected by climate change, (4) are worried about climate change, and (5) support environmentally friendly policies. (See the Appendix for details of all variables.) These variables are highly correlated with an average pairwise correlation coefficient of 0.73, indicating the existence of an underlying driver of the links between these variables. Factor analysis shows that the factor with the largest eigenvalue explains 84.78% of the variance among the 11 variables. We therefore use this factor as a summary measure of belief in climate change and humanity's role in it.

Based on the sample median value of climate change belief, we divide job postings into two subsamples – those in counties with high versus low belief. We then examine whether the main effects documented in our baseline test differ between the two subsamples. The results are presented in Table 6. We find that the disaster effect on job vacancy duration is only significant in regions with a stronger public belief in climate change, and the difference in the coefficients of *Disaster* × *Worse E* between the high- and low-belief groups is statistically significant. These results support our argument that heightened environmental awareness resulting from climate events drives the observed labor market aversion to environmental underperformers.

5.2 Disruption of Firm Operations

Second, we conduct two tests to assess whether low environmental performers' operations suffer more from climate disasters than other firms. We begin by directly examining whether firms with worse environmental performance are exposed to greater physical shocks from climate disasters. Using measures of climate risk and climate exposure developed by Sautner et al. (2023), we find no significant relationship between environmental performance and climate risk or exposure, either on average or after disasters (Table OA-5).[19]

Next, we analyze whether climate disasters affect the vacancy durations in counties that neighbor the counties suffering significant damage from the disasters. Although firms' operations in these neighboring counties are barely affected by the disasters, as evidenced by their small

[19] We also examine whether employees perceive a declining business outlook for low environmental performers relative to that for high environmental performers after disasters and find no evidence to support this. We describe this analysis in Section 6.2.

damage amounts, job seekers from these counties likely experience the climate disasters through personal encounters, friends, and local news coverage due to their geographical proximity (Dessaint and Matray 2017; Gallagher, 2014). Specifically, we define the 14 unimpacted counties that are geographically closest to counties impacted by disasters as the *Disaster_neighbor* area.[20] When calculating the distance between two counties, we define a county's location as the average latitude and longitude of all cities in the county. On average, neighboring counties are 83.7 miles from the impacted counties, with three-quarters having no damage and the remaining reporting a median damage amount of USD 46,454. In this test, the control area includes all other unaffected counties.

We re-estimate Equation (1) by replacing *Disaster* with *Disaster_neighbor* and present the results in Table 7. The coefficient on *Disaster_neighbor* × *Worse E* is positive and statistically significant, suggesting that job seekers in neighboring counties also become less willing to work for environmentally underperformers. The results from these two analyses alleviate the concern that our main findings are driven by climate disasters disrupting the operations of low environmental performers more than they do to high environmental performers.

5.3 Changes in Labor Demand or Hiring Strategies

Third, we examine whether the extended vacancy duration of low environmental performers is driven by changes in their labor demand or hiring strategies with four tests. We first investigate whether climate disasters change firms' labor demand differently. Using the total number of job postings in a given location to capture firms' labor demand, we show that firms with poor environmental performance do not experience a significant change in labor demand following

[20] We choose 14 because our sample counties have at most 14 adjacent counties. Our results are robust to using 12, 13, 15, or 16 closest unaffected counties (untabulated).

disasters compared to other firms (tabulated in Table 8). This finding is consistent with that hiring involves significant searching and training costs, and thus firms may rationally choose to maintain their headcount plans rather than make costly adjustments in the short term (Anderson et al. 2003).

Next, we explore whether low environmental performers reduce salary after climate disasters relative to other firms. To assess this possibility, we examine whether the likelihood of salary disclosure and salary amount differ between high and low environmental performers following disasters. We scrape the description of each job posting to obtain information about the salary for the position. First, we examine whether firms adjust their tendencies to voluntarily disclose salary information after a disaster and find no supporting evidence (Table 9 Column (1)).[21] In Column (2), we further document insignificant changes in the disclosed salary amount for worse environmental performers compared to other firms following a climate event.[22] In summary, the results suggest that the prolonged job vacancy duration for poor environmental performers following disasters is unlikely to be driven by salary changes. Moreover, the findings indicate that poor environmental performers do not raise salaries in response to hiring difficulties, likely due to the adjustment frictions such as internal pay-equity concerns among current employees (Card et al. 2012; Breza et al. 2018).

Furthermore, we explore whether our main results are driven by firms adjusting their job requirements after a climate disaster. Specifically, we analyze jobs that have been posted before the treatment.[23] Among these jobs, we classify vacancies that are filled during or after the month when the disasters occur as the impacted group and the others as the unimpacted group. While the

[21] In this test, we remove job postings in locations with salary disclosure mandates (i.e., Colorado on and after Jan. 1, 2021; Jersey City in New Jersey on and after April 13, 2022; Ithaca in New York State on and after Sept. 1, 2022; New York City in New York State on and after Nov. 1, 2022; and Westchester county in New York State on and after Nov. 6, 2022).

[22] In this test, we include job postings with either voluntarily or mandatorily disclosed salary amounts.

[23] Because we define an area as affected in month t if the area experienced a disaster between months $t-6$ and t, this test uses jobs posted before $t-6$.

posting content for both groups is unaffected by the treatment, applicants for treated jobs are likely impacted. We find results consistent with the main analyses (tabulated in Online Appendix Table OA-6).

Lastly, we explore whether poor environmental performers alter their hiring strategies only in areas experiencing climate disasters to enhance their environmental performance. For example, firms may become more selective in hiring for green job positions that require environment-related skills (e.g., environmental science skills), resulting in longer job vacancy durations. Using O*NET codes to distinguish green versus nongreen jobs, following Darendeli et al. (2022), we find that job vacancy duration increases significantly for nongreen job postings (Online Appendix Table OA-7 Column (1)). This result alleviates concerns that our main findings arise from firms' increased efforts to select candidates for green jobs to enhance their environmental reputations. We also analyze firm-state-year environmental-violation records using fine amounts from the Violation Tracker database to assess whether environmental underperformers improve their environmental performance after disasters (Online Appendix Table OA-8 Columns (2)–(3)). The insignificant coefficients on *Disaster* × *Worse E* indicate no substantial changes in environmental performance, further ruling out the explanation that firms adjust recruiting strategies only in the disaster-struck region to enhance their environmental practices.

5.4 Workplace Safety

Finally, we assess whether our main findings can be attributed to job seekers' concerns about inadequate worker protection against extreme weather for low-E-performance firms. To do so, we categorize job postings based on climate risk exposure and examine whether the documented main effects are concentrated in jobs with high exposure. Following Xiao (2021), we use the score assigned by the O*NET program based on the question "How often does this job require working outdoors, exposed to all weather conditions" to measure job exposure to climate risk. This score ranges from one to five, with higher scores indicating greater climate exposure. The results in Online Appendix Table OA-8 show an insignificant difference in the coefficients of *Disaster* × *Worse E* between the high- and low-climate-risk-exposure groups. This result, combined with the finding in Section 5.2 that firms' environmental performance is unrelated to their climate-change-related risk or exposure, affirms that workplace safety concerns are not the primary driver of our findings.

Collectively, our findings in section 5 indicate that the prolonged job vacancy durations for environmental underperformers after disasters are likely due to job seekers' heightened awareness of climate change, rather than climate disasters' disruption to firm operations, changes in labor demand or hiring strategies, or workplace safety.[24]

6. Climate Disasters, Hiring Quality, and Current Employees' Preferences

Our findings thus far indicate that job seekers show reduced interest in firms with poor E-performance following a climate disaster. A natural follow-up question is whether climate disasters affect employees at the firm. Presumably, reduced interest from job seekers should result in lower quality employees joining the firm, and if existing employees share the concerns about climate change, they may become less tolerant of poor environmental practices and more inclined to quit. To explore this possibility, we examine whether salient disasters influence new employee quality, existing employees' perceptions of employers, and turnover. Because we directly observe

[24] We also examine whether our main results are driven by increased litigation risk for firms with poor environmental performance following climate disasters. To address this concern, we exclude job postings located in areas covered by the 10 regional offices of the U.S. Environmental Protection Agency (EPA), which are responsible for implementing and enforcing environmental regulations across several states and territories (Fan et al., 2023). The results shown in Table OA-9 remain consistent with our main findings.

employees' comments and flow, these analyses also enable us to test the proposed mechanism, i.e., individuals become more willing to work for firms with better environmental performance following weather disasters due to heightened concerns about climate change.

6.1 Firm Hiring Quality

We begin by investigating the effect of climate disasters on firms' hiring quality using job profile data from Revelio Labs. Revelio Labs aggregates workforce information from online professional profiles (e.g., LinkedIn), company websites, and layoff notices. We focus on new employees who previously worked in the same MSA as the hiring firm.[25] In areas affected by climate disasters, workers are more likely to have directly experienced the events. This restriction thus enables a more precise assessment of how disaster exposure influences workers' employment choices and the subsequent hiring quality of firms. Following Call et al. (2017) and Chen (2024), we use education as a proxy for employee quality and construct firm-MSA level monthly measures of the share of new hires with advanced degrees (*Master%* and *PhD%*). We replace the dependent variable of Equation (1) with these two measures while controlling for firm-MSA and firm-year fixed effects.

Table 10 presents the results. In columns (1) and (2), where the dependent variables are *Master%* and *PhD%*, respectively, the coefficients of *Disaster* × *Worse E* are both negative and statistically significant. These results suggest that, following a climate disaster, compared to high environmental performers, low environmental performers hire fewer highly educated employees.

[25] We use MSA as the location definition since it is the most granular geographic information available from the Revelio Labs dataset.

6.2 Current Employees' Perceptions

Briscoe-Tran (2024) shows that employees possess valuable insights into firms' ESG practices and frequently discuss corporate ESG topics. Grounded on this finding, we investigate whether climate disasters affect employees' perceptions of firms' environmental practices. Specifically, we replace the dependent variable in Equation (1) with current employees' overall ratings of firms and the percentage of environment-related words (as defined by Briscoe-Tran (2024)) in their negative comments about employers, both from Glassdoor. To provide further evidence on whether climate disasters cause greater disruption to the operations of firms with worse environmental performance, we also examine their impact on employees' views of firms' business outlook. This analysis covers years 2013 to 2020, the period for which we have access to the Glassdoor data. We conduct this analysis at the employee review level, which allows us to include employee-level controls, such as gender, age, educational background, employment type (regular worker or not), length of employment, and whether the employee works at the firm's headquarters, all obtained from Glassdoor (Teoh et al. 2023).

Table 11 presents the results. Column (1) uses employees' overall ratings as the dependent variable. The coefficient on *Disaster* × *Worse E* is significantly negative, indicating that, after a climate disaster, employees of poor environmental performers rate their employers more negatively compared to those of other firms. Column (2) uses *Neg_E_Comments*, the percentage of environment-related words in employees' comments in the cons section, as the dependent variable. The coefficient on *Disaster* × *Worse E* is positive and significant, suggesting that, following a climate disaster, employees at poor environmental performers are more likely to focus on environment-related issues in their negative comments compared to those at firms with better environmental performance, reflecting heightened concerns about employers' environmental issues.[26]

Column (3) uses employees' assessment of their firm's business outlook as the dependent variable. The coefficient on *Disaster* × *Worse* E is statistically insignificant, suggesting that employees do not change their expectations about the prospects of firms with poor environmental performance following a climate disaster.

6.3 Employee Turnover

To examine whether a salient disaster influences employees' departure decisions, we use job profile data provided by Revelio Labs to get employees' working history information. Following Trevor and Nyberg (2008), we generate two measures of employee turnover. Specifically, *Join_Better_E-performers* (*Join_Worse_E-performers*) is calculated as the number of employees who leave the firm-MSA in a given month and move to a new employer with better (worse) environmental performance relative to the current firm, scaled by the total number of employees at the firm-MSA in the previous month.[27] We control for firm-MSA and firm-year fixed effects, as we did in the specifications in Table 10. Table 12 reports the results. In column (1), where the dependent variable is *Join_Better_E-performers*, the interaction term *Disaster* × *Worse E* is positive and statistically significant. By contrast, in column (2) with *Join_Worse_E-performers* as the dependent variable, the interaction term is negative and statistically significant. These results

[26] In untabulated placebo analyses, we use *Pos_E_Comments*, *Neg_S_Comments*, *Pos_S_Comments*, *Neg_G_Comments*, *Pos_G_Comments*, *Neg_Litigious_Comments*, and *Pos_Litigious_Comments*, which are constructed using the same logic but focus on the proportion of environment-related words in positive comments or proportion of social- or governance-related words or litigious words from Loughran and McDonald (2011) in negative/positive comments, as dependent variables. The coefficients of *Disaster* × *Worse E* are all statistically insignificant, suggesting that climate disasters do not influence current employees' views on non-environmental dimensions of their employers differentially for firms with high versus low environmental performance.

[27] Our results remain robust if the denominator of the turnover measures is the current month's employee headcount (Li et al. 2022) or the average employee headcount across all months of the previous year (Gu et al. 2023).

suggest that, following a climate disaster, employees at poor environmental performers are more likely to leave for better performing employers and less likely to move to worse ones, compared to those at high environmental performers. Therefore, salient climate events also increase current employees' sensitivity to corporate environmental responsibility and shape their turnover decisions. This result extends prior findings that stronger ESG performers tend to experience lower turnover, as they better fulfill employees' desire for meaning and purpose at work (Carnahan et al. 2017).

Overall, our findings indicate that salient climate events' impact on low environmental performers is not limited to job vacancy duration. They make it harder for these firms to attract high-quality employees, reduce the satisfaction of current employees, and increase employee turnover. These findings are consistent with climate disasters raising individuals' awareness of climate change, leading to a stronger preference for environmentally responsible employers. Furthermore, they highlight the importance of climate events and corporate environmental responsibility in employee satisfaction and retention.

7. Conclusion

Extreme weather aggravated by climate change is a pressing issue that poses significant threats to individuals' daily lives across the globe. We seek to further the understanding of the economic implications of climate change by examining the impact of climate disasters on job seekers' employment preferences. We find that worse environmental performers experience longer job vacancies in areas struck by climate disasters, indicating that these disasters increase hiring difficulties for these firms. This effect holds within a subsample of accounting firms. Additional analyses suggest that the prolonged job vacancies for firms with poor environmental performance following disasters is consistent with climate disasters increasing job seekers' awareness of climate change and is unlikely driven by climate disasters' impact on firms' operations, labor demand, hiring strategies, or workplace safety. Beyond job vacancy duration, we find that, in areas experiencing climate disasters, worse environmental performers are less likely to hire high-quality employees and their current employees express more environment-related concerns and are more likely to move to better environmental performers.

Altogether, our findings provide new insights into how personal experiences with climate disasters influence individuals' preferences for employers and their employment decision-making. By demonstrating that climate disasters influence labor market dynamics, our study contributes to the broader literature on the economic consequences of climate change and illuminates the growing importance of corporate environmental responsibility in attracting and retaining talent.

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Appendix: Variable Definitions

This appendix provides variable definitions. All firm-year level continuous variables are winsorized at the top and bottom 1% of the distribution.

Variables	Definitions	Sources
Variables used in Equation (1) or Robustness Checks		
Duration	The number of days between a job's creation and deletion dates.	LinkUP
Disaster	An indicator variable that equals one if the job posting location experiences disasters with total damage amount of at least \$464,549 (the 90^{th} percentile) in any given month during the previous six months and the current month, and zero otherwise.	SHELDUS
Disaster_neighbor	An indicator variable that equals one if the job posting location is in one of the 14 closest unaffected counties to counties directly impacted by the disaster, and zero otherwise.	SHELDUS
Disaster_current	An indicator variable that equals one if the job posting location experiences disasters with total damage amount of at least \$464,549 (the 90^{th} percentile) in the current month, and zero otherwise.	SHELDUS
Disaster_3 months	An indicator variable that equals one if the job posting location experiences disasters with total damage amount of at least \$464,549 (the 90^{th} percentile) in any given month during the previous three months and the current month, and zero otherwise.	SHELDUS
Disaster_95pct	An indicator variable that equals one if the job posting location experiences disasters with total damage amount of at least \$1,648,826 (the 95^{th} percentile) in any given month during the previous six months and the current month, and zero otherwise.	SHELDUS
Disaster_5type	An indicator variable that equals one if the job posting location experiences disasters directly related to global warming (i.e., drought, flooding, heat, hurricanes, or wildfire) in any given month during the previous six months and the current month, and zero otherwise.	SHELDUS
Worse E	Indicator of worse environmental performers. The variable equals one if the E-score of the firm in the previous year is below the sample median, and zero otherwise.	LSEG
E-perform	E-score of the firm in the previous year.	LSEG
E_Issue_num_high	Indicator variable for a high number of environmental-related issues. The variable equals one if the number of a firm's environmental-related issues number is above the sample median in the previous year, and zero otherwise.	RepRisk
Size	The natural logarithm of the firm's market value of equity at the end of the previous year.	Compustat
ROA	Operating income before depreciation in the previous year divided by total assets at the end of the previous year.	Compustat

Leverage	The ratio of the sum of long-term debt and debt in current liabilities to total assets at the end of the previous year.	Compustat
BM	The book-to-market ratio at the end of the previous year.	Compustat
Age	The number of years from the firm's listing date until the end of the previous year.	Compustat
Annualret	The annual buy-and-hold stock return of the firm in the previous year.	CRSP
Other Variables		
Master%	The percentage of newly hired employees at the firm this month who possess a master's degree or higher.	Revelio Labs
PhD%	The percentage of newly hired employees at the firm this month who possess a PhD degree.	Revelio Labs
High_Climate_Change_ Belief	An indicator variable that equals one if the posting location's public belief in climate change is at or above the sample median, and zero otherwise. Public belief is measured as the factor with the highest eigenvalue based on the factor analysis of 11 variables in The Yale Climate Opinion Maps data (Source: https://climatecommunication.yale.edu/visualizations-data/ycom-us/). The 11 variables include the estimated percentage who think that global warming is happening, the estimated percentage who believe that most scientists think global warming is happening, the estimated percentage who think that global warming is caused mostly by human activities, the estimated percentage who think global warming will harm people in developing countries a moderate amount or a great deal, the estimated percentage who think global warming will harm future generations a moderate amount or a great deal, the estimated percentage who think global warming will harm people in the US a moderate amount or a great deal, the estimated percentage who think global warming will harm them personally a moderate amount or a great deal, the estimated percentage who think global warming will start to harm people in the U.S. now or within 10 years, the estimated percentage who are worried about global warming, the estimated percentage who support funding research into renewable energy sources, and the estimated percentage who support regulating carbon dioxide as a pollutant.	Yale Climate Opinion Maps
N_Job_Postings	The number of job postings at the firm-zip-month level.	LinkUP
Voluntary_salary _disclosure	An indicator variable that equals one if the job posting contains salary information that a firm voluntarily discloses, and zero otherwise.	LinkUp
Salary	The hourly salary amount stated in the job posting. Yearly salaries are converted to hourly rates by dividing the annual amount by 1,920 working hours.	LinkUp
Overall_Rating	Employees' overall rating for the firm.	Glassdoor
Business_Outlook	Employees' assessment of the firm's future business outlook. This variable is based on responses to the question: "Do you	Glassdoor

	believe your company's business outlook will get better, stay the same, or get worse in the next six months?" provided when submitting a review on Glassdoor. The variable is coded as one if the response is "Better," zero if "Same," and negative one if "Worse."	
Neg_E_Comments	The percentage of E-related words in the Cons section of employee comments. E-related words are from Briscoe-Tran (2024).	Glassdoor
Female	An indicator variable that equals one if the employee is a woman, and zero otherwise.	Glassdoor
Employee_Age	The age of the employee.	Glassdoor
Edu_High	An indicator variable that equals one if an employee's highest education is higher than or equal to master, and zero otherwise.	Glassdoor
Work_Regular	An indicator variable that equals one if the employee is a regular full-time worker, and zero otherwise.	Glassdoor
Length_Employ	The number of years that the employee has worked for the firm.	Glassdoor
HQ_State	An indicator variable that equals one if the employee works in the state where the firm's headquarters is located, and zero otherwise.	Glassdoor
Join_Better_E-Performers	The percentage of employees at the firm in the previous month who left the firm to join another firm with a higher E-score (based on the previous year) this month.	Revelio Labs
Join_Worse_E-Performers	The percentage of employees at the firm in the previous month who left the firm to join another firm with a worse E-score (based on the previous year) this month.	Revelio Labs

Figure 1: Dynamic Analysis

This figure shows the temporal dynamics of job vacancy duration relative to climate disaster months. The figure plots the estimated coefficients β_{1n} from the regression:

$$Ln(Duration_{j,i,l,t}) = \sum_{n=-3}^{n=6} \beta_{1,n}\, Disaster_{l,t+n} \times Worse\ E_{i,t} + \sum_{n=-3}^{n=6} \beta_{2,n}\, Disaster_{l,t+n} + \sum_{n=-3}^{n=6} \beta_{3,n}\, Disaster_{l,t+n} \times Size_{i,t} + \tau_{i,y} + \theta_{o,t} + \gamma_{i,l,o} + \varepsilon_{j,i,l,t}.$$

The dashed lines denote a 90% confidence interval. The regression results are reported in Online Appendix Table OA-3.

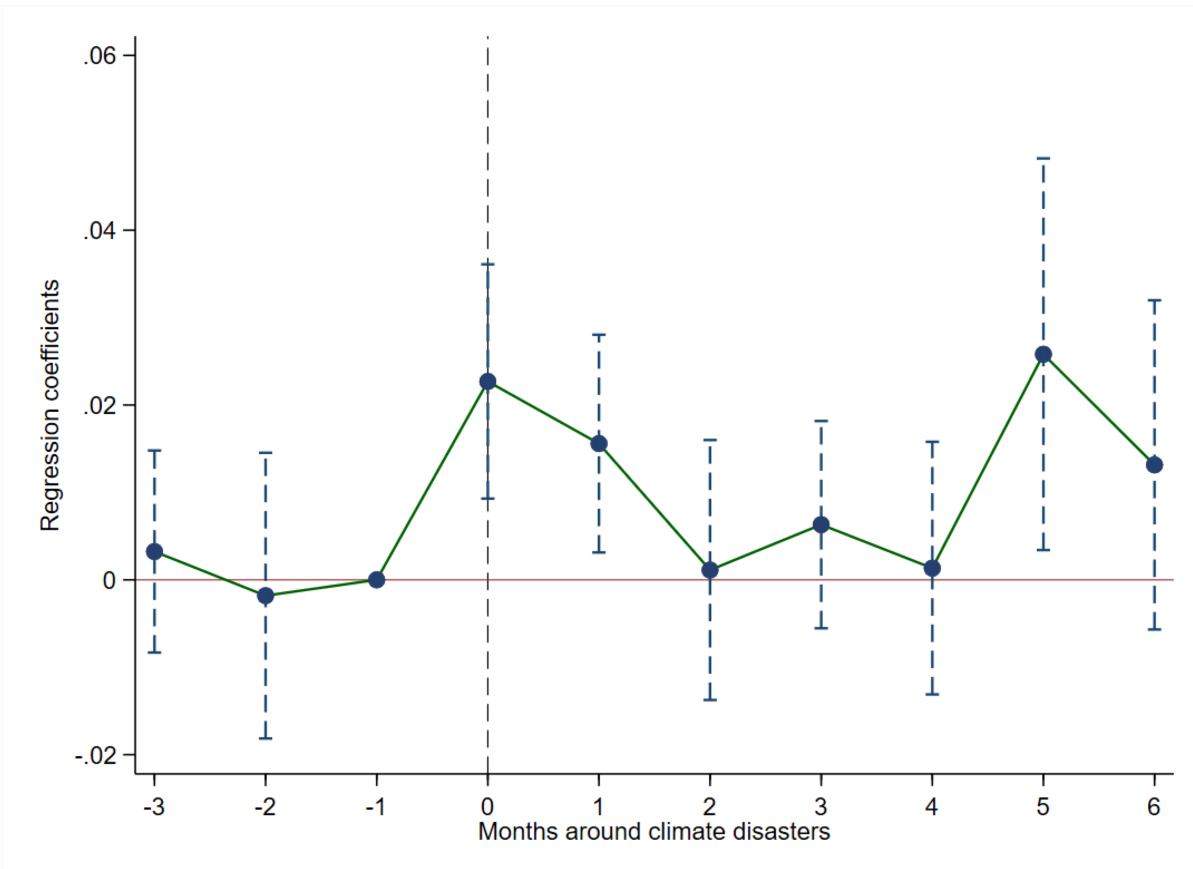

Table 1: Descriptive Statistics: Climate Disasters

Panel A reports the damage amounts and frequencies of climate disasters. Panel B reports the distribution of the damage amounts of disasters at the county-month level. The sample includes county-month observations where at least one of the 13 disaster types occurred.

Panel A: disaster types and damage amount

Disasters	Total damages (in Millions USD)	# of county-months	Average damage per county-month (in Millions USD)
Flooding	136,844.419	18,535	7.383
Hurricane/Tropical Storm	63,123.702	1,623	38.893
Tornado	25,608.647	7,313	3.502
Wildfire	24,455.119	1,733	14.111
Hail	20,801.815	5,623	3.699
Drought	16,978.907	3,080	5.513
Wind	12,794.740	63,867	0.200
Winter Weather	6,077.953	7,253	0.838
Severe Storm/Thunderstorm	2,304.489	49,375	0.047
Landslide	1,326.672	747	1.776
Lightning	398.535	4,956	0.080
Coastal	305.106	1,238	0.246
Heat	36.867	946	0.039

Panel B: Damages of disasters at the county-month level

	Obs.	Mean	SD	P10	P25	Median	P75	P90
Damage amount (in USD)	96,975	3,207,600	95,562,448	944	3,097	13,719	70,000	464,549

Table 2: Descriptive Statistics: Main Variables

Panel A and Panel B report the descriptive statistics and the Pearson correlations of the main variables, respectively. Correlation coefficients that appear in boldface are significant at the 10% or higher level.

Panel A: Descriptive statistics of main variables

Variables	# of Obs	Mean	SD	P10	P25	Median	P75	P90
Posting Level								
Duration	51,406,413	37.001	37.706	4.000	9.000	24.000	52.000	92.000
Zip-month level								
Disaster	1,261,864	0.192	0.394	0.000	0.000	0.000	0.000	1.000
Firm-year level								
E-perform	17,492	0.273	0.279	0.000	0.000	0.189	0.487	0.719
Worse E	17,492	0.822	0.383	0.000	1.000	1.000	1.000	1.000
Size	17,492	8.177	1.653	6.006	7.036	8.116	9.264	10.357
ROA	17,492	0.025	0.030	-0.007	0.006	0.024	0.039	0.058
Leverage	17,492	0.284	0.236	0.017	0.094	0.256	0.412	0.575
BM	17,492	0.446	0.387	0.070	0.186	0.371	0.648	0.958
Age	17,492	16.850	14.078	2.000	5.000	14.000	24.000	41.000
Annualret	17,492	0.158	0.394	-0.301	-0.094	0.121	0.349	0.628

Panel B: Pearson correlations of main variables

	Duration	Disaster	E-perform	Worse E	Size	ROA	Leverage	BM	Age	Annualret
Duration	1									
Disaster	**0.00**	1								
E-perform	**-0.06**	**-0.00**	1							
Worse E	**0.05**	**0.00**	**-0.86**	1						
Size	**0.01**	**0.00**	**0.62**	**-0.54**	1					
ROA	**-0.08**	**-0.01**	**0.09**	**-0.10**	**0.07**	1				
Leverage	**-0.12**	**-0.03**	**0.20**	**-0.18**	**0.01**	**0.60**	1			
BM	**0.03**	**0.02**	**-0.06**	**0.09**	**-0.12**	**-0.45**	**-0.50**	1		
Age	**0.03**	**-0.01**	**0.25**	**-0.26**	**0.26**	**0.02**	**-0.13**	**-0.04**	1	
Annualret	**-0.01**	**0.00**	**-0.01**	**-0.00**	**0.16**	**0.10**	**0.02**	**-0.20**	**0.01**	1

Table 3: Climate Disasters and Job Vacancy Duration

This table reports the effect of climate disasters on job vacancy duration. Column (1) presents a baseline specification with firm-level controls and without fixed effects. Firm controls include Size, ROA, Leverage, BM, Age, Annualret, and Worse E in the prior year. Columns (2) and (3) progressively add occupation-month and firm-occupation-state fixed effects. Column (4) omits firm controls and includes firm-year fixed effects. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)			
	(1)	(2)	(3)	(4)
Disaster × Worse E	0.048*	0.033*	0.028***	0.013***
	(0.025)	(0.019)	(0.010)	(0.005)
Disaster	-0.062	-0.043	-0.024	-0.019
	(0.076)	(0.058)	(0.023)	(0.013)
Disaster × Size	0.004	0.002	-0.000	0.000
	(0.008)	(0.006)	(0.002)	(0.001)
Firm Controls	Yes	Yes	Yes	No
Occupation × Month fixed effects	No	Yes	Yes	Yes
Firm × Occupation × State fixed effects	No	No	Yes	Yes
Firm × Year fixed effects	No	No	No	Yes
Observations	51,406,413	51,397,059	51,003,118	51,002,948
Adjusted R-squared	0.021	0.131	0.311	0.349

Table 4: Climate Disasters and Job Vacancy Duration: Robustness Tests

This table reports robustness tests for our findings in Table 3. In Column (1), we exclude remote-work applicable occupation postings. In Column (2), we exclude jobs in areas with high labor inflows, defined as counties with population inflows at or above the sample median. Column (3) reports the results based on stacked DID analysis. In stacked DID regressions, we include all fixed effects as specified in Equation (1) interacted with cohort indicators, where a cohort includes all postings in zip code regions sharing the same disaster event month and their matched postings in never-affected-regions. In Columns (4) and (5), we define disaster-impacted postings using a one-month and three-month event window, respectively. In Column (6), we define salient disasters using a cutoff at the 95th percentile for total damages. In Column (7), we focus on five types of disasters including drought, flooding, heat, hurricanes/tropical storms, and wildfire. In Column (8), we capture E-performance by the number of E-related negative issues from RepRisk. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)							
	Exclude remote-work applicable occupations	Exclude counties with high labor inflow	Stacked DID	Affected window: current month	Affected window: [-3,0] months	Saliency benchmark: 95%	Disasters directly related to global warming	Worse E measure: high E issues number
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster × Worse E	0.017***	0.021***	0.012***					
	(0.006)	(0.005)	(0.005)					
Disaster_current × Worse E				0.020***				
				(0.006)				
Disaster_3 months × Worse E					0.012**			
					(0.005)			
Disaster_95pct × Worse E						0.009*		
						(0.005)		
Disaster_5type × Worse E							0.010***	
							(0.003)	
Disaster × E_Issue_num_high								0.013*
								(0.007)
Disaster Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disaster Indicator × Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation × Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Occupation × State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,796,038	24,683,877	462,585,317	51,002,948	51,002,948	51,002,948	51,002,948	51,002,948
Adjusted R-squared	0.261	0.353	0.409	0.349	0.349	0.349	0.349	0.349

Table 5: Climate Disasters and Job Vacancy Duration: Accounting Firms

This table reports the effect of climate disasters on job vacancy duration using postings from accounting firms, where a posting is classified as from an accounting firm if the firm's four-digit NAICS code is 5412. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)
	(1)
Disaster × Worse E	0.080***
	(0.025)
Disaster	-0.302***
	(0.105)
Disaster × Size	0.025**
	(0.010)
Occupation × Month fixed-effects	Yes
Firm × Occupation × State fixed-effects	Yes
Firm × Year fixed-effects	Yes
Observations	165,928
Adjusted R-squared	0.682

Table 6: Climate Disasters and Job Vacancy Duration: Climate Change Belief

This table reports the effect of climate disasters on job vacancy duration in two subsamples. In Column (1), we use observations in regions of high climate change belief. In Column (2), we use observations in regions of low climate change belief. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)	
Groups:	High_Climate_Change_Belief = 1	High_Climate_Change_Belief = 0
	(1)	(2)
Disaster × Worse E	0.031***	0.001
	(0.011)	(0.007)
Diff. (z-value)	-0.030**(z=-2.275)	
Disaster	-0.074***	0.007
	(0.023)	(0.020)
Disaster × Size	0.005***	-0.002
	(0.002)	(0.002)
Occupation × Month fixed effects	Yes	Yes
Firm × Occupation × State fixed effects	Yes	Yes
Firm × Year fixed effects	Yes	Yes
Observations	19,098,114	19,045,073
Adjusted R-squared	0.329	0.359

Table 7: Climate Disasters and Job Vacancy Duration: Neighbor County Analysis

This table reports the effect of climate disasters on the difference in job vacancy durations between low and high environmental performers in the 14 closest unaffected neighboring counties of disaster areas. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)
	(1)
Disaster_neighbor × Worse E	0.009**
	(0.004)
Disaster_neighbor	-0.022*
	(0.013)
Disaster_neighbor × Size	0.001
	(0.001)
Occupation × Month fixed effects	Yes
Firm × Occupation × State fixed effects	Yes
Firm × Year fixed effects	Yes
Observations	39,257,147
Adjusted R-squared	0.354

Table 8: Climate Disasters and Labor Demand

This table reports the effect of climate disasters on labor demand. Column (1) presents the specification with firm-level controls and firm, state, and month fixed effects. Firm controls include Size, ROA, Leverage, BM, Age, Annualret, and Worse E in the prior year. Column (2) omits firm controls and includes firm-state and firm-year fixed effects. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(N_Job_Postings)	
	(1)	(2)
Disaster × Worse E	-0.006	-0.006
	(0.004)	(0.003)
Disaster	-0.004	0.022*
	(0.029)	(0.013)
Disaster × Size	0.005	0.002
	(0.004)	(0.002)
Firm Controls	Yes	No
Firm fixed effects	Yes	No
State fixed effects	Yes	No
Month fixed effects	Yes	No
Firm × State fixed effects	No	Yes
Firm × Year fixed effects	No	Yes
Observations	9,357,706	9,351,439
Adjusted R-squared	0.238	0.355

Table 9: Climate Disasters and Salary Disclosure and Amount

This table reports the effect of climate disasters on the likelihood of firms voluntarily disclosing salary information in job postings and the salary amount. Column (1) removes job postings in locations with salary disclosure mandates (i.e., Colorado on and after Jan. 1, 2021; Jersey City in New Jersey on and after April 13, 2022; Ithaca in New York State on and after Sept. 1, 2022; New York City in New York State on and after Nov. 1, 2022; and Westchester county in New York State on and after Nov. 6, 2022). Column (2) includes both voluntarily and mandatorily disclosed salaries. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variables:	Voluntary_salary_disclosure	ln(Salary)
	(1)	(2)
Disaster × Worse E	-0.000	0.024
	(0.001)	(0.019)
Disaster	-0.001	-0.081*
	(0.002)	(0.047)
Disaster × Size	0.000	0.006*
	(0.000)	(0.004)
Occupation × Month fixed effects	Yes	Yes
Firm × Occupation × State fixed effects	Yes	Yes
Firm × Year fixed effects	Yes	Yes
Observations	41,412,745	1,158,230
Adjusted R-squared	0.535	0.765

Table 10: Climate Disasters and Hiring Quality

This table reports the effect of climate disasters on firms' hiring quality. Column (1) measures hiring quality as the percentage of newly hired employees who possess a master's degree or higher. Column (2) measures hiring quality as the percentage of newly hired employees who possess a PhD degree. Both columns control for firm-MSA and firm-year fixed effects. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the MSA level.

Dependent Variables:	Master%	PhD%
	(1)	(2)
Disaster × Worse E	-0.550**	-0.244***
	(0.242)	(0.082)
Disaster	1.035	0.935***
	(0.810)	(0.285)
Disaster × Size	-0.055	-0.083***
	(0.071)	(0.026)
Firm × MSA fixed effects	Yes	Yes
Firm × Year fixed effects	Yes	Yes
Observations	769,695	769,695
Adjusted R-squared	0.145	0.149

Table 11: Climate Disasters and Current Employees' Perceptions

This table reports the effect of climate disasters on current employees' perceptions of their employers. The dependent variables in Columns (1) to (3) are Overall_Rating, Neg_E_Comments, and Business_Outlook, respectively. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variables:	Overall_Rating	Neg_E_Comments	Business_Outlook
	(1)	(2)	(3)
Disaster × Worse E	-0.058*	0.048**	-0.028
	(0.031)	(0.021)	(0.027)
Disaster	-0.029	0.008	-0.007
	(0.104)	(0.047)	(0.068)
Disaster × Size	0.004	-0.001	0.001
	(0.009)	(0.004)	(0.006)
Female	-0.022	-0.001	-0.009*
	(0.017)	(0.008)	(0.006)
Employee_Age	-0.010***	0.001*	-0.002**
	(0.001)	(0.000)	(0.001)
Edu_High	-0.028	0.002	-0.004
	(0.019)	(0.010)	(0.008)
Work_Regular	-0.061***	0.006	-0.029***
	(0.018)	(0.006)	(0.010)
Length_Employ	-0.001	-0.000	-0.006***
	(0.001)	(0.001)	(0.001)
HQ_State	0.098	0.013	-0.008
	(0.202)	(0.066)	(0.155)
Occupation × Month fixed effects	Yes	Yes	Yes
Firm × Occupation × State fixed effects	Yes	Yes	Yes
Firm × Year fixed effects	Yes	Yes	Yes
Observations	54,669	54,669	54,669
Adjusted R-squared	0.144	0.166	0.109

Table 12: Climate Disasters and Employee Turnover

This table reports the effect of climate disasters on employees' turnover decisions. The dependent variables in Columns (1) and (2) are Join_Better E-Performers, and Join_Worse E-Performers, respectively. Both columns control for firm-MSA and firm-year fixed effects. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the MSA level.

Dependent Variables:	Join_Better E-Performers	Join_Worse E-Performers
	(1)	(2)
Disaster × Worse E	0.016**	-0.003**
	(0.007)	(0.001)
Disaster	-0.021	0.002
	(0.023)	(0.002)
Disaster × Size	0.002	0.000
	(0.002)	(0.000)
Firm × MSA fixed effects	Yes	Yes
Firm × Year fixed effects	Yes	Yes
Observations	9,807,734	9,807,734
Adjusted R-squared	0.036	0.113

Online Appendix for

When Disaster Strikes: How Climate Events Influence Employment Preferences

Table OA-1: Descriptive Statistics: Additional Variables

This table reports the descriptive statistics of the additional variables used in the analysis.

Variables	# of Obs	Mean	SD	P10	P25	Median	P75	P90
Posting level								
High_Climate_Change_Belief	38,625,729	0.500	0.500	0.000	0.000	1.000	1.000	1.000
High_climate_exposure	46,663,283	0.520	0.500	0.000	0.000	1.000	1.000	1.000
Voluntary_salary_disclosure	41,735,402	0.026	0.159	0.000	0.000	0.000	0.000	0.000
Salary	1,191,360	19.882	15.008	2.865	13.530	16.610	22.500	30.141
Zip-month level								
Disaster_current	1,261,864	0.034	0.180	0.000	0.000	0.000	0.000	0.000
Disaster_95pct	1,261,864	0.110	0.313	0.000	0.000	0.000	0.000	1.000
Disaster_3 months	1,261,864	0.119	0.323	0.000	0.000	0.000	0.000	1.000
Disaster_pre	1,261,864	0.018	0.135	0.000	0.000	0.000	0.000	0.000
Disaster_5type	1,261,864	0.355	0.479	0.000	0.000	0.000	1.000	1.000
Disaster_neighbor	1,019,520	0.503	0.500	0.000	0.000	1.000	1.000	1.000
Firm-year level								
E_Issue_num_high	17,492	0.037	0.189	0.000	0.000	0.000	0.000	0.000
Orthogonal_SG_in_E_worse	17,492	0.657	0.475	0.000	0.000	1.000	1.000	1.000
Orthogonal_S_in_E_worse	17,492	0.656	0.475	0.000	0.000	1.000	1.000	1.000
Orthogonal_G_in_E_worse	17,492	0.634	0.482	0.000	0.000	1.000	1.000	1.000
Firm-quarter level								
$CCRisk^{Phy}$	81,368	0.000	0.017	0.000	0.000	0.000	0.000	0.000
$CCExposure^{Phy}$	81,368	0.014	0.134	0.000	0.000	0.000	0.000	0.000
Firm-state-year level								
FineDollar_post	294,513	16,122.504	2,473,629.000	0.000	0.000	0.000	0.000	0.000
N_Fine_post	294,513	0.010	0.145	0.000	0.000	0.000	0.000	0.000
Firm-zip-month level								
N_Job_Postings	9,357,730	4.737	8.100	1.000	1.000	2.000	4.000	11.000
Revelio Labs Firm-MSA-month level								
Master%	797,415	35.232	42.083	0.000	0.000	0.000	80.000	100.000
PhD%	797,415	4.194	17.483	0.000	0.000	0.000	0.000	0.000
Join_Better_E-Performers	9,815,086	0.059	0.314	0.000	0.000	0.000	0.000	0.000
Join_Worse_E-Performers	9,815,086	1.130	4.234	0.000	0.000	0.000	0.000	2.500
Glassdoor review level								
Overall_Rating	98,031	3.589	1.221	2.000	3.000	4.000	5.000	5.000
Neg_E_Comments	98,031	0.052	0.706	0.000	0.000	0.000	0.000	0.000
Business_Outlook	98,031	0.389	0.763	-1.000	0.000	1.000	1.000	1.000
Female	98,031	0.386	0.487	0.000	0.000	0.000	1.000	1.000
Employee_Age	98,031	33.532	10.452	22.000	25.000	31.000	40.000	50.000
Edu_High	98,031	0.762	0.426	0.000	1.000	1.000	1.000	1.000
Work_Regular	98,031	0.678	0.467	0.000	0.000	1.000	1.000	1.000
Length_Employ	98,031	4.186	5.171	1.000	1.000	2.000	4.000	9.000
HQ_State	98,031	0.323	0.468	0.000	0.000	0.000	1.000	1.000

Table OA-2: Environment Performance and Job Vacancy Duration

This table reports the association between firms' E-performance and job vacancy duration in the next year. Column (1) presents a baseline specification with firm-level controls and without fixed effects. Columns (2) and (3) progressively add occupation-month and firm-occupation-state fixed effects. All variables are defined in the Appendix of the main paper. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)		
	(1)	(2)	(3)
E-perform	-0.211***	-0.182***	-0.112***
	(0.026)	(0.021)	(0.025)
Size	0.031***	0.013**	0.086***
	(0.008)	(0.006)	(0.008)
ROA	-1.893***	-1.661***	-0.296***
	(0.219)	(0.271)	(0.103)
Leverage	-0.248***	-0.206***	-0.229***
	(0.036)	(0.031)	(0.022)
BM	-0.184***	-0.163***	-0.086***
	(0.020)	(0.015)	(0.013)
Age	0.001**	0.001**	0.013
	(0.000)	(0.000)	(0.035)
Annualret	-0.106***	-0.063***	-0.061***
	(0.015)	(0.013)	(0.008)
Occupation × Month fixed effects	No	Yes	Yes
Firm × Occupation × State fixed effects	No	No	Yes
Observations	51,406,413	51,397,059	51,003,118
Adjusted R-squared	0.021	0.131	0.311

Table OA-3: Climate Disasters and Job Vacancy Duration: A Dynamic Analysis

This table shows the regression results of the dynamic analysis of job vacancy duration surrounding the months of climate disasters. All variables are defined in the Appendix of the main paper and Online Appendix Table OA-10. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)
	(1)
$Disaster_{t-3}$ × Worse E	0.003
	(0.007)
$Disaster_{t-2}$ × Worse E	-0.002
	(0.010)
$Disaster_{t}$ × Worse E	0.023***
	(0.008)
$Disaster_{t+1}$ × Worse E	0.016**
	(0.007)
$Disaster_{t+2}$ × Worse E	0.001
	(0.009)
$Disaster_{t+3}$ × Worse E	0.006
	(0.007)
$Disaster_{t+4}$ × Worse E	0.001
	(0.009)
$Disaster_{t+5}$ × Worse E	0.026*
	(0.013)
$Disaster_{t+6}$ × Worse E	0.013
	(0.011)
$Disaster_{t+n}$	Yes
$Disaster_{t+n}$ × Size	Yes
Occupation × Month fixed effects	Yes
Firm × Occupation × State fixed effects	Yes
Firm × Year fixed effects	Yes
Observations	46,812,221
Adjusted R-squared	0.352

Table OA-4: Climate Disaster and Job Vacancy Duration: Alternative E-performance Measures

This table reports the effect of climate disasters on job vacancy durations using alternative measures of firms' environmental performance. In columns (1)-(3), we capture E performance by LSEG E score orthogonalized with respect to S and G scores, S score, and G score, respectively. All variables are defined in the Appendix of the main paper and Online Appendix Table OA-10. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)		
	(1)	(2)	(3)
Disaster × Orthogonal_SG_in_E_worse	0.008*		
	(0.005)		
Disaster × Orthogonal_S_in_E_worse		0.009**	
		(0.004)	
Disaster × Orthogonal_G_in_E_worse			0.009**
			(0.005)
Disaster	-0.005	-0.006	-0.007
	(0.015)	(0.014)	(0.015)
Disaster × Size	-0.001	-0.001	-0.000
	(0.002)	(0.001)	(0.002)
Occupation × Month fixed-effects	Yes	Yes	Yes
Firm × Occupation × State fixed-effects	Yes	Yes	Yes
Firm × Year fixed-effects	Yes	Yes	Yes
Observations	51,002,948	51,002,948	51,002,948
Adjusted R-squared	0.349	0.349	0.349

Table OA-5: Environmental Performance and Climate Change-related Physical Shock Exposure and Risk

This table reports the relationship between firms' environmental performance and their exposure to climate change-related physical shock risk. Columns (1) and (2) examine the association between environmental performance and physical climate risk and exposure, respectively. Columns (3) and (4) explore whether salient climate disasters lead to differential effects on physical risk and exposure between firms with low and high environmental performance. All regressions control for firm characteristics, and include firm, year, and state fixed effects. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the state level.

Dependent Variables:	$CCRisk^{Phy}$	$CCExposure^{Phy}$	$CCRisk^{Phy}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
E-perform	-0.000	0.001		
	(0.001)	(0.006)		
Disaster × Worse E			-0.000	-0.004
			(0.000)	(0.003)
Disaster			0.001	0.017**
			(0.001)	(0.008)
Disaster × Size			-0.000	-0.002**
			(0.000)	(0.001)
Firm Controls	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Firm fixed-effects	Yes	Yes	Yes	Yes
State fixed-effects	Yes	Yes	Yes	Yes
Observations	81,166	81,166	81,166	81,166
Adjusted R-squared	0.016	0.397	0.016	0.397

Table OA-6: Climate Disasters and Job Vacancy Duration based on Jobs Posted before Treatment

This table reports the effect of climate disasters on job vacancy duration based on jobs posted before the treatment. All variables are defined in the Appendix of the main paper and Online Appendix Table OA-10. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)
	(1)
Disaster_pre × Worse E	0.024**
	(0.009)
Disaster_pre	0.562***
	(0.033)
Disaster_pre × Size	0.019***
	(0.003)
Occupation × Month fixed-effects	Yes
Firm × Occupation × State fixed-effects	Yes
Firm × Year fixed-effects	Yes
Observations	39,257,147
Adjusted R-squared	0.367

Table OA-7: Climate Disasters and Job Vacancy Duration in Non-Green Jobs and Firms' Future E-performance

This table reports the effect of climate disasters on job vacancy duration when excluding green-jobs, and on firms' future environmental violations. Column (1) uses non-green job postings, as defined in Darendeli et al. (2022). Column (2) and Column (3) use the firm-state-year environmental violation records. Firm Controls include Size, ROA, Leverage, BM, Age, Annualret, and Worse E in the prior year. All variables are defined in the Appendix of the main paper and Online Appendix Table OA-10. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)	ln(FineDollar)_post	N_Fine_post
Samples:	Postings excluding green jobs	Firm-State-Year E-violation records	
	(1)	(2)	(3)
Disaster × Worse E	0.014***	-0.010	-0.002
	(0.005)	(0.011)	(0.002)
Disaster	-0.019	0.044***	0.006***
	(0.013)	(0.007)	(0.001)
Disaster × Size	0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.000)
Firm Controls	No	Yes	Yes
Occupation × Month fixed-effects	Yes	No	No
Firm × Occupation × State fixed-effects	Yes	No	No
Firm × Year fixed-effects	Yes	No	No
Firm fixed-effects	No	Yes	Yes
State fixed-effects	No	Yes	Yes
Year fixed-effects	No	Yes	Yes
Observations	50,855,617	290,839	290,839
Adjusted R-squared	0.349	0.069	0.084

Table OA-8: Climate Disasters and Job Vacancy Duration: Jobs' Climate Exposure

This table reports the effect of climate disasters on job vacancy duration separately for two subsamples. In Column (1), we include job vacancies in occupations with high climate risk exposure. In Column (2), we include job vacancies in occupations with low climate risk exposure. All variables are defined in the Appendix of the main paper and Online Appendix Table OA-10. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)	
Group:	High_climate_exposure = 1	High_climate_exposure = 0
	(1)	(2)
Disaster × Worse E	0.013***	0.014**
	(0.005)	(0.006)
Diff. (z-value)	0.001(z=0.149)	
Disaster	-0.022	-0.020
	(0.014)	(0.019)
Disaster × Size	0.001	0.000
	(0.002)	(0.002)
Occupation × Month fixed effects	Yes	Yes
Firm × Occupation × State fixed effects	Yes	Yes
Firm × Year fixed effects	Yes	Yes
Observations	24,090,929	22,210,115
Adjusted R-squared	0.384	0.319

Table OA-9: Climate Disasters and Job Vacancy Duration: Exclude EPA Office Location Postings

This table reports the effect of climate disasters on job vacancy duration, excluding job vacancies in locations close to EPA offices. In Column (1), we exclude postings in the same zip code as EPA offices. In Column (2), we exclude postings in the same county as EPA offices. In Column (3), we exclude postings in the same state as EPA offices. All variables are defined in the Appendix of the main paper and Online Appendix Table OA-10. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the state level.

Dependent Variable:	ln(Duration)		
	Exclude postings in the same zip code as EPA offices	Exclude postings in the same county as EPA offices	Exclude postings in the same state as EPA offices
	(1)	(2)	(3)
Disaster × Worse E	0.013***	0.012**	0.011*
	(0.005)	(0.005)	(0.007)
Disaster	-0.015	-0.019	-0.026
	(0.013)	(0.013)	(0.019)
Disaster × Size	0.000	0.001	0.002
	(0.001)	(0.001)	(0.002)
Occupation × Month fixed effects	Yes	Yes	Yes
Firm × Occupation × State fixed effects	Yes	Yes	Yes
Firm × Year fixed effects	Yes	Yes	Yes
Observations	50,044,988	44,707,837	27,509,160
Adjusted R-squared	0.348	0.355	0.357

Table OA-10: Definitions for Variables not in the Manuscript

This table provides definitions for variables not in the manuscript.

Variables	Definitions	Sources
$Disaster_{t+n}$	An indicator variable that denotes the n^{th} month from the disaster month.	SHELDUS
Disaster_pre	An indicator variable that equals one if the job vacancy is posted before the treatment but filled during or after the disaster month, and zero otherwise.	SHELDUS
Orthogonal_SG_in_E_worse	The residuals of regressing E scores on S and G scores.	LSEG
Orthogonal_S_in_E_worse	The residuals of regressing E scores on S scores.	LSEG
Orthogonal_G_in_E_worse	The residuals of regressing E scores G scores.	LSEG
$CCRisk^{Phy}$	Climate change-related physical risk based on the frequency of the specified bigrams that appear in the firm-quarter's conference call transcripts.	Sautner et al. (2024)
$CCExposure^{Phy}$	Climate change-related physical shock exposure based on the frequency of the specified bigrams that appear in the firm-quarter's conference call transcripts.	Sautner et al. (2024)
ln(FineDollar)_post	Natural logarithm of the environmental violation fine amount of the firm in the next year.	Violation Tracker
N_Fine_post	Number of environmental violation incidents of the firm in the next year.	Violation Tracker
High_climate_exposure	An indicator variable that equals one if the occupation's score, based on survey responses to "How often does this job require working outdoors, exposed to all weather conditions?", is at or above the sample median, and zero otherwise.	U.S. Department of Labor's O*NET program