When Disaster Strikes: How Climate Events Influence Employment Preferences

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Abstract:

This paper examines how experiences with salient climate events affect workers' employment preferences. Using novel data on vacancy duration for online job postings and plausibly exogenous variation in the exposure of firms to significant climate events, we find that it takes longer for exposed firms with lower environmental performance to fill their job vacancies compared with their counterparts with better environmental performance. This effect is consistent with exposure to climate disasters heightening job seekers' awareness of the severity of climate change, leading them to place greater importance on employers' environmental responsibility in their employment decisions. Moreover, employee reviews decline for environmentally underperforming firms and exposed workers are more likely to move to firms with better environmental performance after climate events, suggesting that experiences with climate disasters also change current employees' perceptions of their employers. Our findings highlight the economic consequences of climate risk from the perspective of employment decisions.

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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).[1] Both anecdotal evidence and academic research highlight the significant negative impacts of these events on individuals and businesses (e.g., Barrot and Sauvagnat 2016; Huang et al. 2018; Addoum et al. 2020; Deloitte 2022; Bittle 2023; Pankratz et al. 2023). To date, most empirical studies have focused on the effects of extreme weather on firms' physical assets and operations. However, employees are critical stakeholders and key drivers of firm value (Zingales 2000; Nishesh et al. 2022), making it essential to examine whether climate events influence firms through their workforce. This paper contributes to the literature by examining how experiences with climate disasters shape employees' work preferences.

Human capital has become increasingly important for firms. Hiring challenges and employee turnover pose significant threats to firm growth and performance (Donnangelo 2014; Baghai et al. 2021; Barbanchon et al. 2024). Understanding the factors that influence workers' employment decisions is therefore crucial (e.g., Brown and Matsa 2016; Gao et al. 2024). We hypothesize that personal experiences with climate-related disasters may heighten individuals' sensitivity to firms' environmental performance when making employment choices. Specifically, studies suggest that experiencing extreme weather events can increase awareness of climate change and amplify perceptions of its social and economic risks (Egan and Mullin 2012; Myers et al. 2012; Zaval et al. 2014; Sisco et al. 2017; Hazlett and Mildenberger 2020). As environmental concerns grow, individuals are more likely to scrutinize potential employers' environmental records. Consequently, experiences with climate-related disasters may lead to

[1] We use the terms extreme climate events, climate(-related) disasters, and climate(-related) hazards interchangeably in the paper.

stronger disapproval of corporate environmental irresponsibility, reducing individuals' willingness to work for firms with poor environmental performance.

Nevertheless, if workers already prioritize environmental considerations and avoid firms with poor environmental records, personal experiences with climate events may not significantly change their preferences (Wappenhans et al. 2024). Additionally, given the variety of factors that influence career choices, experiencing a single climate-related disaster may not substantially impact individuals' job preferences. As a result, whether climate disasters affect workers' employment decisions remains an empirical question.

We investigate this question by exploiting the staggered occurrence of climate-related hazards and online job posting data from U.S. public firms. We use job vacancy duration as a proxy for job seekers' preferences. When job seekers perceive a firm negatively, a decrease in labor supply results in longer times for the firm to find qualified candidates and fill a position. We first conduct a large-sample analysis to confirm that firms with high environmental performance tend to fill their job vacancies more quickly, consistent with prior survey evidence suggesting that environmentally responsible firms are more attractive to employees. Next, we find that the time required to fill vacancies increases significantly for firms with low environmental performance compared to those with high environmental performance when local job seekers in a county have experienced climate-related disasters in the past six months. This supports our hypothesis that exposure to climate-related disasters heightens job seekers' preference for environmentally responsible firms.

Our results remain robust across various fixed effects, clustering methods, and alternative measures. Additionally, dynamic effects analyses reveal no pre-trend effects, addressing concerns that contemporaneous unobserved trends, other than the treatment (salient disasters), might confound the treatment effect of interest.

After examining changes in job seekers' preferences, we next investigate the impact of climate disaster exposure on current employees' perceptions of their employers and their intentions to leave. Using job profile data from Revelio Labs, we find that employees at firms with low ESG performance are more likely to move to firms with high ESG performance, while they are less likely to move to firms with even lower ESG performance after experiencing climate-related disasters in the past six months. Additionally, our analysis of employee ratings and comments on Glassdoor reveals that, following climate-related disasters, employees at firms with poor environmental performance rate their employers lower and express greater concern about environmental issues in their comments. These findings collectively suggest that climate-related disasters reduce both job seekers' and current employees' willingness to work for firms that are not environmentally responsible.

Next, we discuss alternative explanations and provide evidence to alleviate these concerns. One key alternative explanation is that our results may be driven by climate disasters affecting firms with high and low environmental scores differently in other dimensions, such as firm operations or labor demand, rather than job seekers' preferences. To address this concern, we incorporate a high-dimensional set of fixed effects, including firm-by-year, occupation-by-year-by-month, and firm-by-occupation-by-state fixed effects. This approach ensures that our coefficient estimates capture variations within firm-year, occupation-month, and firm-location-occupation levels. Furthermore, we find no significant reduction in labor demand for firms with low environmental scores following climate disasters, suggesting that our results are not driven by shifts in hiring needs. Additionally, we exclude counties directly impacted by such disasters but use neighboring counties as the treated group. Job applicants in these neighboring counties are likely aware of the nearby climate disasters, yet the operations of firms in these areas are unaffected. Our inference remains consistent when using neighboring counties as the treated group.

Another possible explanation is that job seekers may avoid firms with poor environmental performance due to concerns that these firms experience greater financial losses following climate-related disasters, potentially leading to wage reductions as a part of damage control efforts. However, our analysis finds no evidence of a more significant decline in future salaries for firms with low environmental scores following such disasters, contradicting this alternative explanation. Another concern is that firms with weaker environmental performance may face greater exposure to the physical risks of climate disasters, potentially affecting their ability to attract suitable candidates. However, our findings indicate that these firms do not experience increased climate-related physical shocks or heightened exposure following salient disasters. Taken together, these tests support our argument that the prolonged job vacancy durations observed for firms with low environmental performance after climate-related disasters are primarily driven by job seekers' heightened preference for environmentally responsible employers rather than alternative explanations.

This paper contributes to several strands of literature. First, we contribute to the literature on the economic consequences of climate risks. Existing studies have shown that extreme temperatures and weather events significantly affect firm revenues, profits, and sales (e.g., Addoum et al. 2023; Pankratz et al. 2023; Tran 2023). Climate risks also influence bond and stock prices (e.g., Choi et al. 2020; Huynh and Xia 2021). Additionally, Huang et al. (2022) find that firms tend to increase their environmental disclosure transparency following natural disasters. Our study is the first to document the impact of climate risks on job seekers' preferences. Given that human capital is a critical asset for firms, changes in job seekers' preferences can have significant implications for corporate performance and long-term competitiveness.

Second, this paper deepens the understanding of the factors that shape job seekers' preferences. Prior research has shown that various firm characteristics influence employer

attractiveness, including stock option offerings (Oyer and Schaefer 2005), financial distress (Brown and Matsa 2016), reputation (Benson et al. 2019), paid sick leave policies (Al-Sabah and Ouimet 2022), social networks (Hacamo and Kleiner 2022), workforce diversity (Choi et al. 2023), organizational structure (Gao et al. 2024), and startups' growth stage (Bernstein et al. 2024). More directly related to our study, existing research underscores the role of corporate environmental performance in attracting job seekers (Turban and Greening 1997; Aiman-Smith et al. 2001). We contribute to this literature by demonstrating that personal experiences with climate-related disasters shape individuals' preferences for employers based on their environmental performance.

Finally, this paper contributes to research on how salient events influence individual decision-making related to firms. Prior studies have examined how investors, analysts, and managers respond to such events (Dessaint and Matray 2017; Alok et al. 2020; Chen et al. 2020; Kong et al. 2021; Bourveau and Law 2023; Lins et al. 2024). Our study shifts the focus to employees, a crucial stakeholder group, and explores how their preferences are shaped by climate-related disasters. In this way, we complement recent work by Huang et al. (2024), which finds that job seekers place greater emphasis on the "Respect" dimension of firm culture following the Black Lives Matter movement. Our findings demonstrate that salient climate events similarly affect firms' 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

2.1.1 Economic consequences of climate risks

Firms are facing escalated concerns related to climate change, which exposes them to physical, reputational, and regulatory risks (Mbanyele and Muchenje 2022). Existing research

has recognized the effects of climate risks on capital market and corporate outcomes. For example, Bolton and Kacperczyk (2021, 2023) and Ilhan et al. (2021) examine how carbon emissions are priced in equity or option markets. Krueger et al. (2020) and Li et al. (2024) document that investors consider climate risks in their investment decisions. With respect to corporate outcomes, climate risks have significant impact on firm sales and financial performance (Huang et al. 2018; Addoum et al. 2020; Pankratz et al. 2023), the cost of capital (Sharfman and Fernando 2008; Chava 2014; Javadi and Masum 2022), and loan contracting terms (Huang et al. 2022). Given its significant effects, climate risk plays a role in various corporate policies, including the use of trade credit (Islam and Wheatley 2021), tax avoidance (Ni et al. 2021), earnings management (Ding et al. 2021), and labor investment decisions (Francoeur et al. 2023). Our paper contributes to this strand of research by investigating how extreme climate events, as a form of climate risk, impact corporate recruiting processes by influencing workers' preferences.

2.1.2 Determinants of workers' preferences for employers

The labor and corporate finance literature explores the interactions between firms and labor markets, identifying various factors that determine individuals' preferences for employers. For instance, Brown and Matsa (2016) find that corporate financial distress results in fewer and lower-quality job applicants, consistent with job seekers avoiding distressed firms to reduce their exposure to unemployment risk. Similarly, Baghai et al. (2021) find that workers with high skills abandon firms that approach bankruptcy. Focusing on economy-wide recessions, Bernstein et al. (2024) find that workers shifted their searches and applications away from less-established startups toward more-established ones during the COVID-19 downturn. Al-Sabah and Ouimet (2022) document that paid sick leave mandates are associated with reduced labor turnover and increased labor supply, mechanisms through which sick leave policies contribute to higher local employment level. Furthermore, Hacamo and Kleiner (2022)

find that social networks, by providing information about firm fundamentals to potential applicants, increase the likelihood of high-ability managers joining the firm. Exploiting the M&A advisory industry as a laboratory, Gao et al. (2024) find that firms with focused organizational form appeal more to high-performing workers than multi-divisional firms, and the resulting relocation of skilled labor shapes the structure of the industry. Overall, this body of research underscores the complex interplay between firm characteristics, labor market conditions, and individual preferences in shaping employment outcomes.

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 enhances their reputation and increases their attractiveness to prospective employees. Jones et al. (2014) further show that factors such as perceived pride, aligned values, and expected favorable employee treatment explain job seekers' preference for employers with environmentally responsible practices. Additionally, these preferences can vary with employees' personal characteristics such as gender, personality and ability (Burbano 2016; Non et al. 2022; Burbano et al. 2024). Our study investigates how personal experiences with climate disasters affect individuals' preferences for employers based on their environmental performance.

2.1.3 Salient events and individual decision making

Salient events have been shown to influence market participants' decision-making. Several studies examine how unexpected terrorist attacks, which induce temporarily negative emotions among the population, affect financial decisions. For example, Chen et al. (2020) find that the incidents of terrorist attacks, by posing exogenous shocks to investor sentiment, are associated with severer IPO underpricing. Wang and Young (2020) document significant aggregate outflows from equity fund into safer government bonds following the occurrence of terrorist activities, consistent with a fear-induced increase in risk aversion. Chen et al. (2020) and

Cuculiza et al. (2020) find that managers and analysts, respectively, tend to issue more pessimistic forecasts after local terrorist attacks. The evidence of these studies indicates the pronounced impact of salient events on individuals' risk perceptions and valuation decisions.

A burgeoning literature investigates the effects of salient climate events on corporate stakeholders' behaviors. This strand of research draws on extant psychology literature to argue that individuals may be influenced by salience bias, wherein they tend to overweight probabilities based on the ease with which events can be recalled. When such a bias is present, subjects overestimate the risk of salient events based on vividness, proximity, or emotional impact (Tversky and Kahneman 1973). For example, recent studies have shown that analysts who experienced major climatic disasters provide less optimistic earnings forecasts and their forecasts become less accurate than those by unaffected analysts (Bourveau and Law 2021; Kong et al.2021; Han et al. 2024).

Similar cognitive biases are observed among investors. Alok et al. (2020) find that relative to the distant funds, funds closer to the disaster zone reduce their portfolio holdings of firms located in the disaster area. Such trading response is transitory and not driven by information advantage, consistent with professional fund managers overestimating the adverse impact of disasters on stocks. Exploiting both the US corporate bond and stock markets, Huynh and Xia (2023) find that investors overreact to natural hazards, as suggested by depressed current bond and stock prices and higher future returns of exposed firms. Fich and Xu (2023) show that institutional investors hit by hurricanes are more likely to endorse an environmental proposal in a non-affected firm immediately after the disaster. However, upon passing environmental proposals, these firms exhibit non-trivial decreases in their market capitalization and downgrades by equity analysts. Choi et al. (2020) document that retail investors, but not institutional investors, sell shares of carbon-intense firms in the month when the local

temperature is abnormally high, consistent with people revising their beliefs about global warming upward when experiencing attention-grabbing weather events.[2]

Exposure to climate events also influences the activities of corporations and regulators. For instance, Huang et al. (2022) documents that firms impacted by natural disasters increase their ESG disclosure transparency in response to a change in investors' risk perception following the strike. Dessaint and Matray (2017) show that managers increase corporate cash holdings of their firms in response to sudden hurricane strikes as the disaster increases their concerns about potential liquidity shocks. Blann and Kleppe (2024) suggest that firms exposed to extreme weather cut their abnormal discretionary expenditure to meet short-term operational and financial goals. Fan, Nguyen, and Wu (2024) find that EPA offices exposed to major hurricanes increase their monitoring efforts at facilities located in their jurisdictions but outside the disaster zone. They further show that such heightened monitoring following disasters elicit greater enforcement charges, reduced pollution, and increased voluntary environmental disclosure of regulated facilities.

Overall, this stream of literature shows how various corporate stakeholders react to salient events. Our study aims to provide a new perspective on this literature by examining the reactions of job applicants.

2.2 Hypothesis Development

Our study examines the effect of climate disasters on job seekers' employment preferences. A salient climate event can drastically disrupt the routines of local community, causing considerable property losses, injuries, and even casualties (e.g., Fan et al. 2024). Exposure to the tangible consequences of climate disasters can heighten individuals' belief in and concern for climate change (Elgan and Mullin 2012; Myers et al. 2012; Zaval et al. 2014; Sisco et al.

[2] Choi et al. (2020) did not test whether the belief updating process is rational or irrational due to a relatively short sample period.

2017). Employees consider nonmonetary attributes—such as an organization's mission and values—when making employment choices, seeking employers whose values align with their own (Ashraf and Bandiera 2018; Cassar and Meier 2018). This increased environmental consciousness is likely to motivate individuals to scrutinize employers' environmental performance more closely and to disapprove of irresponsible corporate activities that can cause widespread environmental and social harm (Jones et al. 2014; Turban and Greening 1997). Therefore, we expect that job seekers will exhibit reduced interest in applying to local firms with poor environmental performance following significant climate events. In other words, environmentally underperforming firms located in the disaster zone become relatively less attractive to workers after such events. Formally stated,

***H1*: Following a climate disaster, disaster-area firms with poor environmental performance become less appealing to workers relative to same-area firms with good environmental performance.**

However, climate disasters may not have an impact on job seekers' employment preferences if individuals' attitude towards corporates' environmental performance remain unchanged after the disaster. This could be the case if job seekers consistently put much less weight on firms' environmental profiles than other factors (e.g., wages) when making their employment decisions. Alternatively, if firms with worse environmental performance take actions, such as increasing salaries to attract job applicants, as a compensation for the heightened disapproval resulting from disaster experience, we may not observe a significant change in job seekers' preferences in response to climate hazards. Furthermore, for job seekers who already prioritize environmental considerations, their preferences may have already led them to avoid firms with poor environmental records, making recent personal experiences with climate-related disasters less likely to further influence their employer preferences. Given these

opposing arguments, whether climate disasters affect firms' job vacancy duration is ultimately an empirical question.

3. Data, Sample, and Measurements

3.1. Data Source and Sample Construction

Table 1 describes the sample selection and filtering process. We obtained our initial job posting data from the LinkUP database between 2010 and 2022,[3] which assembles nearly all online job postings directly from employer websites. LinkUP provides information on posting creation and deletion dates, firm identifiers, the location of the job position tracked to the ZIP code level, and detailed job descriptions. Using its algorithm, LinkUp matches each job with an O*NET (i.e., occupation network) standard occupation code.[4] The database has been widely used in prior research on topics such as the informativeness of job vacancy duration for firms' future profitability (Chen and Li 2023), the impact of COVID-19 on the U.S. corporate hiring (Campello, Kankanhalli, and Muthukrishnan 2024), and the consequences of prolonged accounting job vacancy duration (Hann et al. 2024).

We use CUSIP codes to identify posting firms and exclude postings with vacancy durations exceeding 180 days or shorter than 1 day.[5] Our sample is restricted to U.S.-headquartered firms and job postings for positions located in the United States. To identify climate disasters, we use the natural disaster data in the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which has been widely used in prior literature on

[3] We start from 2010 to be consistent with Refinitiv ESG performance score starting year, and end in 2022 because of LinkUp availability.
[4] The O*NET-SOC taxonomy defines the set of occupations across the world of work. Based on the Standard Occupational Classification external site, the O*NET-SOC taxonomy includes about 900 occupations data collected from job incumbents or occupation experts. More information about O*NET code can be found at https://www.onetonline.org/.
[5] We remove evergreen jobs with vacancy durations of more than 180 days following Chen and Li (2023), and our main results are robust without this restriction.

the effects of climate disasters (Alok et al. 2020; Bourveau and Law 2021; Huynh and Xia 2023). Since SHELDUS reports disasters at the county level while LinkUp reports job locations at the ZIP code level, we match ZIP codes to counties. To minimize noise, we retain only postings in ZIP codes corresponding to a maximum of two counties. A ZIP code is considered to be affected by disaster if at least one of its mapped counties is stricken by disaster.

Environmental ratings are sourced from the Refinitiv ESG database, which assesses firms' relative ESG performance based on publicly reported data including corporate annual reports, ESG or CSR reports, stock exchange filings, the media, nonprofit organizations, government documents, and a variety of other sources. Refinitiv database has been widely used in ESG studies such as Hawn and Ioannou (2016), Dyck et al. (2019), and Wang (2023). We use the Environment Score as our firm-year E-performance measure. Accounting data and stock return data are from Compustat and CRSP, respectively. We require that all postings have non-missing data for the O*NET code and the main variables. Our final sample consists of 51,406,413 job posting observations in 1,261,864 zip-months for 17,492 firm-years.

3.2. Summary Statistics of Climate Disasters

Since the 1960s, SHELDUS has recorded the timing, type, location, and damage estimates of natural disasters in the U.S. Panel A of Table 2 summarizes the frequency and total damage (property + crop damage, inflation-adjusted to 2015 U.S. dollars) for 14 types of climate-related disasters from the SHELDUS database during our sample period.[6] Among the disasters, flooding causes the highest total damage loss ($136,063,483,904) and wind happens most frequently (61,588 county×months), consistent with the findings in extant literature (e.g., Alok et al. 2020). Panel B of Table 2 shows the distribution of damage amount of disasters

[6] We exclude and only exclude 4 types of hazards in SHELDUS that are not directly related to climate change: volcano, avalanche, tsunami/seiche, and earthquake.

aggregated to county × month level.[7] The average (median) damage amount is 3,204,968 (13,719) dollars, with a standard deviation of $95.5 million. Since hazards causing relatively small damage may have limited impact on local residents, we classify disasters with damage exceeding the 90th percentile ($465,551) as salient disaster events.[8]

3.3. Job Vacancy Duration

We use job vacancy duration as a proxy for job seekers' preferences. 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). Job seekers are less likely to apply for firms they perceive unfavorably, leading to fewer applications. Conditional on insignificant changes in labor demand,[9] a lower volume of applications reduces the likelihood of a firm successfully matching with a qualified candidate, thereby prolonging the time required to fill the vacancy.[10]

Following Chen and Li (2023), we measure job vacancy duration as the number of days between a job's creation and deletion dates. To validate the measure, Chen and Li (2023) show that the patterns of univariate variations of vacancy duration across job skill requirements, employee turnover, and unemployment rate are consistent with those patterns from Job Openings and Labor Turnover Survey (JOLTS) data. Although firms may hire employees without posting the positions online, prior research shows that LinkUp data broadly covers job

[7] Multiple disasters could strike the same county-month, in which cases we aggregate the damage amount of all types of disasters recorded in SHELDUS.

[8] For robustness checks, we use 95 percentile of damage amount, or 5 types of disasters related to global warming to define disaster-affected county×months, the empirical implications hold the same, and the regression results are presented in the Appendix B.

[9] We test this assumption in our context and find that the number of job vacancies posted by firms with worse environmental performance relative to those posted by firms with better environmental performance does not change significantly following climate disasters (Table OA-3).

[10] In a validation test, using historical labor force data between 2010 and 2022 from the Bureau of Labor Statistics, we find that the correlation between labor force and average posting duration at the county-month level is -0.024*** (t = -14.99), indicating that lower labor supply is associated with longer vacancy durations.

vacancies in US firms and provides a reasonable representation of corporate hiring (Chen and Li 2023; Campello et al. 2024).

4. Main Tests

4.1 Empirical Model and Variable Descriptive Statistics

4.1.1 Empirical model

To begin with, we examine whether job seekers incorporate firms' environmental performance in their decisions. We measure job posting duration as the time taken for firms to fill vacancies and regress the log-transformed duration on firms' prior-year environmental performance:

$$\ln(Duration_{j,i,l,t}) = \alpha\, E\text{-}perform_{i,t} + X_{i,t} + \theta_{o,t} + \gamma_{i,l,o} + \varepsilon_{j,i,l,t}, \quad (1)$$

where for job vacancy *j* posted by firm *i* in zip code location *l* over month *t*, ln(*Duration*) is the natural logarithm of the number of days to fill the vacancy. *E-perform* denotes the environmental performance of a firm as captured by the Refinitiv E-score of prior year. We control for basic firm-level characteristics ($X_{i,t}$) at the end of the quarter preceding month *t*, including firm size, ROA, leverage, book-to-market ratio, firm age, and annual stock return, which may also affect job seekers' preferences. $\theta_{o,t}$ represents occupation-by-year-by-month fixed effects and $\gamma_{i,l,o}$ denotes fixed effects for firm-by-state-by-occupation combinations. Occupation is defined by Standard Occupational Classification (SOC) obtained from O*NET system. We cluster standard errors by state in our analyses.[11] If firms with worse environmental performance take longer to fill vacancies, we expect α to be negative.

Next, we test our main hypothesis on the effect of climate disasters on job seekers' preferences. Our model specification is as follows:

$$\ln(Duration_{j,i,l,t}) = \beta_1\, Impacted_{l,t} \times \text{Worse } E\text{-}perform_{i,t} + \beta_2\, Impacted_{l,t}$$

[11] The results are robust to clustering standard errors by firm.

$$+ \beta_3 Impacted_{l,t} \times Size_{i,t} + \tau_{i,t} + \theta_{o,t} + \gamma_{i,l,o} + \varepsilon_{j,i,l,t}, \quad (2)$$

where $Impacted_{l,t}$ equals one if zip code l where the job is located experienced a climate disaster between month t-6 and month t, and zero otherwise. We consider a six-month lasting effect based on the assumption that individuals' preferences persist over a certain period.[12] *Worse E-perform* denotes firms with worse environment performance and equals one if Refinitiv E-score is lower than the posting sample median, 0.5963. The individual effects of $Worse\ E\text{-}perform_{i,t}$ are absorbed by firm-by-year fixed effects ($\tau_{i,t}$). Firm-by-year fixed effects also address the potential confounding effects of firm characteristics. We control for $Impacted_{l,t} \times Size_{i,t}$ to alleviate the concerns for the positive correlation between firm size and E-performance score. By focusing on within firm-by-state-by-occupation (controlling for $\gamma_{i,l,o}$), and within occupation-by-year-by-month changes (controlling for $\theta_{o,t}$), our specification removes the possibility that the relationship is driven by changes in the composition of employers or jobs observed in the data. We cluster standard errors by state.[13] If firms with worse environmental performance experience greater sensitivity in job vacancy duration in disaster-affected ZIP-months, we expect β_1 to be positive.

4.1.2 Variable descriptive statistics

Panel A of Table 3 presents descriptive statistics, while Panel B reports Pearson correlations for key variables. Variable definitions are detailed in the Appendix. We winsorize all firm-year accounting and stock return variables at the top and bottom 1% of the distribution to minimize the effect of outliers. The average (median) posting duration is 37.001 (24.000) days, and the standard deviation is 37.706, which implies that more than half of the posted positions are filled within 1 month. 19.3% of zip-months are affected by salient disasters. The average (median) environmental performance score in Refinitiv is 0.273 (0.189), and the

[12] Our results are robust to using current month, or current month and a 3-months lasting effect time window as disaster impacted time window. The regression results are presented in the Appendix B.
[13] The results are robust to clustering standard errors by firm.

standard deviation is 0.279. The average (median) firm size is 8.177 (8.116), the average (median) ROA is 0.025 (0.024), the average (median) leverage is 0.284 (0.256), the average (median) book-to-market ratio is 0.446 (0.371), the average (median) firm listed age is 16.850 (14.000), and the average (median) firm annual return is 0.158 (0.121), consistent with the firm characteristics in extant literature (e.g., Fich and Xu 2021; Li et al. 2022; Moss et al. 2023; Briscoe-Tran 2024).

In panel B of Table 3, job posting vacancy duration exhibits a weak positive correlation with the disaster indicator (0.001), a moderate negative correlation with the environmental performance score (-0.057), and stronger negative correlations with firm ROA (-0.078) and leverage (-0.121). While firms' environmental performance scores show moderate correlations with firm leverage (0.195) and firm age (0.255), it has a high correlation with firm size (0.618), consistent with the observations in extant literature (e.g., Darendeli et al. 2022). Given the strong correlation between environmental performance and firm size, our main analyses include an interaction term between worse environmental performance and firm size to control for this potential confounder.

4.2 Main Results

4.2.1 Environment Performance and Job Seekers' Preferences

In Equation (1), we examine whether job seekers incorporate firms' environmental performance in their decisions. We expect that, on average, job seekers prefer firms with higher environmental performance, leading to shorter job vacancy durations for these firms. Table 4 presents the regression results. Column (1) includes SOC-by-year-by-month fixed effects, while Column (2) further adds firm-by-SOC-by-state fixed effects. In both specifications, the E-performance coefficient is negative and statistically significant at the 1% level. Economically, the results from column (2) suggest that one standard deviation increase in E-performance is associated with 3.08% (= $-(e^{(-0.112*0.279)} - 1)$) reduction in the time required to

fill job vacancies. This is consistent with our expectation that job seekers prefer firms with higher E-performance. Additionally, we find that firms with larger size, lower ROA, higher leverage, lower book-to-market ratio, and lower annual stock returns take longer to fill their vacancies. Overall, our regression findings align with prior survey-based evidence, confirming that job seekers consider firms' environmental performance when making employment decisions.

4.2.2 Baseline results

To examine whether exposure to climate disasters affects job seekers' preferences, we first perform a survival analysis of job vacancy durations and compare the survival curves between 0 and 1 values of the interaction term *Impacted* × *Worse E-perform*. Figure 1 presents the Kaplan-Meier survival estimates, depicting the probability that a job vacancy remains unfilled over time. The y-axis is the proportion of the job postings "at risk" of not being filled (or surviving), while the x-axis shows the days since the job was posted online. The survival curve can be split into two groups (i.e., job postings following a climate disaster for firms with poor environmental performance vs. those not) to provide univariate evidence of the impact of salient climate events on the time for firms with poor E-performance to fill the position. The divergence between the two plots suggests that firms with poor environmental performance take longer to fill vacancies following a climate disaster compared to other firms. Also, the figure suggests that this effect persists over the entire month and is more pronounced for longer-duration postings than for positions filled within a few days.

Table 5 displays the results from estimating Equation (2), which tests H1. Column (1) presents a baseline model without fixed effects, while Columns (2) to (4) progressively add occupation-by-year-by-month, firm-occupation-state, and firm-year fixed effects. Across all four columns, the coefficients of the interaction term *Impacted* × *Worse E-perform* are positive

and statistically significant. To gauge the economic significance, the coefficient of 0.014 in Column (4) indicates that within areas affected by a climate disaster, the duration of job vacancies increases by 1.41% (= $e^{(0.014)} - 1$) for firms with poor environmental performance compared to that of firms with better environmental performance, which amount to 14.09% (=1.41%*37.001/(38.867-35.165)) of the duration mean value difference between better and worse E-performance firms. These results support H1's expectation that the duration of job vacancies increases following a climate disaster for firms with poor environmental performance located in the disaster-affected area.[14]

4.3 Dynamic Analysis

To validate the parallel trend assumption in interpreting the difference-in-differences estimates, we examine the pre-trends by generating indicator variables for three months before the disaster, the month of disaster occurrence, and six months after the disaster, respectively ($Impacted_{t+n}$, where n ranges between -3 and +6 and indicates the months between 3 months before and 6 months after the disaster). Should we find no significance for any pre-disaster month dummies, it indicates that the job vacancy duration does not significantly differ between high E-performance firms and low E-performance firms before the disaster, thereby supporting the validity of the parallel trends assumption.

We re-estimate our main specification using observations that experienced at most one disaster within the three months before to six months after the disaster, replacing the main treatment with $Impacted_{t+n} \times Worse\ E\text{-}perform_{i,t}$. The regression result is in the Online Appendix Table OA-1. Figure 2 shows the timing of disaster effects on poor E-performance firms around the disaster strike time. The shaded area denotes a 90% confidence interval. We

[14] In untabulated results, we assess the cost of climate disasters on firms with poor environmental performance from the perspective of stock performance. We find that, during the observation period from the month of a climate disaster at a firm's headquarters to three months afterward, cumulative abnormal returns (DGTW-adjusted, Fama–French three-factor model, market value-weighted adjusted, or equal-weighted adjusted) decline significantly for firms with poor environmental performance compared to those with better environmental performance.

indeed find that the timing of observed effects lines up with disaster strike time. That is, substantial duration effects only emerge in the current, second, and fifth months following the disaster. This finding mitigates concerns that unobserved contemporaneous trends, rather than the disaster treatment, drive the observed effects. Furthermore, the dynamic analysis results show no significant effect in the sixth months after the disaster struck, potentially because local job seekers may have relocated as enough time has passed since the disaster (Gutmann and Field 2010).

4.4 Neighborhood Area Test

One key challenge in our baseline research design is that climate-related disasters may not only influence local job seekers' subjective preferences but also directly disrupt the hiring process, potentially affecting high and low E-performing firms differently. To address this issue, we follow Dessaint and Matray (2017) and define three geographic perimeters based on proximity to the disaster area: the disaster zone, the neighborhood area, and the remainder of the U.S. mainland. The disaster zone encompasses all counties directly impacted by the disaster (i.e., *Impacted* = 1). The neighborhood area is constructed by matching each impacted county with its fourteen geographically closest counties, excluding those in the disaster zone. [15] County distances are computed using the average latitude and longitude of all cities in the county. This matching process yields a set of matched counties comprising the neighborhood area and a separate set of non-matched counties representing the remainder of the US mainland. On average, counties in the neighborhood area are 55.777 miles from the affected counties.

In this analysis, we isolate job postings within the disaster zone to account for the direct effects of disasters on local job seekers. Job postings in the neighborhood area are included in

[15] We find that a county in our sample has at most 14 adjacent counties. To obtain a balanced neighbor county list for each affected county, we use the 14 closest non-affected counties here as neighborhood areas. Our results remain the same when we use 12, 13, 15, or 16 rather than 14 nearest non-affected counties. We drop the directly impacted counties from the 14 closest county list if included.

the treatment group, as disasters are expected to be salient events for job seekers in these areas due to their proximity to the affected zone. As a near-miss event, the disaster likely captured their attention, given that they narrowly avoided being directly affected. In contrast, job postings in the remainder of the U.S. mainland are assigned to the control group, as climate disasters in distant regions are unlikely to influence their job seeker decisions. Some job seekers in the control group may even be entirely unaware of the disaster, particularly if they reside in areas where climate-related risks are perceived as negligible.

Table 6 presents the results of estimating Equation (2) with this refined treatment definition. Column (1) uses the 14-nearest-county definition for the neighborhood area, while Column (2) expands the definition to 20-nearest counties for robustness checks. The coefficients on *Impacted_neighbor* × *Worse E-perform* in both columns are both positive and statistically significant, indicating that job seekers in counties neighboring those affected by climate-related disasters are less willing to work for E-underperforming firms. These results are consistent with H1, reinforcing the idea that climate disasters heighten job seekers' sensitivity to firms' environmental practices.

5. Current Employees' Decisions

Our findings to this point establish that job seekers exhibit reduced interest in firms with poor environmental performance following a salient disaster. A natural follow-up question is whether incumbent employees have similar reactions. If they share the same concerns, they could be less tolerant of environmental violations and more likely to leave the firms with unsatisfactory E-performance after experiencing climate events. To gauge this possibility, we examine whether salient disasters differentially affect (1) employee turnover, specifically whether employees are more likely to move to firms with better environmental performance and less likely to move to firms with worse environmental performance, and (2) current employee overall ratings and E-related comments about their employers. If salient disasters

change current employees' sensibility to environmental issues, we expect to observe a higher likelihood of employees flowing to better environmental performers, a lower likelihood of employees flowing to worse environmental performers, and more negative E-related comments about their current employers.

5.1 Employee Turnover Decisions

Carnahan et al. (2017) document that law firms with stronger CSR performance experience lower turnover rates, as they better fulfill employees' desire for meaning and purpose at work. To examine whether a salient disaster influences employees' turnover decisions, we use firm-MSA-month level turnover rates constructed from public résumé data provided by Revelio Labs.[16] Revelio Labs aggregates workforce information from online professional profiles, company websites, and layoff notices. Since online profiles are more common among white-collar workers, Revelio Labs applies proprietary algorithms to adjust for the underrepresentation of lower-tier workers. From this dataset, we obtain the number of employees leaving a firm-MSA each month and the total number of employees at the same firm-MSA-month.

Specifically, *Turnover_To_Better_E-performers* (*Turnover_To_Worse_E-performers*) is measured as the number of employees who depart the firm-MSA in a given month and move to the next employer with better (worse) environmental performance relative to the current firm, divided by the total employees at the firm-MSA in the previous month following Trevor and Nyberg (2008).[17] Then we replace the dependent variable of Equation (2) with *Turnover_To_Better_E-performers* and *Turnover_To_Worse_E-performers* respectively, and estimate the regression using the sample at the firm-MSA-month level.

[16] We use MSA as the aggregated location since it is the most detailed geographic information available from the Revelio Lab.

[17] The results remain robust if deflated by the current month's employee headcount following Li et al. (2022) or by average employee headcount across all months of last year's employee headcount following Gu et al. (2023) when constructing employee flow turnover measures.

Table 7 presents the results controlling for firm-MSA and firm-year fixed effects. In column (1) using *Turnover_To_Better_E-performers* as the dependent variable, we find a positive and significant coefficient on *Impacted* × *Worse E-perform*, and in column (2) using *Turnover_To_Worse_E-performers* as the dependent variable, we find a negative and significant coefficient on *Impacted* × *Worse E-perform*, consistent with current employees being more inclined to flow to a better E-performing firm, and less willing to flow to a worse E-performing firm, after a climate disaster. Collectively, our findings indicate that salient climate events heighten employees' awareness of corporate environmental responsibility, influencing their turnover decisions.

5.2 Current Employees' Perceptions

Briscoe-Tran (2024) shows that employees have useful information about firms' ESG practices and discuss corporate ESG topics on Glassdoor, a crowd-sourcing company that collects employee reviews. Using the E-related word list from Briscoe-Tran (2024), we test whether a salient disaster changes current employee perspectives about their employers. Specifically, we replace the dependent variable of the Equation (2) with the overall rating and the percentage of E-related words in employees' textual comments on Glassdoor. This analysis covers the period 2014-2019. We include review-level controls including the employee's gender, age, educational background, whether the employee is a regular worker, length of employment, and whether the employee works in the firm headquarters (Teoh et al. 2023).

Table 8 presents the regression results. Column (1) uses each review's overall rating as the dependent variable. The coefficient of *Impacted* × *Worse E-perform* is significantly negative, which indicates that following a climate disaster, current employees rate poorly E-performing firms more negatively. Column (2) uses *Comment_E_cons* as the dependent variable, which equals the E-related word percentage in the employee's Cons comment. The coefficient on *Impacted* × *Worse E-perform* is positive and significant, suggesting that employees express

greater concerns about their employers' environmental performance following a disaster. In contrast, when we use *Comment_E_pros*, which equals the E-related word percentage in the employee's Pros comment, as the dependent variable (Column (3)), we find an insignificant coefficient on *Impacted* × *Worse E-perform*, indicating that current employees' positive views related to environment issues do not change after climate disasters.[18] In summary, following climate disasters, employees of firms with worse E-performance tend to rate their employers lower and express greater concern about environmental issues compared to those at firms with better E-performance. These findings suggest that climate disasters increase employees' sensitivity to firms' environmental performance, reinforcing the importance of corporate environmental responsibility in employee retention and satisfaction.

6. Alternative Explanations

Our model specification in Equation (2) employs an approach to examine the differential impacts of salient disasters on firms with poorer environmental performance relative to better performers. To mitigate potential confounding effects, we include firm-by-year, occupation-by-year-by-month, and firm-by-occupation-by-state fixed effects, ensuring that our coefficient estimations focus on within-firm-year, occupation-month, and firm-location-occupation variations, strengthening the causal interpretation of our findings. Furthermore, the neighborhood area test in Section 4.4 addresses alternative explanation concerns that climate-related disasters might just directly damage local firms or disrupt the hiring process, rather than influencing job seekers' preferences.

[18] In untabulated results, we also use *Comment_S_cons*, *Comment_S_pros*, *Comment_G_cons*, and *Comment_G_pros*, constructed in the same logic as *Comment_E_cons* and *Comment_E_pros* but focus on the S- or G-related words in employee comment, as dependent variables respectively. The coefficients of *Impacted* × *Worse E-perform* are all insignificant, providing a reasonable indication that current employees' views related to social and governance toward their poor environmental performance employers are not affected by the natural disaster.

However, beyond our proposed mechanism – where heightened job seeker awareness of environmental protection reduces their willingness to work for environmentally irresponsible firms following a disaster – two alternative mechanisms from the job seeker side could potentially lead to our findings: (1) Compensation concerns: Job seekers may expect poorly E-performing firms suffering greater losses following climate-related disasters, potentially affecting employee salaries. As a result, they may place greater importance on firms' E-performance when making employment decisions; (2) Workplace safety concerns: After experiencing a climate disaster, individuals may worry that firms with poor E-performance are more vulnerable to physical shocks and may be exposed to higher workplace safety risks in future extreme weather events.

To explore whether job seekers' concerns about compensation or firm physical shock exposure drive our findings, we conduct two analyses. First, we examine whether salary disclosure and salary amount are different between high and low E-performing firms following disasters. Second, we examine whether environmentally underperforming firms are exposed to relatively higher physical risks following climate-related disasters, and whether our main results are stronger in jobs with higher climate risk exposure than the others.

Additionally, to further alleviate concerns from the labor demand side, we directly investigate whether environmentally underperforming firms decrease labor demand or make more efforts to improve E-performance following disasters.

6.1 Salary

We scrape the description context of each job posting in LinkUP to obtain information about the salary for the position. First, we examine whether firms adjust their voluntary salary disclosure behavior in response to a disaster. To ensure accuracy, we exclude postings where salary disclosure is mandatory. Column (1) of Table 9 shows no significant change in the likelihood of voluntary salary disclosure. Moving to salary level, we also find insignificant

changes in the disclosed salary amount for E-underperforming firms following a climate event (Column (2)). In summary, the results suggest that the prolonged job vacancy duration for poorly E-performing firms following disasters is less likely driven by job seekers' concerns about uncompetitive salaries.

6.2 Climate Physical Shocks

To assess whether environmentally underperforming firms face greater climate-related physical risks, we obtain climate change-related physical shock risk and exposure from Sautner et al. (2024), which utilizes conference call transcripts to construct firm-quarter-level measurements of climate change-related physical shock exposure and risk. The exposure is quantified as the extent to which climate change-related physical shock topics capture the attention of call participants, and the risk is measured by the relative frequency of the climate change-related physical shock bigrams mentioned in the same sentence with the words "risk", "uncertainty", or their synonyms.[19] We define each firm's location based on its headquarters state from 10-K filings and identify whether a firm is affected by climate disasters based on disaster impact at the headquarters location.[20]

Table 10 presents the results. In Columns (1) and (2), we assess whether climate change-related physical shock risk and exposure vary with a firm's environmental performance. The coefficients on E-perform are statistically insignificant, suggesting that poorly E-performing firms do not face significantly higher climate-related physical risks or exposure. In Columns (3) and (4), we further examine whether the relative climate physical shock risk increases for E-underperforming firms after disasters. The coefficients on *Impacted* × *Worse E-perform* are negative and insignificant, indicating that these firms do not experience higher climate-related physical risk or exposure post-disaster. These findings contradict the demand-side explanation

[19] See Sautner et al. (2023) page 1459-1462 for more details of measurement constructions.
[20] We obtain the historical firm-year level headquarters location from Loughran-McDonald header data, downloading from: https://sraf.nd.edu/sec-edgar-data/10-x-header-data/

that worse E-performing firms face greater exposure to physical risks that contribute to prolonged job vacancy durations following salient disasters.

Next, we categorize job postings based on climate risk exposure and test whether our main effects differ across job types. If workplace safety concerns were the primary driver, we would expect stronger effects for jobs with high climate risk exposure. Following Xiao (2021), we use U.S. Department of Labor's O*NET program data to measure job exposure to climate risk based on responses to: "How often does this job require working outdoors, exposed to all weather conditions?" Each occupation receives a score from 1 to 5, with higher scores indicating greater climate exposure. We classify job postings into high- and low-exposure groups based on the median score and estimate Equation (2) separately for both groups (Table OA-2). The results show that the increase in job vacancy duration following disasters is more pronounced for jobs with low climate exposure. However, the difference in coefficients between the two groups is not statistically significant, suggesting that workplace safety concerns are not the primary driver of our findings.

6.3 Other Alternative Explanations

Additionally, we directly investigate whether the prolonged job vacancy duration for environmentally underperforming firms following salient disasters can be attributed to changes in labor demand or firms' efforts to improve E-performance. First, we examine labor demand by analyzing job posting volumes at the firm-zip-month level (Table OA-3). The coefficients on Impacted × Worse E-perform are negative but statistically insignificant, indicating no significant reduction in labor demand for E-underperforming firms after disasters, contradicting the demand-side explanation that these firms decrease hiring after disasters. Second, we explore whether firms with poor E-performance alter their hiring strategies to improve environmental performance. Using O*NET codes to distinguish green vs. non-green jobs following Darendeli et al. (2022), we find that job vacancy duration increases significantly

only for non-green job postings (Table OA-4). This suggests that E-underperforming firms do not selectively delay hiring for green jobs, alleviating concerns about firms strategically adjusting recruitment to enhance their environmental reputation. Lastly, we analyze firm-state-year E-violation records with fine amounts from the Violation Tracker database to assess whether E-underperforming firms improve their environmental performance after disasters (Table OA-5).[21] The insignificant coefficients on Impacted × Worse E-perform indicate no substantial changes in E-performance, further ruling out the demand-side explanation that firms adjust recruiting strategies to enhance their environmental practices.

Our findings collectively indicate that prolonged job vacancy durations for E-underperforming firms after disasters are not driven by concerns about compensation, workplace safety, firm vulnerability to physical shocks, changes in labor demand, or firms' efforts to improve E-performance. Instead, they are most consistent with increased job seeker awareness of climate change issues, leading to greater preference for environmentally responsible employers.

7 Robustness Checks

7.1 Issues with Firms Changing Posting Strategies After Disaster

While our main findings are consistent with the unfavorable attitudes of job seekers toward E-underperforming firms following a climate disaster, we recognize the concern that firms may adjust their recruiting and job posting strategies after being struck by a disaster, potentially driving our results. To mitigate this concern, we redefine the $Impacted_{l,t}$ variable as 1 if the job vacancy was posted no more than 15 days before a climate disaster in location *l*, and 0 otherwise. Besides, we exclude the job postings located where a salient disaster strikes in months *t*, *t*-1, *t*-2, *t*-3, *t*-4, *t*-4, or *t*-6 to mitigate post-disaster posting effects, and remove job postings filled

[21] Using the Refinitiv E-Score next year as dependent variable leads to the same empirical implication.

before the next month to make the redesigned treated sample "be really treated", that is, ensure that the redesigned treated sample's vacancy period cover the disaster striking time.

We re-estimate our main specification using this revised definition of $Impacted_{l,t}$ and present the results in Column (1), Appendix B. The coefficient on the interaction term *Impacted* × *Worse E-perform* is significantly positive, which corroborates our baseline findings and alleviates the concern that our results are driven by changes in firms' recruiting strategies.

7.2 Issues with Remote Job Seekers

In our baseline test, the location information reflects the job posting location, however, some positions allow remote work, meaning a job seeker in a disaster-unaffected area could accept a job in a disaster-affected area, and vice versa. To address this concern, we exclude all job postings with O*NET codes identified as remote work applicable, following Dingel and Neiman (2020), to ensure that job seekers are tied to the job posting location. Then we re-estimate our main specification and present the results in Column (2), Appendix B. The coefficient on the interaction term *Impacted* × *Worse E-perform* is significantly positive, confirming that our baseline findings are not driven by remote job seekers.

7.3 Alternative Measures of Exposure to Saliant Climate Disaster

Our inferences rely on proper measurement of disaster-affected location-times. Therefore, we conduct several procedures to ensure that our main finding is robust to alternative ways of measuring disaster-affected location-times.

Specifically, in the order of columns (3) – (6) in Appendix B, our findings remain robust across all alternative measures of defining $Impacted_{l,t}$ to be one (and zero otherwise) if: job location *l* experienced a salient disaster in month *t* (Column (3)); job location *l* experienced a salient disaster in month *t*, *t*-1, *t*-2, or *t*-3. Besides (Column (4)), our finding is robust to changing the definition of salient disaster location of $Impacted_{l,t}$ to equal to one (and zero otherwise) if in month *t*, *t*-1, *t*-2, t-3, t-4, t-5, t-6, job location *l*'s aggregated disaster damage

amount exceeds the 95 percentile value (Column (5)); job location *l* experienced at least one of the 5 types of disasters more directly related to global warming (i.e., drought, flooding, heat, hurricanes, and wildfire) following Huang et al. (2022) (Column (6)).

7.4 Alternative Measures of Environmental Performance

Our primary measure of E-performance, i.e., the E-rating from Refinitiv, is designed to transparently and objectively measure a firm's relative ESG performance based on publicly available data. However, one may argue that job seekers may not have direct access to this rating when forming perceptions about firms' E-performance. To mitigate this concern, we rerun our main tests using a media-based E-performance measure obtained from the RepRisk database. RepRisk daily screens over 80,000 media, regulatory, and commercial documents for negative ESG-related issues. Once an issue is identified, RepRisk analysts conduct additional filtering and analyses to verify that the issue is indeed ESG-related, remove duplicates, and identify the specific nature of the issue and classify it into one of 30 predefined ESG categories. Each issue is assigned two proprietary scores of *Severity* (the magnitude of the perceived impact of the issue) and *Reach* (the influence or the readership of the source documents). Table OA-6 shows that our findings are robust to three alternative ways of measuring E-performance: (1) consider a firm-year as having worse E-performance if the number of E-related issues is greater than the sample median; (2) consider a firm-year as having worse E-performance if *Severity* is higher than the sample median; (3) consider a firm-year as having worse E-performance if *Reach* higher than the sample median.

Another concern with our environmental performance measures is the potential correlation among E, S, and G scores, which may cause the worse E-performance indicator to also reflect poor S or G performance.[22] To address this issue, we regress E on S or G and use the residuals

[22] In our sample, the Pearson correlation coefficient is 0.830 between E-score and S-score, and 0.435 between E-score and G-score.

as the orthogonal component to isolate E-performance. Table OA-7 demonstrates that our findings remain robust when E-performance is measured after orthogonalizing (1) both S and G, (2) S alone, and (3) G alone, alleviating the concern that our findings are driven by correlations with social or governance factors.

7.5 Firm-location-month aggregated main results

Our main tests use job posting as the unit of analysis, which may raise concerns that unmeasured job-specific characteristics may influence our findings. To mitigate this concern, we aggregate job postings to the firm-ZIP-month level, and use the averaged *Duration* as the dependent variable. We then re-estimate our main specification using weight least squares regressions, where the weight is the number of postings of each firm-zip-month group before aggregation. Table OA-8 presents the baseline results, and Table OA-9 presents the results for the dynamic analysis. Our main findings remain robust to using this firm-location-month aggregated sample.

8. Conclusion

Extreme climate is a pressing issue that poses significant threats to individuals' daily lives across the globe. In this study, we seek to understand the economic implications of climate risks by examining the impact of climate disasters on job seekers' employment preferences regarding corporate environmental performance. Using novel job posting datasets in the U.S. market, we find that firms with poorer E-performance experience longer job vacancy durations following climate disasters, indicating that climate disasters lead to increased difficulties in hiring for these firms. Dynamic analysis reveals significant effects over time post-disaster. Beyond job seekers, we find that current employees exposed to a disaster exhibit worse overall ratings and express more environment-related concerns about their environmentally underperforming employers, and those employers experience increased employee outflow to

better E-performers, and decreased employee outflow to worse E-performers following the disaster, consistent with the notion that job seekers and employees reduce tolerance for environmentally irresponsible employers following a climate disaster, thus extending the hiring process for the underperforming firms.

Additional analyses show that the prolonged job vacancy duration for firms with poor E-performance following disasters is more likely to be driven by job seekers' increased awareness of climate change issues, which makes them prefer working for environmentally responsible firms. 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 disruptive climate disasters influence labor market dynamics, our study contributes to the broader literature on the economic consequences of climate risks and sheds light on the growing importance of corporate environmental responsibility in attracting and retaining talent.

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Figure 1: Survival Analysis

Figure 1 shows the Kaplan–Meier estimate of the survival function based on our baseline samples and restricted analysis time window within the first 30 days of the postings. The figure presents evidence of the interaction of *Impacted* and *Worse E-perform* on the likelihood of the posting position not being filled, that is, surviving in the job market. Lower (higher) lines indicate a higher (lower) likelihood of filling the vacancy at the same analysis time.

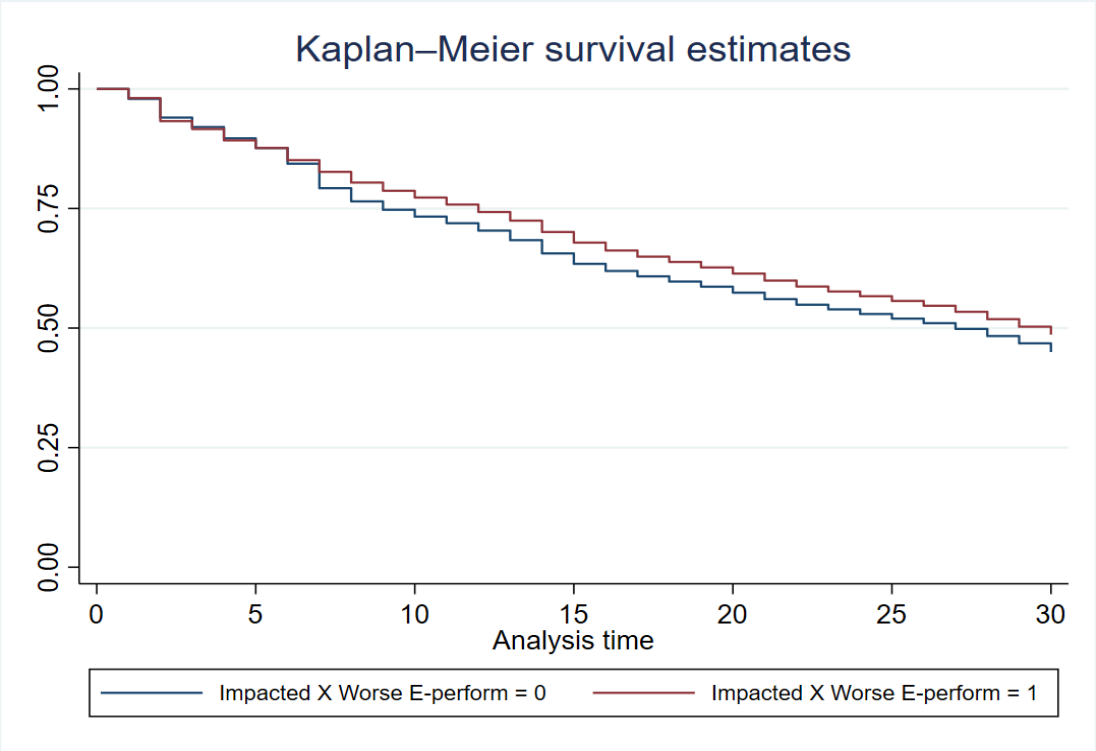


Figure 2: Dynamic Analysis

This figure shows the dynamic impact on job vacancy duration of poor E-performance firms around a climate disaster. The figure plots coefficients β_{1n} from the following specification:

$$\mathrm{Ln}(Duration_{j,i,l,t}) = \sum_{n=-3}^{n=4} \beta_{1,n}\, Impacted_{\mathrm{l,t+n}} \times \mathrm{Worse}\; E-perform_{i,t} + \sum_{n=-3}^{n=4} \beta_{2,n}\, Impacted_{\mathrm{l,t+n}} \times \mathrm{Size}_{i,t} + \beta_3\, Impacted_{\mathrm{l,t}} + \tau_{i,t} + \theta_{o,t} + \gamma_{i,l,o} + \varepsilon_{j,i,l,t},$$

The solid line denotes point estimates. The shaded area denotes a 90% confidence interval. The regression result table is in Online Appendix Table OA-1.

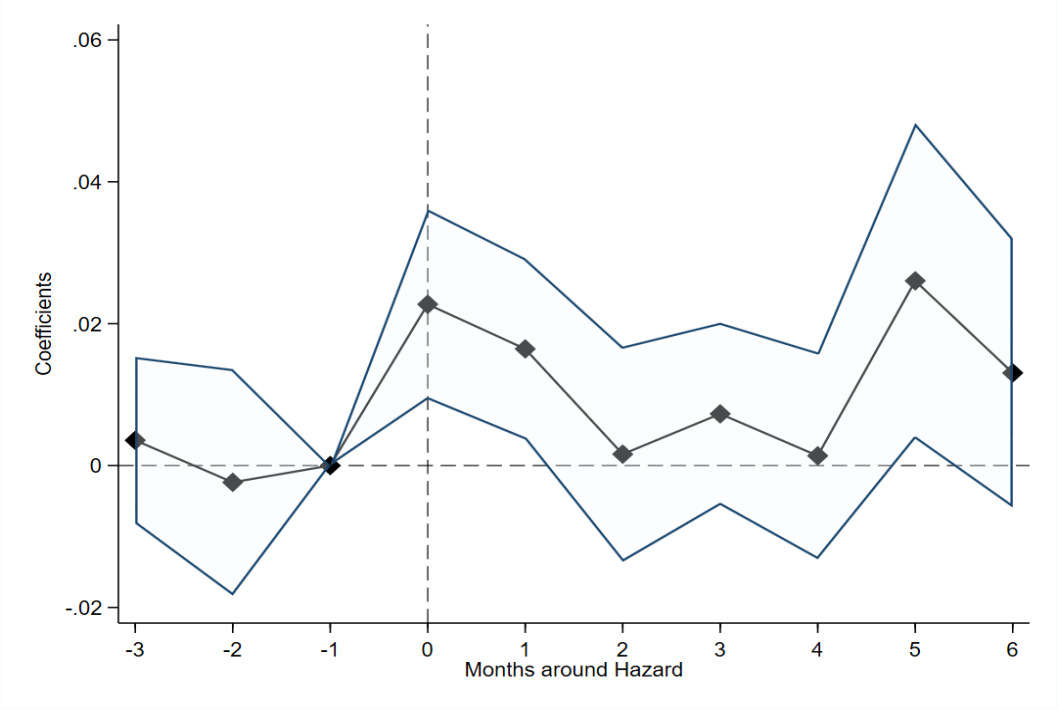


Table 1: Sample Selection

This table lists the sample selection procedures.

Sample Selection Criteria	Number of Observations
Total number of postings (2010-2022)	163,855,124
After dropping firms NA CUSIP	86,986,766
After dropping Duration not in [1,180]	79,179,030
After dropping NA zip & zip mapping to > 2 counties	67,474,771
After dropping headquarter not in the US	57,958,788
After dropping NA ONET code	57,958,700
After dropping NA Environmental rating in Refinitiv	51,927,578
After dropping NA variables in the baseline test	51,406,413

Table 2: Distribution of Climate-related Disaster Types and Damage Amount

Panel A and Panel B report the descriptive statistics of climate-related disaster damage amount and frequency by disaster type, and county-month aggregated disaster damage amount, respectively.

Panel A: disaster types and damage amount

Disaster	Damage amount	Freq. (# of county×month)	Freq. %	Average Loss/county×month
Flooding	136,063,483,904	17,576	10.902	7,741,436
Hurricane/Tropical Storm	63,122,718,720	1,575	0.977	40,077,917
Tornado	25,467,711,488	7,148	4.434	3,562,914
Wildfire	24,451,571,712	1,714	1.063	14,265,794
Hail	19,721,185,280	5,351	3.319	3,685,514
Drought	16,955,762,688	3,053	1.894	5,553,804
Wind	12,581,768,192	61,588	38.203	204,289
Winter Weather	5,886,562,816	6,940	4.305	848,208
Severe Storm/Thunder Storm	2,244,480,512	47,780	29.638	46,975
Landslide	1,292,412,288	722	0.448	1,790,045
Lightning	373,000,352	4,628	2.871	80,596
Coastal	276,678,304	1,184	0.734	233,681
Heat	36,866,504	930	0.577	39,641
Fog	19,635,982	164	0.102	119,732

Panel B: County-month aggregated disaster damage amount distribution

VarName	Obs	Mean	SD	Min	P5	P10	P25	Median	P75	P90	P95	Max
Damage amount	97,061	3,204,968	95,500,000	0	254	944	3,097	13,719	70,000	465,551	1,647,187	12,100,000,000

Table 3: Descriptive Statistics

Panel A reports the descriptive statistics; Panel B reports the Pearson correlations among the main variables, correlation coefficients that appear in boldface are significant at the 10% level.

Panel A: Descriptive statistics of main variables

VarName	Obs	Mean	SD	Min	P10	P25	Median	P75	P90	Max
Posting Level										
Duration	51,406,413	37.001	37.706	1.000	4.000	9.000	24.000	52.000	92.000	180.000
Zip-month level										
Impacted	1,261,864	0.193	0.395	0.000	0.000	0.000	0.000	0.000	1.000	1.000
Firm-year level										
Worse E-perform	17,492	0.822	0.383	0.000	0.000	1.000	1.000	1.000	1.000	1.000
E-perform	17,492	0.273	0.279	0.000	0.000	0.000	0.189	0.487	0.719	0.985
Size	17,492	8.177	1.653	4.996	6.006	7.036	8.116	9.264	10.357	13.839
ROA	17,492	0.025	0.030	-0.025	-0.007	0.006	0.024	0.039	0.058	0.246
Leverage	17,492	0.284	0.236	0.000	0.017	0.094	0.256	0.412	0.575	2.439
BM	17,492	0.446	0.387	-0.908	0.070	0.186	0.371	0.648	0.958	1.636
Age	17,492	16.850	14.078	0.000	2.000	5.000	14.000	24.000	41.000	52.000
Annualret	17,492	0.158	0.394	-0.548	-0.301	-0.094	0.121	0.349	0.628	1.394

Panel B: Correlations of main variables

	Duration	Impacted	Worse E-perform	E-perform	Size	ROA	Leverage	BM	Age	Annualret
Duration	1									
Impacted	**0.001**	1								
Worse E-perform	**0.049**	**0.002**	1							
E-perform	**-0.057**	**-0.003**	**-0.863**	1						
Size	**0.011**	**0.002**	**-0.539**	**0.618**	1					
ROA	**-0.078**	**-0.010**	**-0.104**	**0.093**	**0.068**	1				
Leverage	**-0.121**	**-0.026**	**-0.176**	**0.195**	**0.007**	**0.601**	1			
BM	**0.026**	**0.018**	**0.090**	**-0.062**	**-0.123**	**-0.449**	**-0.496**	1		
Age	**0.032**	**-0.007**	**-0.255**	**0.254**	**0.262**	**0.022**	**-0.127**	**-0.035**	1	
Annualret	**-0.008**	**0.002**	**-0.001**	**-0.008**	**0.157**	**0.103**	**0.019**	**-0.197**	**0.012**	1

Table 4: Environment Performance and Job Duration

This table reports the results of estimating the firm E-performance effect on job vacancy duration next year from Equation (1). Columns (1) to (3) report the results of estimating the Equation augmented with no fixed effect, occupation-by-year-by-month fixed effects, and occupation-by-year-by-month and firm-by-occupation-by-state fixed effects, respectively. The observation differences among columns result from dropping singletons when controlling for 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.

Dep. 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)
Observations	51,406,413	51,397,059	51,003,118
R-squared	0.021	0.133	0.325
Fixed Effects	No	SOC-Month	SOC-Month Firm-SOC-State
Cluster	State	State	State

Table 5: Baseline Results

This table reports the results of estimating the climate disaster effect on job seekers' preferences for poor E-performance firms from Equation (2). Columns (1) - (4) report the results of estimating the equation augmented with no fixed effects, occupation-by-year-by-month fixed effects, occupation-by-year-by-month and firm-by-occupation-by-state fixed effects, occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects, respectively. The observation differences among columns result from dropping singletons when controlling for 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.

Dep. Variable:	ln(Duration)			
	(1)	(2)	(3)	(4)
Impacted × Worse E-perform	0.047*	0.032*	0.027***	0.014***
	(0.025)	(0.019)	(0.010)	(0.005)
Impacted	-0.062	-0.043	-0.023	-0.019
	(0.077)	(0.058)	(0.023)	(0.013)
Impacted × Size	0.004	0.002	-0.000	0.000
	(0.008)	(0.006)	(0.002)	(0.001)
Firm-Year Control Variables	Yes	Yes	Yes	No
Observations	51,406,413	51,397,059	51,003,118	51,002,948
R-squared	0.021	0.133	0.325	0.363
Fixed Effects	No	SOC-Month	SOC-Month Firm-SOC-State	SOC-Month Firm-SOC-State Firm-Year
Cluster	State	State	State	State

Table 6: Neighbor County Results

This table reports the results of estimating the climate disaster effect on job seekers' preferences for poor E-performance firms from Equation (2) excluding samples directly impacted by the climate disaster, but redefining impacted areas as neighbor counties geographically close to the directly impacted county. Columns (1) and (2) report the results of estimating the equation augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects. Singletons are dropped. Column (1) uses 14 closest non-directly-affected counties as neighborhood areas, and Column (2) uses 20 closest non-directly-affected counties as neighborhood areas, both excluding samples in the directly disaster-impacted counties. 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.

Dep. Variable:	ln(Duration)	
	(1)	(2)
Impacted_neighbor × Worse E-perform	0.010**	
	(0.004)	
Impacted_neighbor	-0.025**	
	(0.011)	
Impacted_neighbor × Size	0.001	
	(0.001)	
Impacted_neighbor_20 × Worse E-perform		0.014***
		(0.004)
Impacted_neighbor_20		-0.027*
		(0.014)
Impacted_neighbor_20 × Size		0.001
		(0.001)
Observations	39,216,968	39,470,623
R-squared	0.370	0.369
Fixed Effects	SOC-Month	SOC-Month
	Firm-SOC-State	Firm-SOC-State
	Firm-Year	Firm-Year
Cluster	State	State

Table 7: Employee Flow Turnover

This table reports the results of estimating the climate disaster effect on current employees' desire to leave the worse E-performance firms and flows to better or worse E-performance firms by replacing dependent variables of Equation (2) using the firm-MSA-month aggregated employee job profile sample. Column (1) uses employee turnover flowing to better E-performance firms than the current firm as the dependent variable. Column (2) uses employee turnover flowing to worse E-performance firms than the current firm as the dependent variable. Both columns control for firm-by-MSA and firm-by-year fixed effects. Singletons are dropped. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the MSA level.

Dep. Variable:	Turnover_To Better E-performers	Turnover_To Worse E-performers
	(1)	(2)
Impacted × Worse E-perform	0.015**	-0.003**
	(0.007)	(0.001)
Impacted	-0.014	0.002
	(0.024)	(0.002)
Impacted × Size	0.001	0.000
	(0.002)	(0.000)
Observations	9,807,734	9,807,734
R-squared	0.052	0.128
Fixed Effects	Firm-MSA	Firm-MSA
	Firm-Year	Firm-Year
Cluster	MSA	MSA

Table 8: Current Employee Perceptions

This table reports the results of estimating the climate disaster effect on current employees' perspectives for poor E-performance firms by replacing dependent variables of Equation (2) using the Glassdoor review sample. Columns (1) - (3) use overall rating, E-related word percentage in Cons comment, and E-related word percentage in Pros comment as dependent variables, respectively. All columns control for occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects. Singletons are dropped. All main 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.

Dep. Variables:	Overall_rating	Comment_E_cons	Comment_E_pros
	(1)	(2)	(3)
Impacted × Worse E-perform	-0.049*	0.036**	-0.002
	(0.026)	(0.015)	(0.017)
Impacted	-0.006	-0.007	0.049
	(0.087)	(0.046)	(0.037)
Impacted × Size	0.001	0.001	-0.004
	(0.008)	(0.004)	(0.003)
Female	-0.042**	-0.004	-0.014*
	(0.016)	(0.008)	(0.007)
EmployeeAge	-0.011***	0.001	0.001**
	(0.001)	(0.000)	(0.000)
Edu_coll	0.024	-0.003	0.006
	(0.019)	(0.007)	(0.004)
Edu_high	0.002	0.003	0.018
	(0.029)	(0.010)	(0.016)
Work_regular	-0.066***	-0.007	-0.008
	(0.021)	(0.008)	(0.006)
Lengthemploy	-0.001	0.000	0.001
	(0.002)	(0.001)	(0.001)
HQ_state	0.085	0.016	0.009
	(0.255)	(0.114)	(0.032)
Observations	49,961	49,722	49,894
R-squared	0.437	0.394	0.345
Fixed Effects	Occupation-Month Firm-Occupation-State Firm-Year	Occupation-Month Firm-Occupation-State Firm-Year	Occupation-Month Firm-Occupation-State Firm-Year
Cluster	State	State	State

Table 9: Testing Alternative Explanations: Salary disclosure and salary amount

This table reports the results of estimating the climate disaster effect on the firm salary disclosure and disclosed salary amount of the poor E-performance firms by replacing dependent variables of Equation (2) using the salary disclosed in the LinkUP job posting description. Column (1) applies the voluntary salary disclosure indicator as the dependent variable, and removes the samples in location-time where mandatory salary disclosure is implemented (Colorado state on and after 1st January 2021; Jersey city in New Jersey state on and after 13th April 2022; Ithaca in New York state on and after 1st September 2022; New York city in New York state on and after 1st November 2022; and Westchester county in New York state on and after 6th November 2022); and (2) uses natural logarithm value of disclosed salary amount as the dependent variable, where yearly salary type is converted to hourly salary through divided by working hours. The reported results are augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects. Singletons are dropped. 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.

Dep. Variables:	Voluntary_salary_disclosure	ln(salary)
	(1)	(2)
Impacted × Worse E-perform	-0.000	0.024
	(0.001)	(0.018)
Impacted	-0.001	-0.082*
	(0.002)	(0.047)
Impacted × Size	0.000	0.007*
	(0.000)	(0.004)
Observations	41,412,745	1,158,230
R-squared	0.545	0.778
Fixed Effects	SOC-Month Firm-SOC-State Firm-Year	SOC-Month Firm-SOC-State Firm-Year
Cluster	State	State

Table 10: Testing Alternative Explanations: Climate Change-related Physical Shock Exposure and Risk

This table reports the results of estimating the differences in climate change-related physical shock exposure and risk among firms with varying levels of environmental performance, and whether salient disasters exert heterogenous effects on climate change-related physical shock exposure and risk between firms of better and poorer environmental performance. Climate change-related physical shock exposure and risk data are from Sautner et al. (2024). Columns (1) and (3) use Climate change-related physical shock risk as the dependent variable, and Columns (2) and (4) use Climate change-related physical shock exposure as the dependent variable. Columns (1) to (4) are augmented with firm, year, and state fixed effects. Singletons are dropped. 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.

Dep. Variables:	$CCRisk^{Phy}$	$CCExposure^{Phy}$	$CCRisk^{Phy}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
E-perform	-0.000	0.001		
	(0.001)	(0.006)		
Impacted × Worse E-perform			-0.000	-0.004
			(0.000)	(0.003)
Impacted			0.001	0.016**
			(0.001)	(0.008)
Impacted × Size			-0.000	-0.002**
			(0.000)	(0.001)
Firm-Year Control Variables	Yes	Yes	Yes	Yes
Observations	81,166	81,166	81,166	81,166
R-squared	0.058	0.423	0.058	0.423
Fixed Effects	Firm, Year, State	Firm, Year, State	Firm, Year, State	Firm, Year, State
Cluster	State	State	State	State

Appendix A: Variable definitions

This table explains the variable definitions used in the paper. All firm-year accounting and stock return variables are winsorized at the top and bottom 1% of the distribution.

Variable	Definition	Source
Variables for Hypothesis tests		
Duration	Day counts between job posting delete date and create date	LinkUP
Impacted	Indicator of salient disaster, equals 1 if: All types of disasters' total loss amount in the location ≥ 465,551USD (90 percentile) in at least one month between the current month to previous 6 months, and 0 otherwise	SHELDUS
Worse E-perform	Worse E performance indicator, equals 1 if the E performance score of the firm in the previous year ≤ posting sample median E performance score and 0 otherwise	Refinitiv
E-perform	E-score of the firm in the previous 1 year	Refinitiv
Size	Natural logarithm of market value of the firm in the previous 1 year = ln(annual close price (prcc_f)* common shares outstanding (csho))	Compustat
ROA	Return on Assets of the firm in the previous 1 year = operating income before depreciation (oibdp) / Total Assets (at)	Compustat
Leverage	leverage ratio of the firm in the previous 1 year = (Long term debt (dltt)+Debt in current liabilities (dlc)) / Total Assets (at)	Compustat
BM	Book-to-market ratio of the firm in the previous 1 year = Total common/ordinary equity (ceq) /(annual close price (prcc_f)* common shares outstanding (csho))	Compustat
Age	Firm listed age of the previous year	Compustat
Annualret	Firm annual stock return of the previous year	CRSP
Variables for supplemental tests		
Turnover_To_Better_E-performers	100 * the number of employees who depart the firm of the month and move to a better E-perform firm than the current firm in the next position / the employee count of the firm-MSA in the last month	Revelio Lab
Turnover_To_Worse_E-performers	100 * the number of employees who depart the firm of the month and move to a worse E-perform firm than the current firm in the next position / the employee count of the firm-MSA in the last month	Revelio Lab
Overall_rating	Overall rating for the firm in the review	Glassdoor
Comment_E_cons	E-related word percentage in comments' Cons section * 100	Glassdoor, Briscoe-Tran (2024)
Comment_E_pros	E-related word percentage in comments' Pros section * 100	Glassdoor, Briscoe-Tran (2024)

Female	Indicator variable that equals one if an employee is a women and zero if an employee is a man; otherwise, it is recorded as missing	Glassdoor
EmployeeAge	Employee age	Glassdoor
Edu_coll	Indicator variable that equals one if an employee's highest education is college and zero if an employee's education is higher or lower than college; otherwise, it is recorded as missing	Glassdoor
Edu_high	Indicator variable that equals one if an employee's highest education is higher than college and zero if an employee's education is lower than or equal to college; otherwise, it is recorded as missing	Glassdoor
Work_regular	Indicator variable that equals one if an employee is a regular full-time worker and zero if an employee is part time, contract, intern, freelance, or other type of worker; otherwise, it is recorded as missing	Glassdoor
Lengthemploy	The year count of employment in the current	Glassdoor
HQ_state	indicator variable that equals one if an employee works in the state in which the firm's headquarters is located, and equals zero if an employee works in a state that is different from the state in which the firm's headquarters is located; otherwise, it is recorded as missing	Glassdoor
Voluntary_salary _disclosure	Indicator variable that equals one if the job posting discloses salary in a non-mandatory salary disclosure area	LinkUp
Salary	Disclosed hourly salary amount in the job posting, yearly salary is converted to hourly salary by divided by 1920 working hours	LinkUp
$CCRisk^{Phy}$	Climate change-related physical risk measured by Sautner, Vilkov, and Zhang (2024), based on the frequency of the specified bigrams that appear in the firm-quarter's conference call transcripts	Sautner, Vilkov, and Zhang (2024)
$CCExposure^{Phy}$	Climate change-related physical shock exposure measured by Sautner, Vilkov, and Zhang (2024), based on the frequency of the specified bigrams that appear in the firm-quarter's conference call transcripts	Sautner, Vilkov, and Zhang (2024)

Appendix B: Robustness Checks – Replace Measurement of Disaster Impacted Indicator

This table reports the results of estimating the climate disaster effect on job seekers' preferences for poor E-performance firms from Equation (2) by altering the measurement of salient disaster and affected time window. $Impacted_{l,t}$ equals one (and zero otherwise) in Column (1) if the job was posted no more than 15 days before a climate disaster in location l, and remove job postings being deleted before the next month, or located where a salient disaster strikes in months t, t-1, t-2, t-3, t-4, t-4, or t-6; and in Column (2) the same as *Impacted* used in baseline test but excluding remote-work applicable occupation samples; In the order of columns (3)-(4), $Impacted_{l,t}$ equals one (and zero otherwise) if job location l experienced a salient disaster (3) in month t, (4) in month t, t-1, t-2, t-3, respectively. In the order of columns (5)-(6), $Impacted_{l,t}$ equals one (and zero otherwise) if in month t, t-1, t-2, t-3, t-4, t-5, t-6, (5) job location l's aggregated disaster damage amount exceeds the 95 percentile value; (6) job location l experienced at least one of the 5 types of damage amount disasters that related to global warming during our sample period (i.e., drought, flooding, heat, hurricanes/tropical storms, and wildfire); This table reports the results of estimating the equation augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year 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.

Dep. Variables:	ln(Duration)					
Sample:	Exclude posting deletion before the next month or *Impacted* = 1	Exclude remote-work occupations	Full	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)
Impacted_pre15days × Worse E-perform	0.018***					
	(0.006)					
Impacted × Worse E-perform		0.010**				
		(0.005)				
Impacted_current × Worse E-perform			0.020***			
			(0.006)			
Impacted_3 months × Worse E-perform				0.012**		
				(0.005)		
Impacted_95pct × Worse E-perform					0.009*	
					(0.005)	
Impacted_5type × Worse E-perform						0.010***
						(0.003)
Impacted Indicator Control	Yes	Yes	Yes	Yes	Yes	Yes
Impacted Indicator × Size Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,735,972	24,277,148	51,002,948	51,002,948	51,002,948	51,002,948
R-squared	0.323	0.371	0.363	0.363	0.363	0.363
Fixed Effects	SOC-Month	SOC-Month	SOC-Month	SOC-Month	SOC-Month	SOC-Month
	Firm-SOC-State	Firm-SOC-State	Firm-SOC-State	Firm-SOC-State	Firm-SOC-State	Firm-SOC-State
	Firm-Year	Firm-Year	Firm-Year	Firm-Year	Firm-Year	Firm-Year
Cluster	State	State	State	State	State	State

Online Appendix for

When Disaster Strikes: How Climate Events Influence Employment Preferences

Table OA-1: Parallel Trend Regression Result

This table shows the regression results of Figure 2, which examines the dynamic impact on job vacancy duration of poor E-performance firms around a climate disaster. Column (1) reports the results of estimating the model augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the state level.

Dep. Variables:	ln(Duration)
	(1)
$Impacted_{t-3}$ × Worse E-perform	0.004
	(0.007)
$Impacted_{t-2}$ × Worse E-perform	-0.002
	(0.010)
$Impacted_{t}$ × Worse E-perform	0.023***
	(0.008)
$Impacted_{t+1}$ × Worse E-perform	0.016**
	(0.008)
$Impacted_{t+2}$ × Worse E-perform	0.002
	(0.009)
$Impacted_{t+3}$ × Worse E-perform	0.007
	(0.008)
$Impacted_{t+4}$ × Worse E-perform	0.001
	(0.009)
$Impacted_{t+5}$ × Worse E-perform	0.026*
	(0.013)
$Impacted_{t+6}$ × Worse E-perform	0.013
	(0.011)
Impactedt+n Controls	Yes
Impactedt+n × Size Controls	Yes
Observations	47,064,022
R-squared	0.366
Fixed Effects	SOC-Month
	Firm-SOC-State
	Firm-Year
Cluster	State

Table OA-2: High vs. low climate exposure jobs

This table reports the results of estimating the effect of climate disasters on job seekers' preferences from Equation (2) separately for two subsamples of job vacancies: jobs with high exposure if the occupation's score is higher than or equal to the median value, and jobs with low exposure to climate otherwise. The difference in the coefficients on Impacted * Worse E-perform between the two groups is tested and the z-value is reported. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. The results are augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects. Standard errors are clustered at the state level.

Dep. Variables:	ln(Duration)	
Groups:	High exposure to climate	Low exposure to climate
	(1)	(2)
Impacted × Worse E-perform	0.013***	0.014**
	(0.005)	(0.006)
Diff. (z-value)	0.001(z=0.126)	
Impacted	-0.022	-0.019
	(0.014)	(0.019)
Impacted × Size	0.001	0.000
	(0.002)	(0.002)
Observations	24,090,929	22,210,115
R-squared	0.397	0.334
Fixed Effects	SOC-Month Firm-SOC-State Firm-Year	SOC-Month Firm-SOC-State Firm-Year
Cluster	State	State

Table OA-3: Labor Demand – Firm-location-month job posting number

The extended duration of job vacancies may be attributable to decreased labor demand of environmentally underperforming firms following salient disasters. To further investigate this possibility, we examine whether firms with poorer environmental performance reduce their job postings following salient climate disasters. This table reports the results of estimating the climate disaster effect on job posting numbers for poor E-performance firms using firm-zip-month aggregated samples. Column (1) reports the results of estimating the model augmented with firm-by-state, and firm-by-year 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. The dependent variable is the firm-zip-month level job posting number. The coefficients on Impacted×Worse E-perform are negative but statistically insignificant, suggesting that the environmentally underperforming firms do not exhibit an obvious reduction in labor demand following the disaster, which is inconsistent with the demand-side alternative explanation that poorly E-performing firms decrease labor demand after extreme climate events.

Dep. Variables:	Job posting number
	(1)
Impacted × Worse E-perform	-0.249
	(0.163)
Impacted	-0.122
	(0.775)
Impacted × Size	0.069
	(0.081)
Observations	9,351,439
R-squared	0.101
Fixed Effect	Firm-State
	Firm-Year
Cluster	State

Table OA-4: Green jobs vs. others

This table reports the results of estimating the climate disaster effect on job seekers' preferences from Equation (2) separately for two subsamples of job vacancies: Green jobs defined as related to environmental activities in Darendeli et al. (2022) and others. Column (1) uses non-green job postings, and Column (2) uses green job postings. The difference in the coefficients on Impacted × Worse E-perform between the two groups is tested and the z-value is reported. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. The results are augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year fixed effects. Standard errors are clustered at the state level. Our results show that the increase in job vacancy duration following disasters is pronounced only for non-green job postings, with the difference in the coefficient of Impacted×Worse E-perform between the two groups being significant at the 10% level. This result alleviates the concerns on the labor demand side that E-underperforming firms become more careful in selecting candidates for green job positions in order to improve their environmental performance.

Dep. Variables:	ln(Duration)	
Groups:	Exclude green jobs	Only green jobs
	(1)	(2)
Impacted × Worse E-perform	0.014***	-0.038
	(0.005)	(0.028)
Diff. (z-value)	0.051*(z=1.836)	
Impacted	-0.020	0.079
	(0.013)	(0.105)
Impacted × Size	0.000	-0.005
	(0.001)	(0.009)
Observations	50,855,617	143,200
R-squared	0.362	0.585
Fixed Effects	SOC-Month Firm-SOC-State Firm-Year	SOC-Month Firm-SOC-State Firm-Year
Cluster	State	State

Table OA-5: Future E-performance based on violations

This table reports the results of estimating the climate disaster effect on the future operating performance of the poor E-performance firms by replacing dependent variables of Equation (2) using the E-violation records next year of the firm-state from the Violation Tracker database. Columns (1) and (2) use the natural logarithm value of fine amount and violation record count as dependent variables, respectively. All variables are defined in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. The results are augmented with firm, state, and year fixed effects. Standard errors are clustered at the state level. The coefficients on Impacted×Worse E-perform are negative but statistically insignificant, indicating that the E-performance of underperforming firms does not exhibit obvious improvement following the disaster, which is inconsistent with the demand-side explanation that poorly E-performing firms change their recruiting strategies to improve their E-performance after extreme climate events.

Dep. Variables:	ln(FineDollar)_post	Finetimes_post
	(1)	(2)
Impacted × Worse E-perform	-0.004	-0.001
	(0.010)	(0.002)
Impacted	0.042***	0.007***
	(0.007)	(0.001)
Impacted × Size	-0.001	-0.000
	(0.001)	(0.000)
Worse E-perform	0.031***	0.004***
	(0.011)	(0.001)
Size	0.025***	0.003***
	(0.006)	(0.001)
ROA	-0.422***	-0.070***
	(0.131)	(0.026)
Leverage	0.029*	0.004
	(0.017)	(0.003)
BM	-0.004	-0.002
	(0.008)	(0.002)
Age	0.095***	0.009***
	(0.022)	(0.002)
Annualret	-0.020***	-0.003***
	(0.006)	(0.001)
Observations	290,805	290,805
R-squared	0.080	0.095
Fixed Effects	Firm, Year, State	Firm, Year, State
Cluster	State	State

Table OA-6: Robustness checks – Media-based Measurement of E-performance

This table reports the results of estimating the climate disaster effect on job seekers' preferences for poor E-performance firms from Equation (2) by altering the measurement of firm E-performance. In columns (1) – (3), we capture E-performance by the number of environmental negative news, news severity, and news reach, respectively. This table reports the results of estimating the model augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year 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.

Dep. Variables:	ln(Duration)		
	(1)	(2)	(3)
Impacted × env_num_high	0.010*		
	(0.005)		
Impacted × severity_high		0.006	
		(0.005)	
Impacted × reach_high			0.019**
			(0.008)
Impacted	-0.003	-0.001	-0.019
	(0.014)	(0.015)	(0.015)
Impacted × Size	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.001)
Observations	51,002,948	51,002,948	51,002,948
R-squared	0.363	0.363	0.363
Fixed Effects	SOC-Month	SOC-Month	SOC-Month
	Firm-SOC-State	Firm-SOC-State	Firm-SOC-State
	Firm-Year	Firm-Year	Firm-Year
Cluster	State	State	State

Table OA-7: Robustness checks

S-G-Orthogonal Measurement of E-performance

This table reports the results of estimating the climate disaster effect on job seekers' preferences for poor E-performance firms from Equation (2) by altering the measurement of firm E-performance. Specifically, we regress E on S or G and use the residuals as the orthogonal component to capture E performance. In columns (1) – (3), we capture E-performance by the orthogonal S and G, S, and G, respectively, and define worse E-performance by sample median. This table reports the results of estimating the model augmented with occupation-by-year-by-month, firm-by-occupation-by-state, and firm-by-year 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.

Dep. Variables:	ln(Duration)		
	(1)	(2)	(3)
Impacted × Orthogonal_SG_in_E_worse	0.008*		
	(0.005)		
Impacted × Orthogonal_S_in_E_worse		0.009**	
		(0.004)	
Impacted × Orthogonal_G_in_E_worse			0.009**
			(0.005)
Impacted	-0.003	-0.001	-0.019
	(0.014)	(0.015)	(0.015)
Impacted × Size	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.001)
Observations	51,002,948	51,002,948	51,002,948
R-squared	0.363	0.363	0.363
Fixed Effects	SOC-Month	SOC-Month	SOC-Month
	Firm-SOC-State	Firm-SOC-State	Firm-SOC-State
	Firm-Year	Firm-Year	Firm-Year
Cluster	State	State	State

Table OA-8: Robustness checks

Firm-location-month aggregated baseline results

This table reports the results of estimating the climate disaster effect on job seekers' preferences for poor E-performance firms from Model (2) using firm-zip-month aggregated sample. Column (1) reports the results of estimating the model augmented with firm-by-state, and firm-by-year fixed effects, weighted by the posting number of the firm-zip-month. 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.

Dep. Variables:	ln(Duration)_mean
	(1)
Impacted × Worse E-perform	0.016***
	(0.005)
Impacted	-0.013
	(0.018)
Impacted × Size	0.000
	(0.002)
Observations	9,351,439
R-squared	0.549
Fixed Effect	Firm-State
	Firm-Year
Cluster	State

Table OA-9: Robustness checks

Firm-location-month aggregated dynamic results

This table shows the dynamic impact on job vacancy duration of poor E-performance firms around a climate disaster using firm-zip- month augmented with firm-by-state, and firm-by-year fixed effects, weighted by the posting number of the firm-zip-month. 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.

Dep. Variables:	ln(Duration)
	(1)
$Impacted_{t-3}$ × Worse E-perform	0.008
	(0.008)
$Impacted_{t-2}$ × Worse E-perform	-0.010
	(0.008)
$Impacted_{t}$ × Worse E-perform	0.024**
	(0.012)
$Impacted_{t+1}$ × Worse E-perform	0.018***
	(0.005)
$Impacted_{t+2}$ × Worse E-perform	0.002
	(0.009)
$Impacted_{t+3}$ × Worse E-perform	0.004
	(0.008)
$Impacted_{t+4}$ × Worse E-perform	-0.007
	(0.008)
$Impacted_{t+5}$ × Worse E-perform	0.034
	(0.025)
$Impacted_{t+6}$ × Worse E-perform	0.015
	(0.020)
$Impacted_{t+n}$ Controls	Yes
$Impacted_{t+n}$ × Size Controls	Yes
Observations	8,652,278
R-squared	0.552
Fixed Effect	Firm-State
	Firm-Year
Cluster	State