Do firms mitigate climate impact on employment? Evidence from US heat shocks *

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Abstract

Using establishment-level data, we show that firms operating in multiple counties in the United States respond to heat-related damages by reallocating employment towards unaffected locations. Such employment reallocation increases with the severity of damages, is stronger among larger and financially stable firms with more ESG-oriented investors, and is aided by credit availability and competitive labor markets. Reallocation is observed also at the extensive margin of opening of establishments. In the cross-section of industries and the choice of reallocation counties, firm response appears to be aimed at preventing heat-related decline in productivity. In contrast, single-location firms simply downsize in response to heat-related damages. Overall, the mitigation response of multi-establishment firms acts as a "heat insulator" for the economy by reducing the impact of heat shocks on aggregate employment even as it redistributes activity spatially.

Keywords: Climate change, Mitigation, Heat risk, Global warming, Adaptation
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I Introduction

> *"Heat stress is projected to reduce total working hours worldwide by 2.2 per cent and global GDP by US$2,400 billion in 2030. For workers and businesses to be able to cope with heat stress, appropriate policies, technological investments and behavioural change are required."* – International Labor Organization Report (2019)

Climate-related disasters are expected by many scientists to become increasingly frequent in the coming decades. Among the various facets of climate change, heat-related hazards are the leading cause of deaths in the U.S. and account for the majority of projected damages due to climate change (Vaidyanathan et al., 2020; Hsiang et al., 2017).[1] Besides raising energy expenditures, extreme heat conditions can adversely affect firms by lowering labor productivity, which directly affects their profitability, and exposing workers to injuries and fatalities, which can have indirect consequences due to the growing pressure on firms from employees and investors to meet sustainable business standards. Historically, economies adapted to, and in turn mitigated the impact of such heat shocks on employment and economic activity by undertaking migration via inter-regional trade or informal diversification mechanisms (see, e.g., Giné et al., 2012 and Baez et al., 2017).

In this paper, we investigate whether modern corporations that organize employment across multiple establishments effectively act as "heat insulators" for the economy. In particular, we ask whether multi-establishment firms mitigate heat exposure by reorganizing employment and production spatially, what factors aid or impede such a response, and whether such a response leads to a spatial redistribution of economic activity. Understanding such mitigation by firms is also important because heat risk is not explicitly covered under the 1988 Stafford Act governing FEMA Aid policy and in part due to the practical difficulties in developing private insurance market for heat stress (CLEE, 2020). However, assessing the total expected scope of firms' mitigation strategies and their economic consequences has been challenging (Hinkel et al., 2014).

We tackle these questions by using establishment-level data from Dun & Bradstreet Global Archive Files (D&B) and disaster information from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) over the period from 2009 to 2020. We motivate our analysis by first showing that multi-location firms are more resilient to heat shocks than single-location firms, as single-location firms generally reduce employment in the locations

[1] According to the Spatial Hazard Events and Losses Database for the United States (SHELDUS), there were 5,702 fatalities associated with heat-related disasters between 1960 and 2020. The second highest number of fatalities were due to Hurricane/Storm, which caused 1,847 deaths during the same period.

affected by a heat shock. Interestingly, the reduction of single-location employment is associated with an increase in their job postings, suggesting that the reduction is more likely to be driven by a labor supply rather than a demand shock. For multi-location firms, we find an increase in employment and job postings at their unaffected establishments, suggesting that these firms mitigate heat exposure by reorganizing employment and production spatially. In the cross-section of multi-location firms, workforce reallocation is more pronounced among firms that are larger, less leveraged, and held by more climate-concerned investors. In time-series, we find that firm-led mitigation is becoming stronger in response to the intensifying and evolving nature of heat disasters.

Firm-level labor flows affect aggregate employment growth at the county level. We show that heat shocks result in modest and temporary decline in employment growth in the affected counties. Importantly, the spatial reallocation by multi-location firms results in higher employment growth in counties that are less directly exposed to heat risk themselves, but that are connected to the heat-affected areas via firm networks. We also examine whether these county-level patterns are driven by locals or by migrants workers from other counties. We find that the negative impact in the heat-affected counties and the positive spillover effect on the unaffected ones is both driven by employment changes in the local population. Our muted results on migration are in line with Behrer and Bolotnyy, 2023, who study migration in response to other types of natural disasters. These results indicate that firms' ability to reallocate their workforce geographically lowers the long-run economic impact of climate change, especially via the spatial redistribution channel.

Turning to the specifics of such firm-level mitigation of heat risk, having a diversified geographical presence benefits the firms in two ways. First, it lowers the chances of all their sites facing a heat wave at once which, in turn, enables then to provide more stable employment opportunities to their workers. Second, it enables them to reallocate workforce across regions with varying exposure to climate shocks. To show that multi-location firms fare better in response to heat shocks, we create establishment-level heat exposure measure as the log of "hot days" in its county, where a hot day is defined as a day experiencing loss (property, crop, injury, or fatality) due to heat hazard according to the SHELDUS database. We find that while establishments of single-location firms experience a decline in employment following heat exposure, those of multi-location firms suffer disproportionately less and even gain workers in the long run. For example, we find that while one hot day lowers employment growth of single-location firms by 1.04 pp over three years, multi-location firms experience no such decline. We also study how geographical diversification interacts with firm size, and find that while small firms generally downsize exhibiting lower labor demand, single location firms experience employee exodus irrespective of their size.

Next, we provide evidence of across-county employment reallocation in multi-location firms in response to heat shocks following an approach similar to Giroud and Mueller, 2019. Specifically, we calculate a "peer shock" measure for each establishment as the total number of hot days (scaled by their relative employment) that its sister establishments (i.e., those of the same firm) experienced in a given year. Our empirical strategy then compares the employment growth in two establishments in the same county-year that are exposed to different shocks in other regions due to differences in firms' establishment networks. This specification allows us to control for any time-varying local economic shocks that may affect local employment growth. We find that a 1% increase in peer shock measure is associated with a 1% increase in establishments' employment growth over three years. To gauge the economic magnitude of these results, consider a firm with two equal-sized establishments in separate counties. Our results suggest that a hot day in one location is associated with a 0.7% increase in employment growth in the other establishment. In supplementary analysis, we also find that the probability of the aforementioned firm to enter a new location increases by 0.07 pp, and this response in stronger in new locations that are less exposed to heat stress. These results suggests that firms respond to heat shocks by reallocating resources from affected areas to less affected ones.

Firms may need significant resources to reorganize their geographical presence and hedge climate risk, as it requires expanding production capacity and training new staff at unaffected locations. However, with costly external financing, firms may face a tradeoff between spending on climate risk management and thereby building resiliency versus maintaining cash buffers to avoid financial distress (See, e.g., Acharya et al., 2021). This implies that financially constrained firms might struggle in pursuing the spatial mitigation strategy. Indeed, we find stronger response among larger, profitable firms with lower leverage and credit risk. These results indicate that while employment reallocation can dampen the adverse impact of heat shocks on aggregate employment, the associated costs are borne by firms. We also find that employment reallocation is higher when investors are ESG-affiliated (Cohen et al., 2020) and perceive greater climate risk, as measured by earnings call transcripts (Sautner et al., 2023). These findings suggest that environment-oriented investors concerned about climate risk can help firms in combating climate change whereas financial constraints impede such a response.[2]

The direction of firm reallocation also sheds light on how heat shocks affect the firms. Extreme heat conditions can ramp up energy costs and lower firm cash flows at affected lo-

[2] Asset managers are increasingly incorporating physical climate risk in their investment decisions. See Bloomberg article dated October 22, 2023 (link). Thus, lowering exposure to extreme climate events by relocating their workforce can lower firms' cost of capital in the long run.

cations. Since resources are optimally allocated across locations, a negative cash flow shock will require financially constrained firms to cut jobs across all their locations leading to a negative spillover effect (Giroud and Mueller, 2019). In contrast, heat shocks can cause positive spillover across establishments if they depress local labor productivity by causing discomfort and absenteeism among workers (Somanathan et al., 2021). This is because a negative productivity shock lowers optimal employment levels and frees up resources that financially constrained firms can deploy elsewhere. Our results on employment reallocation are consistent with the second channel, i.e., with the role of productivity shocks. To verify this idea, we explore heterogeneity across industry groups and find that industries where workers have significant outdoor exposure, e.g., mining and construction, exhibit the maximum amount of mitigation in our sample. We also find that industries most amenable to teleworking exhibit weaker mitigation activity. Collectively, our results suggest that the firms are relocating to minimize heat-related losses in labor productivity.

Finally, understanding local factors that aid firm mitigation can help policymakers combat climate change more effectively. Therefore, we examine which counties are most appealing for firms looking to relocate their workforce in the wake of heat shocks. First, we find that consistent with firms mitigating their future climate change exposure, employment growth is stronger in unaffected counties with lower *projected* heat-related damage, as measured by estimates of Spatial Empirical Adaptive Global-to-Local Assessment System (SEAGLAS) by Hsiang et al., 2017. Turning to economic factors, higher GDP growth and credit availability (as measured by per-capita bank loan originations) increase mitigation-driven employment growth. Finally, labor market competition, measured by lower employment concentration across firms (employment HHI) and weaker enforcement of non-compete agreements, also supports firms' response. From a policy perspective, these results underline that enhancing credit access and fostering a competitive labor market can not only help local economies attract companies but also help policymakers leverage the support of the corporate sector in minimizing the adverse consequences of rising temperatures.

We next evaluate employment reallocation as a long-term mitigation strategy against the evolving nature of heat shocks. Heat waves are becoming longer and more *acute* over time.[3] They are also increasingly *compounded* by other natural disasters like hurricanes and wildfires (Raymond et al., 2022). Relatedly, communities experiencing *chronic* heat conditions historically may have responded on their own reducing the need for firms to step in. If firms' response is stronger against *acute* heat shocks and *compound* climate episodes in areas under *chronic* stress, then firm-driven mitigation will become more useful over time.[4]

[3]See Environmental Protection Agency report dated July 2022 (link).

[4]We define heat shocks as acute if they are accompanied by a non-zero property damage. Compound

On the other hand, if mitigation works best for milder events or if local communities are acclimatized to chronic heat conditions, the usefulness of firms' spatial mitigation channel would be limited in the long run. We find that mitigation response is higher after more acute heat hazards – those causing non-zero property damage, and when heat shocks are accompanied by other disasters. Firms also respond more strongly against heat shocks in chronically affected counties defined as those with higher historical incidences of heat shocks. These results underscore the importance of firm-driven climate mitigation policies for their long-term productivity.

While the Dun & Bradstreet data has several advantages in terms of its granularity and easy accessibility, it also has certain limitations relative to the Administrative Census data (Crane and Decker, 2020). We take several steps to ensure that those limitations do not impact the validity of our empirical results. The first issue is with the inaccurate coverage of very small firms. Since our focus is on large multi-location firms, we drop all companies employing fewer than 100 employees in our sample. The second issue is related to the imputation of employment numbers likely causing low volatility in employment. To address this issue, we drop all imputed data points and consider only actually reported values in our analysis. Third, we look at long-term employment changes over a six-year horizon which limits the concerns with small year-over-year changes. Finally, we substitute employment growth with the change in the number of firms' active establishments as the (extensive margin) outcome variable throughout our analysis and find consistent results. We run several additional tests to confirm the robustness of our baseline results on within-firm reallocation. We use alternative ways to define peer shocks at the establishment level, using alternative weighting schemes and threshold-temperature-based measures of hot days. Additionally, while our baseline specification uses firm and county-year fixed effects, we augment it with firm-year and county-industry-year fixed effects to further ensure that our results are driven by *within-firm* reallocation across affected and unaffected establishments.

Related Literature Our paper is related to several recent papers studying the effects of extreme weather events on firm performance. Extreme heat can adversely impact local employment, revenue, and aggregate economic growth (Addoum et al., 2020; Jin et al., 2021; Dell et al., 2012). However, Addoum et al., 2023 finds that this average masks a bi-directional effect, where some industries are harmed while others benefit. Heat shocks also impact firms' financial performance (Pankratz et al., 2023) but there is some evidence that hotter regions

climate episodes are defined as heat shocks occurring concurrently with another type of natural disaster like hurricane, wildfires, etc. Finally, counties under chronic stress are defined as those with the average annual number of hot days over the 1960-2008 time period exceeding the median value.

are more resilient to subsequent heat shocks (Behrer and Park, 2017). Other papers show that temperature shocks significantly increase energy costs and lower productivity of manufacturing plants, with the effect mainly concentrated on smaller establishments (Ponticelli et al., 2023). Extreme temperatures can also depress labor productivity by causing fatigue, exhaustion, and absenteeism among workers (Graff Zivin and Neidell, 2014; Somanathan et al., 2021; Baumgartner et al., 2023).

A smaller literature has studied how firms respond to climate change-related shocks. Pankratz and Schiller, 2021 shows that firms are more likely to terminate existing supplier relationships when realized temperature shocks exceed expectations. Lin et al., 2020 shows that power plants increase investments in flexible production technologies in response to long-term climate change and Castro-Vincenzi, 2023 shows that car manufacturers move their production sites away from flood-affected regions. Bartram et al., 2022 documents that firms respond to local carbon regulation by shifting production to unaffected states. We contribute to this literature by showing that in addition to regulatory shocks, firms also respond to shocks related to physical climate risk by shifting their employment to less affected areas.

Finally, our paper relates to the literature on firms' establishment networks. Such networks can propagate economic shock across distant regions (Giroud and Mueller, 2015, 2019) and generate aggregate fluctuations in the economy (Gabaix, 2011). Multiple establishments within a firm compete for valuable resources, leading to codependency in organizational structure across those establishments (Gumpert et al., 2022). Multi-region firms can have functioning internal labor markets and can efficiently deploy workers across regions (Tate and Yang, 2015). We document positive spillover effects of climate shocks due to firms' internal employment reallocation decisions, that are consistent with this literature.

II Data

A Dun & Bradstreet (D&B)

Establishment-level data for our study comes from the Global Linkage file in the D&B Historical Global Archive database. D&B gathers data from firms as well as other sources and distributes it for purposes such as marketing and credit scoring.[5] D&B sources data from various sources including state secretaries, Yellow Pages, court documents, and credit inquiries,

[5]While businesses aren't legally required to contribute or provide accurate information, D&B is driven by profitability motives to ensure data accuracy. Moreover, the credibility of individual businesses in terms of credit and other partnerships might hinge on the precision of the data they submit.

in addition to direct telephone outreach to businesses. Every establishment is allocated a distinct *dunsnumber* that remains constant, even if the business relocates or undergoes an acquisition.

These files contain detailed information on the location and number of employees working at the establishment level. They also consist of international business records that contain ownership relationships linking them together in a family tree structure. The database contains a *global-ultimate-duns-number* for every establishment, which we use as the firm identifier. For our analysis, we focus on establishments located in the United States. Our sample ranges from 2009 to 2020. Table 1 presents the summary statistics of key variables used in our analysis. The median firm in our sample employs 20 employees and has one establishment in a given county.

Concerns regarding D&B data Numerous recent studies have used D&B database and its derivative National Establishment Time Series (NETS) to study employment growth in the United States (Denes et al., 2020; Farre-Mensa et al., 2020; Borisov et al., 2021). D&B data is free of survivorship-bias. Another key advantage of the data is that, unlike the comparable Census Longitudinal Business Database (LBD) data, it does not require a long and tedious approval process before the researchers can access the data. Due to easier access, analysis using the publicly available D&B data is accessible to the broader community in addition to those having access to the restricted Census datasets (Addoum et al., 2023). However, there are important differences between the D&B data and the Census LBD data as outlined by Crane and Decker, 2020. Most importantly, there are concerns regarding imputation of data and coverage of small firms. We address these and other concerns in several ways.

The first concern relates to the large amount of imputation in establishment-level variables like sales and employment. Following Denes et al., 2020, we only use actual, nonimputed values of employment and employment growth in our analysis. We do not use sales data since a vast majority of those observations are imputed. A related issue is the low volatility of the employment data at the annual frequency. To address this concern, we use both short-term (1 year) and long-term (upto 6 years) employment changes throughout our empirical analysis and show that all our results hold beyond the short period suffering from stickiness in the data.

The second concern is about the coverage of small firms. Barnatchez et al., 2017 discuss that D&B has too many establishments with 10 or fewer employees. We remove all firms that employed fewer than 100 employees on average over our sample period to address this issue. The employment share of excluded firms is tiny. Furthermore, since we focus on the mitigation activity of multi-establishment firms, the exclusion of very small firms which usually operate in a single location has a trivial impact on our main analysis.[6] Thus, our sample is slightly skewed towards larger firms in the economy. This exclusion addresses the coverage issue since the correlation between D&B and Census for such large firms is very high. Removing small firms also helps with the imputation problem since the extent of imputation is very low from larger firms and we do not lose a lot of data by removing imputed observations for such firms. Another associated issue is related to the coverage in agriculture, mining, and construction industry. We show that our results hold separately across each industry group and are not driven by these specific industries.

To further address potential concerns with the employment data, we use alternative variables to quantify firms' reallocation activity. Specifically, we use the fact that, barring small firms, the D&B data is representative of the U.S. business activity in the cross-section. Thus, we use the number of establishments with non-zero value of actual employment as our alternative outcome variable. The error in identifying the presence of an establishment is likely to be lower relative to that in recording its current employment. We show that all our results on employment growth at the firm-county level (intensive margin) are consistent with those using change in the number of active establishments (extensive margin) as the outcome variable.

B Lightcast

Our job postings data comes from Lightcast (previously Burning Glass). These data are collected daily from over 65,000 websites, such as national and local job boards, job posting aggregators, and company career sites. The company then applies a deduplication process for collected postings, with over 80% of all postings being deduplicated. For each posting in the database, we know the posting firm and time, as well as the post location and occupation. We first aggregate these postings to firm-county-year-level, and then match to D&B data based on name, county, and 2-digit SIC industry code of the establishment.

In some analyses, we further classify posts based on their exposure to extreme temperatures based on O*NET Work Context database. This database contains exposure scores for almost 900 different occupations based on how often the job requires working in very hot (above 90F degrees) or very cold (below 32F degrees) temperatures. We use 50/100 score cutoff to define an exposed occupation, which covers around 28% of all occupations.

[6] Excluding firms employing fewer than 100 employees also removes non-employer firms which are omitted from the Census datasets (Neumark et al., 2007).

Finally, we scale the postings based on lagged number of employees in a given firm-county using the D&B employment data. As shown in Table 1, the number of vacancies that an average establishment advertises in a given year is around 7% of its previous year's number of employees, with these figures being 1.8% and 5.1% for exposed and non-exposed occupations, respectively.

C Heat-related disasters

We obtain county-level data on disasters from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). The database contains information on the date and duration of an event, the affected location (county and state), and the direct losses caused by the event (property and crop losses, injuries, and fatalities) from 1960 to the present. Several other papers have used this data to measure extreme heat events (e.g. Alekseev et al., 2022). We aggregate the data at the county-year level and our primary variable of interest ($\#$ Hot Days$_{c,t}$) is defined as the total number of days when heat-related hazards affected a county c in a given year t. Figure 1 shows US counties that experienced one or more hot days throughout our sample period (2009 to 2020) and suggests that heat shocks are geographically dispersed across the United States.

C.1 Relationship with temperature-based heat shocks

Besides the SHELDUS measure, previous literature has used daily temperature data and defined "hot days" as days when the temperature exceeded long-term historical averages or specific threshold levels (e.g., 90F or 100F) (e.g. Addoum et al., 2020). We use the SHELDUS data because of two reasons. First, it records events that caused significant damage to the locality. In contrast, short-term spikes in daily temperatures may not be salient enough to impact firms' location choices. Secondly, leveraging information on property damages allows us to categorize events based on severity, enabling analysis of firm responses to mild and acute events separately.

We examine the relationship between the number of hot days as defined by SHELDUS and those defined as the number of days when the daily average temperature exceeded the 99th percentile value for a given county between 1982 to 2020 (i.e., the period for which PRISM data on daily temperatures at the county level is available). Table 2 shows that, perhaps unsurprisingly, the number of SHELDUS hot days is positively associated with the number of temperature-based hot days measure. Interestingly, we find that this relationship is stronger in counties with higher community risk factor (as defined by the FEMA Risk

Index data), which is consistent with the idea that higher temperatures are more damaging in areas that are more vulnerable to climate risk. We use the temperature-based number of hot days measure in our robustness tests and obtain results consistent with those using our main measure.

III Establishment-level results

A Impact of heat shocks: Single vs. multi-location firms

Extreme heat events and the resulting damages to firms are often localized. Therefore, the menu of locations available to the firms offers a credible mitigation strategy (Kahn, 2014). Put simply, firms can shift from disaster-prone areas to safer ones. While moving into new areas might be costly, firms that already operate some establishments in safer locations can just hire more employees there. This spatial mitigation strategy is the central focus of our paper. A direct inference of this is that firms operating in multiple locations would be more resilient to heat shocks. Thus, we start our analysis by contrasting the total employment growth at single and multi-location firms after facing similar exposure to heat-related disasters.

To study how heat shocks affect employment across firms, we estimate the following specification:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = {} & \gamma^k \times \text{Own Shock}_{c,t} \times \text{Single Location}_f \\ & + \delta^k \times \text{Own Shock}_{c,t} + \alpha_f + \alpha_c + \alpha_t + \varepsilon_{f,c,t}.\end{aligned} \quad (1)$$

Here, $\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in firm f's log employment in count c from year t to $t+k$. Own $\text{Shock}_{c,t}$ is $\text{Log}(1+\text{Hot Days}_{c,t})$, where Hot $\text{Days}_{c,t}$ is the total number of hot days in count c in year t according to SHELDUS. Single Location_f indicates that firm f existed in a single county throughout our sample period. We employ firm and county fixed-effects to absorb differences in growth rates across firms and counties. We also include year fixed-effects to absorb aggregate fluctuations and cluster standard errors at the firm level.[7]

We present estimation results in Table 3. In Panel A, we find that heat shocks adversely

[7]Note that in subsequent analyses where we focus on the effects of Peer Shock on multi-location firms, we will tighten our specification by employing county-year fixed effects to facilitate comparison between establishments within the same county based on their differential exposure to shocks based on their establishment networks. Here, however, we employ county and year fixed effects separately as Own Shock is defined county-year-level.

affect establishments of single-location firms. Specifically, the coefficient with respect to $k = 2$ implies that one hot day lowers employment growth at establishments of single location firms by 1.09 pp. This is economically significant relative to the average 3-year growth rate of 2.6% over our sample period.

Notably, we find that establishments of multi-location firms do not experience a proportional decline in their workforce (if anything, we find slight increase over longer horizons). Thus, although these firms may suffer a direct impact in their affected locations, they are likely hiring workers in their unaffected locations leading to a recovery in the long term and potentially giving them an advantage over single-location firms. Overall, this preliminary evidence suggests that spatial labor reallocation by multi-location firms can mitigate the impact of heat shocks on aggregate employment.

Next, in order to better understand whether changes in establishments' employee count is mainly driven by supply or demand side forces, we look into job postings. The main idea of the exercise is that a reduction in actual employment accompanied with an increase in job postings is more likely to be mainly driven by a labor supply shock (employees are resigning from affected locations), whereas a reduction in actual employment accompanied with a decrease in job postings is more likely to be mainly driven by a labor demand shock (firms are downsizing in a given location).

Table 3 Panel B shows these results. We find that the effects on employment growth and job postings seem to be negatively correlated: single-location firms seem to increase their job postings as their employment count decreases, suggesting that the decrease in employment is likely to be driven by employees leaving affected firms resulting in a labor shortage. On the other hand, multi-location firms reduce postings over the long horizon as their actual employment increases.

A.1 Firm size and number of locations

Heat shocks may induce adaptation efforts from both firms and workers. Worse environmental conditions may render the operations of constrained firms' unprofitable forcing them to downsize and lower their labor demand. At the same time, workers may see value in switching jobs after experiencing unpleasant conditions at their workplace. Our results in Table 3 indicate that employment reallocation from single- to multi-location firms in response to a own heat shock is driven by workers. This suggests that from the perspective of climate shocks, workers see value in geographical diversification of their employers. To further disentangle firm-driven vs. worker-driven reallocation, we divide firms according to their size and single/multi location status. For size, we divide firms into large and small depending on their average employment being above- or below- median during our sample period. Specifically, we divide firms into four groups — (a) large and multi-location, (b) small and multi-location, (c) large and single-location, and (d) small and single-location. Then, we examine how establishment of these various types of firms response to hot days in their county.

Table 4 presents the results. The baseline coefficient of Own Shock refers to large multi-location firms. Panel (A) corresponds to employment growth and Panel (B) corresponds to job postings. We find that, in general, small firms see a weaker employment growth compared to large firms. Among both small and large categories, single-location firms lose more workers than multi-location firms. Notably, a negative relationship between employment growth and job postings appears only for single-location firms. E.g., small multi-location firms lose workers but do not increase their job postings. These results are consistent with the notion that small firms are less resilient to heat shocks and their diminished employment growth is driven by firm demand for workers. On the other hand, workers exit single-location firms in favor of multi-location firms leading to employment reallocation across the two categories.[8]

Our results indicate that geographical diversification is important for firms to retain their existing workers and attract new ones. Why would workers prefer to work for establishments of multi-location firms? Multi-location firms might be more resilient to localized climate shocks, as they have an option to shift operations to their unaffected plants. This can reduce the likelihood of firm going out of business and increase job security at an average establishment. Indeed, we find that multi-location firms respond to heat shocks by increasing employment at their unaffected locations.[9] Overall, our results highlight the benefits that firms obtain through geographical diversification.

B Firm mitigation: Reallocation to unaffected peer counties

Next, we directly examine how multi-establishment firm networks affect the impact of heat shocks on aggregate employment. Our empirical analysis closely follows prior studies on firm networks (Giroud and Mueller, 2019; Giroud and Rauh, 2019). In particular, we look at

[8] We redo this test after employing more granular county × year fixed effects and find consistent results. See Table A5.

[9] While we focus on the resilience of multi-location firms, there might be other reasons why workers may prefer to work for them. E.g., multi-location firms can provide opportunities to relocate without switching jobs, which might be valuable to workers. Alternatively, regional diversification might help firms in providing cheaper health insurance and other non-wage benefits as all their employees are not exposed to the same localized climate shock.

employment growth in *one* establishment after its *peer* establishments owned by the *same* firm face a heat-related disaster. If there is a positive spillover, it indicates that spatial reallocation by firms reduces the overall impact of heat shocks on employment. Conversely, a negative spillover would suggest that firm networks can transmit the impact of climate shocks across regions amplifying their overall impact. To understand whether firm networks help mitigate or instead amplify climate risks, we aggregate data at the firm-county-year level and focus on firms with non-zero employment in two or more counties. The median firm in our sample is present in 4 counties and has 20 employees and 1 establishment per county.

We calculate the exposure of each establishment to heat shocks at peer establishments (i.e., those belonging to the same firm) by summing up hot days across peer locations after weighting them by the relative size of the establishments. I.e., for firm f, county c, and year t, we calculate

$$\text{Peer Shock}_{f,c,t} = \text{Log}(1 + \#\text{ Hot Days, Other}_{f,c,t}) \tag{2}$$

where

$$\#\text{ Hot Days, Other}_{f,c,t} = \sum_{c' \neq c} \frac{\text{Employment}_{f,c',t-2}}{\text{Employment}_{f,c,t-2}} \times \#\text{ Hot Days}_{c',t}$$

The # Hot Days, $\text{Other}_{f,c,t}$ variable measures the total number of hot days in peer locations (indexed by c') after weighting them by their lagged-employment relative to county c. We use several alternative ways to create this measure and show that our results are not sensitive to this choice in the robustness section.

Our baseline specification to detect across-establishment mitigation by firms is

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t} \tag{3}$$

where $\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. We use firm fixed-effects (α_f) to absorb differential growth rates across firms. We also use county-year fixed-effects ($\alpha_{c,t}$) to absorb county-level fluctuations that may impact employment growth at an establishment. It also absorbs the effect of heat shocks in the establishment's own location at c. We cluster standard errors at the county level.

Results are shown in Table 5 Panel A. We find a positive spillover effect of heat shocks within the firm network. A 1% increase in the peer shock measure is associated with roughly 1% increase in employment growth over a 3-year period (see coefficient corresponding to $k = 2$). To put the economic magnitude of this coefficient into perspective, consider the following stylized example: Suppose a firm employs an equal number of employees in county

c and c'. Based on our findings, one hot day in c' corresponds to a 0.7% ($1 \times \ln(2)$) uptick in employment growth at this firm's branch in county c. The average employment growth over the same horizon is 2.4%, which highlights the economic significance of our spillover effect.

Panel B shows the spillover effect of heat shocks on connected establishments' job postings. Unlike in the previous analysis where we focused on affected counties, here we find that the effect on employment growth is positively correlated with the effect on job postings. This highlights that heat stress in a county indeed seems to induce multi-location firms to increase their employment at unaffected peer counties, increasing their labor demand.

B.1 Robustness

We conduct several robustness tests to ensure that our main results are not sensitive to the limitations posed by our data or our choice of measurements and econometric specifications.

We first explore alternative ways to measure peer shocks. For establishments in county c, we use the ratio of employment at peer location (c') and that at their own location (i.e., at c) as the weighting variable in our primary measure (Peer Shock$_{f,c,t}$). This measure accounts for the initial size of the establishment (with respect to whom the peer shock is being measured) and builds on the intuition that the operations at big establishments may not be severely impacted by a hot day in locations where the firm has a handful of employees. However, this measure does not account for the fact that if the firm has multiple unaffected locations, the impact of heat shock at one location can be distributed across all unaffected locations, and the shock applicable to a given location might be small. Moreover, even though we use employment at $t-2$ to create peer shock for year t, one may have concerns regarding its mechanical correlation with our outcome measures, which is employment changes relative to year $t-1$. To address this concern, we calculate peer shock as the employment-weighted average hot days across all the peer locations. Specifically, we define

$$\text{Peer Shock, Alt}_{f,c,t} = \text{Log}(1 + \sum_{c' \neq c} \frac{\text{Employment}_{f,c',t-2}}{\sum_{c' \neq c} \text{Employment}_{f,c',t-2}} \times \#\text{ Hot Days}_{c',t})$$

We re-estimate our baseline specification with this alternative measure and present the results in Table 6 Panel (b). We find that the new measure gives similar results as our original measure.

Next, we address the concern that employment-based weights may suffer from previously discussed concerns about the D&B employment numbers. We leverage the fact that the recording of establishment presence is reasonably accurate in the D&B data and use the number of establishments to calculate the weighting variable. Specifically, we use the ratio of establishment counts in county c' and c to compute an alternative measure of peer shocks (Peer Shock, Est-Wt$_{f,c,t}$). We compute a third alternative measure (Peer Shock, Eq-Wt$_{f,c,t}$) using the simple average of hot days across all peer counties and use it in our baseline specification. Finally, to address concerns about outliers driving our results, we also use a binary peer shock measure (Peer Shock, Top Tercile$_{f,c,t}$) that is one when the value of peer shock lies in the top tercile of the distribution, and zero otherwise. Panel (b) of Table 6 shows that the results with these alternative measures are consistent with those using our primary measure.

We also examine whether our results are driven by the choice of using SHELDUS hot days measure instead of a temperature-based measure. Specifically, we create an alternative peer shock measure by defining hot days as the number of days when the average daily temperature exceeded the 99th percentile value for the county between the 1982-2020 period (i.e., the period for which the daily temperature data at the county level was available in PRISM). We find that results using this alternative definition of hot days is similar to those in our baseline specification.

Next, we explore alternative sets of specifications. In our baseline specification, we use firm and county-year fixed-effects. We do not use firm-county fixed effects because our outcome variable (ΔLog(Employment)$_{f,c,t-1\to t+k}$) is the annual change in employment at the firm-county level. Furthermore, we do not employ firm-year fixed effects because we want to incorporate aggregate firm response to heat shocks. With just the firm fixed-effect, the coefficient of peer shock can either be driven by employment reallocation to the firm's unaffected locations or by the aggregate growth of firms that have a large presence in heat-impacted regions. However, since firms exposed to heat shocks likely suffer an aggregate decline in employment growth, our baseline specification likely underestimates the size of the spillover effect. To verify this conjecture, we re-estimate our baseline specification with both firm-year and county-year fixed effects and present the results in Table 6 Panel (c). We find that after controlling for aggregate firm-level fluctuations, the coefficient of peer shock more than doubles in magnitude, which is consistent with our conjecture. We also augment our baseline specification to absorb local industry fluctuation by including firm and county-industry-year fixed-effects obtaining results consistent with our baseline. We also get similar results after excluding firm fixed effects (i.e., including only county $\times$ year fixed effects). Lastly, re-estimate our baseline specification after double clustering the standard errors at the county and firm level and find consistent results.

Next, we address concerns related to the employment data in D&B. Since D&B data is very close to Census in terms of cross-sectional snapshots, we now look at the number of active establishments that a firm has in a given county to understand their reallocation behavior. In other words, we use the change in the number of establishments of firm f in county c from year $t-1$ to $t+k$ as an alternative outcome variable in the baseline specification. This specification has two benefits. First, it benefits from the fact that D&B is much more accurate in recording the presence of an active establishment in comparison to the accuracy of their actual employment data (which in itself is of high quality for our sample firms). Second, it shows that firms mitigate climate risk by closing their establishments in affected locations and opening new establishments in unaffected regions. In other words, it sheds light on the impact of climate shocks on establishments across the *extensive margin.* Results presented in Table 6 (Panel (d)) show that one hot day in a particular county leads to a 0.03% increase in the number of peer county establishments within a 3-year period. These results show that the spatial reallocation strategy that firms employ against heat-related disasters works across both intensive and extensive margins.

Next, we examine whether firms respond differently to heat shocks accompanied by workplace accidents compared to those without them. To do so, we collect establishment-level data on workplace accidents from the Occupational Safety and Health Administration (OSHA) website. We then disaggregate our peer shock measure into two categories based on the presence or absence of workplace injuries or fatalities in the affected county. Table A9 shows that firms reallocate workers in response to shocks, both with and without associated workplace injuries and fatalities.

Finally, we address the concern that our peer shock measure may be persistent, in which case, our baseline results may reflect the effect of multiple shocks experienced by an establishment over the years. In order to isolate the contemporaneous and lagged effect of a peer shock in a single year, we estimate a distributed lag model. Specifically, we regress employment growth in a given year against the current and the lagged values of the peer shock variable. Figure A2 shows the cumulative effect of peer shock in year t over the period of k years (where k is between 0 and 5). The results are consistent with our baseline specification both in terms of the magnitude and the statistical significance.

The findings in this section reinforce the idea that firm networks insure the economy against climate-related risks. In particular, spatial reallocation of workforce can be seen as one way in which firms are addressing the challenges posed by global warming to their own operations and the broader economy. This also underscores the importance of large multi-establishment firms in any comprehensive economic policy aimed at tackling climate change.

IV Aggregate outcomes

Next, we explore if heat shocks affect county level outcomes. Doing so sheds light on whether the spatial reallocation channel that we have documented using establishment-level data has aggregate macroeconomic implications. We proceed in two steps. First, we look at how various county-level macroeconomic indicators evolve after the county experiences a heat shock. Specifically, we estimate the following regression:

$$\Delta Y_{c,t-1\to t+k} = \beta_1 \times \text{Own Shock}_{c,t} + \beta_2 \times \text{Peer Shock}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t} \tag{4}$$

$\Delta Y_{c,t-1\to t+k}$ denotes change in macroeconomic outcomes of county c from year $t-1$ to $t+k$. Own $\text{Shock}_{c,t}$ is $\text{Log}(1 + \text{Hot Days}_{c,t})$, where Hot $\text{Days}_{c,t}$ is the total number of hot days in count c in year t according to SHELDUS. Peer shock measure (Peer $\text{Shock}_{c,t}$) for county c in year t as $\text{Log}(1 + \text{Hot Days, Other}_{c,t})$, where Hot Days, $\text{Other}_{c,t}$ is defined as:

$$\text{Hot Days, Other}_{c,t} = \sum_f \frac{\text{Employment}_{f,c,t-2}}{\text{Employment}_{c,t-2}} \times \text{Hot Days, Other}_{f,c,t}$$

In other words, county-level peer shock measure is lagged-employment-weighted average of firm-level peer shock measure. Thus, counties with large presence of multi-location companies will have links to many other counties and would likely benefit (from our channel) if heat shocks affect any of those linked counties. In other words, we expect a positive association between aggregate employment growth and peer shock at the county level. We employ county fixed-effects to absorb cross-sectional differences in growth rates across counties. We also employ year fixed-effects to control for aggregate fluctuations.

We present the results in Table 7. Panel (a) shows that in the immediate aftermath of the heat shock, employment growth shrinks in the county. Specifically, Column (1) shows that one hot day in the county reduces employment growth by 0.26 pp within a year. Over longer horizons, the point estimate stays negative but becomes statistically insignificant as the effect is measured more imprecisely. Peer counties, on the other hand, exhibit an increase in employment growth after counties associated with them through firm networks experience a heat-related disaster. One standard deviation increase in the peer shock measure increases employment growth by 2.4 pp.

Diminished employment growth in response to heat shock can be driven either by an outmigration of workers or by a decline in employment opportunities of locals. Similarly, employment growth in response to peer shocks can provide job opportunities for migrants as well as locals. To understand whether locals or migrants are driving the change in employment growth, we decompose employment growth into two groups and examine the effect of own shocks and peer shocks on the two groups separately.

Specifically, we decompose employment growth from $t-1$ to $t+k$ into inflow of workers from other counties and employment growth of local population. We use the IRS SOI data to measure county-to-county migration of workers for each year in our sample period. The benefit of using IRS data to measure migration is that it is derived from tax return data, which means that it captures migrants that are either self-employed or employed by other firms. Thus, net inflow of migrants can be interpreted as employment growth driven by migrant population. The remaining about of county-level employment growth can be attributed to the locals. We present these results in Panels (B) and (C) of Table 7. These results highlight that both the own shock and peer shock effect is driven by locals and is not explained by migration in and out of the county. Thus, they align with Behrer and Bolotnyy, 2023 who find little to no impact of hurricanes on out-migration, highlighting the strength of deep economic and social ties in determining worker mobility.

Overall, these county-level results are consistent with our earlier firm-level findings suggesting that as a result of economic shocks, economic activity seems to be reallocated from affected areas to unaffected ones through firms' establishment networks.

In addition to counties, we also ask whether the local shocks have a measurable impact at firm-level, but don't find any measurable direct impact on firm profitability, return on assets, asset growth, or expected stock returns. This is perhaps unsurprising, because any individual shock represents a relatively small fraction of an average firm's total operations (an average shock affects around 2% of an average firm's employees), and shocks have little correlation across geographical locations.[10] This is in stark contrast to aggregating results to county-level, where shocks are by design highly correlated, and as such explains why we find aggregate results at county but not at firm-level. These results are presented in the online appendix (Figure A4 and Table A6).

A Reallocation and firm entry in new locations

In the previous section, we found that companies facing heat shocks in one location often increase employment and establishments in their other locations. Such firms might also open new establishments in areas where they weren't before, especially in regions less exposed to

[10]Note that for smaller firms with fewer establishments (for which we don't have data), any individual shock should be more impactful.

heat shocks.

To study this, we first aggregate our establishment-level data at the firm level. The median firm in our sample employs around 200 employees and is located in 5 counties. We calculate firm exposure to heat shocks as the fraction of firm's employees impacted by heat shocks across the firm's locations. Specifically, we calculate heat shock for firm f in year t (Firm $\text{Shock}_{f,t}$) as

$$\text{Firm Shock}_{f,t} = \text{Log}(1 + \#\text{ Hot Days, Firm}_{f,t}) \tag{5}$$

where

$$\#\text{ Hot Days, Firm}_{f,t} = \sum_{c} \frac{\text{Employment}_{f,c,t-2}}{\text{Employment}_{f,t-2}} \times \#\text{ Hot Days}_{c,t}.$$

We use employment weighting to ensure that our heat shock measure is comparable across firms. Additionally, we use employment in year $t-2$ as the weighting variable to avoid mechanical correlation between the exposure measure and our outcome variables (employment changes with respect to year $t-1$). The proportion of single-location firms in our sample is 30%, and their hot days measure is equal to the annual number of hot days in their county. The average number of hot days experienced by our sample firm in a given year is 0.6. Thus, Firm $\text{Shock}_{f,t}$ is zero if the firm did not experience any heat shock during the year and then increases with the number of hot days experienced by the firm's various establishments.

Then, we estimate the following equations:

$$\text{Entry In New County}_{f,t} = \gamma \times \text{Firm Shock}_{f,t-1} + \alpha_f + \alpha_t + \varepsilon_{f,t} \tag{6}$$

Entry In New $\text{County}_{f,t}$ is an indicator variable that is one if the firm f opens an establishment in year t in a county where it did not had any establishment in the past. We first look at entry in any new county and then examine entry into counties that are less exposed to heat stress. α_f and α_t denote firm and year fixed-effects respectively.

Table 8 presents the results. The first column shows the entry of affected firms in any new county. We find that 1 standard deviation increase in firm shock increase the probability of entry into a new county by 0.09 pp (0.53×0.177). Alternatively, consider a firm with equal employment in two counties. One hot day in one of the counties increases the probability of entering a new county by 0.07 pp (0.40×0.177) In the next set of columns, we examine if firms' entry response is stronger in counties that have a lower exposure to heat stress. We classify counties as having a lower exposure to heat stress if they have a below-median value of expected heat damage, energy damage, and labor damage (as a proportion of GDP). In the last column, we look at counties with below median value of chronic heat stress (i.e., counties that have experienced fewer heat shocks in the past). Consistent with our conjecture, we find that the entry response is generally stronger if the new county has a lower exposure to heat stress.

In summary, these results suggest that firms hit by heat shocks in their existing locations expand into new counties, particularly into those with a lower exposure to extreme heat conditions. This is important for two reasons. First, it shows that heat shocks may affect firm boundary along the spatial dimension. Second, it suggests that as heat-related disasters become increasingly more likely, aggregate economic activity may shift towards areas less prone to hot conditions.

V Heterogeneity

A Heterogeneity across firms

We now explore heterogeneity in firm characteristics to demonstrate that firms absorb the costs associated with mitigation, and that financially healthier firms are better positioned to manage climate risks by redistributing their workforce across different locations. We augment our baseline model by introducing an interaction between the peer shock variable and various firm characteristics. Specifically, we compute the size (represented by total employment), leverage (book value of debt over assets), z-score (Altman, 1968), and gross profitability (gross profit over assets) for all firms in our dataset. These firms are then categorized into two groups based on whether their financial characteristic lies above or below the median value in each year. Subsequently, we estimate the following equation:

$$\begin{aligned}\Delta \text{Log(Employment)}_{f,c,t-1\to t+k} = {} & \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{Firm Characteristic}_{f,t-1} \\ & + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned} \tag{7}$$

In this equation, ΔLog(Employment)$_{f,c,t-1\to t+k}$ represents the change in log employment for firm f in county c from year $t-1$ to $t+k$. Peer Shockf, c, t indicates the total heat shock at peer establishments' locations, as computed in Equation (2). Firm Characteristic$f, t-1$ denotes the financial attributes (including indicators for large size, low leverage, high z-score, and high profitability) of firm f in year $t-1$. Following our baseline specification, we apply firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects and cluster standard errors at the county level. Table 9 shows how financial health affect firms' mitigation behavior over a

3-year timeframe (i.e., coefficients for $k = 2$). Our findings reveal that firms with greater size, lower leverage, higher z-score, and increased profitability tend to relocate a higher proportion of their workforce in response to heat shocks. These results provide suggestive evidence that firms factor in the costs of mitigation, and stronger financial condition enhances their resilience to climate shocks through the mechanism of spatial reallocation.

Next, we delve into whether the market's perception of a firm's exposure to climate risk influences its mitigation efforts. There is increasing evidence that institutional investors value climate risk disclosures of their portfolio companies (Ilhan et al., 2023). Investor perception can impact a firm's actions in two ways. First, it can inform the management that investors are pricing climate risks and prompt them to hedge their exposure to avoid a higher cost of capital (Giglio et al., 2021). Second, managers may gain valuable insights into how their firm operations will be impacted by climate risk from market participants and they may decide to act accordingly. We employ three measures created by Sautner et al., 2023 to quantify climate change exposure at the firm level. The first measure (Climate exposure) is the normalized frequency of climate-related bigrams in earnings call reports. The second measure (Climate risk) is the relative frequency with which climate bigrams appear alongside words like "risk", "uncertainty", or their synonyms. The third measure (Climate sentiment) is the relative frequency with which climate-related bigrams appear alongside positive or negative tone words.

We use these measures as firm characteristics as re-estimate Equation (8). Figure 2 plots the interaction coefficient (δ^k) after k years following the shock. It shows that firms with higher climate exposure, risk, and sentiment measures tend to reallocate more workers in response to climate shocks (Panels (a), (b), and (c)). In panel (d), we follow the ESG-classification of Cohen et al., 2020 to examine the share of ESG-affiliated mutual fund investors as a firm characteristic.[11] We find that firms with a larger share of such investors exhibit greater mitigation activity. Overall, these results suggest that investor perception about firms' climate exposure and their inclination towards ESG issues motivate firms to shift their workforce away from heat shocks, enhancing the resilience of their overall employment against rising temperatures.

B Role of county characteristics

When a disaster hits a particular establishment, the firm can hire workers across a number of peer locations. We now explore what regional characteristics (apart from projected damages)

[11] We classify a fund as green if it has "ESG" or "green" in its name, or if it is listed as an ESG fund either by USSIF (The Forum of Sustainable and Responsible Investment) or by Charles Schwab.

influence a firm's decision to choose one peer location over the others. First, we study the role of projected heat-related damages in a given county. The reallocation of the workforce may require firms to reorganize their operations and is likely to be costly. To avoid incurring this cost again, firms would likely move into places that are less exposed to heat stress in the future. Climate scientists have built several models to estimate economic damages from climate change in the United States at county-level for various hazards including heat waves. We use Spatial Empirical Adaptive Global-to-Local Assessment System (SEAGLAS) of Hsiang et al., 2017 to quantify the projected heat-related damage at the county level. SEAGLAS first estimates how annual temperature distributions are projected to change as a consequence of climate change in different counties, and then converts these shifts into estimates of economic damages using hazard-specific dose-response functions. See Acharya et al., 2022 for more detailed discussion of the measure.

The four measures we use are projected heat damage, and its three components: damages related to climate change-induced increase in energy expenditures, decrease in labor productivity in industries where workers are directly exposed to outside temperatures ("high-risk labor"), and decrease in labor productivity in other industries ("low-risk labor"). All these measures are scaled by the local GDP. We conjecture that if the firms are readjusting their workforce to mitigate heat risk, they are less likely to hire workers in peer locations with high projected damages. On the other hand, if the reallocation activity is driven by some other factor, we do not expect systematic differences across peer locations along this dimension. To verify our conjecture, we estimate the following specification:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} &= \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{County Characteristic}_{c,t-1} \\ &\quad + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned} \tag{8}$$

Figure 3 shows that consistent with our hypothesis, employment growth is weaker in regions with higher projected damages. Among different components of our heat damage measure, we find that the results are mainly coming from exposure to energy damages and high-risk labor productivity, with little evidence for low-risk labor. These results are similar to Acharya et al., 2022 who find the same two components being the main channels through with heat damages are related to asset prices. Overall, these results support our argument that firms are reallocating their workforce to mitigate their heat exposure and not due to any other reason.

C Heterogeneity across industries

Excessive heat may damage firm productivity in multiple ways. It can adversely impact labor productivity if the workforce is exposed to outdoor conditions (Graff Zivin and Neidell, 2014). It can also increase energy expenses due to air-conditioning and other heat-resistant technologies making it prohibitively expensive to maintain a large establishment (Ponticelli et al., 2023). Finally, it can affect local demand particularly impacting the firms in the non-tradable sector. To understand what aspect of heat-related issues firms are trying to mitigate through labor reallocation, we examine the heterogeneity in mitigation activity across industries. Specifically, we augment our baseline specification with industry information and estimate the following regression:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f(i),c,t-1\rightarrow t+k} = \; & \delta^k \times \text{Peer Shock}_{f(i),c,t} \times \text{Industry}_i \\ & + \gamma^k \text{Peer Shock}_{f(i),c,t} + \alpha_{f(i)} + \alpha_{c,t} + \varepsilon_{f(i),c,t}\end{aligned}$$

$\Delta\text{Log(Employment)}_{f(i),c,t-1\rightarrow t+k}$ is the change in log employment of firm f (in industry i) in county c from year $t-1$ to $t+k$. Peer $\text{Shock}_{f(i),c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (2). Industry_i indicates broadly defined industries categorized as 2-digit SIC codes. We employ firm ($\alpha_{f(i)}$) and county-year ($\alpha_{c,t}$) fixed-effects and cluster standard errors at the county level.

We then calculate the marginal impact of Peer $\text{Shock}_{f(i),c,t}$ across each industry and plot the impact corresponding to a 3-year period following the shock (i.e., $k = 2$) in Figure 4. The two industries exhibiting the highest reallocation are construction and mining. Certain industrial activities (e.g., mining) are perceived to be location specific. However, our results are consistent with the idea that heat-affected mining companies are altering their capacity utilization and increasing extraction in unaffected peer locations. An alternative explanation is firms switching to more capital-intensive production processes in the affected areas. The two industries with the lowest reallocation are FIRE (finance, insurance, and real estate) and retail trade. Overall, these results suggest that the physical stress experienced by the workers through unavoidable outdoor exposure is a key issue affecting firm's mitigation choice.

To understand the importance of other climate-related issues, we look at industry characteristics like the possibility of teleworking and tradability. For teleworking, we use the measure of Dingel and Neiman, 2020 that classifies the feasibility of working at home for all occupations based on surveys from the Occupational Information Network (O*NET), and aggregates this to industry-level. For tradability, we use the geographical concentration-based classification of Mian and Sufi, 2014, where tradability is determined based on the idea that tradable industries are likely to be more geographical concentrated. Table 10 shows that tradable industries and industries amenable to teleworking exhibit lower mitigation. Overall these results show that the concerns that firms are trying to address are related to physical stress (and associated decline in productivity) experienced by workers and the local product demand.[12]

VI Mitigation and the nature of climate shock

Having established our baseline results on firm mitigation of heat risk and explored firm heterogeneity, we now study how the nature of climate shock affects this mitigation.

A Clustering of heat risk

If a mild heat shock occurs as a one-time event, companies can address it using temporary solutions. However, when heat shocks are severe or happen in succession, permanent measures such as workforce reallocation become necessary. Consequently, our study examines whether firms' efforts to mitigate are more robust in the face of more severe or clustered heat shocks, referred to as heat spells. To begin, we modify our measure of peer shocks to study acute shocks. Roughly 28% of the heat disasters in our dataset result in some form of measurable property damage, with the average damage incurred by this subset amounting to $247,000. We establish an alternative measure for peer shocks (Peer Shock $(\text{Acute})_{f,c,t}$) by considering only hot days that led to non-zero property damage.[13] Next, we introduce a second measure (Peer Shock $(\text{Spells})_{f,c,t}$) to capture heat shocks occurring as spells. Many regions in the recent past have experienced elongated spells of extremely high temperatures. For example, Phoenix set a record of 31 consecutive days of temperatures above 110F in July 2023.[14] To examine how such spells affect our mitigation channel, we adjust our peer shock measure to encompass periods of three or more consecutive hot days. We then re-evaluate our baseline model using these modified measures and present the outcomes in Table 12.

In Panel (a), we present our baseline results for comparison. Panel (b) demonstrates that mitigation efforts are more pronounced in response to acute heat shocks. This indicates that firms adopt more lasting mitigation strategies when faced with more extreme shocks. In Panel

[12]Extreme temperatures can also cause worker injuries and fatalities (Park et al., 2021), further lowering their productivity and incentivizing firms to reallocate their workforce.

[13]Heat shocks often cause property damage by weakening buildings' foundations and roofs (causing leakage). Extreme temperatures can also cause electrical failures due to overheating.

[14]See CBS news article dated August 1, 2023 (link).

(c), we show that the response to heat spells is similar to our baseline effect, highlighting the impact of such spells on firms' mitigation response.

We then delve into whether heat shocks in counties already grappling with long-term climate change trigger a more substantial reaction from firms. On one hand, past exposure may render counties more resilient to future heat shocks if they invested in heat-resistant infrastructure following prior shocks. On the other hand, new heat shocks could exacerbate the strain on already deteriorating infrastructure, motivating firms to adopt longer-term mitigation strategies. Agents in counties with frequent heat shocks may also have more precise information about the likelihood and duration of the disasters, further increasing their local investments in mitigation and/or willingness to migrate (Acharya et al., 2023). Thus, understanding the impact of "chronic" heat stress on counties can shed light on the long-term impact of global warming (Dell et al., 2014). We compute the average number of hot days experienced by each county from 1960 (the start of the PRISM sample) to 2008 (the start of our D&B sample). Counties ranking in the top quintile (20%) of this distribution are classified as chronically heat stressed. Subsequently, we revise our peer shock measure to encompass hot days in counties with chronic stress and denote it as Peer Shock $(\text{Chronic})_{f,c,t}$. Table 12 (Panel (d)) illustrates that the response to such shocks is more pronounced that our original shocks, suggesting that current shocks build upon firms' past experience and intensify their inclination to relocate away from heat-stressed counties.

In summary, these findings demonstrate that the relocation of firms away from counties becomes more pronounced when these counties experience more extreme heat shocks and long-term climate degradation.

B Other climate hazards

Our main focus in this study is on how companies shift their workforce in reaction to heat shocks. In this section, we look at "compound" climate shocks, i.e., the simultaneous occurrence of heat shocks alongside other natural disasters. For example, Maui experienced a devastating episode of wildfires in August 2023 which was likely exacerbated by rising temperatures and hurricane-like wind conditions.[15] The frequency of multiple hazards occurring in close proximity like this is projected to significantly increase in the future (Jones et al., 2020; Raymond et al., 2022). Such compound disasters may result in higher economic damages compared to a single disaster (Chen et al., 2024) and managing them may require a more comprehensive and costly approach (Zscheischler et al., 2020). Hence, these combined shocks

[15]See The Washington Post report dated August 12, 2023 (link).

could potentially drive firms to exit the impacted county, resulting in a stronger response in terms of workforce reallocation.

In addition to heat-related dangers, the PRISM dataset covers four other types of hazards: droughts, wildfires, hurricanes and storms, and earthquakes. To explore the idea of compound shocks, we modify our measure of heat shocks to account for hot days that coincide with other disasters in the same year. For example, Peer Shock (Heat + Drought)$_{f,c,t}$ is calculated using hot days in county c which experienced a drought in year t. We then update our main model with these adjusted measures and present the findings in Panel (a). Our results demonstrate that, except for earthquakes (where we have too few co-occurrences), employment reallocation is stronger in response to compound shocks. Firm response towards heat disasters is most amplified by concurrent hurricanes and storms followed by drought events. At the same time, concurrent wildfires do not appear to increase firms' response to heat shocks. These results highlights the increasing significance of spatial strategies to mitigate the effects of more frequent combined climate shocks.

Subsequently, we delve into whether firms make similar workforce adjustments when facing other natural disasters in isolation. For each of the alternative disasters, we create a measure that counts the number of days a county experienced that disaster in a given year. We then update our main model with these new measures and present the outcomes in Figure 5 Panel (b). Our findings reveal that firms handle all forms of climate risks by relocating their workforce from affected establishments to unaffected ones. The effect is the largest for hurricanes and storms followed by heat and wildfires. Firms' response is the smallest in case of droughts and earthquakes.

VII Conclusion

In this paper, we studied how firms respond to extreme temperature shocks by reallocating their labor force across geographies. We found that firms operating in multiple counties respond to these shocks by shifting employment to unaffected counties, consistent with firms adjusting their operations to mitigate climate change related risks. Single location firms simply lose employees in affected counties.

We found that the effect is stronger for firms that are more profitable, less levered and financially constrained, consistent with financial constraints being an impediment for efficient resource reallocation. We also found that the effect is stronger for firms that are more concerned about their climate change exposure and that have a larger fraction of ESG funds as their owners, suggesting that more concerned managers and owners responds more proactively to extreme temperature shocks. Vacancies are more likely to be migrated to counties with strong local economies, and to counties with lower ex-ante climate change exposure.

We also found that counties experiencing heat shocks experience employment shift from small to large firms within the county. Such shocks also increase the employment in peer counties (i.e., those linked to it through firm networks) through the firm mitigation channel. This increase is driven by firms hiring new workers in the peer counties and not by work-related migration across counties.

Taken together, our results have implications on how we should expect firms adjust their operations if heat waves intensify in the future as a consequence of climate change. Future work on this topic can explore if firms adjust their fixed capital and labor composition in response to rising temperatures, channels (exit versus voice) through which climate-concerned investors affect firm mitigation strategies, and the broader macroeconomic implications of spatial redistribution of economic activity resulting from firm mitigation of heat risk. We have likely only scratched the surface of a promising line of research inquiry linking climate change to industrial and economic organization via the corporate finance channel.

References

Acharya, V. V., H. Almeida, Y. Amihud, and P. Liu (2021). Efficiency or resiliency? corporate choice between financial and operational hedging.

Acharya, V. V., T. Johnson, S. Sundaresan, and T. Tomunen (2022). Is physical climate risk priced? evidence from regional variation in exposure to heat stress. Technical report, National Bureau of Economic Research.

Acharya, V. V., T. Johnson, S. Sundaresan, and S. Zheng (2023). Disasters with unobservable duration and frequency: Intensified responses and diminished preparedness. Technical report, National Bureau of Economic Research.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2020). Temperature shocks and establishment sales. *The Review of Financial Studies 33*(3), 1331–1366.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2023). Temperature shocks and industry earnings news. *Journal of Financial Economics 150*(1), 1–45.

Alekseev, G., S. Giglio, Q. Maingi, J. Selgrad, and J. Stroebel (2022). A quantity-based approach to constructing climate risk hedge portfolios. Technical report, National Bureau of Economic Research.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance 23*(4), 589–609.

Baez, J., G. Caruso, V. Mueller, and C. Niu (2017). Heat exposure and youth migration in central america and the caribbean. *American Economic Review 107*(5), 446–450.

Barnatchez, K., L. D. Crane, and R. Decker (2017). An assessment of the national establishment time series (nets) database.

Bartram, S. M., K. Hou, and S. Kim (2022). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics 143*(2), 668–696.

Baumgartner, S., T. Schober, A. Stomper, and R. Winter-Ebmer (2023). Banking on snow: Bank capital, risk, and employment. *Risk, and Employment (April 30, 2023)*.

Behrer, A. P. and V. Bolotnyy (2023). Moving to adaptation? understanding the migratory response to hurricanes in the united states. Technical report, The World Bank.

Behrer, A. P. and J. Park (2017). Will we adapt? temperature, labor and adaptation to climate change. *Harvard Project on Climate Agreements Working Paper*, 16–81.

Borisov, A., A. Ellul, and M. Sevilir (2021). Access to public capital markets and employment growth. *Journal of Financial Economics 141*(3), 896–918.

Castro-Vincenzi, J. (2023). Climate hazards and resilience in the global car industry. Technical report, Technical report, Working Paper.

Chen, C., L. Schwarz, N. Rosenthal, M. E. Marlier, and T. Benmarhnia (2024). Exploring spatial heterogeneity in synergistic effects of compound climate hazards: Extreme heat and wildfire smoke on cardiorespiratory hospitalizations in california. *Science Advances 10*(5), eadj7264.

CLEE (2020). Insuring extreme heat risk. Technical report, Center for Law, Energy, and the Environment.

Cohen, L., U. G. Gurun, and Q. H. Nguyen (2020). The esg-innovation disconnect: Evidence from green patenting. Technical report, National Bureau of Economic Research.

Crane, L. D. and R. A. Decker (2020). Research with private sector business microdata: The case of nets/d&b. Technical report, Working paper.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature 52*(3), 740–798.

Denes, M., S. T. Howell, F. Mezzanotti, X. Wang, and T. Xu (2020). Investor tax credits and entrepreneurship: Evidence from us states. *The Journal of Finance*.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? *Journal of public economics 189*, 104235.

Farre-Mensa, J., D. Hegde, and A. Ljungqvist (2020). What is a patent worth? evidence from the us patent "lottery". *The Journal of Finance 75*(2), 639–682.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica 79*(3), 733–772.

Giglio, S., B. Kelly, and J. Stroebel (2021). Climate finance. *Annual Review of Financial Economics 13*, 15–36.

Giné, X., L. Menand, R. Townsend, and J. Vickery (2012). Microinsurance: a case study of the indian rainfall index insurance market. *Handbook of the Indian economy*, 167–94.

Giroud, X. and H. M. Mueller (2015). Capital and labor reallocation within firms. *The Journal of Finance 70*(4), 1767–1804.

Giroud, X. and H. M. Mueller (2019). Firms' internal networks and local economic shocks. *American Economic Review 109*(10), 3617–3649.

Giroud, X. and J. Rauh (2019). State taxation and the reallocation of business activity: Evidence from establishment-level data. *Journal of Political Economy 127*(3), 1262–1316.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1–26.

Gumpert, A., H. Steimer, and M. Antoni (2022). Firm organization with multiple establishments. *The Quarterly Journal of Economics 137*(2), 1091–1138.

Hinkel, J., D. Lincke, A. T. Vafeidis, M. Perrette, R. J. Nicholls, R. S. Tol, B. Marzeion, X. Fettweis, C. Ionescu, and A. Levermann (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences 111*(9), 3292–3297.

Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, et al. (2017). Estimating economic damage from climate change in the united states. *Science 356*(6345), 1362–1369.

Ilhan, E., P. Krueger, Z. Sautner, and L. T. Starks (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies 36*(7), 2617–2650.

Jin, Z., F. W. Li, Y. Lin, and Z. Zhang (2021). Do firms adapt to rising temperatures? evidence from establishment-level data. *Evidence from Establishment-Level Data (August 20, 2021)*.

Jones, M. W., A. Smith, R. Betts, J. G. Canadell, I. C. Prentice, and C. Le Quéré (2020). Climate change increases the risk of wildfires. *ScienceBrief Review 116*, 117.

Kahn, M. E. (2014). Climate change adaptation: lessons from urban economics. Technical report, National Bureau of Economic Research.

Lin, C., T. Schmid, and M. S. Weisbach (2020). Climate change and corporate investments: Evidence from planned power plants. *Fisher College of Business Working Paper (2019-03)*, 026.

Martin, I. W. and C. Wagner (2019). What is the expected return on a stock? *The Journal of Finance 74*(4), 1887–1929.

Mian, A. and A. Sufi (2014). What explains the 2007–2009 drop in employment? *Econometrica 82*(6), 2197–2223.

Neumark, D., J. Zhang, and B. Wall (2007). Employment dynamics and business relocation: New evidence from the national establishment time series. In *Aspects of worker well-being*, Volume 26, pp. 39–83. Emerald Group Publishing Limited.

Pankratz, N., R. Bauer, and J. Derwall (2023). Climate change, firm performance, and investor surprises. *Management Science*.

Pankratz, N. and C. Schiller (2021). Climate change and adaptation in global supply-chain networks. In *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC, European Corporate Governance Institute–Finance Working Paper*, Number 775.

Park, J., N. Pankratz, and A. Behrer (2021). Temperature, workplace safety, and labor market inequality.

Ponticelli, J., Q. Xu, and S. Zeume (2023). Temperature and local industry concentration. Technical report, National Bureau of Economic Research.

Raymond, C., L. Suarez-Gutierrez, K. Kornhuber, M. Pascolini-Campbell, J. Sillmann, and D. E. Waliser (2022). Increasing spatiotemporal proximity of heat and precipitation extremes in a warming world quantified by a large model ensemble. *Environmental Research Letters 17*(3), 035005.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy 129*(6), 1797–1827.

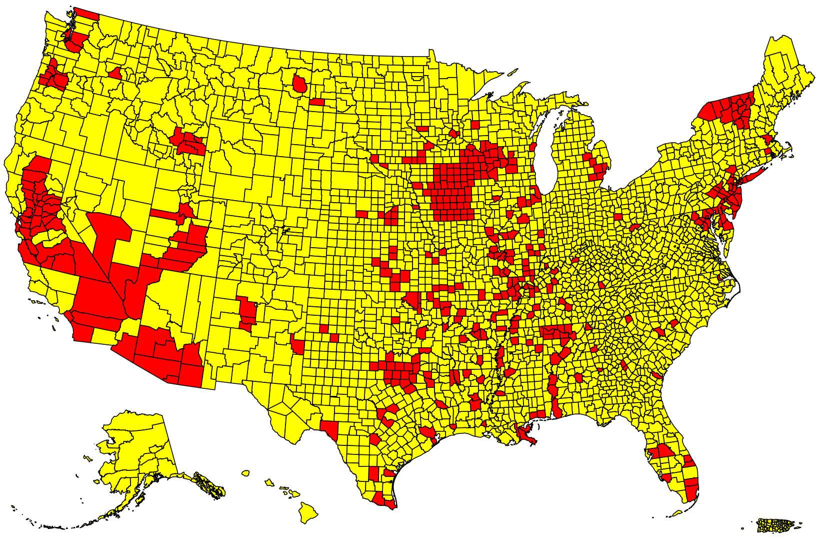
Tate, G. and L. Yang (2015). The bright side of corporate diversification: Evidence from internal labor markets. *The review of financial studies 28*(8), 2203–2249.

Vaidyanathan, A., J. Malilay, P. Schramm, and S. Saha (2020). Heat-related deaths—united states, 2004–2018. *Morbidity and mortality weekly report 69*(24), 729.

Zscheischler, J., O. Martius, S. Westra, E. Bevacqua, C. Raymond, R. M. Horton, B. van den Hurk, A. AghaKouchak, A. Jézéquel, M. D. Mahecha, et al. (2020). A typology of compound weather and climate events. *Nature reviews earth & environment 1*(7), 333–347.

VIII Figures and tables

Figure 1: Heat shocks across the US



Notes: Figure 1 shows the counties that experienced one or more hot days throughout our sample period of 2009 to 2020. Hot Days are days when a loss (property, crop, injury, or fatality) occurred from a heat hazard according to the SHELDUS database.

Table 1: Summary Statistics

	Mean	SD	1%tile	25%tile	Median	75%tile	99%tile
Panel (A): Firm-county-year sample							
Employment	118	659	1	7	21	79	1,521
# Establishments	2.3	5.7	1	1	1	2	18
# Hot Days	.47	3	0	0	0	0	11
# Hot Days, Other	1,092	14,693	0	0	.74	123	17,928
Δ Log(Employment) (%)	.8	29	-69	0	0	0	88
Own Shock	.12	.47	0	0	0	0	2.5
Peer Shock	2.4	2.9	0	0	.55	4.8	9.8
Total Postings/L.Employment (%)	7	27	0	0	0	0	200
Exposed Postings/L.Employment (%)	1.8	42	0	0	0	0	30
Non-Exposed Postings/L.Employment (%)	5.1	20	0	0	0	0	149
Panel (B): Firm-year sample							
Single Location	.3	.46	0	0	0	1	1
Employment	1,074	8,526	27	140	232	514	14,538
# Establishments	21	196	1	3	5	11	271
# Hot Days, Firm	.59	3	0	0	0	0	11
Δ Log(Employment) (%)	2.1	38	-88	0	0	0	113
Firm Shock	.19	.52	0	0	0	0	2.5
Entry In New County	.12	.32	0	0	0	0	1
Panel (C): County-year sample							
Employment	21,840	76,801	20	1,172	3,606	11,931	323,537
Δ Log(Employment) (%)	1.3	7.8	-21	-1.6	0	3.6	29
Δ Log(Employment), Locals (%)	-.27	3	-6.8	-1.7	-.25	1.1	7.7
Δ Log(Employment), Migrants (%)	.18	2.4	-3.4	-.56	.039	.82	4.8
Own Shock	.03	.24	0	0	0	0	1.6
Peer Shock	6.2	1.5	2.9	5.3	6.2	7.1	10

Notes: Table 1 presents the summary statistics of the main variables used in the empirical analysis.

Table 2: Determinants of SHELDUS Heat Shock

	# Hot Days			
# Days(T≥99Pctile)	0.116***	0.117***	0.109***	0.066***
	(0.003)	(0.005)	(0.006)	(0.006)
# Days(T≥99Pctile)				0.076***
× High Social Vulnerability/Low Resilience				(0.009)
County FE		✓	✓	✓
Year FE			✓	✓
Observations	113,763	113,763	113,763	113,763
$\bar{y}$	0.728	0.728	0.728	0.728
Adj. R^2	0.014	0.022	0.082	0.083

Notes: Table 2 shows the relationship between the number of disaster days in the SHELDUS data with the number of temperature-based hot days. We estimate the following specification:

$$\text{\# Hot Days}_{c,t} = \text{\# Days(T}\geq\text{99Pctile)}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t}$$

Hot Days$_{c,t}$ is the number of hot days in county c in year t according to the SHELDUS data. # Days(T≥99Pctile)$_{c,t}$ is the number of days in year t when the average temperature in county c was above its 99th percentile value over the 1982-2020 period. In the final column, we interact the main independent variable with a dummy variable (High Social Vulnerability/Low Resilience) that equals one for counties with high community risk factor (high social vulnerability/low community resilience) according to FEMA Risk Index data. We employ county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table 3: Establishment response to own shock

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (A-1): Average establishment						
Own Shock	0.024	-0.090	-0.005	0.031	0.243	0.327**
	(0.056)	(0.096)	(0.126)	(0.133)	(0.156)	(0.147)
Panel (A-2): Establishments of single- vs. multi-location firms						
Own Shock	0.018	-0.076	0.057	0.150	0.396**	0.438***
	(0.058)	(0.102)	(0.130)	(0.133)	(0.160)	(0.146)
Single Location × Own Shock	0.152	-0.360	-1.508**	-2.850***	-3.586***	-2.575***
	(0.299)	(0.520)	(0.663)	(0.761)	(0.686)	(0.556)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	5,664,113	4,826,630	4,106,215	3,460,396	2,868,812	2,330,678
$\bar{y}$	0.802	1.898	2.618	3.488	4.190	5.072

	Total Postings/L.Employment$_{t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (B-1): Average establishment						
Own Shock	0.038	0.182	0.217*	0.089	-0.222	-0.266**
	(0.103)	(0.135)	(0.119)	(0.113)	(0.146)	(0.122)
Panel (B-2): Establishments of single- vs. multi-location firms						
Own Shock	0.021	0.153	0.179	0.053	-0.265*	-0.290**
	(0.107)	(0.138)	(0.118)	(0.113)	(0.146)	(0.120)
Single Location × Own Shock	0.340	0.567**	0.760***	0.704***	0.865***	0.491**
	(0.223)	(0.262)	(0.244)	(0.258)	(0.192)	(0.222)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1,391,478	1,277,856	1,106,821	950,763	803,600	663,195
$\bar{y}$	7.027	7.334	7.623	8.016	8.292	8.587

Notes: Table 3 shows how establishments respond to heat shocks in their county. Panel (A-1) shows the effect on employment growth at an average establishment and Panel (A-2) shows the effect on the establishments of single- and multi-location firms. Similarly, Panel (B-1) shows the effect on job postings on an average establishment whereas Panel (B-2) shows the effect broken down by single- and multi-location firms. The outcome variable in Panels (A-1) and (A-2) is ΔLog(Employment)$_{f,c,t-1\to t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panels (B-1) and (B-2) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Own Shock$_{c,t}$ equals Log(1+# Hot Days) in county c in year t. We employ firm (α_f), county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table 4: Establishment response to own shock: Role of firm size

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.153*	0.169	0.381**	0.613***	0.931***	0.975***
	(0.081)	(0.138)	(0.177)	(0.182)	(0.218)	(0.196)
Single-Location/Small $\times$ Own Shock	-0.238	-0.983	-2.375***	-4.632***	-5.390***	-4.285***
	(0.336)	(0.683)	(0.909)	(1.077)	(0.946)	(0.764)
Single-Location/Large $\times$ Own Shock	0.364	-0.090	-1.100*	-1.531**	-2.385***	-1.500**
	(0.444)	(0.560)	(0.636)	(0.668)	(0.676)	(0.654)
Multi-Location/Small $\times$ Own Shock	-0.739***	-1.308***	-1.706***	-2.410***	-2.758***	-2.746***
	(0.170)	(0.280)	(0.351)	(0.399)	(0.414)	(0.430)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	5,664,113	4,826,630	4,106,215	3,460,396	2,868,812	2,330,678
$\bar{y}$	0.802	1.898	2.618	3.488	4.190	5.072
Adj. R^2	0.012	0.033	0.052	0.073	0.096	0.122

	Total Postings/L.Employment$_{t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.033	0.137	0.191*	0.076	-0.198	-0.203
	(0.126)	(0.147)	(0.113)	(0.110)	(0.149)	(0.133)
Single-Location/Small $\times$ Own Shock	0.173	0.605**	0.750**	0.522*	0.547**	-0.011
	(0.280)	(0.294)	(0.307)	(0.288)	(0.235)	(0.310)
Single-Location/Large $\times$ Own Shock	0.537**	0.554	0.745**	0.893***	1.131***	0.958***
	(0.258)	(0.353)	(0.336)	(0.319)	(0.298)	(0.308)
Multi-Location/Small $\times$ Own Shock	-0.041	0.054	-0.040	-0.077	-0.229	-0.296*
	(0.133)	(0.142)	(0.151)	(0.167)	(0.180)	(0.173)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1,391,478	1,277,856	1,106,821	950,763	803,600	663,195
$\bar{y}$	7.027	7.334	7.623	8.016	8.292	8.587
Adj. R^2	0.324	0.334	0.354	0.377	0.386	0.391

Notes: Table 4 shows how establishments of respond to heat shocks in their county. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1 \to t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Own Shock$_{c,t}$ equals Log(1+# Hot Days) in county c in year t. We interact Own Shock with indicator variables for whether the establishment belongs to a single-location firm, and whether it belongs to a small firm. We employ firm (α_f), county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table 5: Establishment response to peer shock

Panel (A): Employment growth of average establishment

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.612***	0.728***	1.016***	1.351***	1.640***	1.802***
	(0.018)	(0.027)	(0.038)	(0.049)	(0.060)	(0.069)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	5,555,947	4,726,836	4,015,440	3,378,682	2,797,336	2,267,285
$\bar{y}$	0.770	1.785	2.424	3.214	3.899	4.748
Adj. R^2	0.012	0.027	0.041	0.057	0.075	0.092

Panel (B): Job postings of average establishment

	Total Postings/L.Employment$_{t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.803***	0.663***	0.591***	0.577***	0.480***	0.415***
	(0.036)	(0.033)	(0.034)	(0.033)	(0.033)	(0.029)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	1,352,263	1,243,747	1,076,981	924,851	781,349	644,505
$\bar{y}$	7.048	7.342	7.632	8.032	8.312	8.610
Adj. R^2	0.317	0.325	0.346	0.369	0.379	0.384

Notes: Table 5 shows how establishments respond to heat shocks in their peer counties. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Peer Shock$_{c,t}$ equals Log(1+# Hot Days, Other) in county c in year t. We employ firm (α_f), county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table 6: Firm mitigation: Reallocation to unaffected peer counties

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (a): Baseline specification						
Peer Shock	0.612***	0.728***	1.017***	1.352***	1.640***	1.803***
	(0.018)	(0.027)	(0.038)	(0.049)	(0.060)	(0.069)
Panel (b): Robustness - Alternative measures of Peer Shock						
Peer Shock, Alt	0.701***	0.449***	0.322***	0.731***	1.123***	1.092***
	(0.058)	(0.073)	(0.090)	(0.110)	(0.136)	(0.150)
Peer Shock, (Est-Wt)	0.304***	0.031*	0.080***	0.229***	0.378***	0.388***
	(0.014)	(0.017)	(0.022)	(0.028)	(0.034)	(0.038)
Peer Shock, (Eq-Wt)	0.154**	0.518***	0.903***	0.899***	0.947***	0.645***
	(0.068)	(0.095)	(0.109)	(0.131)	(0.146)	(0.136)
Peer Shock (Top Tercile)	1.718***	1.895***	2.747***	3.823***	4.642***	5.317***
	(0.087)	(0.136)	(0.187)	(0.245)	(0.307)	(0.359)
Peer Shock (T≥99Pctile)	0.452***	0.779***	1.115***	1.448***	1.825***	2.053***
	(0.014)	(0.022)	(0.031)	(0.042)	(0.051)	(0.057)
Panel (c): Robustness - Alternative fixed effects and clustering						
Firm×Year and County×Year FE						
Peer Shock	1.171***	2.093***	2.893***	3.598***	4.172***	4.785***
	(0.030)	(0.051)	(0.072)	(0.092)	(0.112)	(0.129)
Firm and County×Industry×Year FE						
Peer Shock	0.807***	1.069***	1.494***	1.995***	2.360***	2.640***
	(0.025)	(0.039)	(0.055)	(0.070)	(0.089)	(0.105)
County×Year FE						
Peer Shock	0.277***	0.394***	0.486***	0.602***	0.741***	0.890***
	(0.010)	(0.016)	(0.021)	(0.027)	(0.033)	(0.040)
Double clustering at County and Firm level						
Peer Shock	0.612***	0.728***	1.017***	1.352***	1.640***	1.803***
	(0.038)	(0.049)	(0.066)	(0.083)	(0.098)	(0.104)
Panel (d): Robustness - Alternative outcome						
	ΔLog(Establishments)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.133***	0.022***	0.039***	0.110***	0.178***	0.198***
	(0.006)	(0.007)	(0.009)	(0.012)	(0.016)	(0.018)
Observations	5,556,578	4,727,432	4,015,976	3,379,161	2,797,759	2,267,637
$\bar{y}$	0.770	1.785	2.424	3.213	3.899	4.748
Adj. R^2	0.010	0.026	0.040	0.055	0.072	0.090

Notes: Table 6 shows the results of our baseline specification (Panel (a)) given by Equation (3) along with several robustness tests (Panels (b), (c), and (d)). In panel (b), we define our peer shock measure in alternative ways. In panel (c), we use alternative set of fixed effects and clustering levels. In panel (d), we use alternative set of outcome variables.

Table 7: County response to own and peer shock

Panel (A): Employment growth

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	-0.380**	-0.753***	-0.641**	-0.611	-0.493	-0.544
	(0.179)	(0.265)	(0.326)	(0.415)	(0.399)	(0.407)
Peer Shock	1.614***	4.363***	6.576***	7.481***	7.228***	6.230***
	(0.253)	(0.469)	(0.752)	(0.900)	(0.886)	(0.889)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,310	25,505	22,680	19,853	17,006	14,169
$\bar{y}$	1.376	2.258	3.366	4.655	5.826	7.030
Adj. R^2	0.190	0.221	0.322	0.402	0.535	0.635

Panel (B): Employment growth (Locals)

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	-0.112*	-0.168**	-0.258***	-0.225**	-0.181*	-0.110
	(0.063)	(0.075)	(0.081)	(0.090)	(0.098)	(0.092)
Peer Shock	0.082	0.110	0.070	0.288**	0.427***	0.397**
	(0.057)	(0.079)	(0.102)	(0.140)	(0.159)	(0.187)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,482	25,581	22,725	19,883	17,057	14,216
$\bar{y}$	-0.241	-0.369	-0.675	-1.056	-1.885	-2.264
Adj. R^2	0.513	0.518	0.631	0.675	0.720	0.780

Panel (C): Employment growth (Migrants)

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.016	0.042	0.093	0.089	0.123	0.158**
	(0.029)	(0.047)	(0.061)	(0.081)	(0.086)	(0.067)
Peer Shock	0.079*	0.054	-0.013	0.003	0.084	0.062
	(0.043)	(0.078)	(0.108)	(0.130)	(0.131)	(0.120)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,572	25,726	22,884	20,032	17,172	14,325
$\bar{y}$	0.231	0.432	0.599	0.807	1.059	1.288
Adj. R^2	0.485	0.635	0.731	0.807	0.878	0.927

Notes: Table 7 shows outcomes in a county after heat shocks hit it and its peer counties. We aggregate data at the county-year level and estimate the following specification:

$$\Delta Y_{c,t-1\to t+k} = \beta_1 \times \text{Own Shock}_{c,t} + \beta_2 \times \text{Peer Shock}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t}$$

$\Delta Y_{c,t-1\to t+k}$ denotes the total employment growth (Panel (A)), employment growth of locals (Panel(B)), and employment growth due to migrant inflow (Panel (C)) of county c from year $t-1$ to $t+k$. Own Shock is Log(1 + # Hot Days$_{c,t}$) and Peer Shock is Log(1 + # Hot Days, Other$_{c,t}$). # Hot Days$_{c,t}$ is number of hot days in county c and # Hot Days, Other$_{c,t}$ is the employment weighted number of hot days in c's peer counties in year t. We employ county (α_c) and year (α_t) fixed-effects. We cluster standard errors at the county level.

Table 8: Reallocation and firm entry in new locations

	Entry In New County × 100					
	Overall	Low Heat damage/GDP	Low Energy damage/GDP	Low Labor damage/GDP (high-risk)	Low Labor damage/GDP (low-risk)	Low Chronic Heat Stress
Firm Shock	0.177*	0.252***	0.241***	0.201**	0.284***	0.169*
	(0.092)	(0.077)	(0.077)	(0.079)	(0.075)	(0.086)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	540,874	540,874	540,874	540,874	540,874	540,874
$\bar{y}$	8.833	6.411	6.329	6.415	5.873	7.328
Adj. R^2	0.270	0.244	0.245	0.243	0.236	0.251

Notes: Table 8 shows firms entering into new counties after experiencing a heat shock in one of their locations. The regression equation we estimate is:

$$\text{Entry In New County}_{f,t} = \gamma \times \text{Firm Shock}_{f,t-1} + \alpha_f + \alpha_t + \varepsilon_{f,t}$$

Entry In New County$_{f,t}$ is an indicator variable that is one if the firm f opens an establishment in year t in a county where it did not had any establishment in the past. In the first column, we look at the firm entry in any new county. In the next set of columns, we examine firms' entry into counties according to their exposure to heat-related characteristics. E.g., the outcome variable in the second column is an indicator variable that is one if the firm f entered a county with below-median value of expected heat damage/GDP. Firm Shock$_{f,t-1}$ is the exposure of firm f to heat shocks in year $t-1$ as defined in equation (5). α_f and α_t denote firm and year fixed-effects respectively. Standard errors are clustered at the firm level.

Table 9: Heterogeneity across firms: Firm financials

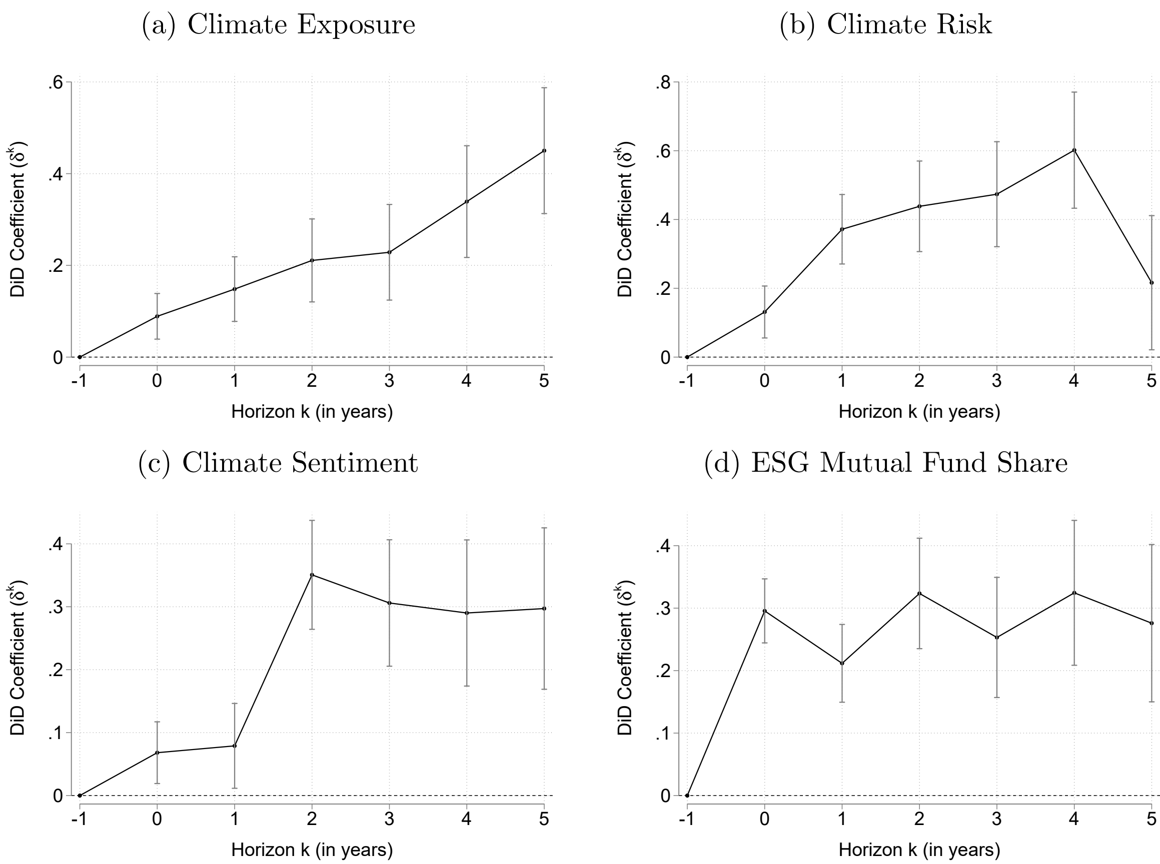
	ΔLog(Employment)$_{t-1,t+k}$ × 100				
	k=+2	k=+2	k=+2	k=+2	k=+2
Peer Shock	0.263***	2.016***	1.972***	2.002***	0.672
	(0.066)	(0.083)	(0.087)	(0.095)	(0.856)
Large Firm	-11.377***				-12.162***
	(0.295)				(0.830)
Large Firm × Peer Shock	1.091***				1.401*
	(0.066)				(0.849)
Low Leverage		-0.275			-0.701
		(0.565)			(0.586)
Low Leverage × Peer Shock		0.533***			0.534***
		(0.091)			(0.094)
High Z-Score			0.525		-0.467
			(0.506)		(0.558)
High Z-Score × Peer Shock			0.305***		0.117
			(0.070)		(0.082)
High Profitability				6.645***	7.461***
				(0.563)	(0.595)
High Profitability × Peer Shock				0.176**	0.047
				(0.080)	(0.091)
Firm FE	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓
Sample	Full D&B	Compustat	Compustat	Compustat	Compustat
Observations	4,015,976	463,256	463,256	463,256	463,256
$\bar{y}$	2.424	4.206	4.206	4.206	4.206
Adj. R^2	0.043	0.035	0.035	0.036	0.036

Notes: Table 9 shows the relationship between firm financials and labor reallocation in response to heat shocks. The regression equation we estimate is:

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{Firm Characteristic}_{f,t-1} + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

ΔLog(Employment)$_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. We present results corresponding to a 3-year horizon (i.e., $k = 2$). Peer Shock$_{f,c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (2). Firm Characteristic$_{f,t-1}$ denotes the financial characteristics (indicators for large size, low leverage, high z-score, and high profitability) of firm f in year $t-1$. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Figure 2: Heterogeneity across firms: Investor perception

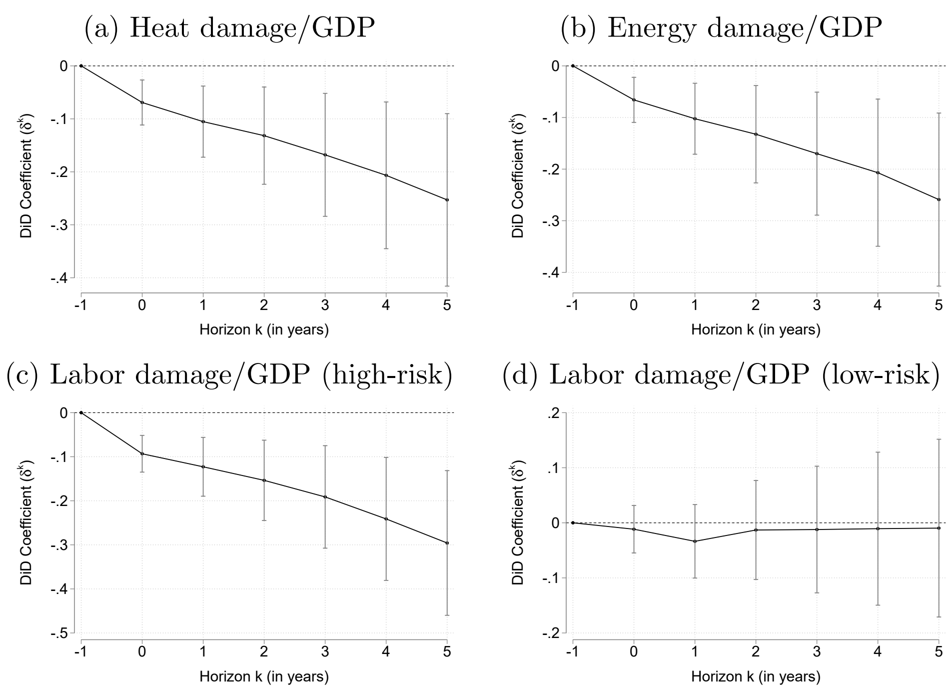


Notes: Figure 2 shows the relationship of investor beliefs and composition with labor reallocation in response to heat shocks (3-year horizon). The regression equation we estimate is:

$$\begin{aligned}\Delta \text{Log(Employment)}_{f,c,t-1\to t+k} &= \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{Firm Characteristic}_{f,t-1} \\ &\quad + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned}$$

ΔLog(Employment)$_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer Shock$_{f,c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (2). Firm Characteristic$_{f,t-1}$ denotes climate-related exposure, risk, and sentiment (Panels (a), (b), and (c)) of firm f in year $t-1$ according to their earnings call transcript as measured by Sautner et al., 2023. It also denotes the share of ESG-affiliated mutual funds holding the firm's shares in Panel (d). We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Figure 3: Role of heat-related county characteristics

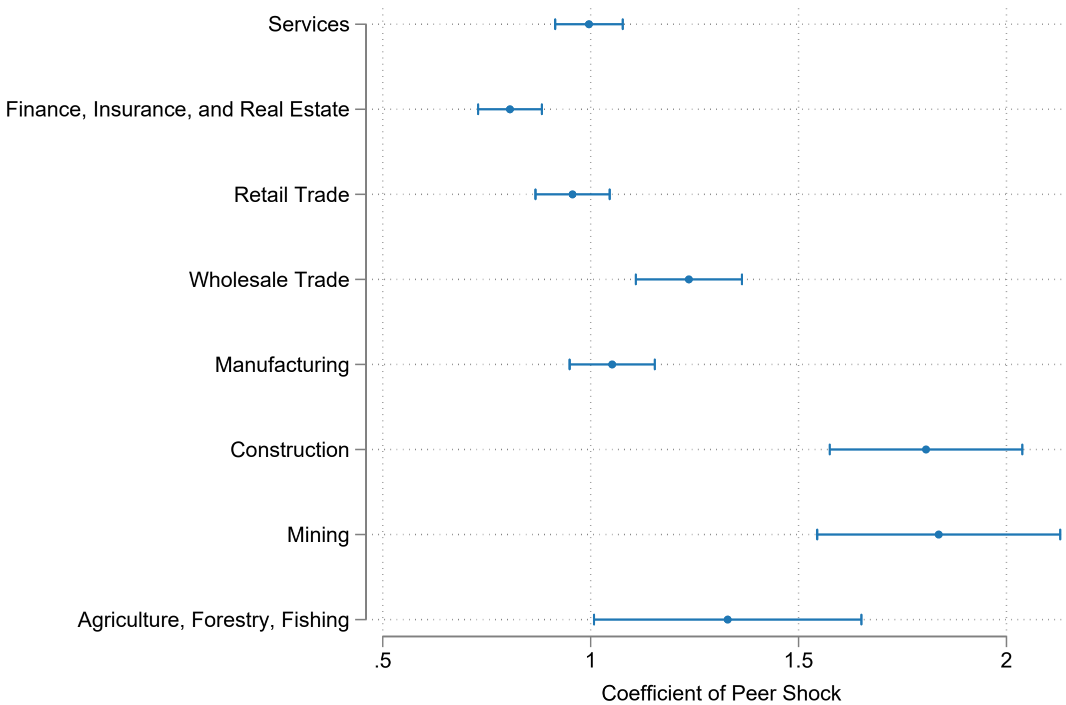


Notes: Figure 3 shows the county-level factors that influence firms' decision to reallocate into that county when its establishments elsewhere are impacted by heat shocks. We estimate

$$\Delta \text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{County Characteristic}_{c,t} + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

and plot the interaction coefficient (δ^k) with respect to each county characteristic. α_f and $\alpha_{c,t}$ denote firm and county-year fixed-effects and standard errors are clustered at the county level.

Figure 4: Mitigation across industries - I



Notes: Figure 4 shows the extent of mitigation across broadly defined industries. The regression we estimate is:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f(i),c,t-1\to t+k} &= \delta^k \times \text{Peer Shock}_{f(i),c,t} \times \text{Industry}_i \\ &\quad + \gamma^k \text{Peer Shock}_{f(i),c,t} + \alpha_{f(i)} + \alpha_{c,t} + \varepsilon_{f(i),c,t}\end{aligned}$$

$\Delta\text{Log(Employment)}_{f(i),c,t-1\to t+k}$ is the change in log employment of firm f (in industry i) in county c from year $t-1$ to $t+k$. Peer Shock$_{f(i),c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (2). Industry$_i$ indicates broadly defined industries categorized as 2-digit SIC codes. We employ firm ($\alpha_{f(i)}$) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level. The figure plots the marginal effect of Peer Shock$_{f(i),c,t}$ on 3-year employment change (i.e., corresponding to $k = 2$) separately by industry.

Table 10: Mitigation across industries

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (a): Teleworking						
Peer Shock	0.453***	0.783***	1.099***	1.436***	1.760***	2.002***
	(0.023)	(0.032)	(0.044)	(0.055)	(0.068)	(0.077)
Telework × Peer Shock	0.222***	-0.078***	-0.116***	-0.119***	-0.164***	-0.271***
	(0.018)	(0.023)	(0.030)	(0.035)	(0.041)	(0.043)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	5,545,208	4,717,622	4,007,575	3,372,004	2,791,784	2,262,784
$\bar{y}$	0.771	1.786	2.423	3.212	3.898	4.746
Adj. R^2	0.012	0.027	0.041	0.057	0.075	0.092
Panel (b): Non-Tradability						
Peer Shock	0.624***	0.710***	1.004***	1.333***	1.620***	1.779***
	(0.018)	(0.028)	(0.039)	(0.051)	(0.061)	(0.069)
Non-Tradable × Peer Shock	-0.077***	0.122***	0.088**	0.130***	0.148***	0.174***
	(0.020)	(0.029)	(0.038)	(0.047)	(0.055)	(0.059)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	5,556,578	4,727,432	4,015,976	3,379,161	2,797,759	2,267,637
$\bar{y}$	0.770	1.785	2.424	3.213	3.899	4.748
Adj. R^2	0.012	0.027	0.041	0.057	0.075	0.092

Notes: Table 10 shows that firm mitigation varies with industry characteristics. The regression equation we estimate is:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f(i),c,t-1\to t+k} &= \delta^k \times \text{Peer Shock}_{f(i),c,t} \times \text{Industry Characteristic}_{i,t-1} \\ &\quad + \gamma^k \text{Peer Shock}_{f(i),c,t} + \alpha_{f(i)} + \alpha_{c,t} + \varepsilon_{f(i),c,t}\end{aligned}$$

ΔLog(Employment)$_{f(i),c,t-1\to t+k}$ is the change in log employment of firm f (in industry i) in county c from year $t-1$ to $t+k$. Peer Shock$_{f(i),c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (2). Industry Characteristic$_{i,t-1}$ denotes high teleworking ability and tradability of industry i. We employ firm ($\alpha_{f(i)}$) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Table 11: Establishment response to peer shock - Role of firm size

Panel (A): Employment growth

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.633***	0.734***	1.024***	1.362***	1.653***	1.809***
	(0.019)	(0.028)	(0.038)	(0.050)	(0.061)	(0.070)
Small Firm $\times$ Peer Shock	-0.581***	-0.170***	-0.215***	-0.322***	-0.404***	-0.222***
	(0.031)	(0.043)	(0.053)	(0.060)	(0.066)	(0.070)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	5,555,947	4,726,836	4,015,440	3,378,682	2,797,336	2,267,285
$\bar{y}$	0.770	1.785	2.424	3.214	3.899	4.748
Adj. R^2	0.012	0.027	0.041	0.057	0.075	0.092

Panel (B): Job postings

	Total Postings/L.Employment$_{t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.828***	0.671***	0.577***	0.569***	0.478***	0.417***
	(0.037)	(0.033)	(0.034)	(0.032)	(0.032)	(0.029)
Small Firm $\times$ Peer Shock	-0.231***	-0.083	0.146**	0.099	0.031	-0.025
	(0.049)	(0.053)	(0.058)	(0.064)	(0.059)	(0.057)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	1,352,263	1,243,747	1,076,981	924,851	781,349	644,505
$\bar{y}$	7.048	7.342	7.632	8.032	8.312	8.610
Adj. R^2	0.317	0.325	0.346	0.369	0.379	0.384

Notes: Table 11 shows how establishments of respond to heat shocks in their peer counties. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Peer Shock$_{c,t}$ equals Log(1+# Hot Days, Other) in county c in year t. We interact Peer Shock with indicator variables for whether the establishment belongs to a small firm. We employ firm (α_f), county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table 12: Climate clusters in affected counties

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (a): Heat stress (baseline)						
Peer Shock	0.612***	0.728***	1.017***	1.352***	1.640***	1.803***
	(0.018)	(0.027)	(0.038)	(0.049)	(0.060)	(0.069)
Panel (b): Acute heat stress						
Peer Shock (Damages)	0.708***	0.920***	1.546***	1.822***	2.113***	2.014***
	(0.021)	(0.031)	(0.049)	(0.057)	(0.063)	(0.068)
Panel (c): Heat spells						
Peer Shock (Temporal)	0.594***	0.675***	0.937***	1.257***	1.540***	1.674***
	(0.017)	(0.025)	(0.035)	(0.045)	(0.054)	(0.062)
Panel (d): Chronic heat stress						
Peer Shock (Chronic)	0.771***	0.885***	1.196***	1.555***	1.824***	2.012***
	(0.021)	(0.030)	(0.041)	(0.053)	(0.063)	(0.074)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	5,556,578	4,727,432	4,015,976	3,379,161	2,797,759	2,267,637
$\bar{y}$	0.770	1.785	2.424	3.213	3.899	4.748

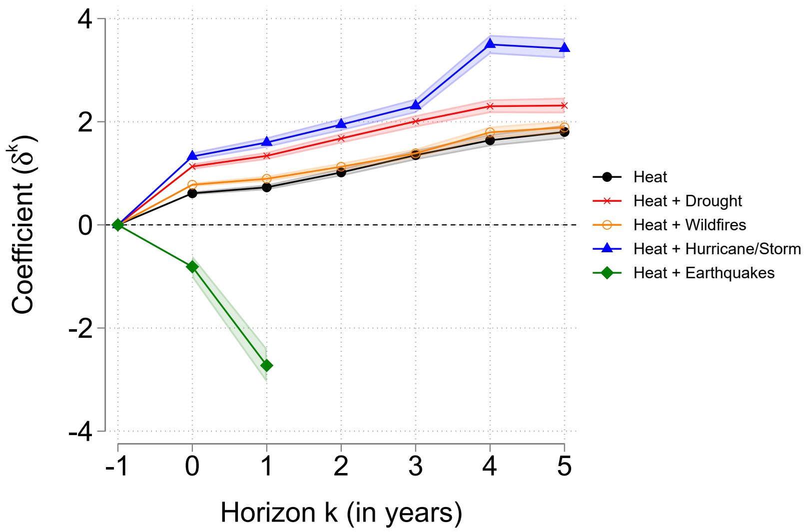
Notes: Table 12 shows mitigation in response to different types of heat shocks. We estimate the following specification:

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock (Type)}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

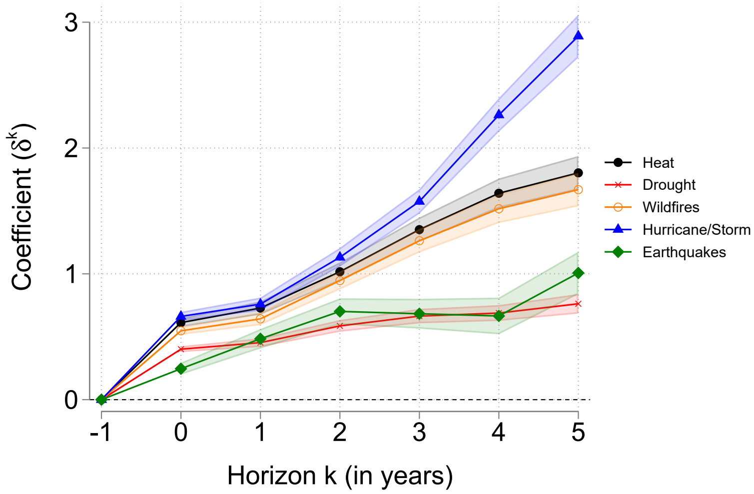
ΔLog(Employment)$_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer Shock$_{f,c,t}$ (Panel (a)) denotes total heat shock at peer establishments' location as calculated in Equation (2). Peer Shock (Damages)$_{f,c,t}$ (Panel (b)) denotes peer shock calculated using hot days that were accompanied by non-zero property damage according to SHELDUS. Peer Shock (Spells)$_{f,c,t}$ (Panel (c)) denotes peer shock calculated using hot days that occurred in a consecutive spell of three or more days. Finally, Peer Shock (Chronic)$_{f,c,t}$ (Panel (d)) denotes peer shock calculated using hot days occurring in counties suffering from chronic heat stress. These counties lie in the top quintile of the distribution of the number of hot days during the 1960-2008 period. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Figure 5: Other climate hazards

(a) Combined with heat hazard



(b) Single hazard



Notes: Figure 5 shows firm mitigation in response to different types of climate disasters. The regression equation we estimate is:

$$\Delta \text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock (Type)}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

$\Delta \text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. In Panel (a), we calculate peer shock using the hot days that coincided with another type of disaster in the same year. In panel (b), Peer Shock $(\text{Type})_{f,c,t}$ denotes the peer shock calculated using the annual number of days the peer counties suffered from a specific type of disaster. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Appendix A Firm-level results

First, we test whether local heat shocks have a measurable impact on firm-level accounting measures using the following specification:

$$\Delta\text{Outcome}_{f,t-1\to t+k} = \gamma^k \times \text{Firm Shock}_{f,t} + \alpha_f + \alpha_t + \varepsilon_{f,t}$$

$\Delta\text{Outcome}_{f,t-1\to t+k}$ is the change in financial outcomes of firm f from year $t-1$ to $t+k$. We present results corresponding to 3-year change (i.e., $k = 2$). Firm $\text{Shock}_{f,t}$ is the exposure of firm f to heat shocks in year t as defined in equation 5. α_f and α_t denote firm and year fixed-effects respectively. Standard errors are clustered at the firm level.

Results are presented in Table A6. Perhaps unsurprisingly, we don't find any significant effects on profitability, ROA, or asset growth at firm-level, because individual shocks represents a relatively small fraction of an average firm's total operations, and shocks have little correlation across geographical locations.

Next, even if any individual heat shock is too small to have a significant effect on the bottom-line of a geographically diversified firm, investors may learn from these episodes new information about firm's ability to conduct firm-wide climate adaptation measures in the future, that may result in significant savings across locations as such episodes become more frequent and costly in the future. To investigate this hypothesis, we study how the expected returns on affected firms respond to shocks. We use $SVIX_{f,t}$ of Martin and Wagner (2019) as our measure of conditional expected return.[16]

In particular, we estimate the following:

$$\text{SVIX}_{s,f,t} = \sum_{h=-5}^{h=6} \gamma^h \times \text{Treated}_{s,f,t-h} \times \text{Post}_{s,t-h} + \alpha_{s,f} + \alpha_{s,t} + \varepsilon_{f,t}$$

$\text{SVIX}_{s,f,t}$ is Martin and Wagner (2019) measure of firm f's stock market performance in month t. For each stack s, $\text{Treated}_{s,f}$ is an indicator variable that is one if firm f had one or more establishments in the affected county, and zero otherwise. $\text{Post}_{s,t-h}$ is the event time relative to the disaster. α_f and α_t denote firm and month fixed-effects respectively. Standard errors are clustered at the firm level. Results are shown in Figure A4. In total, we find little evidence that local heat shocks affect expected returns at firm-level.

[16]In addition to $SVIX_{f,t}$, the conditional expected return measure of Martin and Wagner (2019) also depends on $SVIX_t$ (SVIX of the market index), and $\overline{SVIX_t}$ (the value-weighted average of $SVIX_{f,t}$ across all the stocks in the market index). Since these measures are feasibly only available for the constituents of S&P 500 index and we want to extend our sample to other firms as well, we only focus on $SVIX_{f,t}$ which fully captures the cross-sectional variation in expected returns of Martin and Wagner (2019) measure.

Appendix B Mitigation by varying distance from the shock

We next explore the distance between heat-impacted establishment and the peer establishments where the firms hire more workers. Examining the geographical distance at which mitigation operates can shed light on the frictions that firms face in undertaking this activity. For example, if reallocation mostly occurs is regions far away from the impacted location, it suggests that heat impact and its resulting damage may not be very localized. On the other hand, if reallocation is limited to the vicinity of the shock, it may suggest that local factors determining firms' business inhibit them from changing their operating environment drastically. Since firms bear the expenses related to mitigation, we then expect mitigation activity to decay with distance from shock. To investigate this idea, we define alternative distance-based peer shock variables as follows:

$$\text{Peer Shock}_{f,c,t,(d_1,d_2)} = \text{Log}(1 + \text{Hot Days, Other}_{f,c,t,(d_1,d_2)})$$

where

$$\# \text{ Hot Days, Other}_{f,c,t,(d_1,d_2)} = \sum_{c' \neq c} \frac{\text{Employment}_{f,c',t-2}}{\text{Employment}_{f,c,t-2}} \times \# \text{ Hot Days}_{c',t} \times (\text{I}(\text{Distance})_{c,c'} \in (d_1, d_2])$$

Here, $\text{I}(\text{Distance})_{c,c'} \in (d_1, d_2]$ denotes an indicator variable that equals one if the distance between counties c and c' lies between d_1 and d_2 miles, and zero otherwise. We then follow our baseline specification and regress employment growth against these modified peer shock measures for various distance bands. We present the corresponding results in Table A4. The results highlight that employment growth is highest for the zero to 100 mile radius and then generally decays with distance (with the exception of the largest distance band of 500 to 750 mile radius). These results are consistent with idea that mitigation becomes more expensive with distance. It also suggests that local economic ties are important for firms. As a result, they avoid moving their activity too far away from their original place of business in response to heat shocks. On the flip side, these results also highlight the limitations associated with spatial mitigation approach in dealing with climate risk.

Appendix C Salient examples of spatial reallocation

Small Companies (exactly two locations)

1. Heat wave in San Diego, CA 2016 (News Link): Fidelity Home Energy, Inc. (Construction) reduced 143 workers in San Diego (FIPS code: 6073) and added 47 workers in Alameda (FIPS code: 6001).

2. Heat wave in Orange County, CA 2012 (News Link): Memorial Health Services Corporation (Services) reduced 992 workers in Orange (FIPS code: 6059) and added 574 workers in Los Angeles (FIPS code: 6037).

3. Heat wave in Harris County, TX 2018 (News Link): Nippon Shokubai America Industries, Inc. (Manufacturing) reduced 107 workers in Harris (FIPS code: 48201) and added 47 workers in Hamilton (FIPS code: 47065).

Large Companies (more than two locations)

1. Heat wave in Dallas County, TX 2016 (News Link): Walmart Inc. (Retail) reduced 1,952 workers in Dallas (FIPS code: 48113) and added 489 workers in Benton (FIPS code: 5007).

2. Heat wave in Dallas County, TX 2012 (News Link): Home Depot Inc. (Retail) reduced 253 workers in Dallas (FIPS 48113) and added 51 workers in Maricopa (FIPS code: 4013), Polk (FIPS code: 12105), and Suffolk (FIPS code: 36103) counties.

3. Heat wave in Jackson County, MO 2012 (News Link): Honeywell International Inc. (Manufacturing) reduced 104 workers in Jackson (FIPS 29095) and added 40 workers in Pinellas (FIPS code: 12103) county.

Appendix D Appendix figures and tables

Table A1: Establishment response to own shock: Matched sample

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (A-1): Average establishment						
Own Shock	-0.070	-0.175	-0.174	-0.273**	0.012	0.027
	(0.072)	(0.112)	(0.120)	(0.134)	(0.163)	(0.147)
Panel (A-2): Establishments of single- vs. multi-location firms						
Own Shock	-0.088	-0.169	-0.110	-0.151	0.143	0.066
	(0.073)	(0.106)	(0.109)	(0.128)	(0.161)	(0.149)
Single Location $\times$ Own Shock	0.361	-0.121	-1.220*	-2.345***	-2.512***	-0.775
	(0.503)	(0.608)	(0.659)	(0.747)	(0.753)	(0.799)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1,391,478	1,215,641	1,056,100	906,274	763,981	628,700
$\bar{y}$	0.685	1.569	2.321	3.231	3.847	4.600

	Total Postings/L.Employment$_{t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (B-1): Average establishment						
Own Shock	0.038	0.182	0.217*	0.089	-0.222	-0.266**
	(0.103)	(0.135)	(0.119)	(0.113)	(0.146)	(0.122)
Panel (B-2): Establishments of single- vs. multi-location firms						
Own Shock	0.021	0.153	0.179	0.053	-0.265*	-0.290**
	(0.107)	(0.138)	(0.118)	(0.113)	(0.146)	(0.120)
Single Location $\times$ Own Shock	0.340	0.567**	0.760***	0.704***	0.865***	0.491**
	(0.223)	(0.262)	(0.244)	(0.258)	(0.192)	(0.222)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1,391,478	1,277,856	1,106,821	950,763	803,600	663,195
$\bar{y}$	7.027	7.334	7.623	8.016	8.292	8.587

Notes: Table A1 shows how establishments respond to heat shocks in their county using the D&B-Burning Glass matched sample. Panel (A-1) shows the effect on employment growth at an average establishment, Panel (A-2) shows the effect on establishment growth at establishments of single- and multi-location firms, and Panel (B) shows the effect on job postings. The outcome variable in Panels (A-1) and (A-2) is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Own Shock$_{c,t}$ equals Log(1+# Hot Days) in county c in year t. We employ firm (α_f), county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table A2: Establishment response to peer shock: Matched sample

Panel (A): Employment growth of average establishment

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.375***	0.380***	0.579***	0.804***	0.990***	1.023***
	(0.020)	(0.031)	(0.040)	(0.050)	(0.058)	(0.067)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	1,352,263	1,180,595	1,024,939	878,691	740,013	607,770
$\bar{y}$	0.640	1.432	2.076	2.885	3.480	4.210
Adj. R^2	0.001	0.022	0.045	0.070	0.092	0.117

Panel (B): Job postings of average establishment

	Total Postings/L.Employment$_{t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.803***	0.663***	0.591***	0.577***	0.480***	0.415***
	(0.036)	(0.033)	(0.034)	(0.033)	(0.033)	(0.029)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	1,352,263	1,243,747	1,076,981	924,851	781,349	644,505
$\bar{y}$	7.048	7.342	7.632	8.032	8.312	8.610
Adj. R^2	0.317	0.325	0.346	0.369	0.379	0.384

Notes: Table A2 shows how establishments respond to heat shocks in their peer counties using the D&B-Burning Glass matched sample. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Peer Shock$_{c,t}$ equals Log(1+# Hot Days, Other) in county c in year t. We employ firm (α_f), county (α_c) and year (α_t) fixed-effects. Standard errors are clustered at the county level.

Table A3: County response to own and peer shock

Panel (A): Wage growth

	ΔLog(Wage)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.012	-0.142	-0.223	-0.098	-0.114	-0.096
	(0.080)	(0.116)	(0.140)	(0.164)	(0.157)	(0.128)
Peer Shock	-0.064	0.221	0.294	0.848	0.803*	0.178
	(0.211)	(0.399)	(0.599)	(0.534)	(0.430)	(0.480)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,732	25,846	22,970	20,093	17,221	14,343
$\bar{y}$	2.974	5.593	8.131	10.665	12.975	15.572
Adj. R^2	0.035	0.094	0.190	0.321	0.479	0.610

Panel (B): Change in labor force participation rate

	ΔLabor force participation rate$_{t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.059	-0.007	-0.098	-0.070	-0.017	0.039
	(0.048)	(0.056)	(0.060)	(0.066)	(0.073)	(0.073)
Peer Shock	0.050	0.071	0.125	0.213**	0.106	0.202*
	(0.038)	(0.060)	(0.080)	(0.093)	(0.124)	(0.121)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,050	25,392	22,551	19,723	16,899	14,079
$\bar{y}$	-0.140	-0.284	-0.426	-0.578	-0.738	-0.887
Adj. R^2	0.075	0.153	0.252	0.377	0.491	0.564

Notes: Table A3 shows outcomes in a county after heat shocks hit it and its peer counties. We aggregate data at the county-year level and estimate the following specification:

$$\Delta Y_{c,t-1\to t+k} = \beta \times \text{Shock}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t}$$

$\Delta Y_{c,t-1\to t+k}$ denotes the change in average annual wage of county c from year $t-1$ to $t+k$. Shock$_{c,t}$ is Own Shock (Log(1 + # Hot Days$_{c,t}$)) in Panels (A) and Peer Shock (Log(1 + # Hot Days, Other$_{c,t}$)) in Panels (B), where # Hot Days$_{c,t}$ is number of hot days in county c in year t. We employ county (α_c) and year (α_t) fixed-effects. We cluster standard errors at the county level.

Table A4: Mitigation across varying distance from the shock

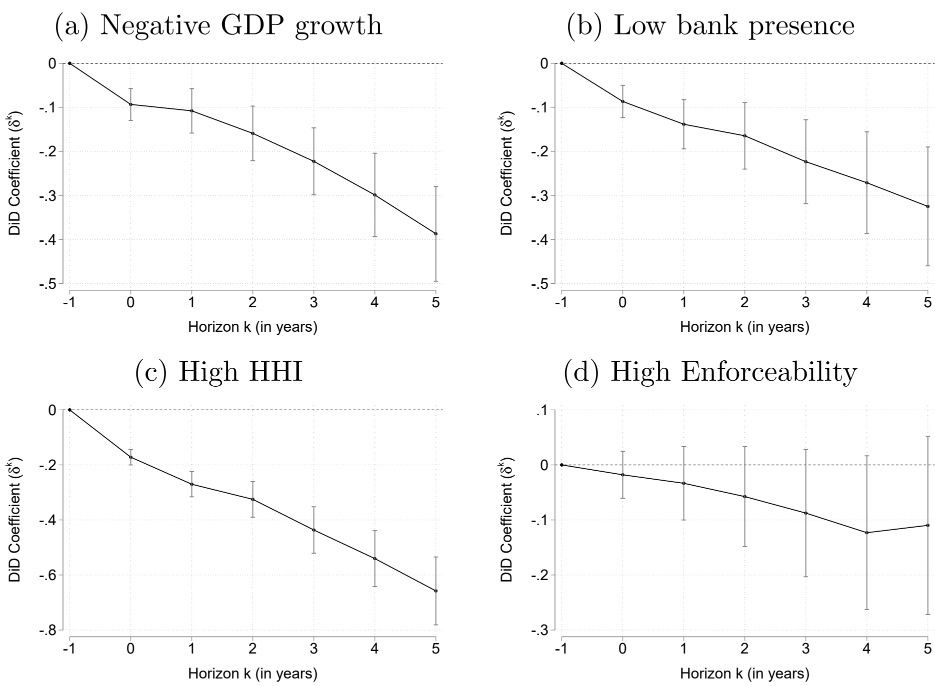
	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock$\leq$100	0.482***	0.680***	0.907***	1.072***	1.183***	1.330***
	(0.038)	(0.053)	(0.069)	(0.085)	(0.094)	(0.108)
Peer Shock$\in$(100,250]	0.360***	0.449***	0.585***	0.735***	0.828***	0.837***
	(0.027)	(0.037)	(0.047)	(0.060)	(0.074)	(0.086)
Peer Shock$\in$(250,500]	0.251***	0.259***	0.363***	0.475***	0.531***	0.535***
	(0.018)	(0.026)	(0.035)	(0.045)	(0.055)	(0.065)
Peer Shock$\in$(500,750]	0.384***	0.429***	0.591***	0.781***	0.901***	0.967***
	(0.018)	(0.027)	(0.037)	(0.051)	(0.061)	(0.071)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	5,556,578	4,727,432	4,015,976	3,379,161	2,797,759	2,267,637
$\bar{y}$	0.770	1.785	2.424	3.213	3.899	4.748
Adj. R^2	0.012	0.027	0.042	0.057	0.075	0.092

Notes: Table A4 shows employment mitigation by firms at varying distances from the shock. We estimate the following regression equation:

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \sum_{(d_1,d_2)} \delta^k_{(d_1,d_2)} \times \text{Peer Shock}_{f,c,t,(d_1,d_2)} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

ΔLog(Employment)$_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer Shock$_{f,c,t,(d_1,d_2)}$ denotes peer shock calculated using hot days at peer establishments located between d_1 and d_2 miles away from county c. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Figure A1: Role of other (non-heat-related) county characteristics

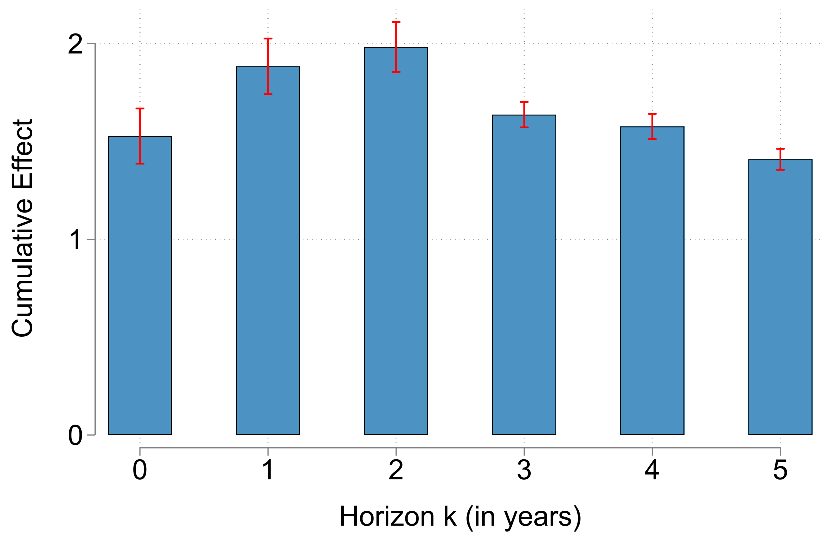


Notes: Figure A1 shows the county-level factors that influence firms' decision to reallocate into that county when its establishments elsewhere are impacted by heat shocks. We estimate

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} &= \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{County Characteristic}_{c,t} \\ &\quad + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned}$$

and plot the interaction coefficient (δ^k) with respect to each county characteristic. α_f and $\alpha_{c,t}$ denote firm and county-year fixed-effects and standard errors are clustered at the county level.

Figure A2: Firm mitigation: Estimation using distributed lag model



Notes: Figure A2 shows the impact of heat stress on the employment growth at peer locations. We estimate the following distributed lag specification:

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t} = \sum_{h=0}^{h=5} \beta^h \times \text{Peer Shock}_{f,c,t-h} + \alpha_{f,t} + \alpha_{c,t} + \varepsilon_{f,c,t}$$

$\Delta\text{Log(Employment)}_{f,c,t-1\to t}$ is the change in log employment of firm f in county c from year $t-1$ to t. Peer $\text{Shock}_{f,c,t-h}$ denotes the value of peer shock h years ago. We employ firm-year ($\alpha_{f,t}$) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level. The figure plots the cumulative coefficients, i.e., $\sum_{h=0}^{h=k} \beta^h$ against years relative to the shock (k).

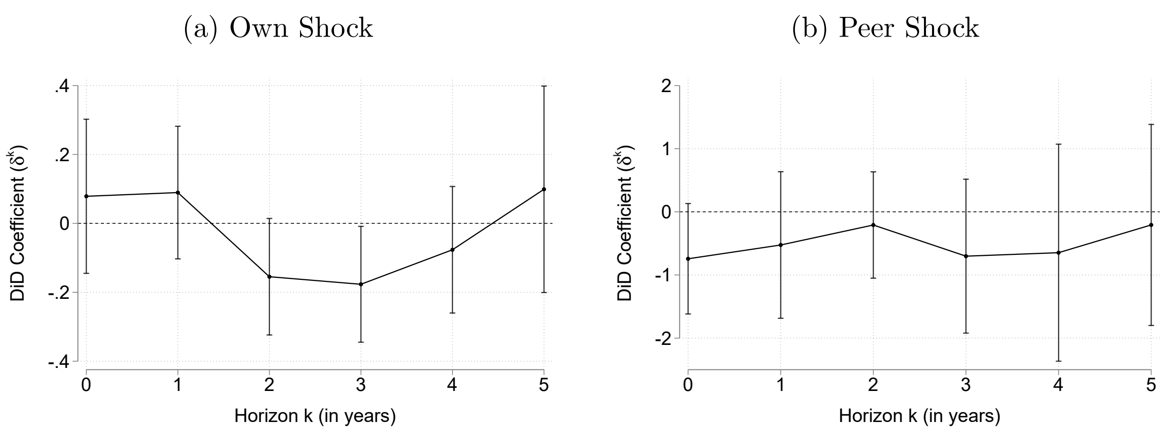
Table A5: Establishment response to own shock: Role of firm size

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Single-Location/Small $\times$ Own Shock	-0.213	-0.935	-2.298**	-4.499***	-5.350***	-4.209***
	(0.346)	(0.700)	(0.925)	(1.084)	(0.953)	(0.762)
Single-Location/Large $\times$ Own Shock	0.367	-0.076	-1.074*	-1.487**	-2.432***	-1.545**
	(0.449)	(0.563)	(0.640)	(0.655)	(0.665)	(0.626)
Multi-Location/Small $\times$ Own Shock	-0.743***	-1.299***	-1.704***	-2.412***	-2.797***	-2.780***
	(0.173)	(0.284)	(0.355)	(0.400)	(0.418)	(0.429)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	5.66e+06	4.83e+06	4.11e+06	3.46e+06	2.87e+06	2.33e+06
$\bar{y}$	0.802	1.898	2.619	3.489	4.190	5.072
Adj. R^2	0.011	0.031	0.050	0.071	0.093	0.119

	Total Postings/L.Employment$_{t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Single-Location/Small $\times$ Own Shock	0.176	0.600**	0.769***	0.582**	0.587**	0.022
	(0.293)	(0.300)	(0.290)	(0.269)	(0.234)	(0.311)
Single-Location/Large $\times$ Own Shock	0.513*	0.420	0.610*	0.881***	1.077***	0.938***
	(0.285)	(0.403)	(0.350)	(0.316)	(0.298)	(0.292)
Multi-Location/Small $\times$ Own Shock	-0.031	0.050	-0.051	-0.072	-0.199	-0.278
	(0.137)	(0.142)	(0.149)	(0.165)	(0.181)	(0.176)
Firm FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	1.39e+06	1.28e+06	1.11e+06	9.50e+05	8.03e+05	6.62e+05
$\bar{y}$	7.030	7.338	7.626	8.020	8.296	8.592
Adj. R^2	0.320	0.329	0.350	0.372	0.381	0.386

Notes: Table A5 shows how establishments of respond to heat shocks in their county. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Own Shock$_{c,t}$ equals Log(1+# Hot Days) in county c in year t. We interact Own Shock with indicator variables for whether the establishment belongs to a single-location firm, and whether it belongs to a small firm. We employ firm (α_f) and county $\times$ year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Figure A3: Migration

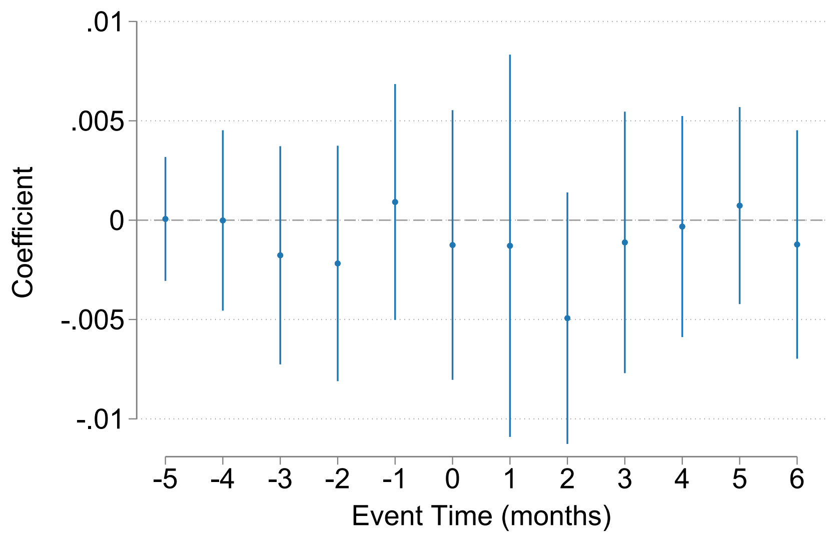


Notes: Figure A3 shows the impact of heat shocks on employment-related migration. We aggregate the data at the household level and estimate the following regression:

$$\text{In-Migration}_{h,c,t} = \gamma^k \times \text{Shock}_{c,t-k} + \alpha_D + \alpha_c + \alpha_t + \epsilon_{w,c,t}$$

In-Migration$_{w,c,t}$ is an indicator that equals one if any member of the household h residing in county c in year t migrated into their current location for a work-related reason during the previous year. Shock$_{c,t-k}$ denotes the own shock (Panel (a)) and peer shock (Panel (b)) variables at the county level. We employ fixed-effects at the demographic (i.e., age, sex, race, hispanic status, and education), county, and year level (denoted by α_D, α_c, and α_t, respectively). We use CPS weights to estimate weighted regression coefficients and cluster standard errors at the county level.

Figure A4: Impact of heat shocks on stock market performance



Notes: Figure A4 shows the impact of heat shocks on the stock market performance of public firms. We aggregate the data at the stack-firm-month level where each stack s correspond to a heat-related shock at the county level. We estimate the following stacked event-study regression:

$$\text{SVIX}_{s,f,t} = \sum_{h=-5}^{h=6} \gamma^h \times \text{Treated}_{s,f,t-h} \times \text{Post}_{s,t-h} + \alpha_{s,f} + \alpha_{s,t} + \varepsilon_{f,t}$$

$\text{SVIX}_{s,f,t}$ is the Martin-Wagner measure of firm f's stock market performance in month t. For each stack s, $\text{Treated}_{s,f}$ is an indicator variable that is one if firm f had one or more establishments in the affected county, and zero otherwise. $\text{Post}_{s,t-h}$ is the event time relative to the disaster. α_f and α_t denote firm and month fixed-effects respectively. Standard errors are clustered at the firm level.

Table A6: Effect on firm financials for public firms

	ΔROA	ΔGross Profit	ΔLog(Assets)
Firm Shock	0.001	0.005	-0.011
	(0.004)	(0.004)	(0.010)
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	13,820	13,833	14,512
$\bar{y}$	-0.003	-0.008	0.192
Adj. R^2	0.147	0.175	0.431

Notes: Table A6 shows the effect of heat shocks on financials of public firms. The regression equation we estimate is:

$$\Delta \text{Outcome}_{f,t-1\to t+k} = \gamma^k \times \text{Firm Shock}_{f,t} + \alpha_f + \alpha_t + \varepsilon_{f,t}$$

$\Delta \text{Outcome}_{f,t-1\to t+k}$ is the change in financial outcomes of firm f from year $t-1$ to $t+k$. We present results corresponding to 3-year change (i.e., $k = 2$). Firm $\text{Shock}_{f,t}$ is the exposure of firm f to heat shocks in year t as defined in equation 5. α_f and α_t denote firm and year fixed-effects respectively . Standard errors are clustered at the firm level.

Table A7: Robustness: County-level results using QCEW data

	Panel (A): ΔLog(Employment)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.136*	0.167	0.169	0.068	0.220	0.239
	(0.073)	(0.121)	(0.153)	(0.175)	(0.179)	(0.152)
Peer Shock	0.602***	0.931**	1.422**	1.716**	1.685**	1.129*
	(0.188)	(0.442)	(0.669)	(0.874)	(0.854)	(0.585)

	Panel (B): ΔLog(Establishments)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	-0.002	0.036	0.009	0.171	0.088	0.148
	(0.060)	(0.106)	(0.141)	(0.158)	(0.150)	(0.133)
Peer Shock	0.325**	0.688***	0.741**	0.897***	0.898**	1.138***
	(0.128)	(0.227)	(0.299)	(0.344)	(0.350)	(0.367)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	30,412	27,339	24,276	21,212	18,153	15,087
$\bar{y}$	0.585	1.191	1.748	2.262	2.886	3.465
Adj. R^2	0.071	0.184	0.305	0.441	0.588	0.708

Notes: Table A7 shows outcomes in a county after heat shocks hit it and its peer counties using data from Quarterly Census of Employment and Wages (QCEW). We aggregate data at the county-year level and estimate the following specification:

$$\Delta Y_{c,t-1\to t+k} = \beta \times \text{Shock}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t}$$

$\Delta Y_{c,t-1\to t+k}$ denotes the change in employment (Panel (A)) or number of establishments (Panel (B)) of county c from year $t-1$ to $t+k$. Shock$_{c,t}$ is Own Shock (Log(1+# Hot Days$_{c,t}$)) or Peer Shock (Log(1 + # Hot Days, Other$_{c,t}$)). We employ county (α_c) and year (α_t) fixed-effects. We cluster standard errors at the county level.

Table A8: Impact of county characteristics (affected county)

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (A): Community Risk						
Peer Shock	0.111***	0.299***	0.416***	0.728***	0.771***	0.782***
	(0.025)	(0.038)	(0.045)	(0.060)	(0.070)	(0.078)
Peer Shock (High Vulnerability/Low Resilience)	0.592***	0.509***	0.706***	0.723***	1.011***	1.184***
	(0.026)	(0.036)	(0.048)	(0.055)	(0.069)	(0.087)
Panel (B): Unionization						
Peer Shock	0.306***	0.477***	0.679***	1.093***	1.301***	1.620***
	(0.019)	(0.031)	(0.047)	(0.062)	(0.076)	(0.092)
Peer Shock (High Union Membership)	0.383***	0.315***	0.419***	0.312***	0.411***	0.216**
	(0.023)	(0.034)	(0.049)	(0.058)	(0.072)	(0.086)
Firm FE	✓	✓	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓	✓	✓
Observations	5,556,578	4,727,432	4,015,976	3,379,161	2,797,759	2,267,637
$\bar{y}$	0.770	1.785	2.424	3.213	3.899	4.748
Adj. R^2	0.012	0.027	0.042	0.057	0.075	0.093

Notes: Table A8 shows mitigation in response to different types of heat shocks. We estimate the following specification:

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \sum_{\text{Type}} \delta^{k,\text{Type}} \times \text{Peer Shock}^{\text{Type}}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

ΔLog(Employment)$_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer Shock$^{\text{Type}}_{f,c,t}$ denotes peer shock calculated using hot days across (a) all peer counties, (b) peer counties with high community risk factor (high social vulnerability/low community resilience) according to FEMA Risk Index data, and (c) peer states with above-median union membership rate. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Table A9: Reallocation with Heat-Related Injuries/Fatalities

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock (Without Injuries)	0.560***	0.685***	0.918***	1.140***	1.389***	1.580***
	(0.017)	(0.027)	(0.037)	(0.046)	(0.057)	(0.068)
Peer Shock (With Injuries)	0.210***	0.199***	0.314***	0.508***	0.606***	0.578***
	(0.016)	(0.023)	(0.031)	(0.042)	(0.055)	(0.070)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	5,555,947	4,726,836	4,015,440	3,378,682	2,797,336	2,267,285
$\bar{y}$	0.770	1.785	2.424	3.214	3.899	4.748
Adj. R^2	0.012	0.027	0.042	0.058	0.075	0.093

Notes: Table A9 shows the results of our baseline specification using peer shocks with varying degrees of workplace injuries/fatalities. Here, we focus on workplace injuries/fatalities likely caused by heat stress. We estimate the following specification:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\rightarrow t+k} &= \delta^k \times \text{Peer Shock (Without Injuries)}_{f,c,t} \\ &+ \gamma^k \times \text{Peer Shock (With Injuries)}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned}$$

ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$ is the change in log employment of firm f in county c from year t-1 to t+k. Peer Shock (Without Injuries)$_{f,c,t}$ is equal to Log(1+# Hot Days (Other, Without Injuries)$_{f,c,t}$) where # Hot Days(Other, Without Injuries)$_{c,t}$ is the total number of SHELDUS hot days in peer counties that did not feature any workplace injuries or fatalities (as per the OSHA data). Peer Shock (With Injuries)$_{f,c,t}$ corresponds to hot days accompanied by workplace injuries/fatalities in the county. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.