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 reducing employment in the affected locations and increasing it in 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 **JEL Classification:** D22, E24, G31, J21, L23, Q54

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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. While both types of firms generally reduce employment in the

[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.

locations affected by a heat shock, we find that multi-location firms increase employment at their unaffected establishments while single-location firms simply downsize. 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. At an aggregate level, the spatial reallocation by firms results in higher employment and economic growth in counties that are less directly exposed to heat risk themselves, but that are connected to the heat-affected areas via firm networks. These results indicate that firms' ability to reallocate their workforce geographically lowers their climate risk and affects 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. Second, it enables them to reallocate workforce across regions with varying exposure to climate shocks. We calculate firms' realized heat exposure as the employment-weighted-average of "hot days" across all their locations, 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. Figure 1 shows the relationship between firms' heat exposure in year t and their employment growth from year $t-1$ to $t+k$. We find that while both single-location and multi-location firms experience an immediate decline in employment following heat exposure, multi-location firms suffer disproportionately less in the long run. For example, we find that while one standard deviation increase in firm exposure lowers employment growth of single-location firms by 0.47% over three years, multi-location firms experience no such decline. We then provide direct evidence of within-firm employment reallocation 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 locations. 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

[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.

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] 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.

These firm decisions on where to allocate employment have broader geographical conse-

[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 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.

quences.[5] Collectively, our results imply that while counties experiencing heat shocks could lose employment, other counties connected to them via firm networks should see their employment rise.[6] We find that counties experience a significant increase in employment after other counties associated with them through firm networks face heat shocks. We also find that such counties experience an increase in the number of establishments operating within their boundaries. Overall, our results indicate that firms' mitigation activity creates a positive spillover effect of heat shocks in a county on peer-counties' employment and number of establishments.

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.

[5]When firms shift employment towards their unaffected establishments, they can do so by physically moving current employees or by hiring new workers. Using household-level data on migration from the Current Population Survey (CPS), we rule out large-scale relocation of existing workers and find evidence of firms hiring new workers locally where the reallocation occurs. Our muted results on migration are in line with Behrer and Bolotnyy, 2023, who study migration in response to other types of natural disasters.

[6]Interestingly, we find that the negative impact of heat shock on county-level employment is small and temporary. Analyzing this further using establishment-level data, we find that the muted impact is driven by employees transitioning from smaller firms to larger ones after experiencing heat shocks. This is consistent with Ponticelli et al., 2023, who also show within-county movements across smaller and larger firms in response to warmer than usual temperatures.

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 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.[7] D&B sources data from various sources including state secretaries, Yellow Pages, court documents, and credit inquiries, 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

[7] 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.

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.[8] 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 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 du-

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

ration 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 $\text{Days}_{c,t}$) is defined as the total number of days when heat-related hazards affected a county c in a given year t. Figure 2 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.

B.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 Empirical 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.

We 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 ($\text{Firm Shock}_{f,t}$) as

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

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, $\text{Firm Shock}_{f,t}$ 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.

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

$$\begin{aligned} \Delta\text{Log(Employment)}_{f,t-1\to t+k} = {} & \gamma^k \times \text{Firm Shock}_{f,t} \times \text{Single Location}_f \\ & + \delta^k \times \text{Firm Shock}_{f,t} + \alpha_f + \alpha_t + \varepsilon_{f,t}. \end{aligned} \tag{2}$$

Here, $\Delta\text{Log(Employment)}_{f,t-1\rightarrow t+k}$ is the change in firm f's log employment from year t to $t+k$. Single Location_f indicates that firm f existed in a single county throughout our sample period. We employ firm fixed-effects to absorb differences in growth rates across firms. We also include year fixed-effects to absorb aggregate fluctuations and cluster standard errors at the firm level.

We present estimation results in Figure 1. Specifically, we plot the marginal effect of heat shock on single-location (estimated by $\delta^k + \gamma^k$) and multi-location firms (estimated by δ^k) over k-year horizon. We find that heat shocks adversely affect single-location firms and lower their 3-year employment growth by 1% as indicated by the coefficient with respect to $k = 2$. This implies that one standard deviation increase in firm-level exposure to hot days translates into a 0.47% decline in the employment growth rate in these firms. This is economically significant relative to the average 3-year growth rate of 5.6% over our sample period. The downsizing of small firms can be driven by a decrease in labor productivity (Graff Zivin and Neidell, 2014) or see a spike in energy costs (Ponticelli et al., 2023) due to excessive heat.

Notably, we find that multi-location firms do not experience a proportional decline in their workforce. While such firms experience a negative growth rate of 1% in the year following the heat shock, the trend reverses back to zero over the next two years. Thus, although these firms seem to suffer an immediate 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.

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 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

$$\text{Peer Shock}_{f,c,t} = \text{Log}(1 + \#\text{ Hot Days, Other}_{f,c,t}) \tag{3}$$

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

$$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t} \tag{4}$$

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.

We plot the estimated coefficients (δ^k) in Figure 3 and 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. We present these results in a tabular format in Table 3 (Panel (a)). Overall, these results highlight that heat stress in a county induce multi-location firms to increase their employment at unaffected peer counties.

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 3 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 3 shows that the results with these alternative measures are consistent with those using our primary measure.

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)$_{f,c,t-1\rightarrow t+k}$) 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 3 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 3 (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.

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. We present these results in Table 4.

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 A1 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.

B.2 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:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = {} & \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{Firm Characteristic}_{f,t-1} \\ & + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned} \tag{5}$$

In this equation, $\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ 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 (3). 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 5 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 (6). Figure 4 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.[9] 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 employ-

[9]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.

ment against rising temperatures.

B.3 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) 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:

$$\begin{aligned}\Delta \text{Log}(\text{Employment})_{f,c,t-1\to t+k} &= \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{County Characteristic}_{c,t-1} \\ &\quad + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned} \tag{6}$$

Figure 5 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.

Next, we study the role of economic distress. On the one hand, firms may avoid distressed locations because such locations may lack good public amenities and access to capital required to complement their newly-hired labor. On the other hand, distressed locations may have lower wages which the firm can benefit from. We use two measures to quantify economic distress at the county level. The first measure is Negative $\text{GDP}_{c,t}$, which is an indicator of negative GDP growth in county c in year t. The second measure aims to quantify access to credit. Following Rajan and Ramcharan, 2023, we measure the availability of credit as per-capita loan originations for each county in the given year.[10] We then create a dummy variable called Low Bank $\text{Presence}_{c,t}$ which indicates that county c had below median level of credit availability in year t. We use these two variables as county characteristics in Equation (6) and present the results in Figure 6 (Panels (a) and (b)). We find that employment growth is lower in peer counties suffering from economic distress and weaker credit availability.

Finally, we study the role of labor market conditions. Peer counties with high employment concentration and limited labor mobility might inhibit firms from hiring workers in that county. We calculate employment HHI at the county year level and use it as a proxy for concentration. To avoid mechanical correlation with our outcome measure, we use the employment information lagged by two years. We also look at the enforceability of non-compete agreements across the states to proxy for labor mobility. Specifically, we use the index developed by Starr, 2019 which uses survey data as a quantitative measure of non-compete enforceability. Figure 6 (Panels (c) and (d)) shows that employment growth at peer counties is lower in counties having more concentrated labor markets and higher non-compete enforceability. Overall, these results highlight the importance of regional economic and labor market conditions in determining firms' mitigation strategy, and reveal indirectly that firms appear to be *optimizing* employee location across their establishments.

B.4 Mitigation 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.,

[10]Data on bank lending comes from Fed Board's CRA analytics program (link).

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:

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

$\Delta\text{Log(Employment)}_{f(i),c,t-1\to t+k}$ is the change in log employment of firm f (in industry i) in county c from year $t-1$ to $t+k$. Peer $\text{Shock}_{f(i),c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (3). 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 7. 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 6 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.

B.5 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

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

Here, $\text{I(Distance)}_{c,c'} \in (d_1, d_2]$ 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 7. 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.

IV Reallocation and firm entry in new locations

In the last 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 heat shocks. To examine this idea formally, we estimate the following equations:

$$\text{Entry In New County}_{f,t} = \gamma \times \text{Firm Shock}_{f,t-1} + \alpha_f + \alpha_t + \varepsilon_{f,t} \tag{7}$$

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. We first look at entry in any new county and then examine entry into counties that are less exposed to heat stress. Firm Shock$_{f,t-1}$ is the exposure of firm f to heat shocks in year $t-1$ as defined in equation (1). 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 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.[11] 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.[12] 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 9.

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 (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

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

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

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 9 (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.[13] 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 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 $(\text{Heat} + \text{Drought})_{f,c,t}$ 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

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

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 8 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.

VI Aggregate outcomes

We then 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:

$$\Delta Y_{c,t-1\to t+k} = \beta \times \text{Own Shock}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t} \tag{8}$$

$\Delta Y_{c,t-1\to t+k}$ denotes change in macroeconomic outcomes of county c from year $t-1$ to $t+k$. Own Shock$_{c,t}$ is Log(1 + Hot Days$_{c,t}$), where Hot Days$_{c,t}$ is the total number of hot days in count c in year t according to SHELDUS. 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 Figure 9.

Panel (a) shows that in the immediate aftermath of the heat shock, employment growth shrinks by 0.5% within the 1-year period. However, it recovers back to the initial level in the following years. Panel (c) shows a similar decline and subsequent reversal in the number of establishments operating in the county. Panel (e) shows that, as argued above, between-firm reallocation leads to an increase in employment concentration in the county proxied by employment HHI index. These patterns are likely driven by the labor reallocation across firms within the same county. We examine this within-county reallocation in Section VII.B. All these results align with those in Ponticelli et al., 2023, who show similar trends using the Census data.

Since our primary mitigation channel operates through firm networks we next investigate how heat shocks in a particular county affects other counties linked to it through firm networks. To explore that, we create a peer shock measure (Peer Shock$_{c,t}$) for county c in year t as Log$(1 + \text{Hot Days, Other}_{c,t})$, where Hot Days, 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 substitute the Own Shock$_{c,t}$ measure with Peer Shock$_{c,t}$ measure in Equation (8) and re-estimate the specification. We present the results in Figure 9. Panel (b) shows that counties exhibit an increase in employment growth after counties associated with them through firm networks experience a heat-related disaster. Panel (d) shows a similar trend in the number of operating establishments.

To verify that our results are not driven by any limitations in the Dun & Bradstreet data, we estimate our county-level regressions using publicly-available census data (i.e., Quarterly Census of Employment and Wages) at the county-year level. We find that the results using the census data (see Table A3) are similar to those using the D&B data, both in terms of direction and magnitude. Overall, these results show that counties having many multi-location firms benefit in the aggregate from the spatial mitigation channel that we document in this paper.

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.[14] 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.

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

VII Discussion

A Migration

Finally, note that firms have two methods to redistribute their workforce across locations. First, they can replace workers from affected areas by hiring new employees in unaffected regions. This method circumvents the costs associated with relocating employees, but introduces potential expenses related to training new hires. Second, they can transfer existing employees between the two location which may also require compensating employees for relocation costs. To discern which of these strategies firms predominantly use, we examine the distinct implications each has on worker flows between counties. Specifically, if local hiring is predominant, we would expect no influx of workers into unaffected counties linked to affected ones. Conversely, physical relocation of workers would lead to an uptick in migration in such counties.

We explore this issue using migration data from the Current Population Survey (CPS) from 2009 to 2020. The survey asks workers whether they relocated in the previous year and the reason associated with such a move. We use the "WHYMOVE" variable in the data to identify workers that move across counties due to any work-related reason. We then aggregate the data at the household-year level and look at whether heat shocks in a county affect the inflow and outflow of workers with respect to that county. We estimate the following equation:

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

$\text{In-Migration}_{w,c,t}$ 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. $\text{Shock}_{c,t-k}$ denotes the own shock and peer shock 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. Results are presented in Figure A2.

Panel (a) shows that counties experience a slight decline in in-migration when they experience a heat-related disaster. This is expected since prospective migrants may be deterred by the extreme climate conditions and lack of stable jobs due to firms mitigating by moving to less heat-exposed counties. Notably, as shown in Panel (b), there is no significant increase in migration into unaffected counties when their peer counties experience shocks. This result goes against the idea of firms physically relocating workers into the unaffected locations. These results 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. They are also consistent with a large literature highlighting substantial moving costs that households incur when relocating to a different location (Bartik et al., 1992; Davies et al., 2001; Bayer et al., 2016; Beaudry et al., 2014). Overall, these results suggest that the mechanism through which firms reallocate workers across locations is by laying off existing workers in impacted locations and hiring fresh talent in regions that remain unaffected.

B Within-county reallocation

So far, we have focused on employment reallocation within firms that occurs across their various locations. We found that employment growth at an establishment increases when its peer establishments experience a heat shock. Next, we inquire if heat shocks cause workers to move from one company to another within the area affected by heat shocks. Thus, we now look at employment growth at an establishment when its own county experienced a heat-related disaster. Such disasters can hurt worker productivity and local labor supply. At the same time, they can increase expenses or lower product demand depressing firms' requirement for workers. To study this question, we regress change in log employment of firm f in county c from year $t-1$ to $t+k$ against heat shocks in county c. This heat shock measure (Own Shock$_{c,t}$) is defined as Log$(1 + \text{Hot Days}_{c,t})$, where Hot Days$_{c,t}$ is the number of hot days in county c in year t according to SHELDUS. We employ firm, county, and year fixed-effects and present the results in Table A2. Results in Column (1) show that we do not find a significant impact of heat shocks on the employment growth of an average firm; however, we show next that this average result masks considerable heterogeneity.

Dealing with heat shocks can be costly, and not all firms may have the resources to make the required investments. For example, a small firm may lack the proper infrastructure or quality of medical insurance to protect its workers against extreme heat and its impact forcing it to downsize. Larger firms in the vicinity having spare capacity can benefit from the excess labor supply and hire these laid-off workers. Therefore, it is possible that the null impact of heat shocks on an average firm is driven by the downsizing of small firms and simultaneous growth of larger firms. To verify this conjecture, we create a small firm indicator (Small Firm$_{f,t}$) which equals one if the firm f had less than median number of employees in year t, and zero otherwise. We then regress 3-year employment growth against the interaction of Own Shock$_{c,t}$ and Small Firm$_{f,t}$ and present the result in Column (2).

Consistent with the aforementioned argument, we find that one hot day in a county shrinks the employment growth in a small firm establishment by 1.21%. At the same time, employment growth at large firms *increases* by 0.25%. This suggests that workers separating from small firms are likely gaining employment at the large companies. Figure A3 shows the employment growth in small firms and large firms for a full six year period following the shock and highlights that this between-firm reallocation activity increases till five year period following the shock and stabilizes after that. In column (3), we employ county-year fixed effects to focus on the relative growth rate of small vs. large firms. We find that the change in growth rate of small firms 3 years after experiencing a hot day is 1.2% lower than that of larger firms. In the final column, we control for the single location status of the firm and find that the small firm effect is not driven by the fact that most of them are single location firms. This results are consistent with Ponticelli et al., 2023 who show that temperature shocks lead to higher employment concentration in the manufacturing sector.

VIII 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 reducing employment in the affected county and increasing it in unaffected ones, consistent with firms adjusting their operations to mitigate climate change related risks. Single location firms simply scale down their employment.

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.

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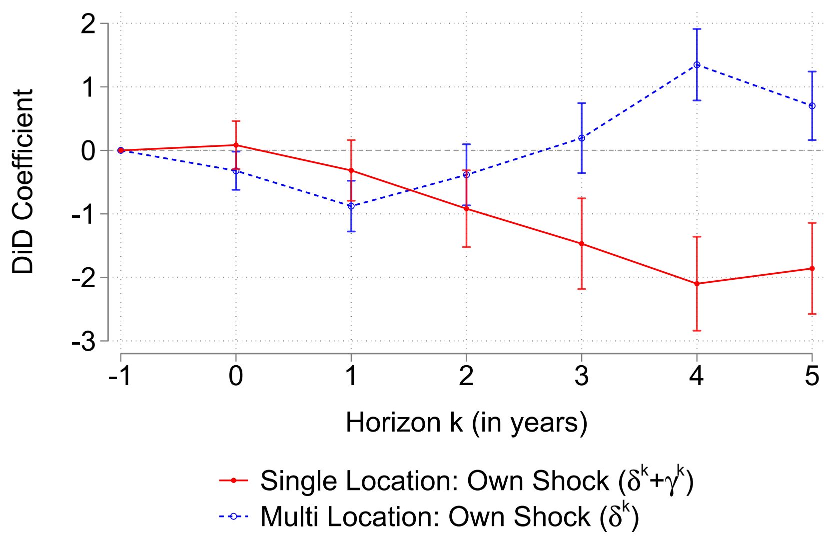
IX Figures and tables

Figure 1: Impact of heat shocks: single vs. multi-location firms

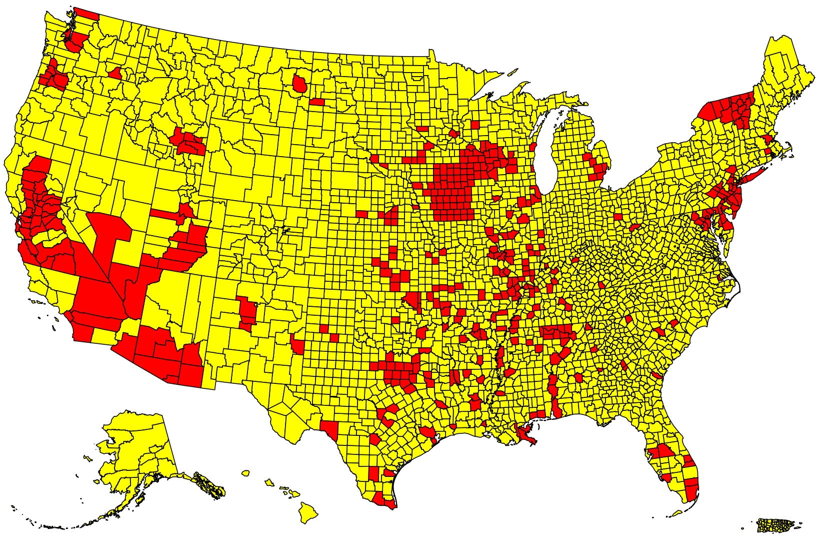


Notes: Figure 1 shows the impact of heat shocks on single and multi-location firms. We aggregate the data at the firm-year level and estimate the following regression:

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

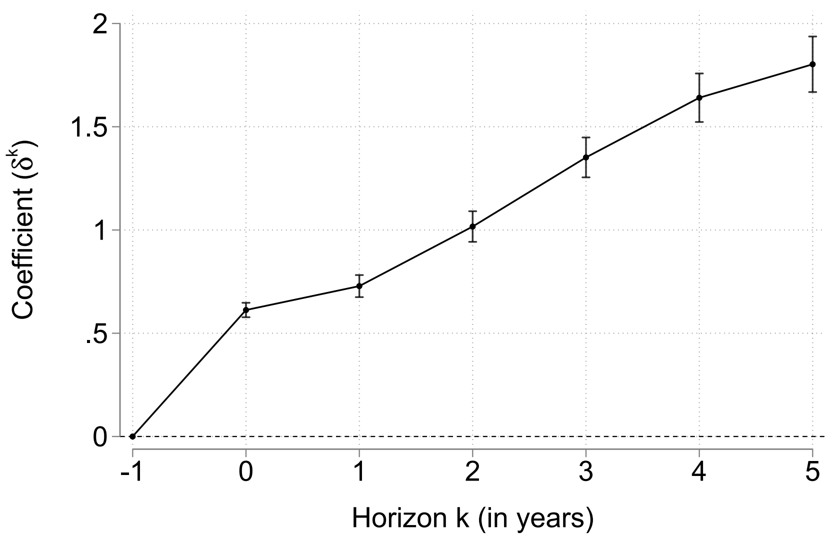
$\Delta\text{Log(Employment)}_{f,t-1\to t+k}$ is the change in firm f's log employment from year t to $t+k$. Firm Shock$_{f,t}$ is the exposure of firm f to heat shocks in year t as defined in equation (1). Single Location$_f$ indicates that firm f existed in a single county throughout our sample period. α_f and α_t denote firm and year fixed-effects respectively. Standard errors are clustered at the firm level. The figure plots the total marginal effect of heat shocks on single ($\delta^k + \gamma^k$) and multi-location (δ^k) firms k years after the shock.

Figure 2: Heat shocks across the US



Notes: Figure 2 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.

Figure 3: Firm mitigation: Reallocation to unaffected peer counties

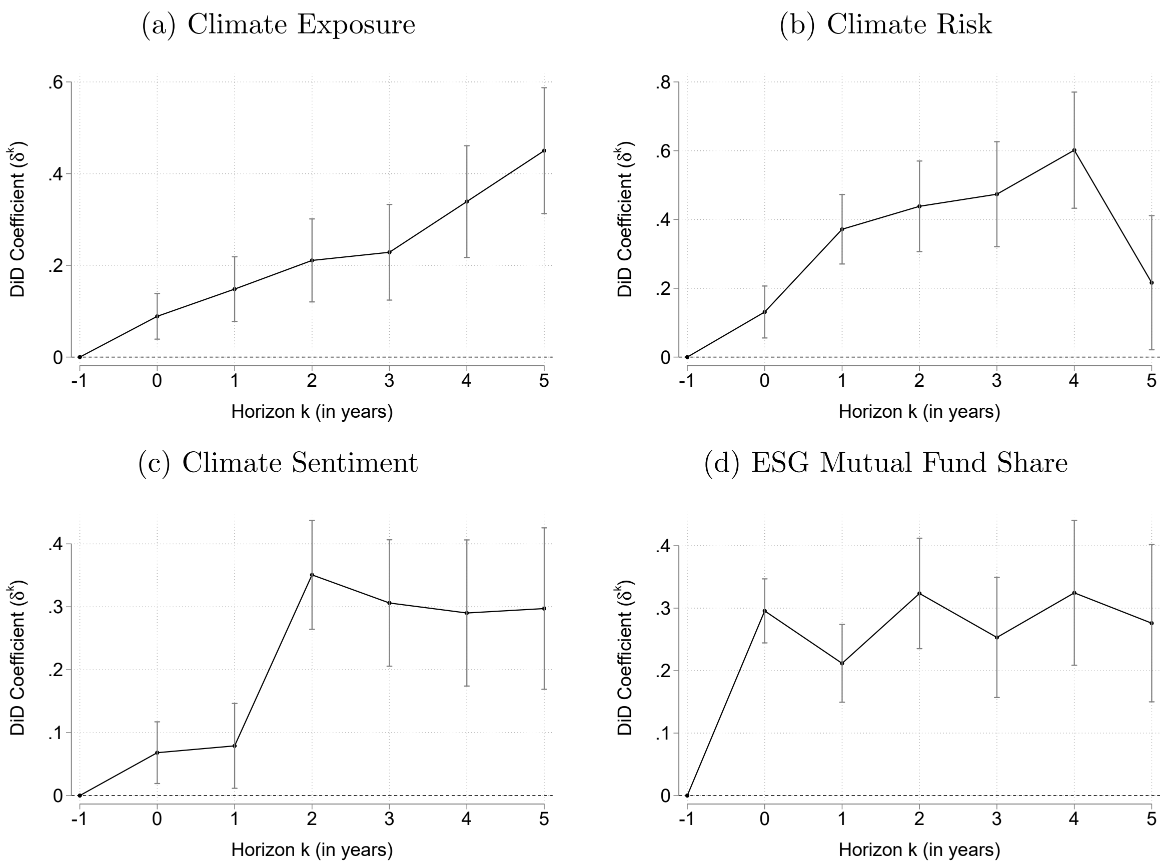


Notes: Figure 3 shows the positive spillover of climate shocks within a firm network. We aggregate the data at the firm-county-year level and estimate the following regression:

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

$\Delta\text{Log(Employment)}_{f,c,t-1\rightarrow t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer $\text{Shock}_{f,c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (3). We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level. The figure plots the coefficient δ^k against years relative to the shock (k).

Figure 4: Heterogeneity across firms: Investor perception

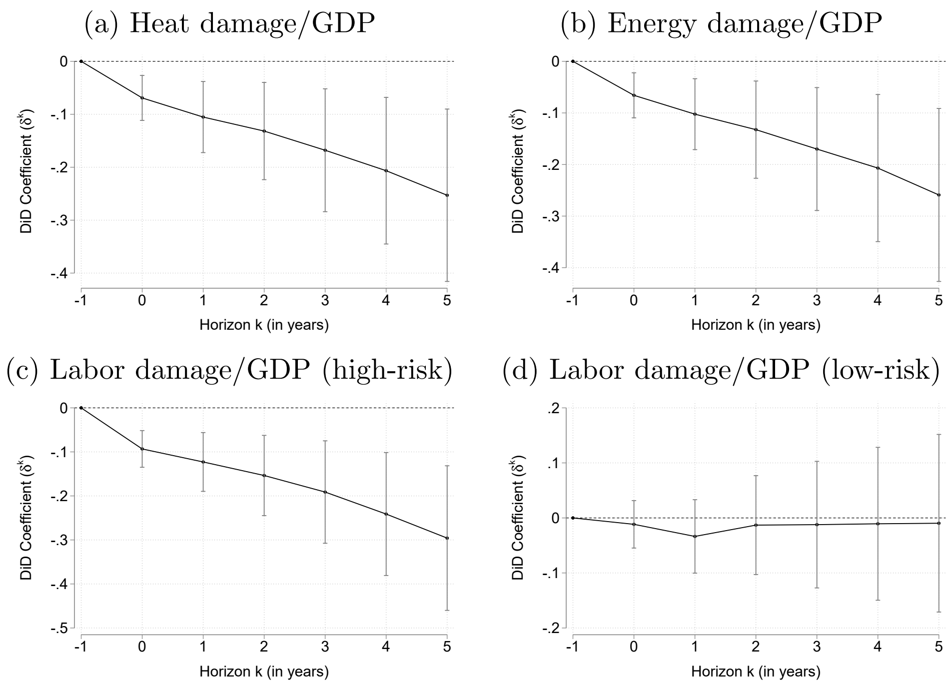


Notes: Figure 4 shows the relationship of investor beliefs and composition with labor reallocation in response to heat shocks (3-year horizon). The regression equation we estimate is:

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

$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer $\text{Shock}_{f,c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (3). Firm $\text{Characteristic}_{f,t-1}$ 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 5: Role of heat-related county characteristics

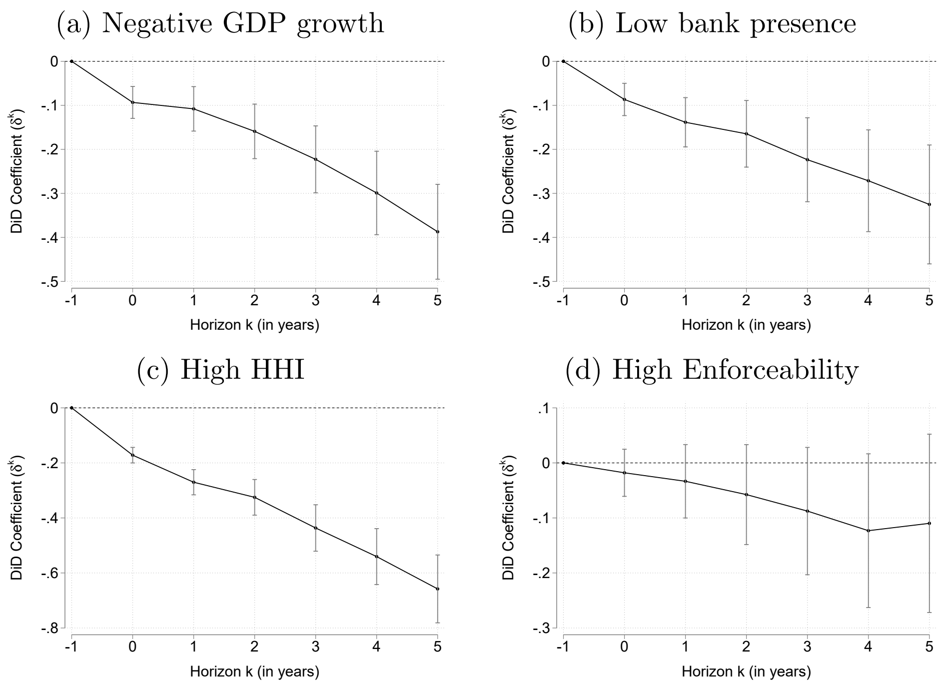


Notes: Figure 5 shows the county-level factors that influence firms' decision to reallocate into that county when its establishments elsewhere are impacted by heat shocks. We estimate

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

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

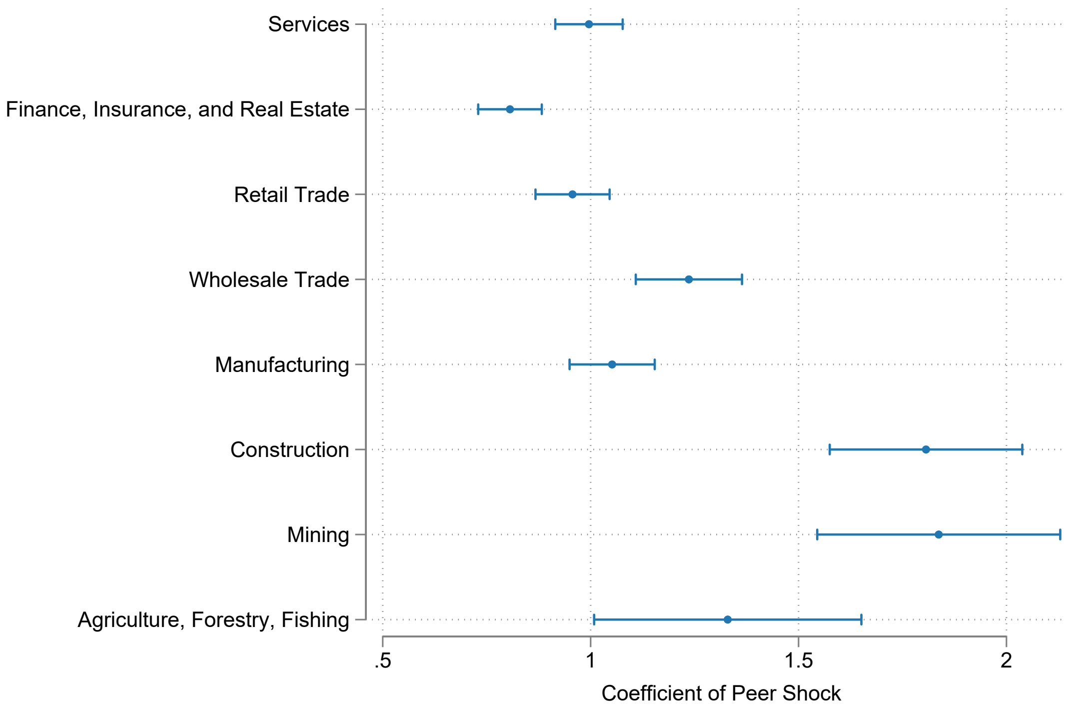


Notes: Figure 6 shows the county-level factors that influence firms' decision to reallocate into that county when its establishments elsewhere are impacted by heat shocks. We estimate

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

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 7: Mitigation across industries - I



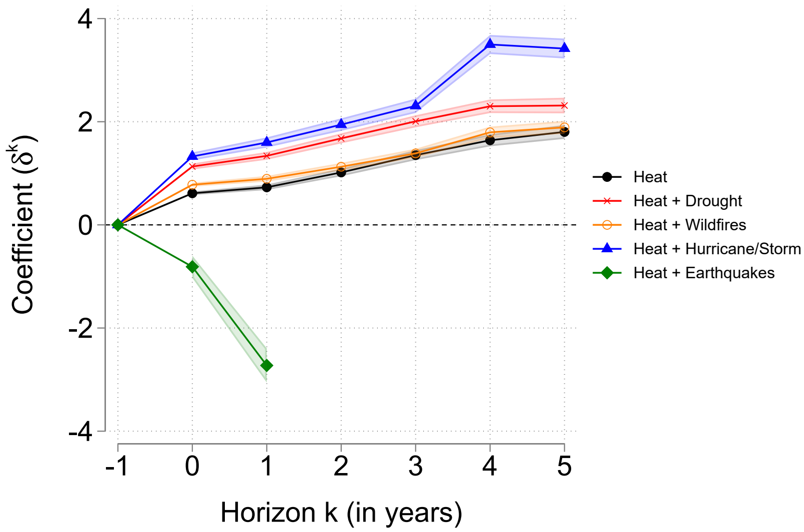
Notes: Figure 7 shows the extent of mitigation across broadly defined industries. The regression we estimate is:

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

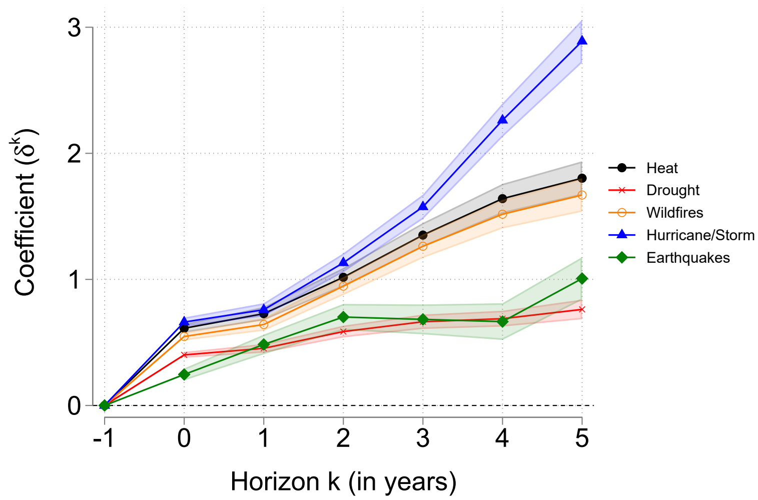
ΔLog(Employment)$_{f(i),c,t-1\to t+k}$ is the change in log employment of firm f (in industry i) in county c from year $t-1$ to $t+k$. Peer Shock$_{f(i),c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (3). Industry$_i$ indicates broadly defined industries categorized 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.

Figure 8: Other climate hazards

(a) Combined with heat hazard



(b) Single hazard



Notes: Figure 8 shows firm mitigation in response to different types of climate disasters. The regression equation we estimate is:

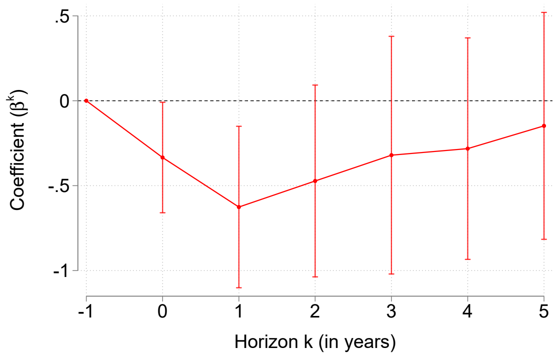
$$\Delta \text{Log(Employment)}_{f,c,t-1 \to t+k} = \delta^k \times \text{Peer Shock (Type)}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

$\Delta \text{Log(Employment)}_{f,c,t-1 \to t+k}$ 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.

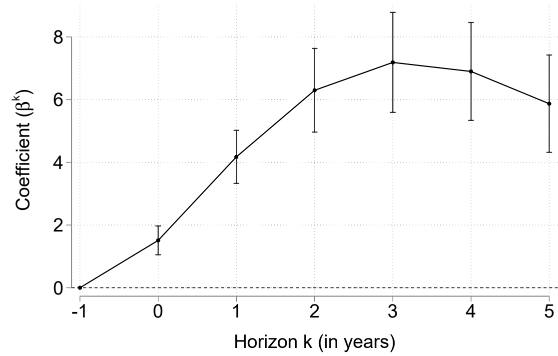
Figure 9: County-level results

Outcome 1: ΔLog(Employment)

(a) Own Shock

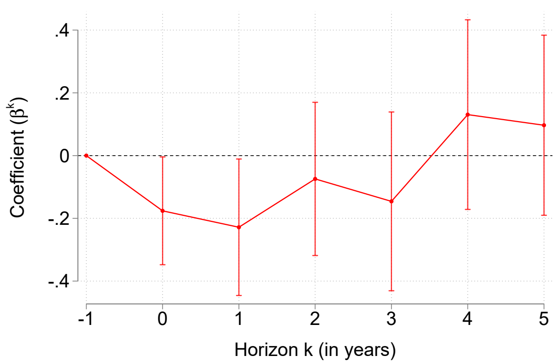


(b) Peer Shock

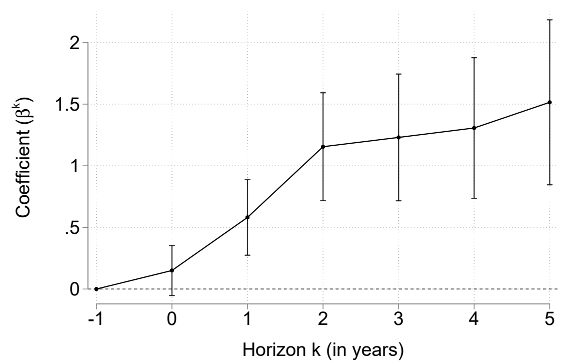


Outcome 2: ΔLog(# Establishments)

(c) Own Shock

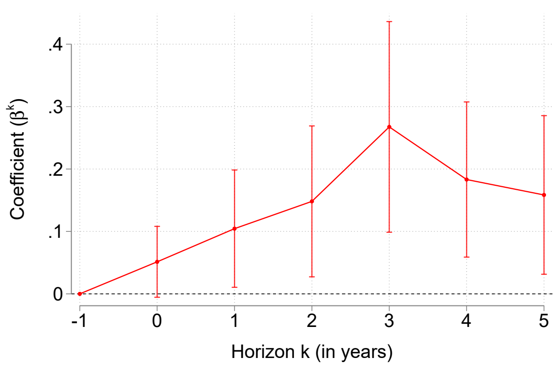


(d) Peer Shock

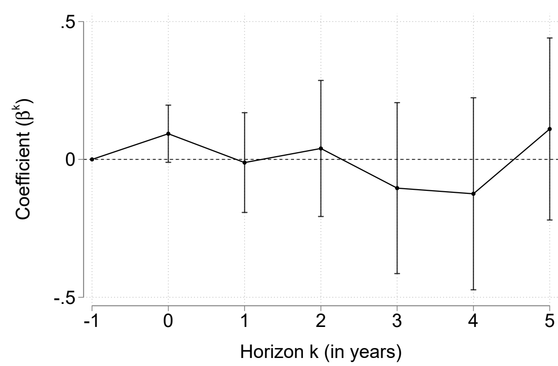


Outcome 3: ΔEmployment HHI

(e) Own Shock



(f) Peer Shock



Notes: Figure 9 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 outcomes (employment, #establishments, employment HHI) of county c from year $t-1$ to $t+k$. $\text{Shock}_{c,t}$ is Own Shock ($\text{Log}(1 + \#\text{ Hot Days}_{c,t})$) in Panels (a), (c), and (e) and Peer Shock ($\text{Log}(1 + \#\text{ Hot Days, Other}_{c,t})$) in Panels (b), (d), and (f). where $\#\text{ Hot Days}_{c,t}$ 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 1: Summary Statistics

	Mean	SD	5%tile	Median	95%tile
Firm-county-year sample					
Employment	106	644	2	20	350
# Establishments	2.2	5.5	1	1	6
# Hot Days	.47	3	0	0	2
# Hot Days, Other	1,095	14,730	0	.75	2,787
Own Shock	.12	.47	0	0	1.1
Peer Shock	2.4	2.9	0	.56	7.9
Firm-year sample					
Single Location	.3	.46	0	0	1
Employment	1,074	8,481	93	233	3,038
# Establishments	21	195	1	5	50
# Hot Days, Firm	.6	3	0	0	3
Firm Shock	.19	.52	0	0	1.4
Entry In New County	.12	.32	0	0	1

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: Firm mitigation: Reallocation to unaffected peer counties

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	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)
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)$_{t-1,t+k} \times 100$					
	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 3 shows the results of our baseline specification (Panel (a)) given by Equation (4) 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 4: Reallocation with Temperature-Based Shocks

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
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)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	5,093,577	4,293,786	3,605,427	2,985,655	2,422,352	1,908,354
$\bar{y}$	0.807	1.238	1.731	2.287	2.796	3.379
Adj. R^2	0.013	0.026	0.043	0.061	0.081	0.098

Notes: Table 4 shows the results of our baseline specification using a temperature-based peer shock measure. We estimate the following specification:

$$\Delta\text{Log(Employment)}_{f,c,t-1\rightarrow t+k} = \delta^k \times \text{Peer Shock (T}\geq\text{99Pctile)}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}$$

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 (T≥99Pctile)$_{f,c,t}$ is equal to Log(1+# Days(T≥99Pctile)$_{c,t}$) where # 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 period where daily temperature data is available in PRISM (i.e., from 1982 to 2020). We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are clustered at the county level.

Table 5: Heterogeneity across firms: Firm financials

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 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 $\times$ Peer Shock	1.091***				1.401*
	(0.066)				(0.849)
Low Leverage		-0.275			-0.701
		(0.565)			(0.586)
Low Leverage $\times$ Peer Shock		0.533***			0.534***
		(0.091)			(0.094)
High Z-Score			0.525		-0.467
			(0.506)		(0.558)
High Z-Score $\times$ Peer Shock			0.305***		0.117
			(0.070)		(0.082)
High Profitability				6.645***	7.461***
				(0.563)	(0.595)
High Profitability $\times$ Peer Shock				0.176**	0.047
				(0.080)	(0.091)
Firm FE	✓	✓	✓	✓	✓
County $\times$ 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 5 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 (3). 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.

Table 6: Mitigation across industries

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	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 6 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 (3). 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 7: Mitigation across varying distance from the shock

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock≤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∈(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∈(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∈(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 × 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 7 shows employment mitigation by firms at varying distances from the shock. We estimate the following regression equation:

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

ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$ 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.

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 (1). α_f and α_t denote firm and year fixed-effects respectively. Standard errors are clustered at the firm level.

Table 9: 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 9 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 (3). 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.

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 1. 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 A1. 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.[15]

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.

[15] 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 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)

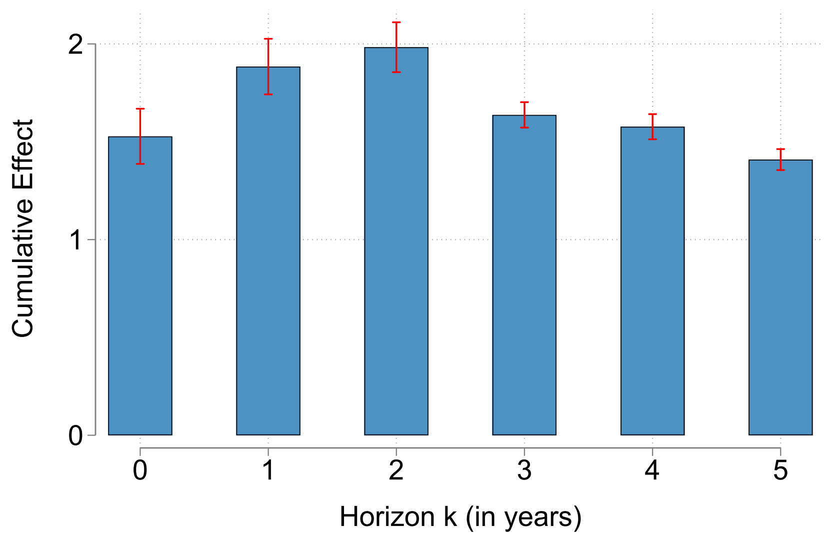
1. Heat wave in Dallas County, TX 2016 (News Link): Walmart Inc. (Retail) reduced 1,952 workers in Dallas (FIPS code: 48113) and added 489 workers in Benton (FIPS code: 5007).

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 C Appendix figures and tables

Figure A1: Firm mitigation: Estimation using distributed lag model



Notes: Figure A1 shows the impact of heat stress on the employment growth at peer locations. We estimate the following distributed lag specification:

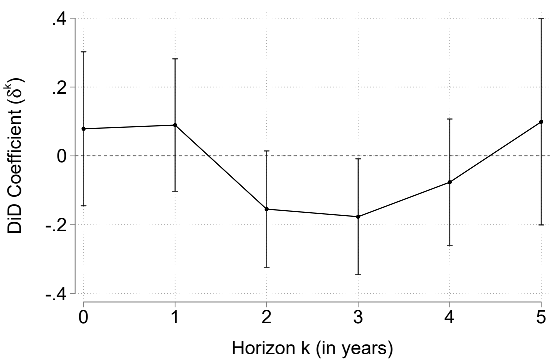
$$\Delta\text{Log(Employment)}_{f,c,t-1\to t} = \sum_{h=0}^{h=5} \beta^h \times \text{Peer Shock}_{f,c,t-h} + \alpha_{f,t} + \alpha_{c,t} + \varepsilon_{f,c,t}$$

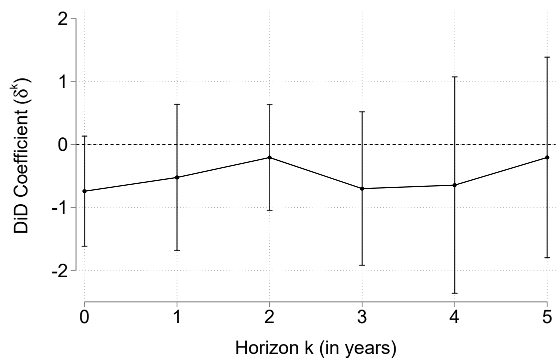
$\Delta\text{Log(Employment)}_{f,c,t-1\to t}$ is the change in log employment of firm f in county c from year $t-1$ to t. Peer $\text{Shock}_{f,c,t-h}$ denotes the value of peer shock h years ago. We employ firm-year ($\alpha_{f,t}$) and county-year ($\alpha_{c,t}$) fixed-effects. Standard errors are 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).

Figure A2: Migration

(a) Own Shock

(b) Peer Shock



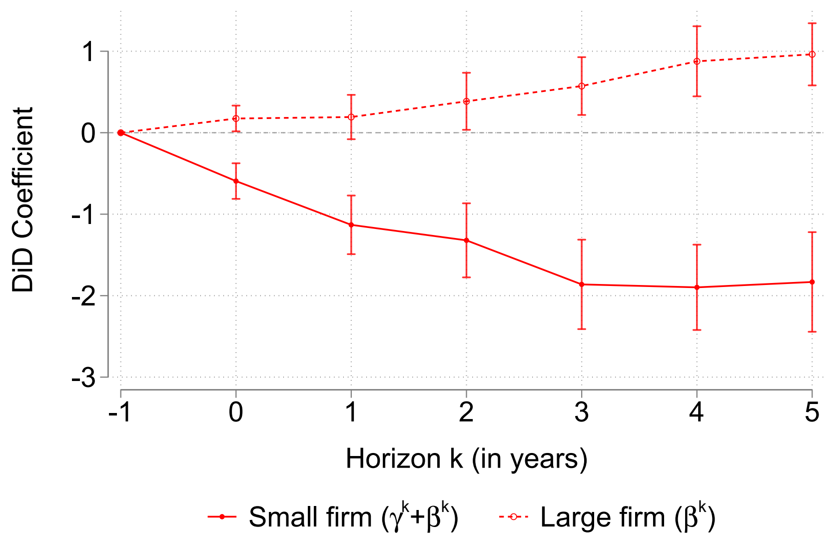


Notes: Figure A2 shows the impact of heat shocks on employment-related migration. We aggregate the data at the household level and estimate the following regression:

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

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 A3: Within-county reallocation

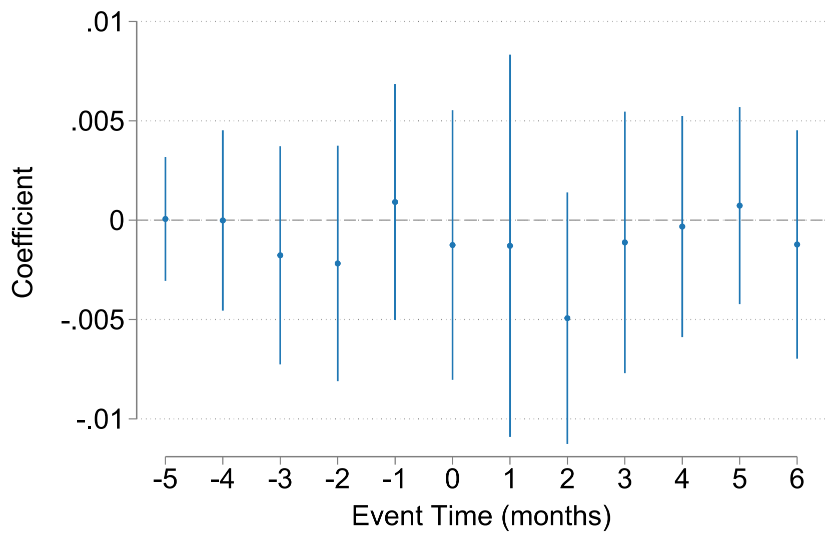


Notes: Figure A3 shows employment reallocation from small firms to large firms in counties experiencing heat shocks. The regression equation we estimate is:

$$\Delta\text{Log(Employment)}_{f,c,t-1\rightarrow t+k} = \gamma^k \times \text{Own Shock}_{c,t} \times \text{Small Firm}_f \\ + \beta^k \times \text{Own Shock}_{c,t} + \alpha_f + \alpha_c + \alpha_t + \varepsilon_{f,c,t}$$

$\Delta\text{Log(Employment)}_{f,c,t-1\rightarrow t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Own Shock$_{f,c,t}$ denotes heat shock in county c in year t. It is calculated as Log(1 + Hot Days, Own$_{c,t}$), where Hot Days, Own$_{c,t}$ is the annual number of heat disaster days according to the SHELDUS database. We employ firm (α_f), county (α_c), and year (α_t) fixed-effects. Standard errors are clustered 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 A1: 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 A1 shows the effect of heat shocks on financials of public firms. The regression equation we estimate is:

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

ΔOutcome$_{f,t-1\rightarrow t+k}$ 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 Shock$_{f,t}$ is the exposure of firm f to heat shocks in year t as defined in equation 1. α_f and α_t denote firm and year fixed-effects respectively . Standard errors are clustered at the firm level.

Table A2: Reallocation across firms

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100			
	k=+2	k=+2	k=+2	k=+2
Own Shock	-0.005	0.355**		
	(0.126)	(0.173)		
Small Firm $\times$ Own Shock		-1.745***	-1.737***	-1.686***
		(0.375)	(0.379)	(0.357)
Single Location $\times$ Own Shock				-0.801
				(0.607)
Firm FE	✓	✓	✓	
County FE	✓	✓		
Year FE	✓	✓		
County $\times$ Year FE			✓	
Observations	4,106,771	4,106,771	4,106,632	4,106,632
$\bar{y}$	2.618	2.618	2.618	
Adj. R^2	0.052	0.052	0.050	0.050

Notes: Table A2 shows employment reallocation from small firms to large firms in counties experiencing heat shocks. The regression equation we estimate is:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} &= \gamma^k \times \text{Own Shock}_{c,t} \times \text{Small Firm}_f \\ &+ \delta^k \times \text{Own Shock}_{c,t} \times \text{Single Location}_f \\ &+ \beta^k \times \text{Own Shock}_{c,t} + \text{FE} + \varepsilon_{f,c,t}\end{aligned}$$

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 $t+k$. We present results corresponding to 3-year employment change (i.e., $k = 2$). Own Shock$_{f,c,t}$ denotes heat shock in county c in year t. It is calculated as Log(1 + Hot Days, Own$_{c,t}$), where Hot Days, Own$_{c,t}$ is the annual number of heat disaster days according to the SHELDUS database. Small Firm$_f$ and Single Location$_f$ are indicator variables that equal one if the firm was small and had a single location throughout our sample period, respectively. We present the set of fixed-effects applied below each column. Standard errors are clustered at the county level.

Table A3: 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 A3 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 A4: 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 A4 shows mitigation in response to different types of heat shocks. We estimate the following specification:

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

$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. 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.