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ABSTRACT

Using establishment-level data, we show that firms operating in multiple counties in the United States respond to heat-related damages by reallocating employment from affected to unaffected locations. This reallocation is also observed as an increase in job postings in unaffected locations, and at the extensive margin as opening of new establishments. The reallocation response intensifies with heat-related damage severity being acute, chronic and compound (with other natural disasters), and is especially pronounced among larger, financially stable firms with ESG-oriented investors. This firm-driven reallocation affects how heat shocks impact aggregate outcomes at the county level, including employment growth, wage growth, labor force participation, and establishment entry rate. Specifically, mitigation behavior by multi-establishment firms acts as a “heat insulator” for the economy, reducing the impact of heat shocks on aggregate employment and wage growth while redistributing economic activity across locations.

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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 and depressing local demand, extreme heat conditions can lower labor productivity. The labor productivity channel directly affects firm profitability, and exposes 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 or via inter-regional trade or informal diversification mechanisms (see, e.g., Giné et al., 2012 and Baez et al., 2017). What role do modern corporations play in the mitigation response?

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 due to the lack of granular data and the complexities in quantifying the impact of extreme temperatures.

We fill this gap in the literature by using establishment-level employment data from Dun & Bradstreet Global Archive Files (D&B) and job postings data from Lightcast (formerly Burning Glass), along with disaster data from the Spatial Hazard Events and Losses Database

[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.

for the United States (SHELDUS), spanning from 2009 to 2020. Our principal finding is that while single-location firms lose workers to establishments of multi-location firms and increase job postings when impacted by *local* heat shocks, multi-location firms experience increase in employment and job postings at *unaffected* establishments. In other words, multi-establishment firms adapt to heat shocks by spatially reorganizing their workforce. Importantly, this firm-driven reallocation affects how heat shocks impact aggregate outcomes, including employment growth, wage growth, labor force participation, and net establishment entry rate at the county level. Specifically, mitigation behavior by multi-establishment firms acts as a "heat insulator" for the economy, reducing the impact of heat shocks on aggregate employment and wage growth while redistributing economic activity across locations.

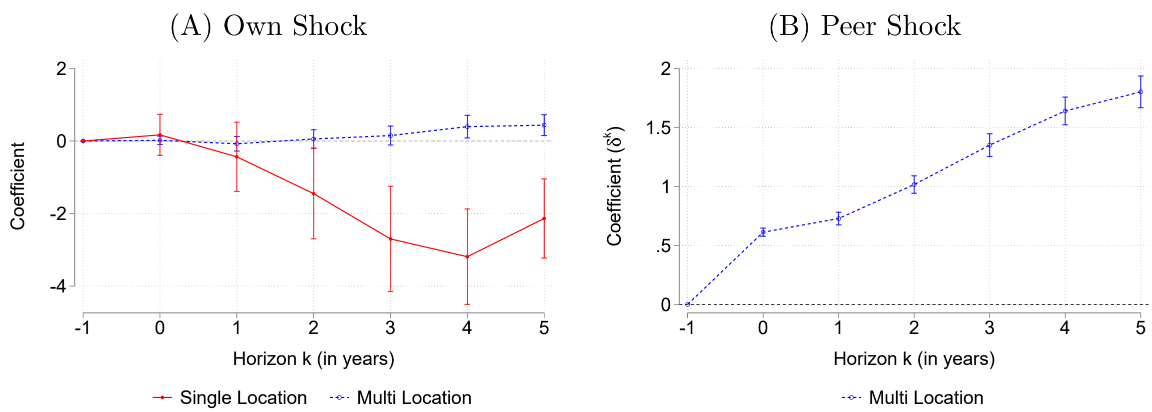
Let us elaborate. To assess how the single-location versus multi-location status of firms affect their resilience to local heat shocks, we construct an establishment-level heat exposure measure, defined as the log of "hot days" in its county, where a hot day is defined as a day experiencing disaster losses (property, crop, injury, or fatality) due to heat hazard according to the SHELDUS database.[2] We find that while one hot day reduces employment growth in single-location firms by 1.05 pp over three years, establishments of multi-location firms show no such decline and even witness a growth of 0.30 pp over a longer six-year horizon (see Figure 1 Panel (A)). Notably, this decline in single-location firms' employment growth corresponds with increased job postings, suggesting that the reduction is driven by reduced labor supply instead of a lower demand for workers. The effects of heat shocks on employment growth and job postings are especially pronounced in industries and occupations more exposed to extreme temperatures. Overall, these findings suggest that heat shocks lead to a worker-driven employment reallocation from single- to multi-location firms *within* the affected county.

Next, we provide evidence of between-county employment reallocation in multi-location firms in response to heat shocks following an approach similar to Giroud and Mueller (2019). Specifically, we calculate a "peer shock" measure for a given establishment as the total number of hot days that its sister establishments (i.e., those of the same firm) experienced in a given year, with hot days of a sister establishment being scaled by its employment relative to that of the given establishment. Our empirical strategy then compares the employment growth of two firms 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 unit increase in peer shock measure is associated with a 1 pp increase in establishments' employment growth over three years (see Figure 1 Panel (B)). To gauge the

[2]The incidence of hot day according to SHELDUS is correlated with the incidence of extremely high temperatures, particularly in counties vulnerable to climate risk according to the FEMA Risk Index.

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 pp increase in employment growth in the other establishment.[3] Interestingly, we find that the effect of peer shock on job postings is positive and significant, indicating that higher employment growth in peer counties is driven by firms demanding more workers in these locations. Overall, these results suggest that firms respond to heat shocks by reallocating resources from affected areas to unaffected ones.[4]

Figure 1: Impact of heat shocks: Own shock vs. peer shock



Notes: Figure 1 shows how heat shocks affect the employment growth of establishments in the affected counties and in the peer counties. The outcome variable is $\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. In Panel (A), we show the effect of own shock on the establishments of both single- and multi-location firms after including firm, year, and county fixed effects. In Panel (B), we show the effect of peer shock on establishments of multi-location firms after including firm and county-year fixed effects. Standard errors are clustered at the county level.

We next explore the mechanisms driving reallocation within multi-location firms and present several results indicating that heat's impact on labor productivity is the primary channel driving our results. First, we observe higher employment growth and job postings at peer locations in industries and occupations where workers are more exposed to extreme temperatures, as classified by the O*NET Work Context database. Second, employment growth is higher at peer establishments in areas with lower *projected* heat-related damage, as measured by estimates of Spatial Empirical Adaptive Global-to-Local Assessment System

[3]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.

[4]We provide several anecdotal examples of firms reallocating their workforce from heat-affected counties to unaffected ones in Appendix A.

(SEAGLAS) by Hsiang et al. (2017). Third, firms' responses are the strongest in sectors like mining and construction, where workers are exposed to outdoor temperatures (Somanathan et al., 2021), and the weakest in finance, insurance, and real estate. Fourth, we find that industries most amenable to teleworking exhibit weaker mitigation activity. Finally, we observe higher reallocation among firms with more ESG-focused investors (Cohen et al., 2020) and greater climate risk exposure, measured by textual analysis of firms' earnings call transcripts (Sautner et al., 2023). The last result is consistent with earlier work in climate finance showing that beliefs play a key role in agents' response to climate change shocks (e.g. Baldauf et al., 2020, Bernstein et al., 2022, Addoum et al., 2023).[5]

Looking at alternative mechanisms, we do not find stronger results in sectors with higher energy intensity, suggesting that the energy cost channel is not the main driver for our results. We also rule out the local demand spillover channel (i.e., that neighboring counties of affected locations also suffer from the adverse demand impact of heat-related shocks) by constructing a measure of establishments' geographical proximity to heat shocks and showing that including this measure in our baseline specification does not affect our main coefficient of interest. Collectively, these results suggest that the firms are relocating primarily to minimize heat-related losses in labor productivity and not due to higher energy costs or depressed local demand due to heat stress.

Firm-level mitigation affects the impact of heat shocks on aggregate employment at the county level. We show that one hot day in a county leads to a modest, temporary decline in employment growth of 0.26 pp in the affected counties. Notably, the spatial reallocation by multi-location firms results in higher employment growth in counties that are less directly exposed to heat risk but are connected to heat-affected areas via multi-location firm networks. E.g., 1 sd increase in the county-level peer shock measure increases employment growth by 2.4 pp. Distinguishing between local employment and cross-county migration, we find that the employment shifts—both negative in heat-affected counties and positive in unaffected peer ones—are primarily driven by changes among the local population.[6] Consistent with the workers switching from single- to multi-location firms in affected counties and increased labor demand in peer counties, we find wage growth declines in the affected counties but rises in the peer counties after a heat shock. Finally, higher labor demand in peer counties also leads to an increase in labor force participation rate and higher net establishment entry rate.

[5] Asset managers are increasingly incorporating physical climate risk in their investment decisions. See Bloomberg article dated October 22, 2023 (https://news.bloomberglaw.com/esg/fund-managers-are-updating-bond-models-to-capture-a-new-risk-1). Thus, lowering exposure to extreme climate events by relocating their workforce can lower firms' cost of capital in the long run.

[6] Our muted results on migration are in line with Behrer and Bolotnyy (2023), who study migration in response to other types of natural disasters.

These results indicate that firms' ability to reallocate their workforce geographically lowers the long-run aggregate impact of climate change, especially via the spatial redistribution channel. At the same time, this redistribution has an adverse impact on the affected local economies by redistributing economic activity across geographies.

Next, we examine the frictions associated with firms' spatial mitigation activity. 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. Hence, 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 a stronger mitigation 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 adjustment costs are borne by firms. Turning to local economic factors, higher GDP growth and credit availability (as measured by per-capita bank loan originations) in the peer establishment's county increase mitigation-driven employment growth. Finally, higher labor market competition at the peer location, measured by lower employment concentration across firms (employment HHI) also supports firms' response. From a policy perspective, these results underline that enhancing credit access and fostering a competitive labor market can help policymakers leverage the support of the corporate sector in minimizing the aggregate consequences of rising temperatures.

Lastly, we 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.[7] 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 adapted, 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 if the frequency and intensity of heat risk and of compound climate risks increase over time.[8]

On the other hand, if mitigation only works for milder events or for local communities

[7] See Environmental Protection Agency report dated July 2022 (https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves).

[8] 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.

that have not experienced and adapted to chronic heat conditions yet, 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.

Related Literature Our paper is related to several recent papers studying the effects of extreme weather events on firm performance (e.g. Addoum et al., 2020; Jin et al., 2021; Dell et al., 2012). Heat shocks impact firms' productivity (Caggese et al., 2023) and 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). Furthermore, Addoum et al. (2023) find that the average masks a bi-directional effect, where some industries are harmed while others benefit. Ponticelli et al. (2023) show that temperature shocks significantly increase energy costs and lower productivity of manufacturing plants, with the effect mainly concentrated on smaller establishments. 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 (2024) shows that firms are more likely to terminate existing supplier relationships when realized temperature shocks exceed expectations. Xiao (2024) finds that extreme heat reduces plant-level labor productivity, and firms respond to this shock by increasing their capital intensity. Similarly, Xiao (2022) finds that firms respond to climate-induced labor risks through automation investments. 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 heat 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 (Stein, 1997; Maksimovic and Phillips, 2002; Gumpert et al., 2022). Multi-region firms can have functioning internal labor markets and can efficiently deploy workers across regions (Tate and Yang, 2015). In contrast to this literature, we document positive spillover effects of climate shocks due to firms' internal employment reallocation decisions aimed at mitigating the impact of heat risk at individual locations.

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.[9] 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.

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.

[9]While businesses are not 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.

The first concern relates to the large amount of imputation in establishment-level variables like sales and employment. Following Denes et al. (2020), we only use actual, non-imputed values of employment and employment growth in our analysis. We do not use sales data since the 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 (up to 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.[10] 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.

For our analysis, we focus on establishments located in the United States and aggregate the data at the firm-county-year level. Our sample ranges from 2009 to 2020. Table 1 presents the summary statistics of key variables used in our analysis. Median employment

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

at the firm-county-year-level is 21. 70% of firms in our sample are multi-location firms. The median firm employs 232 employees and operates in 5 counties in a given year.

B Lightcast

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

In some analyses, we further classify posts based on their exposure to extreme temperatures based on O*NET Work Context database. This database contains exposure scores for almost 900 different occupations based on how often the job requires working in very hot (above 90F degrees) or very cold (below 32F degrees) temperatures. We use 50/100 score cutoff to define an exposed occupation, which covers around 28% of all occupations. Finally, we scale the postings based on lagged number of employees in a given firm-county using the D&B employment data. As shown in Table 1, the number of vacancies that an average establishment advertises in a given year is around 7% of its previous year's number of employees.

C Heat-related disasters

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

C.1 Relationship with temperature-based heat shocks

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

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

III Establishment-level results

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

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

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

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

Here, $\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in firm f's log employment in county c from year $t-1$ to $t+k$. Own $\text{Shock}_{c,t}$ is $\text{Log}(1+\text{Hot Days}_{c,t})$, where Hot $\text{Days}_{c,t}$ is the total number of hot days in county c in year t according to SHELDUS.[11] Single Location_f indicates that firm f existed in a single county throughout our sample period. We employ firm and county fixed effects to absorb differences in growth rates across firms and counties. We also include year fixed effects to absorb aggregate fluctuations and cluster standard errors at the county level.[12]

We present estimation results in Table 3. In Panel (A), we find that heat shocks adversely affect establishments of single-location firms. Specifically, the coefficient with respect to $k = 2$ implies that one hot day lowers employment growth at establishments of single location firms by 1.05 pp ($1.508\times\ln(2)$). This is economically significant relative to the average 3-year growth rate of 2.6% over our sample period.[13]

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

Next, in order to better understand whether changes in establishments' employee count is mainly driven by supply or demand side forces, we look into job postings. The main idea of the exercise is that a reduction in actual employment accompanied with an increase in

[11] To minimize the effect of extremely large values, we log transform the number of hot days. Since we do not use Own $\text{Shock}_{c,t}$ as an outcome variable in our empirical analysis, this transformation does not lead to bias that occurs when an outcome variable with zeros is log transformed (Chen and Roth, 2024).

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

[13] In this and subsequent regressions, the number of observations successively decline as we increase the horizon over which the log employment change is measured. This is because calculating log employment change from $t-1$ to $t+k$ requires non-zero and non-missing employment in both $t-1$ and $t+k$. Due to finite sample, the observations satisfying this criteria become fewer as k increases.

job postings is more likely to be driven by a labor supply shock (employees are resigning from affected locations forcing firms to post more vacancies), whereas a reduction in actual employment accompanied with a decrease in job postings is more likely to be mainly driven by a labor demand shock (firms are downsizing in a given location).

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

A.1 Role of firm size and multi-location status

To further disentangle firm-driven vs. worker-driven reallocation, we divide firms according to their size and single/multi location status. For size, we divide firms into large and small depending on their average employment being above- or below- median during our sample period. Specifically, we divide firms into four groups — (a) large and multi-location, (b) small and multi-location, (c) large and single-location, and (d) small and single-location. Then, we examine how establishments of these various types of firms response to hot days in their county.

Table A1 presents the results. The baseline coefficient of Own Shock refers to large multi-location firms. Panel (A) corresponds to employment growth and Panel (B) corresponds to job postings. We find that, in general, small firms see weaker employment growth compared to large firms. Among both small and large categories, single-location firms lose more workers than multi-location firms. Notably, a negative relationship between employment growth and job postings appears only for single-location firms. E.g., small multi-location firms lose workers but do not increase their job postings. These results are consistent with the notion that small firms are less resilient to heat shocks, and their diminished employment growth is driven by firm demand for workers. On the other hand, workers exit single-location firms in favor of multi-location firms leading to employment reallocation across the two categories.

Our results indicate that geographical diversification is important for firms to retain their existing workers and attract new ones. Why would workers prefer to work for establishments of multi-location firms? Multi-location firms might be more resilient to localized climate shocks, as they have an option to shift operations to their unaffected plants. This can reduce the likelihood of a firm going out of business and increase job security at an average establishment. Indeed, we find that multi-location firms respond to heat shocks by increasing employment at their unaffected locations.[14] Overall, our results point to the benefits that firms can obtain through geographical diversification.

A.2 Disproportionate effect in climate-exposed sectors and occupations

Heat shocks may induce adaptation efforts from both firms and workers. Worse environmental conditions may render the operations of constrained firms unprofitable, forcing them to downsize and lower their labor demand. At the same time, workers may see value in switching jobs after experiencing unpleasant conditions at their workplace. Our results in Table 3 indicate that employment reallocation from single- to multi-location firms in response to an own heat shock is driven by workers. This suggests that from the perspective of climate shocks, workers see value in geographical diversification of their employers. To examine the key mechanism behind such worker-driven mitigation, we examine the heterogeneous impact of heat shocks on climate-exposed occupations and sectors.

The Lightcast data has SOC occupation codes for the job postings. We use the O*Net Work Context database to divide occupations with high and low climate exposure, allowing us to study the response separately across the two groups. The D&B data on employment growth does not breakdown employment by heat-exposure, so we use the Lightcast data to classify industries into high and low climate exposure, where high exposure industries are those with above-median level of job posting rate in climate-exposed occupations. We use these classifications and present the results in Table 4.

Panel (A) shows that the decline in employment growth for single-location firms is stronger among firms in climate-exposed industries, consistent with the idea that workers in those industries are more sensitive to heat shocks. Interestingly, multi-location firms in the exposed industry also suffer losses in employment growth, which suggests that the main beneficiaries of within-county reallocation are the multi-location firms in industries less exposed to climate extremes. At the same time, it suggests that reallocation across firms is both from single- to multi-location firms and from more-climate-exposed to less-climate-exposed industries.

Panel (B) studies the effect on job postings. Since we can divide job postings into high- and low-climate-exposed groups, we further saturate our model by interacting the fixed effects by this classification. Consistent with the worker-driven mitigation channel, we find that the

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

increase in job postings among single-location firms is also higher among climate-exposed occupations. Overall, these results substantiate the conjecture that heat shocks disproportionately affect climate-exposed sectors and occupations, leading to stronger within-county-across-firm reallocation among these groups.

B Firm mitigation: Reallocation to unaffected peer counties

Next, we directly examine how the establishment network of multi-location firms affect the impact of heat shocks on aggregate employment. Our empirical analysis closely follows prior studies on establishment 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 multi-location firms reduces the overall impact of heat shocks on employment. Conversely, a negative spillover would suggest that multi-location firms can transmit the impact of climate shocks across regions, amplifying their overall impact. To understand whether multi-location firms mitigate or amplify heat risk, we restrict our sample to firms with non-zero employment in two or more counties.

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. More precisely, for firm f, county c, and year t, we calculate

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

where

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

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

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

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

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

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

Results are shown in Table 5 Panel (A). We find a positive spillover effect of heat shocks within the firm network. A unit increase in the peer shock measure is associated with roughly 1 pp 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 pp ($1.016 \times \ln(2)$) uptick in employment growth at this firm's branch in county c. The average employment growth over the same horizon is 2.4%, which highlights the economic significance of our spillover effect.

Panel (B) shows the spillover effect of heat shocks on connected establishments' job postings. Unlike the previous analysis focusing on the affected counties, here we find that the effect on the employment growth is positively correlated with the effect on job postings. This highlights that heat stress in a county indeed seems to induce multi-location firms to increase their labor demand and employment growth at unaffected peer counties. For comparing the magnitudes of employment growth and job postings result, consider the change over one-year horizon (i.e., k=0), since the denominator is the same in that case. Continuing with the above example of a firm with two equal-sized establishments, our coefficients imply that one hot day in the peer establishment increases the job posting rate by $0.803 \times \ln(2) = 0.57$ pp. At the same time, it increases employment growth by 0.42 pp. These numbers suggest that an average posting in our data has a 76% conversion rate. Overall, these results suggest that multi-location firms, after experiencing heat shocks at one of their locations, demand more workers and increase employment growth at their other locations.

B.1 Robustness

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

Alternative measures of peer shock 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 $\text{Shock}_{f,c,t}$). 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 A2 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, $\text{Est-Wt}_{f,c,t}$). We compute a third alternative measure (Peer Shock, $\text{Eq-Wt}_{f,c,t}$) 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 $\text{Tercile}_{f,c,t}$) that is one when the value of peer shock lies in the top tercile of the distribution, and zero otherwise. Table A2 Panel (B) shows that the results with these alternative measures are consistent with those using our primary measure.

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

Alternative specifications 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 A2 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 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. Lastly, we get similar results on employment growth when we restrict our analysis to the establishments that are present in the D&B-Lightcast matched sample, which is the sample for which the job postings results are estimated. These results are presented in Table A3.

Alternative outcomes 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 opening new establishments in unaffected peer locations. In other words, it sheds light on the impact of climate shocks on establishments across the *extensive margin*. Results presented in Table A2 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.

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

IV Mechanism

We now focus our attention on the key mechanism that drive firm response in our paper – labor productivity. Heat shocks can cause positive employment spillover across establishments if they depress local labor productivity by causing discomfort and absenteeism among workers in the affected establishment (Somanathan et al., 2021). This is because a negative productivity shock lowers optimal employment levels and frees up resources that firms can deploy elsewhere. To further substantiate that our results are driven by this labor productivity channel, we present several sets of results in this section.

Higher reallocation in climate-exposed sectors and occupations First, we examine the type of workers that firms try to recruit in response to shocks in peer locations. If firms are diversifying their operations away from heat-impacted regions in order to avoid the loss of labor productivity, we expect the labor demand in the unaffected locations to rise strongly in occupations more exposed to extreme climate. Other the other hand, channels related to local cost shocks or demand shocks should not imply differential demand across such occupational groups. Using O*NET work context database, we divide industries and occupations into two groups – those with high or low exposure to climate, and employ our baseline specification to see how employment growth and job posting rate evolves across the two occupational groups.

Table 6 presents the results. Panel (A) shows that, employment reallocation within multi-location firms is stronger in climate-exposed industries, which is consistent with the idea that the impact of heat shocks on labor productivity is higher in these sectors, triggering a stronger reallocation response. The response in the establishments of climate-exposed industries is roughly 20% higher relative to other establishments. Panel (B) shows that the increase in job posting rate, which is our proxy for labor demand, is also higher among climate exposed occupations. This reveals that even within the same firm, heat shocks lead to an occupational reallocation across regions.

Reallocation is towards less heat-exposed counties Second, we explore what regional characteristics influence a firm's decision to choose one peer location over the others. If firms are responding to mitigate heat-induced losses in labor productivity, we expect them to move into places where the workers 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. (2024) for more detailed discussion of the measure.

We use the main SEAGLAS measure, which is the projected heat damage to a county scaled by its GDP. Specifically, we divide counties into those with above- and below-median value of Heat Damage/GDP ratio. We conjecture that if the firms are readjusting their workforce to mitigate heat risk, they are less likely to hire workers in peer locations with high projected damages. On the other hand, if the reallocation activity is driven by some other factor, we do not expect systematic differences across peer locations along this dimension.

To verify our conjecture, we estimate the following specification:

$$\begin{aligned}\Delta\text{Log(Employment)}_{f,c,t-1\to t+k} = \delta^k \times \text{Peer Shock}_{f,c,t} \times \text{Heat Damage/GDP}_c \\ + \gamma^k \text{Peer Shock}_{f,c,t} + \alpha_f + \alpha_{c,t} + \varepsilon_{f,c,t}\end{aligned} \tag{4}$$

Figure 3 shows that consistent with our hypothesis, employment growth is weaker in regions with higher projected damages which are places where workers are more likely to experience heat-related stress in the future. Overall, these results support our argument that firms are reallocating their workforce to mitigate the heat exposure of their employees.

Reallocation across industry sectors Third, we explore the heterogeneity of firm response across broad industry sectors. Heat shocks can adversely impact labor productivity if the workforce is exposed to outdoor conditions (Graff Zivin and Neidell, 2014). This is more prevalent in some industries (e.g. mining and construction) than others (e.g. finance and consulting). To understand how firms in different industries respond, we augment our baseline specification with industry dummies and estimate the following regression:

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

$\Delta\text{Log(Employment)}_{f(i),c,t-1\to t+k}$ 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 (2). Industry_i indicates broadly defined industries categorized as 2-digit SIC codes. We employ firm ($\alpha_{f(i)}$) and county-year ($\alpha_{c,t}$) fixed effects and cluster standard errors at the county level.

We then calculate the marginal impact of Peer $\text{Shock}_{f(i),c,t}$ across each industry and plot the impact corresponding to a 3-year period following the shock (i.e., $k = 2$) in Figure A2. The two industries exhibiting the highest reallocation are construction and mining. Certain industrial activities such as 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.

Muted effect on teleworkers Finally, we look at heterogeneity across industries in terms of teleworking. 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. Table 7 Panel (A) shows that industries amenable to teleworking exhibit lower mitigation consistent with the idea that teleworking protects workers from harsh climate conditions. Overall these findings show that our results are driven by climate impact on labor productivity and not by its effect of localized cost shocks and demand shocks.[15]

Stronger reallocation in ESG-oriented firms 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.[16] We find that firms with a larger share of such investors exhibit greater mitigation activity. Overall, these results suggest that investor perception about firms' climate exposure and their inclination towards ESG issues motivate firms to shift their workforce away from heat shocks, enhancing the resilience of their overall employment

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

[16]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.

against rising temperatures.

Ruling out alternative mechanisms We now examine alternative mechanisms that might affect within-firm employment reallocation due to heat shocks. 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. Additionally, heat shocks can depress local demand. In response, firms may be forced to reduce employment in unrelated establishments (Giroud and Mueller, 2019). The energy cost and local demand channels would both lead to a negative spillover effect, which is inconsistent with our establishment-level results that show a positive spillover effect. We now present additional evidence to rule out these alternative mechanisms.

First, we examine whether employment reallocation is stronger in energy-intensive industries. For energy intensity, we measure self-reported firm-level energy consumption using Refinitiv ESG database. Since this measure is only available for a subset of publicly traded firms, we measure energy intensity at Fama-French 30 industry level using the average firm-level energy intensity of the S&P 500 companies. Even among these companies, the coverage is relatively sparse until very recently, so we use only 2019 energy consumption data which is available for 335 S&P 500 constituents, and assume that energy intensity of a firm is relatively constant over time, and that firms in the same industry have similar energy intensities. In Table 7 Panel (B), we show that firm mitigation response does not significantly vary with energy intensity. These results indicate that while heat shocks may affect energy expenditures, they are not the primary driver of our findings.

Next, we investigate whether firm responses are driven by local demand spillovers, considering the possibility that firm establishments may cluster geographically, leading to employment reallocation through direct spillovers of heat shocks across neighboring regions. The inclusion of county $\times$ year fixed effects directly addresses this concern by comparing establishments within the same county-year, each equally proximate to nearby heat shocks and, therefore, equally exposed to any potential demand spillovers. To further understand the role of regional spillovers, we create a county-level proximity measure, Neighbor Own Shock$_{c,t}$, defined as Log(1+#Hot Days, Neighbor$_{c,t}$), where #Hot Days, Neighbor$_{c,t}$ is the weighted average number of hot days in surrounding counties (weighted by inverse distance). After replacing county-year fixed effects with separate county and year fixed effects, we compare our peer shock measure (based on establishment networks) with Neighbor Own Shock (based on geographic proximity) in a horse race model. Table 7 Panel (C) shows that heat shocks reduce employment growth in counties close to the affected region. Crucially, our peer shock coefficient remains consistent with the baseline, confirming that our main results are not driven by local demand spillovers.

V Aggregate outcomes

Next, we explore if heat shocks affect county-level outcomes. Doing so sheds light on whether the spatial reallocation channel that we have documented using establishment-level data has aggregate macroeconomic implications.

A Employment growth

To study to effect on county-level employment growth, we estimate the following regression:

$$\Delta \text{Log(Employment)}_{c,t-1\to t+k} = \beta_1 \times \text{Own Shock}_{c,t} + \beta_2 \times \text{Peer Shock}_{c,t} + \alpha_c + \alpha_t + \varepsilon_{c,t} \quad (5)$$

$\Delta \text{Log(Employment)}_{c,t-1\to t+k}$ denotes change in employment growth 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 county c in year t according to SHELDUS. Peer shock measure (Peer Shock$_{c,t}$) for county c in year t is Log($1+$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 establishment-level peer shock measure. Thus, counties with a large presence of multi-location companies will have links to many other counties and would likely benefit (from our channel) if heat shocks affected any of those linked counties. In other words, we expect a positive association between aggregate employment growth and peer shock at the county level. We employ county fixed effects to absorb cross-sectional differences in growth rates across counties. We also employ year fixed effects to control for aggregate fluctuations.

We present the results in Table 8. Panel (A) shows that in the immediate aftermath of the heat shock, employment growth shrinks in the county. Specifically, Column (1) shows that one hot day in the county reduces employment growth by 0.26 pp within a year. Over longer horizons, the point estimate stays negative but becomes statistically insignificant as the effect is measured more imprecisely. Peer counties, on the other hand, exhibit an increase in employment growth after counties associated with them through firm networks experience a heat-related disaster. One standard deviation increase in the peer shock measure increases employment growth by 2.4 pp.

Diminished employment growth in response to heat shock can be driven either by an outmigration of workers or by a decline in employment opportunities of locals. Albert et al. (2021) show that dry conditions in Brazil caused outmigration of agricultural workers. Similarly, employment growth in response to peer shocks can provide job opportunities for migrants as well as locals. To understand whether locals or migrants are driving the change in employment growth, we decompose employment growth into two groups and examine the effect of own shocks and peer shocks on the two groups separately.

Specifically, we decompose employment growth from $t-1$ to $t+k$ into inflow of workers from other counties and employment growth of local population. We use the IRS SOI data to measure county-to-county migration of workers for each year in our sample period. The benefit of using IRS data to measure migration is that it is derived from tax return data, which means that it captures migrants that are either self-employed or employed by other firms. Thus, net inflow of migrants can be interpreted as employment growth driven by migrant population. The remaining amount of county-level employment growth can be attributed to the locals. We present these results in Table 8 Panels (B) and (C). These results highlight that both the own shock and peer shock effect is driven by locals and is not explained by migration in and out of the county. Thus, they align with Behrer and Bolotnyy (2023), who find little to no impact of hurricanes on out-migration, highlighting the strength of deep economic and social ties in determining worker mobility.

To verify the robustness of our county level employment growth results, we re-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 coefficients of Peer Shock using the census data (see Table A4) are similar to those using the D&B data. However, the coefficients of Own Shock are more noisy.

B Wage growth, labor force participation rate, and net establishment entry rate

Next, we examine the effect on several other county-level measures. Specifically, we look at wage growth, change in labor force participation rate, and net establishment entry rate. The D&B and the Lightcast databases do not provide information on wages, so we use wages from the Quarterly Census of Employment and Wages (QCEW) at the county-level. Similarly, we get the data on labor force participation rate from the Bureau of Labor Statistics (BLS) and the data on net establishment entry rate from the Business Dynamics Statistics (BDS). We present the results in Table 9. Panel (A) shows that, after a heat shock, wage growth declines in the affected county. This highlights that as workers leave their existing jobs in single-location firms and try to join multi-location firms, they drive down wages at the aggregate level. Panels (B) and (C) show that the overall effect on own shock on labor force participation rate and establishment entry rate is not significant, consistent with within-county employment and economic activity shifting from single-location to multi-location firms.

Notably, we find that wage growth increases after a peer shock, which lines with our establishment-level results about higher labor demand in peer locations. As multi-location firms try to hire new workers, they bid up local wages at the county level. Finally, we also find a positive effect of peer shock on both labor force participation rate and net establishment entry rate, indicating that the increase in employment of local workers is partially stemming from higher participation rate and new plant openings. Overall, these county-level results are consistent with our earlier firm-level findings suggesting that as a result of economic shocks, economic activity seems to be reallocated from affected areas to unaffected ones through firms' establishment networks.

We also ask whether local heat shocks have a measurable impact on firm-level financials. For this analysis, we restrict our sample to public firms with available financial data. We do not find any measurable impact on firm profitability, return on assets, asset growth, or expected stock returns. This is perhaps unsurprising because, within the subset of public firms, any individual shock impacts a relatively small fraction of their total operations (an average shock affects around 2% of an average public firm's employment), and shocks have little correlation across geographical locations. This is in stark contrast to aggregating results to county-level, where shocks are by design highly correlated, and as such explains why we find aggregate results at county but not at firm-level. These results are presented in the online appendix (Figure A3 and Table A5). More details about this analysis is provided in Appendix B.A.

VI Additional results

Next, we examine frictions that might aid or inhibit firms' mitigation response. We also examine the nature of heat shocks in more detail to understand how firms may respond to the evolving nature of climate risks. Finally, we provide additional evidence of workforce reallocation across the extensive margin by documenting firm entry into new locations in response to heat shocks.

A Frictions affecting mitigation activity

A.1 Financial frictions and reallocation investment

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. Importantly, these results provide further evidence that demand shocks and cost shocks are not driving our results, as those would likely have a stronger impact on more constrained firms (Giroud and Mueller, 2019). We augment our baseline model by introducing an interaction between the peer shock variable and various firm characteristics.

We proceed in two steps. First, we study the role of firm size by dividing all the firms in our sample into two groups – large or small – depending on whether they employed more or less than the median number of employees (on average) throughout the sample period. Then we use size as a firm characteristic and estimate the following equation:

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

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 $\text{Shock}_{f,c,t}$ indicates the total heat shock at peer establishments' locations, as computed in Equation (2). Small $\text{Firm}_{f,t-1}$ for firm f in year $t-1$ is an indicator that equals one for small firms and zero for large firms. 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 A6 presents the results. We find that while both large and small firms increase employment growth in the peer county, the effect is smaller for small firms. At the same time, the increase in labor demand (proxied by job postings) is similar for both groups. These results suggest that resources available to large firms enable them to mitigate the impact of local heat shocks to a greater extent.

After looking at firm size, we study a subset of public firms for which we have detailed financials. For firm financials, we compute the leverage (book value of debt over assets), z-score (Altman, 1968), and gross profitability (gross profit over assets) for all firms in this sample. These firms are then categorized into two groups based on whether their financial characteristic lies above or below the median value in each year. Table 10 shows how financial health affects firms' mitigation behavior over a 3-year timeframe (i.e., coefficients for $k = 2$). Our findings reveal that firms with 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.[17]

A.2 Target county's economic conditions and labor market frictions

Next, we study the role of economic distress in firms' target locations. 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 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.[18] We then create a dummy variable called Low Bank Presence$_{c,t}$ which indicates that county c had below median level of credit availability in year t. We interact these two measures with the peer shock measure in our baseline specification and present the results in Figure A4 Panels (A) and (B). We find that employment growth is lower in peer counties suffering from economic distress and weaker credit availability.[19]

Finally, we study the role of labor market conditions. Peer counties with high employment concentration 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. Figure A4 Panel (C) shows that employment growth at peer counties is lower in counties having more concentrated labor markets. Overall, these results highlight the importance of regional economic and labor market conditions in determining firms' mitigation

[17]We also examine the role of spatial frictions by studying how peer shocks affect establishments at varying distance from the affected location. These results are discussed in Appendix B.B.

[18]Data on bank lending comes from Fed Board's CRA analytics program (https://www.federalreserve.gov/consumerscommunities/data$_t$$ables.htm$).

[19]An independent literature looks at the transmission of climate shocks through bank branch networks. See Cortés and Strahan (2017) and Kundu et al. (2021).

strategy and reveal indirectly that firms appear to be *optimizing* employee location across their establishments.

B Nature of heat shocks

Climate change is intensifying with heat waves becoming longer and more *acute* over time.[20] They are also increasingly *compounded* by other natural disasters like hurricanes and wildfires (Raymond et al., 2022). In this section, we explore if firm response varies depending on the nature of climate shock and whether firm mitigation is a potent adaptation strategy in the long run.

B.1 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 ($\text{Peer Shock (Acute)}_{f,c,t}$) by considering only hot days that led to non-zero property damage.[21] Next, we introduce a second measure ($\text{Peer Shock (Spells)}_{f,c,t}$) 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.[22] 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 11.

Panel (A) 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 (B), we show that the magnitude of response to heat

[20] See Environmental Protection Agency report dated July 2022 (https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves).

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

[22] See CBS news article dated August 1, 2023 (https://www.cbsnews.com/news/phoenix-heat-record-monthlong-string-days-110-degrees-or-above-over).

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 1982 (the start of the PRISM sample) to 2008 (the start of our D&B sample). Counties ranking in the top quintile (20%) of this distribution are classified as chronically heat stressed. Subsequently, we revise our peer shock measure to encompass hot days in counties with chronic stress and denote it as Peer Shock $(\text{Chronic})_{f,c,t}$. Table 11 Panel (C) illustrates that the response to such shocks is more pronounced than 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.2 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.[23] 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

[23] See The Washington Post report dated August 12, 2023 (https://www.washingtonpost.com/weather/2023/08/12/hawaii-fires-climate-change-maui).

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 hazards, the SHELDUS dataset covers four other types of hazards: droughts, wildfires, hurricanes and storms, and earthquakes. To explore the idea of compound shocks, we modify our measure of heat shocks to account for hot days that coincide with other disasters in the same year. For example, Peer Shock (Heat + Drought)$_{f,c,t}$ is calculated using hot days in county c which experienced a drought in year t. We then update our main model with these adjusted measures and present the findings in Figure 5. 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 highlight the increasing significance of spatial strategies to mitigate the effects of increasingly frequent combined climate shocks.

C Reallocation and firm entry in new locations

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

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

$$\text{Firm Shock}_{f,t} = \text{Log}(1 + \#\text{ Hot Days, Firm}_{f,t}) \tag{7}$$

where

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

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

Then, we estimate the following equations:

$$\text{Entry In New County}_{f,t} = \gamma \times \text{Firm Shock}_{f,t-1} + \alpha_f + \alpha_t + \varepsilon_{f,t} \tag{8}$$

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

Table 12 presents the results. The first column shows the entry of affected firms into 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 (0.52×0.177). 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 (0.41×0.177). 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 that firm reallocation is driven by heat shocks, we find that the entry response is 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.

VII Conclusion

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

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

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

Taken together, our results have implications on how we should expect firms to adjust their operations if heat waves intensify in the future as a consequence of climate change. Future work on this topic can explore to what extent the adaptation channel we document is a substitute or a complement to other channels documented by the literature, such as adjusting 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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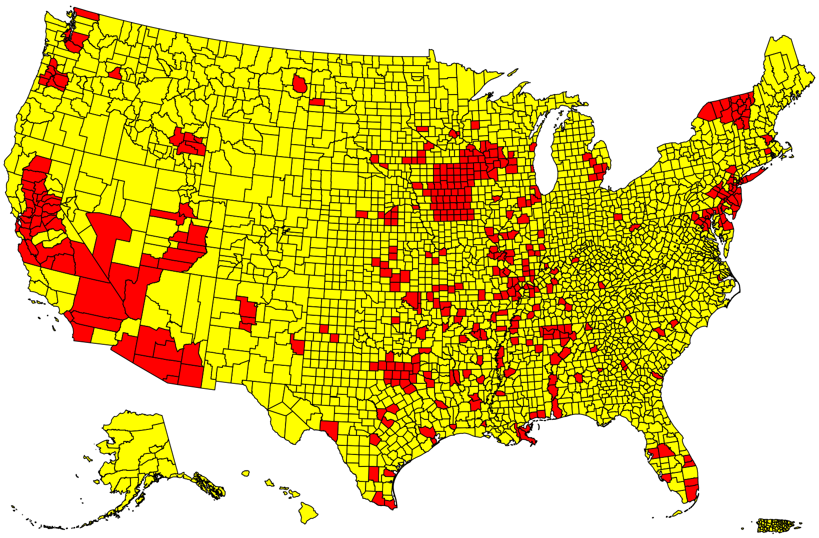
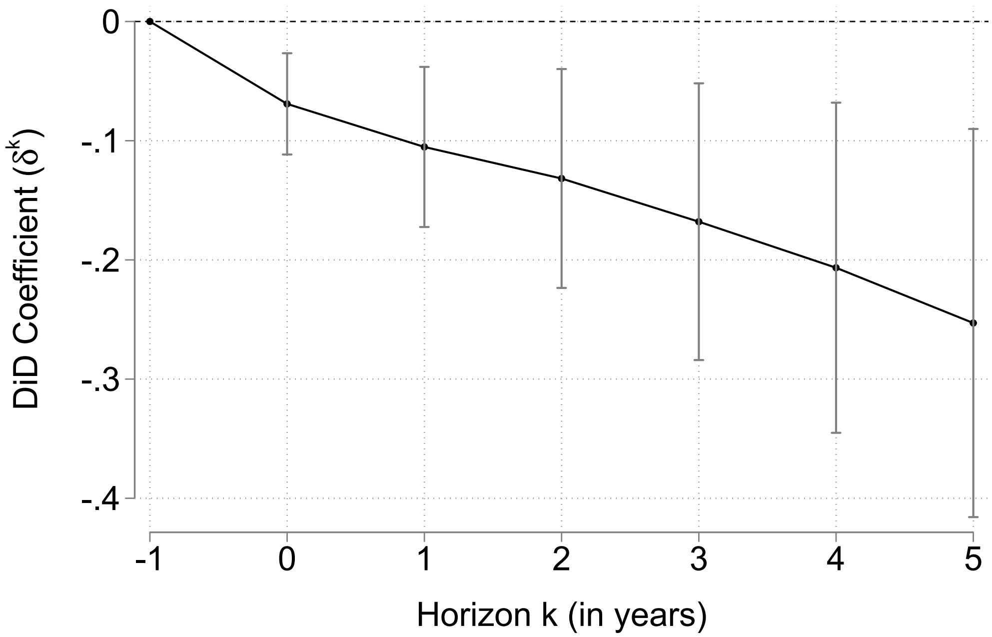
VIII Figures and tables

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: Role of heat-related damage

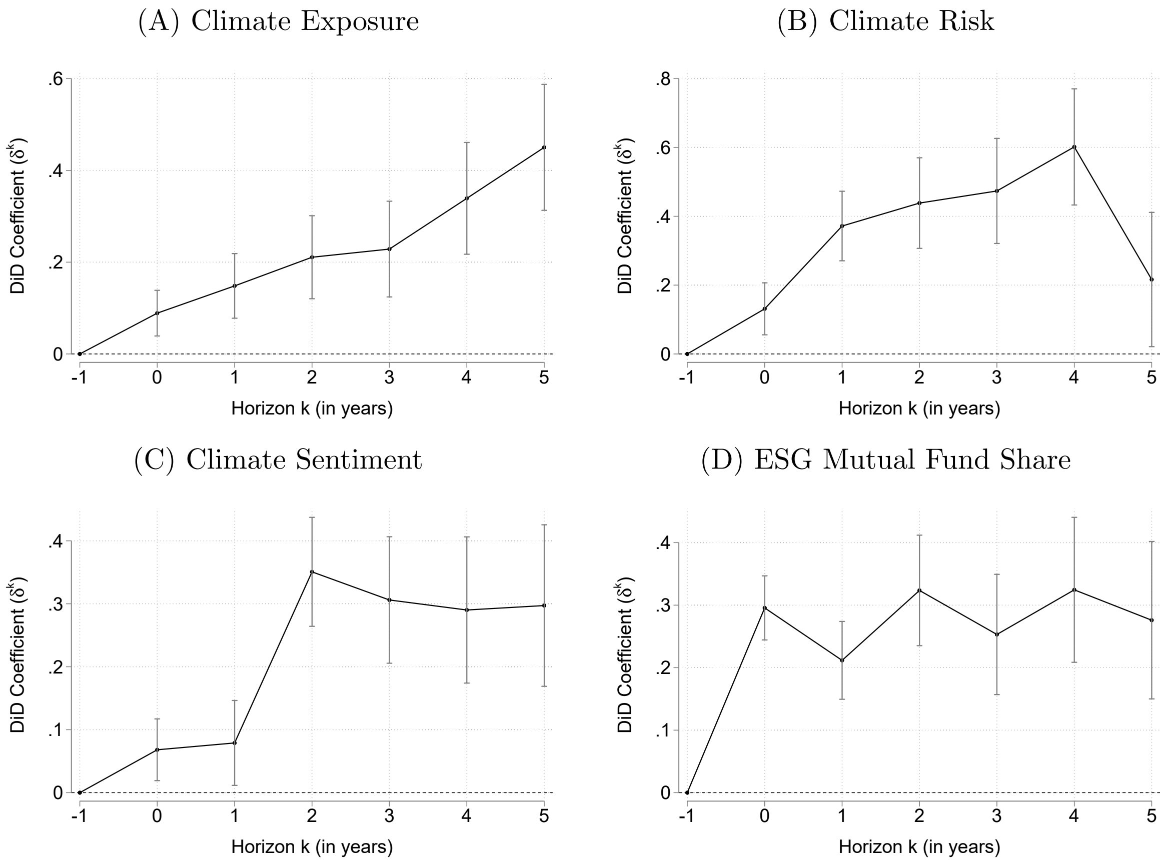


Notes: Figure 3 shows how projected heat-related damage influences firms' decision to reallocate into that county when its establishments elsewhere are impacted by heat shocks. We estimate

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

and plot the interaction coefficient (δ^k) with respect to projected heat damage/GDP following the SEAGLAS measure. α_f and $\alpha_{c,t}$ denote firm and county-year fixed effects and standard errors are clustered at the county level.

Figure 4: Heterogeneity across firms: Investor perception

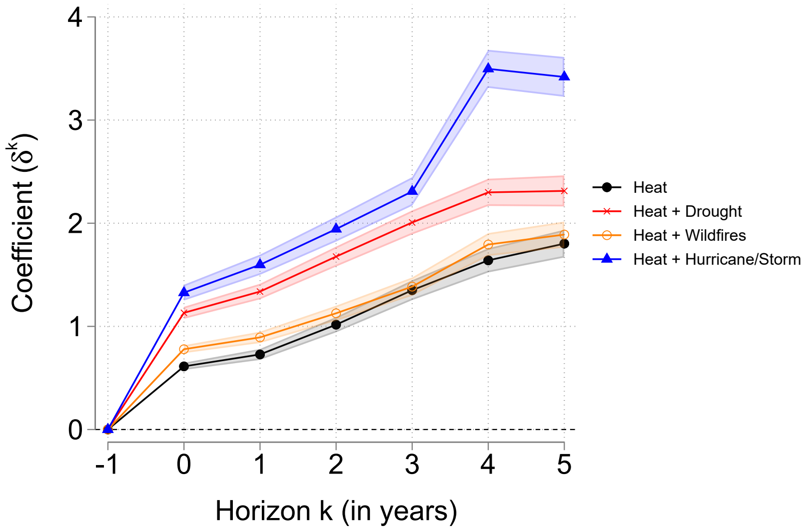


Notes: Figure 4 shows the relationship of investor beliefs and composition with labor reallocation in response to heat shocks (3-year horizon). The regression equation we estimate is:

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

$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ 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 (2). 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: Compound climate hazards



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

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

$\Delta\text{Log(Employment)}_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. We calculate peer shock using the hot days that coincided with another type of disaster in the same year. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed effects. Standard errors are clustered at the county level.

Table 1: Summary Statistics

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

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

Table 2: High temperatures and SHELDUS heat shocks

	# 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:

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

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

Table 3: Establishment response to own shock

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

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

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

Table 4: Establishment response to own shock: Breakdown by sectoral exposure

Panel (A): Employment growth

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.062	0.109	0.264**	0.369***	0.588***	0.570***
	(0.042)	(0.091)	(0.123)	(0.127)	(0.156)	(0.170)
Single Location × Own Shock	0.582**	0.014	-0.868*	-1.808***	-2.484***	-1.475***
	(0.234)	(0.325)	(0.464)	(0.609)	(0.534)	(0.502)
Exposed Industry × Own Shock	-0.102***	-0.272***	-0.366***	-0.408***	-0.457***	-0.358*
	(0.032)	(0.067)	(0.084)	(0.103)	(0.152)	(0.193)
Single Location × Exposed Industry × Own Shock	-0.832***	-0.790**	-0.967*	-1.381**	-1.356*	-1.448**
	(0.254)	(0.359)	(0.514)	(0.617)	(0.721)	(0.731)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	5,627,939	4,796,281	4,080,582	3,438,803	2,850,940	2,316,286
$\bar{y}$	0.666	1.839	2.623	3.511	4.254	5.159
Adj. R^2	0.019	0.040	0.058	0.078	0.101	0.127

Panel (B): Job postings

	Total Postings/L.Employment$_{t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	-0.025	0.131	0.183	0.050	-0.234*	-0.291**
	(0.094)	(0.125)	(0.112)	(0.108)	(0.132)	(0.117)
Single Location × Own Shock	0.345	0.577**	0.756***	0.739***	0.897***	0.453*
	(0.217)	(0.255)	(0.244)	(0.247)	(0.189)	(0.234)
Exposed Occupation × Own Shock	-0.255	-0.049	-0.584	-1.045	-1.275**	-2.233**
	(0.788)	(0.981)	(0.795)	(0.766)	(0.611)	(0.938)
Single Location × Exposed Occupation × Own Shock	0.255	1.315	0.859	0.734	1.819**	4.250***
	(1.810)	(1.802)	(1.409)	(1.154)	(0.855)	(1.539)
Firm FE × Exposed Occupation	✓	✓	✓	✓	✓	✓
County FE × Exposed Occupation	✓	✓	✓	✓	✓	✓
Year FE × Exposed Occupation	✓	✓	✓	✓	✓	✓
Observations	2,782,956	2,555,712	2,213,642	1,901,526	1,607,200	1,326,390
$\bar{y}$	9.209	9.775	10.242	10.861	11.259	11.591
Adj. R^2	0.167	0.171	0.186	0.192	0.199	0.241

Notes: Table 4 shows how establishments respond to heat shocks in their county. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panel (A) is $\Delta\text{Log(Employment)}_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is $\Delta\text{Total Postings/L.Employment}_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Own Shock$_{c,t}$ equals Log(1+# Hot Days) in county c in year t. We interact Own Shock with indicator variable for whether the establishment belongs to a single-location firm (Single Location). Additionally, in Panel (A), we interact Own Shock with indicator variable for whether the establishment belongs to an industry with high climate exposure (Exposed Industry). In Panel (B), we interact Own Shock with indicator variable for whether the job posting had high climate exposure (Exposed Occupation). We employ firm (α_f), county (α_c) and year (α_t) fixed effects. Standard errors are clustered at the county level.

Table 5: Establishment response to peer shock

Panel (A): Employment growth of average establishment

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

Panel (B): Job postings of average establishment

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

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

Table 6: Establishment response to peer shock: Breakdown by sectoral exposure

Panel (A): Employment growth

	ΔLog(Employment)$_{t-1,t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.607***	0.633***	0.901***	1.216***	1.458***	1.684***
	(0.019)	(0.030)	(0.041)	(0.052)	(0.063)	(0.068)
Exposed Industry × Peer Shock	0.004	0.146***	0.180***	0.208***	0.285***	0.170***
	(0.016)	(0.021)	(0.027)	(0.032)	(0.037)	(0.041)
Firm FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Observations	5,519,005	4,695,887	3,989,329	3,356,710	2,779,181	2,252,672
$\bar{y}$	0.779	1.800	2.445	3.242	3.934	4.793
Adj. R^2	0.012	0.027	0.042	0.057	0.075	0.093

Panel (B): Job postings

	Total Postings/L.Employment$_{t+k}$ × 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Peer Shock	0.841***	0.714***	0.643***	0.621***	0.516***	0.464***
	(0.036)	(0.032)	(0.034)	(0.032)	(0.033)	(0.030)
Exposed Occupation × Peer Shock	1.571***	1.446***	1.589***	1.291***	0.697***	0.428*
	(0.267)	(0.288)	(0.403)	(0.337)	(0.236)	(0.232)
Firm FE × Exposed Occupation	✓	✓	✓	✓	✓	✓
County × Year FE × Exposed Occupation	✓	✓	✓	✓	✓	✓
Observations	2,704,526	2,487,494	2,153,962	1,849,702	1,562,698	1,289,010
$\bar{y}$	9.301	9.853	10.331	10.992	11.429	11.771
Adj. R^2	0.140	0.146	0.158	0.171	0.190	0.231

Notes: Table 6 shows how establishments respond to heat shocks in their peer counties. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\to t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Peer Shock$_{f,c,t}$ equals Log(1+# Hot Days, Other) for firm f in county c in year t. # Hot Days, Other$_{f,c,t}$ is the employment-weighted number of hot days across all peer locations for firm f's establishment in county c in year t. In Panel (A), we interact Peer Shock with indicator variable for whether the establishment belongs to an industry with high climate exposure (Exposed Industry). In Panel (B), we interact Peer Shock with indicator variable for whether the job posting had high climate exposure (Exposed Occupation). We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed effects. Standard errors are clustered at the county level.

Table 7: Labor productivity channel and alternative mechanisms

	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): Energy Intensity						
Peer Shock	0.642***	0.719***	1.012***	1.353***	1.676***	1.803***
	(0.019)	(0.029)	(0.041)	(0.052)	(0.063)	(0.072)
High Energy Intensity × Peer Shock	-0.083***	0.031	0.015	-0.006	-0.096**	-0.017
	(0.016)	(0.023)	(0.029)	(0.032)	(0.039)	(0.040)
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
Panel (C): Local demand spillover						
Peer Shock	0.596***	0.723***	0.998***	1.322***	1.608***	1.756***
	(0.017)	(0.027)	(0.037)	(0.048)	(0.058)	(0.066)
Neighbor Own Shock	-2.349***	-2.948***	-3.277***	-5.040***	-2.103**	-2.622***
	(0.411)	(0.542)	(0.682)	(0.843)	(0.953)	(0.942)
Firm FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	5,556,114	4,726,996	4,015,593	3,378,829	2,797,476	2,267,414
$\bar{y}$	0.770	1.785	2.424	3.213	3.899	4.748
Adj. R^2	0.013	0.029	0.043	0.060	0.078	0.096

Notes: Table 7 tests the various mechanisms underlying our results. In Panels (A) and (B), we re-estimate our baseline specification after interacting the peer shock measure with indicators for high teleworking industry and high energy-intensity industry. In these tests, we employ firm ($\alpha_{f(i)}$) and county-year ($\alpha_{c,t}$) fixed effects. In Panel (C), we run a horse race between peer shock measure and a proxy for direct proximity to heat shocks (Neighbor Own Shock$_{c,t}$), which is equal to Log(1+#Hot Days, Neighbor$_{c,t}$), where #Hot Days, Neighbor$_{c,t}$ is the weighted-average number of hot days in all counties $c' \neq c$, with the weights being the inverse of the distance between c' and c. In this panel, we substitute county-year fixed effects with separate county (α_c) and year (α_t) fixed effects so that the coefficient of Neighbor Own Shock$_{c,t}$ can be estimated. Standard errors are clustered at the county level.

Table 8: County response to own and peer shock

Panel (A): Employment growth

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

Panel (B): Employment growth (Locals)

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

Panel (C): Employment growth (Migrants)

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

Notes: Table 8 shows outcomes in a county after heat shocks hit it and its peer counties. We aggregate data at the county-year level and estimate the following specification:

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

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

Table 9: Effect on wages, labor force participation rate, and establishment entry

Panel (A): Wage growth

	ΔLog(Wage)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	-0.400***	-0.473**	-0.589**	-0.617***	-0.624**	-0.514**
	(0.139)	(0.205)	(0.231)	(0.228)	(0.266)	(0.247)
Peer Shock	-0.020	0.504***	0.606**	1.016***	0.869**	0.348
	(0.104)	(0.170)	(0.251)	(0.261)	(0.339)	(0.292)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	27,441	24,682	21,907	19,103	16,325	13,496
$\bar{y}$	2.972	5.607	8.176	10.700	13.062	15.651

Panel (B): Change in labor force participation rate

	ΔLabor force participation rate$_{t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.007	-0.038	-0.087	-0.068	-0.003	-0.035
	(0.037)	(0.052)	(0.056)	(0.061)	(0.066)	(0.071)
Peer Shock	0.022	0.070	0.122*	0.197***	0.135*	0.140
	(0.028)	(0.053)	(0.066)	(0.074)	(0.082)	(0.102)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	27,505	25,033	22,203	19,416	16,622	13,834
$\bar{y}$	-0.127	-0.283	-0.427	-0.576	-0.739	-0.899

Panel (C): Net Establishment Entry Rate

	ΔNet Establishment Entry Rate$_{t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.159	0.206	0.020	-0.116	-0.038	0.011
	(0.104)	(0.136)	(0.134)	(0.205)	(0.098)	(0.068)
Peer Shock	0.241***	0.195*	0.359***	0.236**	0.173*	0.152
	(0.093)	(0.102)	(0.105)	(0.095)	(0.103)	(0.129)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,483	25,629	22,766	19,906	17,050	14,359
$\bar{y}$	0.095	0.187	0.201	0.242	0.230	0.188

Notes: Table 9 shows outcomes in a county after heat shocks hit it and its peer counties. We aggregate data at the county-year level and regress county-level outcomes against own shock and peer shock. The outcome variables are wage growth (Panel (A)), change in labor force participation rate (Panel (B)), and net establishment entry rate (Panel (C)) at the county level. We employ county and year fixed effects. We cluster standard errors at the county level.

Table 10: Heterogeneity across firms: Firm financials

	ΔLog(Employment)$_{t-1,t+k} \times 100$		
	k=+2	k=+2	k=+2
Peer Shock	2.018***	1.973***	2.004***
	(0.083)	(0.087)	(0.095)
Low Leverage	-0.275		
	(0.565)		
Low Leverage × Peer Shock	0.533***		
	(0.091)		
High Z-Score		0.526	
		(0.506)	
High Z-Score × Peer Shock		0.305***	
		(0.070)	
High Profitability			6.653***
			(0.563)
High Profitability × Peer Shock			0.176**
			(0.080)
Firm FE	✓	✓	✓
County × Year FE	✓	✓	✓
Sample	Compustat	Compustat	Compustat
Observations	463,068	463,068	463,068
$\bar{y}$	4.207	4.207	4.207
Adj. R^2	0.035	0.035	0.036

Notes: Table 10 shows the relationship between firm financials and labor reallocation in response to heat shocks. The regression equation we estimate is:

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

ΔLog(Employment)$_{f,c,t-1\to t+k}$ is the change in log employment of firm f in county c from year $t-1$ to $t+k$. We present results corresponding to a 3-year horizon (i.e., $k=2$). Peer Shock$_{f,c,t}$ denotes total heat shock at peer establishments' location as calculated in Equation (2). Firm Characteristic$_{f,t-1}$ denotes the financial characteristics (indicators for 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 11: Climate clusters in affected counties

	ΔLog(Employment)$_{t-1,t+k} \times 100$					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Panel (A): 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 (B): Heat spells						
Peer Shock (Spells)	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 (C): 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 11 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 (Damages)$_{f,c,t}$ (Panel (A)) 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 (B)) 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 (C)) 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 1982-2008 period. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed effects. Standard errors are clustered at the county level.

Table 12: 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 12 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 (7). α_f and α_t denote firm and year fixed effects respectively. Standard errors are clustered at the firm level.

Appendix A Salient examples of spatial reallocation

Small Companies (exactly two locations)

1. Heat wave in San Diego, CA 2016 (https://www.latimes.com/local/lanow/la-me-ln-heat-wave-20160618-snap-htmlstory.html): 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 (https://www.latimes.com/local/lanow/la-me-ln-heat-wave-20160618-snap-htmlstory.html): 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 (https://www.cbsnews.com/news/texas-record-high-temperatures-temps-near-120-degrees-in-southwest-today-2018-07-24): 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 (https://www.cnn.com/2016/07/20/us/weather-heat-wave-trnd/index.html): 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 (https://www.nbcnews.com/news/world/heat-wave-shifts-central-us-drought-hit-west-texas-crosshairs-flna732611): 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 (https://www.nytimes.com/2012/07/08/us/temperatures-soar-as-heat-wave-continues.html): Honeywell International Inc. (Manufacturing) reduced 104 workers in Jackson (FIPS 29095) and added 40 workers in Pinellas (FIPS code: 12103) county.

Appendix B Other results

A Aggregate 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 7. 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 A5. Perhaps unsurprisingly, we do not 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.[24]

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 A3. In total, we find little evidence that local heat shocks affect expected returns at firm-level.

[24] 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.

B Mitigation by varying distance from the shock

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

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

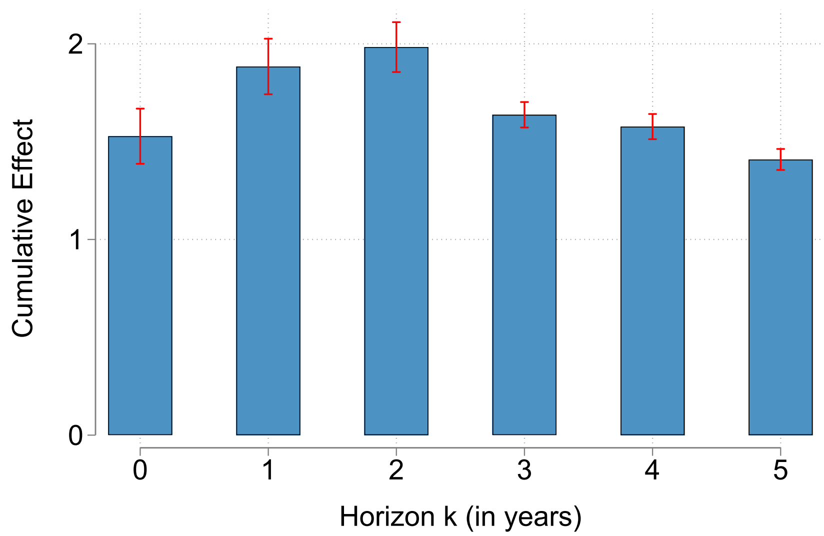
where

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

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 A7. The results highlight that employment growth is highest for the zero to 100 mile radius and then generally decays with distance (with the exception of the largest distance band of 500 to 750 mile radius). These results are consistent with idea that mitigation becomes more expensive with distance. It also suggests that local economic ties are important for firms. As a result, they avoid moving their activity too far away from their original place of business in response to heat shocks. On the flip side, these results also highlight the limitations associated with spatial mitigation approach in dealing with climate risk.

Appendix C Appendix figures and tables

Figure A1: Firm mitigation: Estimation using distributed lag model

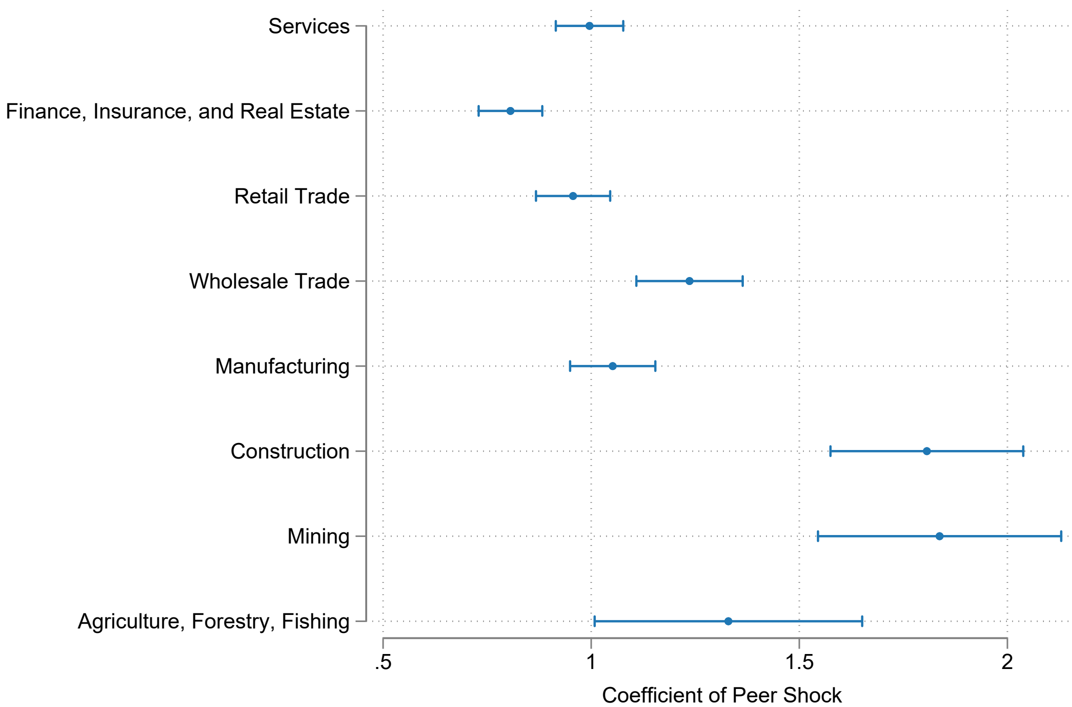


Notes: Figure A1 shows the impact of heat stress on the employment growth at peer locations. We estimate the following distributed lag specification:

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

$\Delta\text{Log(Employment)}_{f,c,t-1\to t}$ 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: Mitigation across industries - I

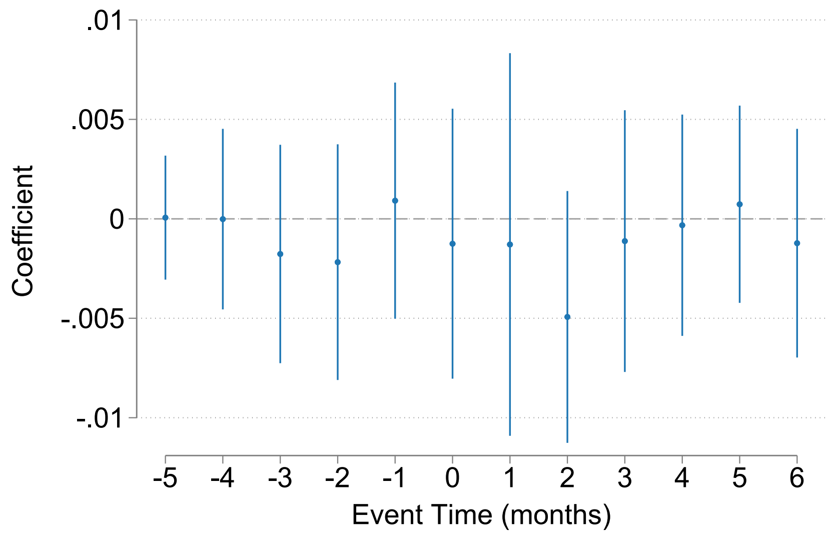


Notes: Figure A2 shows the extent of mitigation across broadly defined industries. The regression we estimate is:

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

$\Delta\text{Log(Employment)}_{f(i),c,t-1\to t+k}$ 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 (2). Industry_i indicates broadly defined industries categorized as 2-digit SIC codes. We employ firm ($\alpha_{f(i)}$) and county-year ($\alpha_{c,t}$) fixed effects. Standard errors are clustered at the county level. The figure plots the marginal effect of Peer $\text{Shock}_{f(i),c,t}$ on 3-year employment change (i.e., corresponding to $k = 2$) separately by industry.

Figure A3: Impact of heat shocks on stock market performance

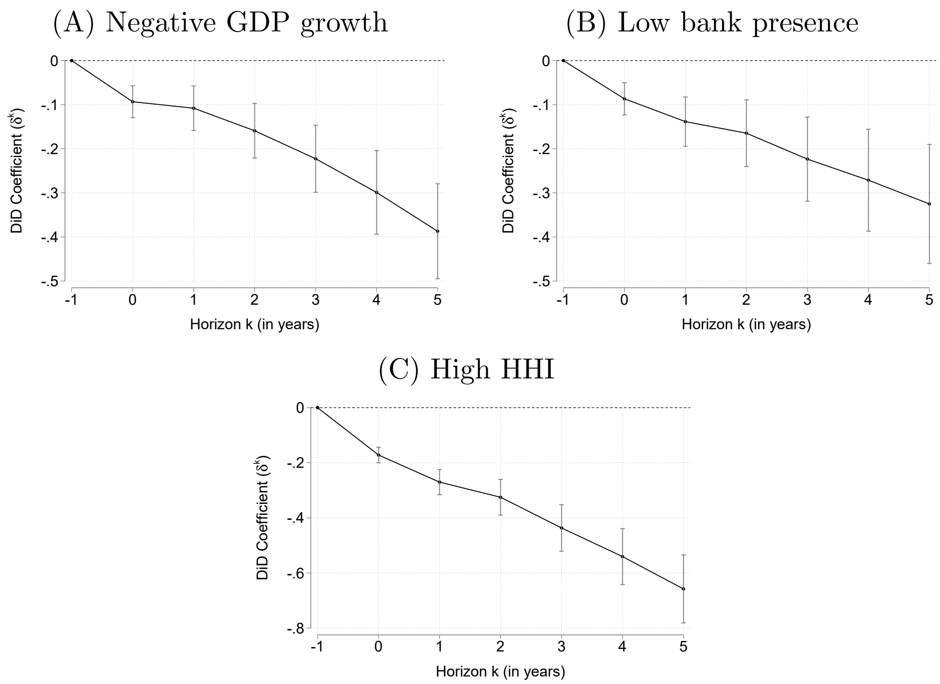


Notes: Figure A3 shows the impact of heat shocks on the stock market performance of public firms. We aggregate the data at the stack-firm-month level where each stack s correspond to a heat-related shock at the county level. We estimate the following stacked event-study regression:

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

$\text{SVIX}_{s,f,t}$ 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.

Figure A4: Role of other (non-heat-related) county characteristics



Notes: Figure A4 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

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

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.

Table A1: Establishment response to own shock: Role of firm size

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

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

Notes: Table A1 shows how establishments of respond to heat shocks in their county. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\to t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Own Shock$_{c,t}$ equals Log(1+# Hot Days) in county c in year t. We interact Own Shock with indicator variables for whether the establishment belongs to a single-location firm, and whether it belongs to a small firm. We employ firm (α_f), county (α_c) and year (α_t) fixed effects. Standard errors are clustered at the county level.

Table A2: 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)
Peer Shock (T$\geq$99Pctile)	0.452***	0.779***	1.115***	1.448***	1.825***	2.053***
	(0.014)	(0.022)	(0.031)	(0.042)	(0.051)	(0.057)
Panel (C): Robustness - Alternative fixed effects and clustering						
Firm$\times$Year and County$\times$Year FE						
Peer Shock	1.171***	2.093***	2.893***	3.598***	4.172***	4.785***
	(0.030)	(0.051)	(0.072)	(0.092)	(0.112)	(0.129)
Firm and County$\times$Industry$\times$Year FE						
Peer Shock	0.807***	1.069***	1.494***	1.995***	2.360***	2.640***
	(0.025)	(0.039)	(0.055)	(0.070)	(0.089)	(0.105)
County$\times$Year FE						
Peer Shock	0.277***	0.394***	0.486***	0.602***	0.741***	0.890***
	(0.010)	(0.016)	(0.021)	(0.027)	(0.033)	(0.040)
Double clustering at County and Firm level						
Peer Shock	0.612***	0.728***	1.017***	1.352***	1.640***	1.803***
	(0.038)	(0.049)	(0.066)	(0.083)	(0.098)	(0.104)
Panel (D): Robustness - Alternative outcome						
	ΔLog(Establishments)$_{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 A2 shows the results of our baseline specification (Panel (A)) given by Equation (3) along with several robustness tests (Panels (B), (C), and (D)). In Panel (B), we define our peer shock measure in alternative ways. In Panel (C), we use alternative set of fixed effects and clustering levels. In Panel (D), we use alternative set of outcome variables.

Table A3: Establishment response to peer shock: D&B-Lightcast matched sample

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

Notes: Table A3 shows how establishments respond to heat shocks in their peer counties. For this test, we restrict analysis to establishments present in our D&B-Lightcast matched sample (i.e., sample from which the job postings results are estimated). The outcome variable is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. Peer Shock$_{f,c,t}$ equals Log(1+# Hot Days, Other) for firm f in county c in year t. # Hot Days, Other$_{f,c,t}$ is the employment-weighted number of hot days across all peer locations for firm f's establishment in county c in year t. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed effects. Standard errors are clustered at the county level.

Table A4: Robustness: County-level results using QCEW data

	ΔLog(Employment)$_{t-1,t+k}$ $\times$ 100					
	k=+0	k=+1	k=+2	k=+3	k=+4	k=+5
Own Shock	0.089	0.141	0.166	0.159	0.390	0.495**
	(0.104)	(0.177)	(0.213)	(0.244)	(0.258)	(0.224)
Peer Shock	0.615***	0.982**	1.541**	1.855**	1.787*	1.161*
	(0.201)	(0.471)	(0.714)	(0.936)	(0.918)	(0.630)
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	28,732	25,846	22,970	20,093	17,221	14,343
$\bar{y}$	0.391	1.288	2.117	2.855	3.503	4.209
Adj. R^2	0.146	0.202	0.308	0.446	0.607	0.728

Notes: Table A4 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:

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

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

Table A5: 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 A5 shows the effect of heat shocks on financials of public firms. The regression equation we estimate is:

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

$\Delta\text{Outcome}_{f,t-1\rightarrow t+k}$ 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 $\text{Shock}_{f,t}$ is the exposure of firm f to heat shocks in year t as defined in equation 7. α_f and α_t denote firm and year fixed effects respectively . Standard errors are clustered at the firm level.

Table A6: Establishment response to peer shock: Role of firm size

Panel (A): Employment growth of average establishment

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

Panel (B): Job postings of average establishment

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

Notes: Table A6 shows how establishments of large and small firms respond to heat shocks in their peer counties. Panel (A) shows the effect on employment growth and Panel (B) shows the effect on job postings. The outcome variable in Panels (A) is ΔLog(Employment)$_{f,c,t-1\rightarrow t+k}$, which is the change in log employment of firm f in county c from year $t-1$ to $t+k$. The outcome variable in Panel (B) is ΔTotal Postings/L.Employment$_{f,c,t+k}$, which is the total job-postings scaled by previous year's employment in year $t+k$. Peer Shock$_{f,c,t}$ equals Log(1+# Hot Days, Other) for firm f in county c in year t. # Hot Days, Other$_{f,c,t}$ is the employment-weighted number of hot days across all peer locations for firm f's establishment in county c in year t. We interact Peer Shock with indicator variables for whether the establishment belongs to a small firm, defined as firm with below-median level of average employment during our sample period. We employ firm (α_f) and county-year ($\alpha_{c,t}$) fixed effects. Standard errors are clustered at the county level.

Table A7: 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 A7 shows employment mitigation by firms at varying distances from the shock. We estimate the following regression equation:

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

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