How Does Climate Change Reshape U.S. Entrepreneurship? A Labor Channel*

Zhanbing Xiao

Sep 2024

Abstract

This paper documents a labor channel through which climate change impacts U.S. entrepreneurship. It reveals that unexpected extreme heat discourages the creation of new firms and jobs, particularly in highly exposed industries. The findings result from significant heat risks to the health and productivity of exposed workers, leading to increased labor-related production and financing costs for business operations. Nevertheless, entrepreneurs who continue to start businesses in heat-exposed industries are typically of higher quality, and their firms are more likely to survive and grow faster over time. Meanwhile, existing firms seize market opportunities and expand their networks, yet this expansion fails to offset the market-wide decline in new business formation. This business decline further contributes to a contraction in aggregate economic activity. Overall, this research underscores the profound impact of climate change on U.S. entrepreneurial activities across counties and industries.

Keywords: Climate Change; Extreme Heat; Climate Adaptation; Entrepreneurship; Job Creation; Labor Costs; Small Business Loans.

JEL Codes: G30, L26, J20, Q54.

*Zhanbing Xiao: The Salata Institute for Climate and Sustainability, Harvard University Email: zhanbingxiao@fas.harvard.edu. For helpful comments and discussions, I thank Jitendra Aswani, Yongqiang Chu, Will Gornall, Gaurav Kankanhalli, Ellen Xiyue Li, Hernan Ortiz-Molina, David Ng, Elena S. Pikulina, Ali Sanati, Lee Seltzer, Matthew Serfling, Peter Tufano, Iris Wang, and Xin Zheng. All errors are my own. Data Axle is the provider of the Licensed Database used to create the YE Time Series. This work/research was authorized to use YE Time Series through the Business Dynamics Research Consortium (BDRC) by the University of Wisconsin's Institute for Business and Entrepreneurship. The contents of this publication are solely the responsibility of the authors. I acknowledge financial support from the Salata Institute for Climate and Sustainability at Harvard University.

1 Introduction

The unprecedented escalation of climate change, particularly extreme heat, has triggered a health crisis and profoundly restructured the U.S. labor market (e.g., Graff Zivin and Neidell, 2014; Park et al., 2021; Lai et al., 2023). Crucially, this health crisis reduces the supply and productivity of affected human capital, leading to lower economic output and worse corporate performance, thereby highlighting a labor channel through which climate change impacts U.S firms (Somanathan et al., 2021; Xiao, 2021; Addoum et al., 2023; Pankratz and Schiller, 2024).[1] A critical yet understudied question is how U.S. businesses adapt to these climate-induced structural changes in the labor market, a concern particularly pivotal for new firms that are inherently vulnerable and heavily reliant on human capital to succeed. This paper aims to shed light on this issue by exploring how climate change impacts the dynamics and vibrancy of U.S. entrepreneurship.

Specifically, this research investigates the impact of extreme heat on U.S. entrepreneurship through a labor channel, emphasizing that climate-driven increases in labor-related production and financing costs discourage business creation. Hypothetically, at least four economic factors contribute to the increased costs of business operations that rely on heat-exposed human capital. First, reduced labor supply and productivity from heat-exposed workers increase labor costs per unit of output and, consequently, decrease operating revenues, leading to lower efficiency of human capital as a production input. Second, employers may need to invest in preventive measures such as cooling facilities to mitigate heat risks, as well as offer enhanced compensation packages and medical care to attract and retain workers. Third, employers face significant reputational damage and litigation risks if workers suffer heat-related injuries or fatalities. Fourth, employers may incur higher financing costs if creditors factor heat risks into small business loan origina-

[1] In Internet Appendix A, I present anecdotal evidence from various sources that highlights the significant heat-related risks faced by small businesses due to climate change. See also Internet Appendix A in Xiao (2021) for general anecdotal evidence on heat risks to workers and related workplace safety issues.

tions. Collectively, these labor-related production and financing costs impose additional financial burdens on entrepreneurs starting and growing small businesses, with further increases anticipated as climate change worsens. Consequently, extreme heat may discourage individuals from starting businesses that rely on heat-exposed human capital.

Supporting this conjecture, my analysis indicates that unexpected extreme heat reduces entrepreneurial activities, particularly in heat-vulnerable industries. The effects are more pronounced in industries where human capital is critical for business growth and in counties where long-run heat risks are greater. Additionally, consistent with the financing channel, small business loans to heat-exposed firms are smaller and carry higher interest rates. However, entrepreneurs who still start businesses in heat-exposed industries tend to be of higher quality, with their businesses more likely to survive and grow. Furthermore, existing firms fill market gaps left by reduced entrants and expand their networks, but this doesn't offset the overall decline in business formation.

Empirically, I measure entrepreneurship by the birth of new firms at the county by four-digit NAICS (NAICS4) industry level, using establishment-level data from the Your Economy Time Series (YTS). YTS tracks the dynamics of U.S. business establishments and provides comprehensive details, including location, industry classification, founding year, closure year, place type (e.g., headquarters, subsidiary, branch, or independent), employment, and parent company. I identify an establishment as a newly created firm if it is standalone, newly founded, and its name and address have not previously appeared, nor has it relocated or changed its name.

To quantify temperature fluctuations across locations and time, I obtain daily grid-level (4×4 km) temperature data for the U.S. from the PRISM Climate Group, covering 1981 to 2022. I then construct a location- and time-specific measure of *heat shocks* for each county and year building on prior works (Perkins and Alexander, 2013; Addoum et al., 2020; Xiao, 2021; Pankratz and Schiller, 2024). Specifically, I define heat shocks as instances when a county experiences abnormally high temperatures over the past three

years, identified by deviations from historical temperature distributions and by absolute temperature levels. The distribution-based requirement captures the abnormal component of temperature fluctuations relative to the historical averages specific to each county and month. The absolute temperature requirement limits the focus to shocks that are extremely hot in an absolute sense. By construction, these heat shocks can be considered random draws from the distribution of temperatures within and across counties, making them plausibly exogenous for any prospective entrepreneur (Auffhammer et al., 2013; Dell et al., 2014).

Each NAICS4 industry's exposure to heat risks through the labor channel is measured by the extent to which its workforce is exposed to high temperatures during production and operational processes, following Xiao (2021). This exposure is quantified using industry- and occupational-level data from the Occupational Employment and Wage Statistics (OEWS) and the Occupational Information Network (O*NET). In particular, OEWS provides information on the occupations required within each NAICS4 industry and the number of employees in each occupation. The O*NET program assigns each occupation a score ranging from 1 to 5, reflecting the intensity of outdoor activities required to fulfill job duties in all weather conditions, including extreme heat. The labor exposure measure is then calculated as the weighted average of the outdoor intensity scores across all occupations within a NAICS4 industry, using the percentage of employees in each occupation as weights.

With the data and measures, I first investigate the causal impact of heat shocks on entrepreneurship across counties and NAICS4 industries from 1999 to 2019. The analysis shows a negative and statistically significant impact of heat shocks on entrepreneurial activity. On average, one past heat shock leads to a 0.8% decline in new firm creation. Importantly, the effects are primarily observed in industries with substantial heat exposure through the labor channel. For instance, industries at the 75^{th} percentile of heat exposure experience a 1.6% decrease in entrepreneurship following heat shocks, while those

with the highest exposure see a 2.4% drop. The findings remain robust after controlling for heterogeneities across counties, industries, and county-by-industry pairs through an extensive set of fixed effects, including county-by-year, county-by-NAICS4 industry, and NAICS4 industry-by-year fixed effects.

The decline in new firm entry in heat-exposed industries also leads to lower job creation. The analysis shows that the number of jobs created by new firms drops by 1.9% in industries with labor exposure at the 75^{th} percentile and by 2.9% in industries with the highest exposure. Together, these findings on firm and job creation support my conjecture that heat risks reduce individuals' incentives to start new businesses in highly exposed industries.

By design, the measure of heat shocks reflects abnormally high temperatures that are beyond expectation and, therefore, are exogenous to individual entrepreneurial decisions. To better understand the timing of heat shocks and alleviate endogeneity concerns, I examine the effects of past, present, and future annual heat shocks on present entrepreneurship. The analysis shows that only past heat shocks negatively affect present entrepreneurship, while future ones do not, indicating that the findings on firm creation are unlikely to be driven by omitted variable bias or reverse causality.

One critical force contributing to the decline in entrepreneurship is that heat risks increase labor costs per unit of output, thereby reducing operating revenues. This stems from lower labor supply and productivity under extreme heat, greater investment in preventive measures to mitigate heat risks, additional compensation and medical care to attract workers, and reputational and litigation risks from heat-related worker injuries. In theory, firms could reduce wages for inefficient workers or replace them with more productive ones or physical assets. However, market frictions often prevent these adjustments, meaning extreme heat lowers output by reducing labor performance, while firms' ability to cut labor costs is limited, leading to higher labor costs per unit of output. Recent work by Xiao (2021) shows that firms exposed to heat through the labor channel

adapt by shifting toward more capital-intensive production functions, effectively mitigating productivity losses. Building on this evidence, I conjecture that the labor channel for reduced entrepreneurship should be more pronounced in industries that requires significant human capital relative to physical assets as a production input. Conversely, in industries where human capital is less critical for business operations, heat risks are less of a concern for entrepreneurial decisions. Supporting this prediction, the analysis shows that the heat-induced decline in entrepreneurship is much weaker in industries with more capital-intensive production functions.

Another economic force contributing to the decline in entrepreneurship could be that creditors charge heat-exposed borrowers for liquidity provisions. Consequently, prospective entrepreneurs in heat-exposed industries face higher financing costs, reducing their incentives and abilities to start new businesses. Using small business loan data from the SBA 7(a) loan program, I find that heat shocks reduce loan amounts and increase interest rates for small businesses exposed to heat through the labor channel. The economic magnitude is significant: loans to small businesses with the highest heat exposure are 1.2% smaller, and interest rates are 1.1% higher. This evidence implies that increased financing costs, driven by heat-induced labor risks, partially contribute to the reduced entrepreneurship in heat-exposed industries.

Furthermore, if the decline in entrepreneurship is indeed driven by concerns over heat risks and associated labor-related costs, the effects should be more pronounced in areas expecting significant temperature increases in the near future. Conversely, if a past heat shock is an isolated event unlikely to recur, increased labor-related business costs would not be expected. Consistent with this conjecture, I find that the decline in entrepreneurship following heat shocks is concentrated in counties with greater expected heat risks in the long run. This evidence further supports the hypothesis that heat risks embedded in the labor channel deter potential entrepreneurs from entering the market.

Additionally, I conduct further analyses to explore the implications of climate change

for U.S. entrepreneurship and employment. I first investigate the long-run performance of new firms established in heat-exposed industries. The analysis reveals that, conditional on entry, these firms tend to survive longer and have larger workforce in the long run. For example, firms in industries at the 75^{th} percentile of heat exposure employ 2% more workers six years after founding. This finding implies that entrepreneurs who continue to start new businesses in heat-exposed industries to be of higher quality, and their businesses are more likely to survive and grow faster over time.

I also investigate how existing firms respond to extreme heat, as reduced firm entry may leave certain consumption demands unmet at affordable prices, creating potential market opportunities for growth. Moreover, existing firms may have greater financial resources and more experience in managing heat-related challenges. My analysis shows that existing firms create more establishments in exposed industries following heat shocks. However, this expansion does not fully offset the county-wide decline in new business formation. This overall business decline, in turn, contributes to a macro-level contraction in aggregate economic activity.

This paper contributes to several strands of literature. First, it adds to the growing literature on the implications of climate change for the financial market and business operations (e.g., Bernstein et al., 2019; Choi et al., 2020; Hong et al., 2020; Ilhan et al., 2021; Bolton and Kacperczyk, 2021; Giglio et al., 2021). More specifically, this paper joins the discussion on the impact of extreme heat on the performance and adaptation strategies of U.S. businesses (e.g., Addoum et al., 2020; Xiao, 2021; Addoum et al., 2023; Acharya et al., 2023; Pankratz et al., 2023; Ponticelli et al., 2023; Xiao, 2023; Ortiz-Molina et al., 2023; Pankratz and Schiller, 2024). My research differs by examining individuals' entrepreneurial decisions in response to heat risks, thereby extending the discussion to the private sector and small businesses. On this, I find that extreme heat discourages new firm and job creation, especially in industries employing large shares of heat-exposed workers. To the best of my knowledge, this paper is the first to study how climate change reshapes

U.S. entrepreneurship across counties and industries via the labor channel. Meanwhile, the findings on entry avoidance echo the call for more research on adaptation to climate change (Fankhauser, 2017).

This paper also broadens our understanding of the determinants of and barriers to entrepreneurship. Existing studies have explored entrepreneurial decisions linked to founder characteristics (e.g., Gompers et al., 2010; Ewens and Townsend, 2020; Engelberg et al., 2022), credit constraints (e.g., Black and Strahan, 2002; Schmalz et al., 2017), financial and labor market dynamics (e.g., Babina, 2020; Hacamo and Kleiner, 2022; Jeffers, 2024), among other factors. More relatedly, a few recent studies explore the impact of climate events on firm and job creation, including Cen (2021) and Jia et al. (2022). In contrast to these works, my paper identifies a labor channel of climate exposure and documents that heat risks in the channel discourage entrepreneurship. The findings highlight that expected labor-related business costs can deter entrepreneurial activities, revealing an important yet understudied labor mechanism in the entrepreneurship literature.

Last, this paper contributes to the literature that investigates frictions in labor markets and their influence on corporate and individual decision-making (e.g., Chen et al., 2011; Matsa, 2018; Kim, 2020; Nishesh et al., 2024). It extends the analysis to a climate context, focusing on heat-induced workplace safety issues and related production and financing costs. My findings support the literature and further demonstrate that labor costs are critical for business operations, particularly for small businesses.

The remainder of this paper proceeds as follows. Section 2 outlines the conceptual framework and economic mechanisms through which extreme heat may discourage entrepreneurship. Section 3 describes the data, measures, and sample for empirical analysis. Section 4 presents the treatment effects of heat shocks on entrepreneurship, dynamic tests, and robustness checks. Section 5 investigates the economic mechanisms and Section 6 provides further analyses and discussions. Section 7 concludes.

2 Conceptual Framework

In this section, I discuss the conceptual framework and economic mechanisms through which extreme heat may deter entrepreneurial activities, focusing on: (1) increased labor costs for business operations; (2) constrained credit access.

2.1 Increased Labor Costs

Heat exposure can cause various heat-related illnesses that endanger workers' health and lives (e.g., Luber and McGeehin, 2008; Mora et al., 2017; Park et al., 2021). For instance, a report by the Atlantic Council estimates that extreme heat is responsible for about 120,000 occupational injuries in the U.S. each year, a figure that could rise to nearly 450,000 without adaptation measures taken.[2] These health issues can impair workers' physical and cognitive abilities, leading to reduced productivity (e.g., Chen and Yang, 2019; Heyes and Saberian, 2019; Somanathan et al., 2021; Xiao, 2021; Lai et al., 2023; LoPalo, 2023). For instance, Somanathan et al. (2021) estimate that annual output in India falls by 2.1% if every day warms by 1°C. Xiao (2021) investigate the same labor channel of climate exposure and document that labor productivity of high-exposure firms drops by about 2% following heat shocks.[3] Collectively, these findings suggest that extreme heat can decrease production outputs and, consequently, operating profits.

Moreover, heat risks may deter exposed individuals from participating in the labor market and supplying their labor (Graff Zivin and Neidell, 2014; Dillender, 2021). For instance, Graff Zivin and Neidell (2014) show that workers in heat-exposure industries work one hour less when the daily maximum temperature exceeds 85°F (29.4°C), and Somanathan et al. (2021) document increased absenteeism associated with both contem-

[2] See "*Extreme Heat: The Economic and Social Consequences for the United States*." Additionally, the report estimates over 8,500 deaths annually associated with high temperatures, a number projected to increase nearly sevenfold to 59,000 by 2050. Furthermore, Park et al. (2021) estimate that high temperatures caused approximately 360,000 worker injuries in California from 2001 to 2018.

[3] I include Figure C.1 from Xiao (2021) in Internet Appendix Section C, which illustrates the treatment effects of heat shocks on firm-level labor productivity losses.

poraneous and past high temperatures. To attract and retain workers, employers may need to invest in preventive measures such as cooling facilities (where feasible) to mitigate heat risks, as well as offer enhanced compensation packages and medical care, which further increase labor costs.[4] Additionally, employers could face significant reputational damage and litigation risks if workers suffer heat-related injuries or fatalities.

In a frictionless market, firms could reduce wages for inefficient workers during hot temperatures or replace them with more productive employees or automated physical assets. However, in reality, firms face numerous frictions that impede their labor adjustments (Taylor, 1999). For instance, labor protection regulations increase workers' bargaining power and limit firms' discretion in wage and firing decisions. Social pressures from local communities and customers compel firms to create a safe and supportive working environment and improve employee welfare (e.g., Edmans, 2011; Xiao et al., 2023). Also, hiring and training new talent, or investing in new production equipment and methods, takes time and requires substantial financial resources. Together, these labor market frictions raise firms' operating leverage and decrease their values (Chen et al., 2011).

Overall, the above discussions indicate that, although extreme heat reduces total output due to lower labor productivity and labor supply, firms' ability to maintain production efficiency by reducing labor-related production costs is limited, thereby leading to *higher labor costs per unit of output*. These labor costs impose substantial financial burdens on firms in heat-exposed industries and reduce their profits, consequently discouraging prospective entrepreneurs from starting new businesses.

2.2 Constrained Credit Access

A critical barrier to new business creation and growth is credit access (e.g., Black and Strahan, 2002; Schmalz et al., 2017; Herkenhoff et al., 2021). For example, Schmalz et al.

[4] A recent study by the Center for American Progress estimates that extreme heat costs U.S. about $1 billion in additional health care expenses each summer from 2016 to 2020. See *"The Health Care Costs of Extreme Heat."*

(2017) show that increases in housing collateral value enable individuals to take on more debt and start new businesses. Meanwhile, another strand of literature documents that natural disasters generate cash flow shocks to business operations and banks incorporate such risks into loan originations and limit credit access for high-risk borrowers. For example, Bergman et al. (2020) show that abnormally high temperatures in the 1980s reduce crop yields in the U.S. farming industry, leading to reduced land prices, higher loan delinquencies, and more bank failures. Brown et al. (2021) find that unexpectedly severe winter weather negatively affects operating cash flows and firms respond by drawing on and increasing the size of their credit lines. Banks charge this liquidity demand via increased interest rates and less borrower-friendly loan provisions. Furthermore, Collier et al. (2024) find that small and independent businesses have more delinquent loans after Hurricane Harvey, while subsidiaries of larger firms do not. In the aftermath, many affected firms apply for new credit, but more than half are denied. Correa et al. (2020) document that banks charge higher spreads on loans to borrowers at risk of physical climate disasters, even if they are not directly affected by the disasters.

To sum up, the evidence indicates that small businesses in heat-sensitive industries are likely to face restricted credit access and increased financing costs if creditors consider heat risks in lending decisions. If this holds true, fewer businesses may be created in heat-exposed industries due to liquidity constraints.

Hypothesis: Heat-induced increases in labor-related production and financing costs discourage the creation of new firms, particularly in highly exposed industries.

3 Data, Measures, and Summary Statistics

3.1 Establishments and Entrepreneurship

I obtain data that tracks dynamics of U.S. business establishments from the Your Economy Time Series (YTS), assembled by the Business Dynamics Research Consortium (BDRC).

BDRC compiles the YTS data based on verified individual establishments collected by Data Axle (formerly Infogroup), using their unique American Business Identifiers (ABIs). YTS focuses on establishments that are actively conducting commercial activities, excluding businesses created solely for housing financial, real estate, or tax reporting purposes, as well as those suspected of never conducting actual commercial operations. The data is available annually from 1997 to 2023 and has been widely used by academic researchers, policymakers, economic development analysts, and for-profit businesses to evaluate business dynamics across the U.S., including Ghent (2021), Campello et al. (2022), Flynn and Ghent (2022), Coyne and Johnson (2023), and Houde et al. (2023).[5]

YTS provides detailed information on each establishment, including its location (e.g., CBSA, city, county, ZIP code, and latitude and longitude), industry classification (e.g., NAICS and SIC codes), founding year, closure year, place type (e.g., headquarters, subsidiary, branch, or independent), employment, parent company, and more. I measure entrepreneurship by the birth of new firms - establishments that are newly created and standalone. A newly created establishment is identified based on its founding year and verification that its name and address did not previously exist, nor has it relocated or changed its name. A standalone establishment is identified by its place type and the ownership structure of the parent company. I aggregate the data at the county-by-NAICS4 industry level and calculate the total number of new firms created, which serves as the primary measure of entrepreneurship in this study.

In sample construction, I exclude establishments and firms in the following industries: utilities (NAICS2 22), finance and insurance (NAICS2 52), religious, civic and social organizations (NAICS3 813), public administration (NAICS2 92), and unclassified (NAICS2 99). Furthermore, for each county, I keep only the top 20 NAICS4 industries based on total employment, as industries outside the top 20 contribute, on average, only 0.3% to

[5]See Kunkle (2018) for a comparison of the YTS data with the BLS's Current Employment Statistics (CES) and Current Population Survey (CPS).

the county's employment.[6] Additionally, I exclude counties in Alaska, Hawaii, and other areas outside the continental U.S.

Figure 1 presents the average annual number of newly established firms for each county in the continental U.S. during the period 1999–2019. As can be seen, entrepreneurial activities are primarily concentrated in the east and west coastal areas, with some presence in the central region.

3.2 Temperatures and Heat Shocks

I obtain data on U.S. daily temperatures and precipitation for the 1981 - 2022 period from the PRISM Climate Group maintained by Oregon State University. PRISM compiles climate observations from diverse monitoring networks and applies rigorous quality controls to develop spatial climate datasets that reveal short- and long-term climate patterns. The data covers 481,631 16-square-kilometer (4×4 km) grids across the U.S. and includes daily mean, minimum, and maximum temperatures, as well as daily precipitation levels. I aggregate the grid-level information to the county level.

The primary goal of this paper is to investigate how *unexpected high temperatures* in the past affect present entrepreneurship. To achieve this, I construct a measure of time- and location-specific heat shocks for each county and year, based on historical temperature distributions. Specifically, I define heat shocks as instances in which a county experiences both relative and absolute heat shocks over the past three years. Relative heat shocks are identified when a county experiences at least 45 days in summer with temperatures exceeding the rolling 90^{th} percentile. Absolute heat shocks are identified when a county experiences at least 240 days in summer with temperatures above 30°C. This definition captures heat shocks in both the relative and absolute sense, i.e., abnormally hot temperatures in hot regions.

[6] In Internet Appendix Section B.2, I apply alternative sample selection thresholds and methods to demonstrate the robustness of the results.

$$
\begin{aligned}
&\textit{Heat Shocks}_{c,t} = \begin{cases} 1 & \textit{Relative Heat Shocks}_{c,t} \quad \& \quad \textit{Absolute Heat Shocks}_{c,t} \\ 0 & \textit{otherwise} \end{cases} \\
&\textit{Relative Heat Shocks}_{c,t} = \textit{No. Hot Days}[\textit{Rolling } 90^{th} \textit{ Percentile}]_{c,t} \geq N_1 = 45 \\
&\textit{Absolute Heat Shocks}_{c,t} = \textit{No. Hot Days}[30^{\circ}\text{C}]_{c,t} \geq N_2 = 240
\end{aligned}
\tag{1}
$$

where c denotes county and t denotes year. *Rolling* 90^{th} *Percentile* refers to the 90^{th} percentile of past temperature distributions, estimated for each county and month using temperature data from 1981 up to the previous year (*1981 to t-1*), with a maximum of 30 years. The term *No. Hot Days*$[$*Rolling* 90^{th} *Percentile*$]_{c,t}$ reflects the total number of summer days with temperatures exceeding the rolling 90^{th} percentile from $t-3$ to t. The choice of N_1=*45* represents an average upward deviation of 12.5% from the historical temperature distribution, relative to the expected 40 days.[7] The term *No. Hot Days*$[30^{\circ}C]_{c,t}$ reflects the total number of summer days with maximum temperatures exceeding $30^{\circ}C$ from $t-3$ to t. The choice of N_2=*240* corresponds to an average of 60 summer days per year with maximum temperatures exceeding $30^{\circ}C$.[8]

This measure of heat shocks is conceptually similar to those used in previous studies to quantify abnormally high temperatures (e.g., Perkins and Alexander, 2013; Addoum et al., 2020; Xiao, 2021; Pankratz and Schiller, 2024). In particular, the requirement for relative shocks captures the abnormal component of temperature fluctuations relative to the county- and time-specific historical averages. The requirement for absolute shocks ensures the focus is on heat shocks that are extreme in absolute terms.

[7] Summer months include June, July, and August, following the definition of meteorological seasons. The meteorological summer season comprises a total of 92 days — 30 days in June, 31 days in July, and 31 days in August. Consequently, assuming no changes in temperature distributions, a typical summer would yield around 10 hot days, i.e., 92/10=9.2 (rounded up to 10). It's worth emphasizing further that N_1=*45* does not simply mean 5 additional hot days in summer relative to the benchmark of 40. Instead, it implies a significant intensification of heat that will cause people to suffer.

[8] In Internet Appendix Section B.1, I apply alternative thresholds for defining heat shocks and demonstrate the robustness of the results.

Figure 2 presents distributions of relative and absolute high temperatures across counties in the continental U.S. As expected, the occurrence of relative heat shocks differs significantly between 2008 and 2014. Consequently, for individuals considering entrepreneurial activities, heat shocks can reasonably be regarded as exogenous. Meanwhile, the occurrence of absolute shocks is concentrated in the southern region.

3.3 Labor Exposure to Climate Risk

I measure each NAICS4 industry's exposure to heat risks through a labor channel following Xiao (2021). This exposure measure reflects the input of human capital that is exposed to high temperatures while performing job duties for production and operations. Specifically, I collect industry-specific occupational data from the Occupational Employment and Wage Statistics (OEWS) provided by the U.S. Bureau of Labor Statistics (BLS). It includes occupations needed in each industry, the number of employees working in each occupation, and wage estimates for each occupation. Then, I gather information on the intensity of outdoor activity for each occupation from the Occupational Information Network (O*NET) program of the U.S. Department of Labor. O*NET assigns each occupation a score reflecting the intensity of outdoor activities required to perform job duties in all weather conditions, including extreme heat. The score ranges from "1" (no exposure) to "5" (daily exposure), with a higher score indicating a greater degree of exposure to changing climates while performing tasks.[9]

Utilizing the OEWS and the O*NET data, I construct an index of labor exposure to climate risk at the NAICS4 industry level in the following way:

$$Labor\ Exposure_{i,t} = \underset{r=1}{\overset{r=20}{\text{Rank}}} \left\{ \sum_{o=1}^{O_{i,t}} \left(\frac{Emp_{i,o,t}}{Emp_{i,t}} \times Score_{o,t} \right) \right\} \tag{2}$$

[9] A score of "1" indicates that workers in this occupation are *never* exposed to any weather conditions during the working process. "2" indicates "*once a year or more but not every month*." "3" indicates "*once a month or more but not every week*." "4" indicates "*once a week or more but not every day*." "5" indicates "*every day*." The score is derived from the question - "*How often does this job require working outdoors, exposed to all weather conditions?*."

where i denotes industry, o denotes occupation, and t denotes year. $O_{i,t}$ is the total number of occupations in industry i and year t. $Score_{o,t}$ is the occupational score of outdoor activity from the O*NET program for occupation o in year t. $Emp_{i,o,t}$ is the number of employees working in occupation o in industry i and year t. $Emp_{i,t}$ is the total number of employees in industry i and year t. This index thus is a weighted average of all occupations' outdoor intensity within a NAICS4 industry. The weight is the percentage of employees working in a given occupation within a NAICS4 industry. With this index, I further create a rank variable $Labor\ Exposure_{i,t}$, ranging from 1 to 20, with 20 indicating the highest exposure. This measure is available for the period 1999 - 2022.

Figure 3 (A) presents the distribution of the labor exposure measure across counties in the continental U.S. The county-level exposure index is calculated as the employment-weighted average of the industry-level measure in Equation (2). The weight is the number of employees working in a NAICS4 industry and a county from the Quarterly Census of Employment and Wages (QCEW) data. The figures reveal a fairly even distribution of high-exposure workers and industries across the U.S., with some concentration in the central region. Figure (B) presents the distribution of the industry-level measure of labor exposure to climate risk across NAICS2 sectors. The x-axis represents NAICS2 sectors and the y-axis represents the measure of labor exposure to climate risk. The dots denote the minimum, the 25^{th} percentile, the median, the 75^{th} percentile, and the maximum of labor exposures across NAICS4 industries in each sector. The key takeaway is that there exist significant variations in workers' climate exposures within and across sectors, highlighting the widespread impact of high temperatures on the entire U.S. economy.[10]

[10]See Xiao (2021) for further discussions of the measure, including the raw datasets, the distribution across labor skill levels, examples of high-exposure industries, and correlations with other climate exposure measures in the literature.

3.4 Additional Data

Quarterly Census of Employment and Wages (QCEW). The data on industry-level employment and wages for each U.S. county is obtained from the BLS's QCEW program. The QCEW program publishes a quarterly count of employment and wages, covering more than 95% of all jobs in the U.S. For this study, I utilize QCEW data that covers all six-digit NAICS industries for more than 3,000 counties, available at the annual frequency from 1990 to 2022.

Temperature Projections. The data on county-level temperature projections is collected from the Centers for Disease Control and Prevention (CDC). This data builds on the Localized Constructed Analogs (LOCA) dataset, derived from 32 Coupled Model Intercomparison Project (CMIP5) models that are widely used in the climate science literature. The CDC processes the raw data on projections of the differences in extreme hot days (90°F/32.2°C) between the reference period (1976 – 2005) and the projected period (2016 - 2045) and aggregates it to the county level.

Small Business Administration(SBA) 7(a) Loans. The data on banks' small business loan originations is sourced from the SBA 7(a) loan program, which is designed to improve capital access for young small businesses that might not qualify for credit through traditional lending channels. The data spans from 1991 to 2024 and provides comprehensive details for each loan, including the bank, the SBA office, the borrower, total loan amount, guaranteed loan amount, maturity, interest rate, jobs supported, and more. Crucially for this study, the data also includes information on the borrower's geographic location and six-digit NAICS industry code, enabling the matching with measures of heat shocks and labor exposures.

County-level Characteristics. County-level data on total population and income is from the Bureau of Economic Analysis (BEA), and county-level data on unemployment rate is from the BLS.

3.5 Summary Statistics

Table 1 presents summary statistics for the variables used in the main empirical analyses. The sample is constructed at the county-by-NAICS4 industry level, including 3,056 counties and 268 NAICS4 industries from 1999 to 2019. On average, each NAICS4 industry in a county sees the creation of 5.7 new firms and 32.2 associated jobs annually. Additionally, about 17.4% of the counties in the sample experience heat shocks. Across all industries, the average exposure to heat shocks through the labor channel is 9.9, while the median exposure level stands at 9.

4 Heat Shocks and Entrepreneurship

4.1 Empirical Methodology

I first estimate the causal impact of unexpected extreme heat on U.S. entrepreneurial activities across counties and NAICS4 industries, which I expect to be negative and statistically significant. The empirical model is as follows.

$$Y_{s,c,i,t} = \mu_{s,t} + \pi_{i,t} + \theta_{c,i} + \beta_1 \, Heat\ Shocks_{s,c,t} + \delta \boldsymbol{X}_{s,c,t} + \varepsilon_{s,c,i,t} \tag{1}$$

$$\begin{aligned} Y_{s,c,i,t} = &\mu_{s,t} + \pi_{i,t} + \theta_{c,i} + \beta_1 \, Heat\ Shocks_{s,c,t} + \beta_2 \, Heat\ Shocks_{s,c,t} \times Labor\ Exposure_{i,t} \\ &+ \beta_3 \, Labor\ Exposure_{i,t} + \delta \boldsymbol{X}_{s,c,t} + \varepsilon_{s,c,i,t} \end{aligned} \tag{2}$$

where s denotes state, c denotes county, i denotes NAICS4 industry, and t denotes year. $Y_{s,c,i,t}$ is the dependent variable for entrepreneurial activities in county c and NAICS4 industry i, measured as the natural logarithm of one plus the number of new firms created. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in county c, and zero otherwise. *Labor Exposure* measures a NAICS4 industry's exposure to climate risks through the labor channel, as defined in Equation (2). $X_{c,t}$ is a

vector of controls at the county level, including the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The models also include various fixed effects to control for unobserved heterogeneity across states, counties, and industries. Specifically, $\mu_{s,t}$ represents state-by-year fixed effects that control for time-varying economic conditions and policy changes in a state. $\pi_{i,t}$ denotes NAICS2 industry-by-year fixed effects, and $\theta_{c,i}$ denotes county-by-NAICS4 fixed effects. In stricter models, I use county-by-year fixed effects to replace state-by-year fixed effects to control for time-varying heterogeneities across counties. I also use NAICS3-by-year and NAICS4-by-year fixed effects to replace NAICS2-by-year fixed effects to better account for heterogeneities across industries.

Model (1) estimate the population average effect of heat shocks on entrepreneurship, captured by the coefficient of *Heat Shocks*, β_1. Model (2) estimates the effect of heat shocks conditional on each NAICS4 industry's heat exposure through the labor channel by adding an interaction term *Heat Shocks* $\times$ *Labor Exposure* and *Labor Exposure*. I expect the coefficients β_1 and β_2 both to be negative and statistically significant. A negative β_1 indicates an overall negative impact of heat shocks on entrepreneurship, while a negative β_2 suggests that this negative impact is more pronounced in industries that employ a large number of workers exposed to heat risks.

4.2 Empirical Results

Table 2 presents estimates of the causal impact of heat shocks on entrepreneurial activities. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. Columns (1) - (3) present the population average effect of heat shocks using Model (1). Across all three columns, the coefficient estimate for *Heat Shocks* is negative and statistically significant, suggesting that heat shocks discourage economy-wide entrepreneurial activities. This

finding is unlikely to be driven by state- or industry-level time-varying dynamics, or any hidden links between counties and industries, as the model in column (3) includes state-by-year, NAICS4-by-year, and county-by-NAICS4 fixed effects. On average, one past heat shock leads to a 0.8% decline in new firm creation.

In column (4), I investigate the labor channel of heat exposure using Model (2). The coefficient estimate of *Heat Shocks* becomes positive and statistically significant, suggesting that industries with hypothetically *zero* heat exposure even experience an increase in new firm creation following heat shocks. Importantly, the coefficient estimate of the interaction term *Heat Shocks* $\times$ *Labor Exposure* is negative and statistically significant. This indicates that high-exposure industries experience reduced entrepreneurial activities and a lower rate of new firm creation following heat shocks, compared to their low-exposure counterparts. The economic magnitude is large: a one-unit increase in labor exposure leads to a 0.2% decline in entrepreneurship.

Based on the estimation, I report the net treatment effects of heat shocks on entrepreneurship for industries in each exposure category (*Labor Exposure = 1 to 20*) in Figure 4 (A) and at the bottom of the table. The results indicate that heat shocks begin to negatively impact entrepreneurship in industries with the median exposure of 10. For industries at the 75^{th} percentile of heat exposure (*Labor Exposure = 15*), new firm creation declines by 1.6% following heat shocks. Industries with the highest exposure (*Labor Exposure = 20*) experience a 2.4% reduction in entrepreneurial activities.

In column (5), I replace state-by-year fixed effects with county-by-year fixed effects to control for time-varying county-level characteristics. The coefficient of *Heat Shocks* $\times$ *Labor Exposure* remains negative and statistically significant, and the economic magnitudes are unchanged, implying that county-level heterogeneities cannot explain the findings. Additionally, I replace NAICS2-by-year fixed effects with NAICS3-by-year fixed effects in column (6) and with NAICS4-by-year fixed effects in column (7). The results still hold, suggesting that the findings are not driven by industry-level heterogeneities.

In summary, the results in this section support my conjecture that extreme heat discourages the entry of new firms, particularly in industries that are highly exposed to heat risks through the labor channel.

4.3 Jobs Created by New Firms

As additional analysis, I examine the jobs created by new firms in Table 3. The dependent variable is the natural logarithm of one plus the number of jobs created by new firms. The analysis in columns (1) - (3) shows that the population average effect of heat shocks on job creation is negative, although statistically insignificant. Importantly, consistent with Table 2, the coefficient estimate of the interaction term *Heat Shocks* $\times$ *Labor Exposure* is negative and significant. This result indicates that heat shocks negatively affect job creation, but only in industries highly exposed to heat risks through the labor channel. In column (4), a one-unit increase in labor exposure leads to a 0.2% decrease in job creation, equivalent to a 2% drop when moving from the 25^{th} percentile to the 75^{th} percentile.

Same as before, I report the net treatment effects of heat shocks on job creation for industries in each exposure category (*Labor Exposure = 1 to 20*) in Figure 4 (B) and at the bottom of the table. As expected, the negative and significant effects of heat shocks on job creation are only observed among high-exposure industries. For instance, for industries with labor exposure at the 75^{th} percentile (*Labor Exposure=15*), the number of jobs created by new firms drops by 1.9% after heat shocks. Industries with the highest exposure (*Labor Exposure = 20*) experience a 2.9% reduction in job creation.

Overall, these findings align with those on firm creation and provide further support for my hypothesis that heat risks discourage entrepreneurial activities in exposed industries.

4.4 Robustness

In Internet Appendix Section B, I conduct additional analyses to demonstrate the robustness of the results in Table 2. I briefly discuss these analyses below.

Alternative Definitions of Heat Shocks. First, I repeat the analysis using different thresholds for defining absolute and relative heat shocks, as shown in Internet Appendix Section B.1 and Table B.1. The results hold, and the economic magnitude increases with higher thresholds.

Alternative Sample Constructions. Second, I test the robustness of the results by reconstructing the sample. Instead of focusing on the top 20 industries in a county, in columns (1) - (4) of Table B.2, I repeat the analysis by including the top 10, 15, 25, and 30 industries in a county, respectively. Furthermore, I include industries that account for more than 1% of total employment in a county in column (5), and those contributing more than 3% in column (6). The coefficient estimate for *Heat Shocks* $\times$ *Labor Exposure* remains negative and statistically significant across all columns.

Alternative Empirical Specifications. Third, to address concerns over the log form of the dependent variable (Cohn et al., 2022), I repeat the analysis by using either the linear regressions model or the fixed effects Poisson model in Table B.3. The dependent variables are the number of new firms created at the county-by-NAICS4 industry level, or a dummy indicating that at least one new firm is created at the county-by-NAICS4 industry level, or the number of new firms created scaled by the number of existing establishments in the same NAICS4 industry and county from the previous year. The results hold and the economic magnitude in column (8) is even larger than that in column (4) of Table 2 (*-0.004 vs. -0.002*).

Sector Breakdowns and Excluding Alternative Channels. Fourth, in Table B.4 and B.5, I repeat the analysis using sector-based subsamples and excluding alternative channels related to lower agricultural outputs and consumer demand. For example, in Table B.4, I

show that the results hold after excluding the agriculture, mining, oil, and gas industries (*NAICS2 11 & 21*), and consumer-oriented industries (*NAICS2 44, 45, 61, 62, 71, & 72*). In Table B.5, I show that the results hold after excluding non-tradable industries. Also, the economic magnitudes are the same as in column (4) of Table 2.

Controlling for Cold Shocks and Precipitation. Fifth, in Table B.6, I show that the results are robust to controlling for other climate events, and the economic magnitudes remain the same.

Alternative Data on County-level Entrepreneurship. Sixth, in addition to YTS, I also quantify entrepreneurial activities at the county level using the business registration data provided by Fazio et al. (2019). The results are consistent and are reported in Table B.7.

4.5 Dynamic Treatment Effects of Heat Shocks

Additionally, I investigate the timing of heat shocks and their dynamic treatment effects on entrepreneurship. To this end, I break down heat shocks defined from Equation (2), which include temperature fluctuations from $t-3$ to t, into annual short-term heat shocks. In particular, for any given county and year, I define annual heat shocks as instances where a county experiences at least 12.5 summer days with temperatures above the rolling 90^{th} percentile, and at least 60 summer days with temperatures above 30°C.

Table 4 presents the results. The dependent variable is the natural logarithm of one plus the number of new firms created in year t. The key independent variables are the interaction terms between *Labor Exposure* and indicators of heat shocks for the respective years from $t-3$ to $t+3$. For instance, *Heat Shocks (T-3)*, *Heat Shocks (T-2)*, *Heat Shocks (T-1)*, *Heat Shocks (T)*, *Heat Shocks (T+1)*, *Heat Shocks (T+2)*, and *Heat Shocks (T+3)* denote heat shocks occurring in the years $t-3$, $t-2$, $t-1$, t, $t+1$, $t+2$, and $t+3$, respectively. In column (1), I examine the influence of heat shocks occurring in year $t-3$. The coefficient estimate for *Heat Shocks* $\times$ *Labor Exposure* is negative and statistically significant, suggesting that past heat shocks can have a long-lasting impact on entrepreneurship decisions for

up to three years. Columns (2), (3), and (4) examine heat shocks occurring in years $t-2$, $t-1$, and t, respectively. All the coefficient estimates for *Heat Shocks* $\times$ *Labor Exposure* are negative and statistically significant. In column (5), I include all annual heat shocks from $t-3$ to t. Among the four coefficient estimates, the one for $t-2$ is the largest, indicating that heat shocks from two years prior have the most significant impact on present entrepreneurial activities. In column (6), I further include future heat shocks occurring in years $t+1$, $t+2$, and $t+3$. The significance of contemporaneous heat shocks disappears while the significance of past heat shocks remains. Most importantly, the coefficient estimates for *Heat Shocks* $\times$ *Labor Exposure* at $t+1$, $t+2$, and $t+3$ are not statistically significant, indicating that future heat shocks have no impact on present entrepreneurial activities.

Taken together, these results demonstrate that past heat shocks negatively affect present entrepreneurial decisions in heat-exposed industries, while future heat shocks do not, thereby alleviating concerns about endogeneity.

5 Economic Mechanisms

Analysis so far has provided consistent and robust evidence demonstrating that extreme heat negatively affects entrepreneurship, particularly in high-exposure industries. The economic rationale is that extreme heat raises labor-related production and financing costs for operations with substantial heat exposure, thereby reducing individuals' incentives to start new businesses. In this section, I provide further evidence to identify heat risks embedded within this labor channel and the underlying mechanisms.

5.1 Labor Utilization in Production

As discussed in Section 2 "Conceptual Framework", one key mechanism behind the decline in entrepreneurship is that extreme heat increases labor costs per unit of output in the production process and consequently reduces operating profits, imposing substantial

financial burdens on businesses in heat-exposed industries. This, in turn, discourages individuals from starting new businesses. In line with this, a recent work by Xiao (2021) finds that heat exposure through the labor channel hurts firm-level labor productivity. Firms adapt by shifting toward more capital-intensive production functions, which helps offset these losses.[11] Motivated by this evidence, I conjecture that the labor channel for reduced entrepreneurship should be more pronounced in industries that require significant human capital relative to physical assets as a production input.

I test the conjecture and present the results in Table 5. In the analysis, I interact *Heat Shocks* $\times$ *Labor Exposure* with *High K/L*, an indicator that equals to one if a NAICS4 industry's capital-labor ratio (*K/L*) is above the sample median, and zero otherwise. The industry-level *K/L* is measured as the median firm's property, plant, and equipment (PPENT) per employee within each NAICS4 industry, using the Compustat data. The sample size is reduced to about half of the original after merging with the industry-level capital intensity measure. In columns (1) and (2), I first verify that the main results in Table 2 hold in this smaller sample. In columns (3) and (4), the coefficient of the triple interaction term *Heat Shocks* $\times$ *Labor Exposure* $\times$ *High K/L* is positive and statistically significant, indicating that the heat-induced decline in entrepreneurship is much weaker in industries with above-median capital-labor ratios. This evidence implies that in industries where human capital is less critical for business operations, heat risks are less of a concern for entrepreneurial decisions.

5.2 Credit Access

Entrepreneurs may face higher financing costs when starting new businesses if creditors take heat risks into account, potentially discouraging their decision to enter the market. I test this financing mechanism using small business loan originations from the SBA 7(a)

[11] More specifically, Xiao (2021) show that (1) exposed firms significantly increase capital-labor ratios after heat shocks; and (2) heat shocks negatively affect labor productivity only in firms with low capital-labor ratios, while firms with high capital-labor ratios remain unaffected.

loan program and present the results in Table 6.[12] In Panel A, the dependent variable is *Log(Loan Amount)*, the natural logarithm of the loan amount. Columns (1) - (4) report the average impact of extreme heat on loan originations, revealing that heat shocks significantly reduce the average loan amount small businesses receive from banks. This result remains robust after controlling for state-by-year, county, business type, industry-by-year, SBA office, and bank fixed effects. Economically, one past heat shock reduces the total loan amount by 0.4%. Columns (5) - (10) report the heterogeneous effects of heat shocks across varying levels of heat exposure. Consistent with my expectation, the interaction term of *Heat Shocks* $\times$ *Labor Exposure* is negative and statistically significant, indicating that the decline in credit access is primarily concentrated in high-exposure industries. Specifically, in column (5), the loan amount is 0.8% smaller for small businesses with heat exposure at the 75^{th} percentile, and 1.2% smaller for small businesses with the highest exposure. The findings remain robust after incorporating an extensive set of fixed effects to account for heterogeneities across banks, SBA offices, locations, and industries. Detailed net treatment effects of heat shocks on loan amounts for each labor exposure category ((*Labor Exposure = 1 to 20*)) are presented in Figure 6 (A).

In Panel B of Table 6, I examine the effects of heat shocks on loan interest rates. Analysis in columns (1) - (4) reveals that the average small business experiences a 0.4% increase in interest rates following heat shocks. Columns (5) - (10) further show that this increase is primarily driven by loans to small businesses in heat-exposed industries. For example, loans to small businesses at the 75^{th} percentile of heat exposure experience a 0.7% increase in interest rates, while those with the highest exposure see an increase of 1.1%. Detailed net treatment effects of heat shocks on loan interest rates for each labor exposure category ((*Labor Exposure = 1 to 20*)) are presented in Figure 6 (B).

In summary, these findings suggest that increased financing costs, driven by heat-related labor risks, partially contribute to the decline in entrepreneurship observed in

[12]Summary statistics for the sample and variables are reported in Internet Appendix Table C.1.

heat-exposed industries.

5.3 Expected Heat Risks

As climate change intensifies, extreme heat events are expected to occur more severely and frequently. If the decline in entrepreneurship is indeed driven by concerns about heat risks and the associated labor-related production and financing costs, the effects should be more pronounced in areas where significant temperature increases are anticipated in the near future. Conversely, if a past heat shock is seen as an isolated event with no expectation of it recurring, businesses would not anticipate increased labor-related costs, and their operations would remain unaffected. To test this conjecture, I examine the impact of heat shocks on entrepreneurial activities conditional on projected temperature increases in each county by 2045.

Table 7 presents the results. In column (1), a county is classified as "*High Projection*" if its projected increase in extreme heat days compared to the historical period is above the sample median. The coefficient estimate for *Heat Shocks* $\times$ *Labor Exposure* is no longer statistically significant. However, the coefficient estimate for the triple interaction term *High Projection* $\times$ *Heat Shocks* $\times$ *Labor Exposure* is negative and statistically significant, indicating that the heat-induced decline in entrepreneurship is most pronounced in areas with substantial projected heat risks in the coming decades. I repeat the analysis in column (2) using a continuous variable for projected temperature increases, and the results remain consistent. Overall, this evidence supports my conjecture that the decline in entrepreneurship results from concerns about heat risks that are expected to significantly raise business costs as climate change worsens.

6 Further Analyses and Discussions

In this section, I provide additional analysis to further explore the implications of climate change for U.S. entrepreneurship, employment, and economic activity.

6.1 Long-term Survival of New Entrant Firms in Heat-Exposed Industries

Despite rising heat risks and associated labor-related costs, some entrepreneurs continue to start new businesses in heat-exposed industries, particularly if they possess specialized knowledge of heat risks or strategies to mitigate related costs. Ex ante, it is unclear whether new firms in more heat-exposed industries are more or less likely to survive compared to those in less exposed industries. On the one hand, additional heat-induced business costs reduce the cash flow of exposed firms, limiting their operational flexibility, investment capacity, and growth potential, thereby reducing their likelihood of survival. On the other hand, entrepreneurs who choose to start businesses in these challenging conditions are likely to be of higher quality, potentially increasing their chances of success. Furthermore, the reduced entry of new firms may lead to lower competition and greater growth opportunities.

I explore this question in Table 8. The dependent variable in columns (1) - (3) is *Log(Survival Years)*, the natural logarithm of the average number of years that newly created firms survive until 2022, measured at the county-by-NAICS4 industry level. The analysis shows that, conditional on entry, new firms in heat-exposed industries have significantly longer survival times. For instance, firms founded in industries at the 75^{th} percentile of heat exposure have a 1.2% longer survival time, while those in the most heat-exposed industries survive 1.8% longer. Furthermore, columns (4) - (6) analyze the average number of jobs maintained by new firms six years after their founding. The results show that firms in high-exposure industries tend to maintain higher employment levels compared to those in low-exposure industries after six years. In particular, firms established in industries at the 75^{th} percentile of heat exposure have 2% more employees, while those in the most heat-exposed industries have 2.7% more employees. These findings collectively suggest that entrepreneurs who start new businesses in heat-exposed industries are typically of higher quality, and their businesses are not only more likely to

survive but also to grow more rapidly over the long term.

6.2 New Establishments Created by Existing Firms

The reduced entry of new firms in heat-exposed industries may leave certain consumption demands unmet at affordable prices. Existing firms, with greater financial resources and practical experience, may be better positioned to scale up operations to meet these consumption demands. This suggests that existing firms could leverage heat-related challenges as growth opportunities, potentially expanding their operations and establishing new plants. However, like new entrants, existing firms also face higher labor-related costs for business operations, which may deter them from expanding their production networks in heat-exposed industries. I investigate this question in Table 9.

In columns (1) - (3), the dependent variable is *Log(1+ New Establishments), Existing*, the natural logarithm of one plus the number of new establishments created by existing firms at the county-by-NAICS4 industry level. In columns (4) - (6), the dependent variable is *Log(1+ New Establishments), All*, the natural logarithm of one plus the number of new establishments created by both new and existing firms at the county-by-NAICS4 industry level. The analysis shows that existing firms indeed establish more new plants in heat-exposed industries following heat shocks. However, the expansion by existing firms does not sufficiently offset the county-wide decline in new entrants. Specifically, the county-wide total number of establishments in industries at the 75^{th} percentile of heat exposure declines by 1.4% following heat shocks.

6.3 Macroeconomic Effects: Total County Income

Considering the importance of firm entry for job creation and business activities (Adelino et al., 2017), the county-wide decline in business formation could lead to a macro-level contraction in aggregate economic output. I test this conjecture using the county-level total personal income data provided by the BEA, which captures the total returns from

capital and labor as production inputs. Table 10 represent the results. The variable *Labor Exposure* denotes a county's exposure to climate risks through the labor channel, calculated as the employment-weighted average of the industry-level measure of labor exposure defined in Equation (2). The weight is the number of employees working in a NAICS4 industry and a county from QCEW. Supporting my conjecture, past heat shocks result in significant declines in county-level total income, and the decline is primarily concentrated in counties with significant shares of heat-exposed workers. For instance, total income drops by 1.4% for counties at the 75^{th} percentile of heat exposure and by 2.3% for counties with the highest exposure. Figure 7 provides additional details of the effects of heat shocks on county-level total income by labor exposure category (1 to 20), based on the estimation in column (4) of Table 10. This evidence indicates that rising heat risks could significantly slow macroeconomic growth in the foreseeable future.

7 Conclusions

The escalating extreme heat, a direct consequence of climate change, presents significant challenges to business operations. This paper explores how these challenges impact individuals' incentives to start new businesses through a labor channel.

Specifically, this paper focuses on health risks associated with high temperatures, which notably reduce the supply and productivity of exposed workers, leading to higher production and operating costs for affected businesses. Meanwhile, creditors restrict credit access to heat-exposed small businesses, which further discourages new market entrants. With global temperatures projected to rise further, these climate-induced business costs are likely to increase substantially, potentially reshaping entrepreneurial incentives and the landscape of new firm creation.

I conjecture that prospective entrepreneurs would consider these heat-induced labor-related production and financing costs when deciding whether to establish a business. Supporting this conjecture, I find that extreme heat discourages new entrants and the cre-

ation of new firms, particularly in industries with substantial heat exposure. The deterrent effect is more pronounced in industries where human capital is critical for business growth and in counties where long-run heat risks are greater. However, entrepreneurs who continue to start businesses in heat-vulnerable industries tend to be of higher quality, and their businesses are more likely to survive and grow more rapidly in the long run. In addition, existing firms fill market gaps left by reduced entrants and expand their networks, but this expansion fails to offset the county-wide decline in new business formation. This overall business decline, in turn, contributes to a macro-level contraction in aggregate economic activity.

To conclude, this research underscores the profound impact of climate change on entrepreneurial activities across counties and industries in the U.S., highlighting the need for targeted policies and interventions to foster business growth while building more resilient and sustainable communities.

References

Acharya, V. V., A. Bhardwaj, and T. Tomunen (2023). Do firms mitigate climate impact on employment? Evidence from US heat shocks. *NBER Working Paper 31967*.

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

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

Adelino, M., S. Ma, and D. Robinson (2017). Firm age, investment opportunities, and job creation. *Journal of Finance 72*(3), 999–1038.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*.

Babina, T. (2020). Destructive creation at work: How financial distress spurs entrepreneurship. *Review of Financial Studies 33*(9), 4061–4101.

Bergman, N. K., R. Iyer, and R. T. Thakor (2020). The effect of cash injections: Evidence from the 1980s farm debt crisis. *Review of Financial Studies 33*(11), 5092–5130.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics 134*(2), 253–272.

Black, S. E. and P. E. Strahan (2002). Entrepreneurship and bank credit availability. *Journal of Finance 57*(6), 2807–2833.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of Financial Economics 142*(2), 517–549.

Brown, J. R., M. T. Gustafson, and I. T. Ivanov (2021). Weathering cash flow shocks. *Journal of Finance 76*(4), 1731–1772.

Campello, M., G. S. Cortes, F. d'Almeida, and G. Kankanhalli (2022). Exporting uncertainty: The impact of brexit on corporate America. *Journal of Financial and Quantitative Analysis 57*(8), 3178–3222.

Cen, X. (2021). Household wealth and entrepreneurial career choices: Evidence from climate disasters. *Available at SSRN 3803436*.

Chen, H. J., M. Kacperczyk, and H. Ortiz-Molina (2011). Labor unions, operating flexibility, and the cost of equity. *Journal of Financial and Quantitative Analysis 46*(1), 25–58.

Chen, X. and L. Yang (2019). Temperature and industrial output: Firm-level evidence from China. *Journal of Environmental Economics and Management 95*, 257–274.

Choi, D., Z. Gao, and W. Jiang (2020). Attention to global warming. *Review of Financial Studies 33*(3), 1112–1145.

Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146*(2), 529–551.

Collier, B. L., L. S. Powell, M. A. Ragin, and X. You (2024). Financing negative shocks: Evidence from hurricane harvey. *Journal of Financial and Quantitative Analysis*, 1–84.

Correa, R., A. He, C. Herpfer, and U. Lel (2020). The rising tide lifts some interest rates: Climate change, natural disasters, and loan pricing. *Available at SSRN 3710451*.

Coyne, D. and C. Johnson (2023). Use of the opportunity zone tax incentive: What the data tell us. *U.S. Department of the Treasury Office of Tax Analysis Working Paper*.

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

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

Dillender, M. (2021). Climate change and occupational health: Are there limits to our ability to adapt? *Journal of Human Resources 56*(1), 184–224.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics 101*(3), 621–640.

Engelberg, J., J. Guzman, R. Lu, and W. Mullins (2022). Partisan entrepreneurship. *NBER Working Paper 30249*.

Ewens, M. and R. R. Townsend (2020). Are early stage investors biased against women? *Journal of Financial Economics 135*(3), 653–677.

Fankhauser, S. (2017). Adaptation to climate change. *Annual Review of Resource Economics 9*(1), 209–230.

Fazio, C., S. Stern, J. Guzman, Y. Liu, and R. Andrews (2019). The startup cartography project: Measuring and mapping entrepreneurial ecosystems. *Research Policy*.

Flynn, S. J. and A. Ghent (2022). Does main street benefit from what benefits wall street? *Journal of Financial and Quantitative Analysis*, 1–37.

Ghent, A. C. (2021). What's wrong with pittsburgh? Delegated investors and liquidity concentration. *Journal of Financial Economics 139*(2), 337–358.

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

Gompers, P., A. Kovner, J. Lerner, and D. Scharfstein (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics 96*(1), 18–32.

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

Hacamo, I. and K. Kleiner (2022). Forced entrepreneurs. *Journal of Finance 77*(1), 49–83.

Herkenhoff, K., G. M. Phillips, and E. Cohen-Cole (2021). The impact of consumer credit access on self-employment and entrepreneurship. *Journal of Financial Economics 141*(1), 345–371.

Heyes, A. and S. Saberian (2019). Temperature and decisions: Evidence from 207,000 court cases. *American Economic Journal: Applied Economics 11*(2), 238–265.

Hong, H., G. A. Karolyi, and J. A. Scheinkman (2020). Climate finance. *Review of Financial Studies 33*(3), 1011–1023.

Houde, J.-F., P. Newberry, and K. Seim (2023). Nexus tax laws and economies of density in e-commerce: A study of amazon's fulfillment center network. *Econometrica 91*(1),

147–190.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *Review of Financial Studies 34*(3), 1540–1571.

Jeffers, J. S. (2024). The impact of restricting labor mobility on corporate investment and entrepreneurship. *Review of Financial Studies 37*(1), 1–44.

Jia, R., X. Ma, and V. W. Xie (2022). Expecting floods: Firm entry, employment, and aggregate implications. *NBER Working Paper 30250*.

Kim, H. (2020). How does labor market size affect firm capital structure? Evidence from large plant openings. *Journal of Financial Economics 138*(1), 277–294.

Kunkle, G. (2018). Business employment data: YTS versus CES and CPS. *Business Dynamics Research Consortium Working paper*.

Lai, W., Y. Qiu, Q. Tang, C. Xi, and P. Zhang (2023). The effects of temperature on labor productivity. *Annual Review of Resource Economics 15*.

LoPalo, M. (2023). Temperature, worker productivity, and adaptation: Evidence from survey data production. *American Economic Journal: Applied Economics 15*(1), 192–229.

Luber, G. and M. McGeehin (2008). Climate change and extreme heat events. *American Journal of Preventive Medicine 35*(5), 429–435.

Matsa, D. A. (2018). Capital structure and a firm's workforce. *Annual Review of Financial Economics 10*(1), 387–412.

Mora, C., B. Dousset, I. R. Caldwell, F. E. Powell, R. C. Geronimo, C. R. Bielecki, C. W. Counsell, B. S. Dietrich, E. T. Johnston, L. V. Louis, et al. (2017). Global risk of deadly heat. *Nature Climate Change 7*(7), 501–506.

Nishesh, N., P. Ouimet, and E. Simintzi (2024). Labor and corporate finance. *Handbook of Corporate Finance*, 647–673.

Ortiz-Molina, H., Z. Xiao, and X. Zheng (2023). Adaptation to climate-induced regulatory risk: A labor perspective. *Unpublished working paper*.

Pankratz, N., R. Bauer, and J. Derwall (2023). Climate change, firm performance, and investor surprises. *Management Science 69*(12), 7352–7398.

Pankratz, N. M. and C. M. Schiller (2024). Climate change and adaptation in global supply-chain networks. *Review of Financial Studies 37*(6), 1729–1777.

Park, J., N. Pankratz, and A. Behrer (2021). Temperature, workplace safety, and labor market inequality. *Available at SSRN 3892588*.

Perkins, S. E. and L. V. Alexander (2013). On the measurement of heat waves. *Journal of Climate 26*(13), 4500–4517.

Ponticelli, J., Q. Xu, and S. Zeume (2023). Temperature, adaptation, and local industry concentration. *NBER Working Paper 31533*.

Schmalz, M. C., D. A. Sraer, and D. Thesmar (2017). Housing collateral and entrepreneurship. *Journal of Finance 72*(1), 99–132.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing.

Journal of Political Economy 129(6), 1797–1827.

Taylor, J. B. (1999). Staggered price and wage setting in macroeconomics. *Handbook of Macroeconomics 1*, 1009–1050.

Xiao, R. (2023). Climate-induced labor risk and firm investments in automation. *Unpublished working paper*.

Xiao, Z. (2021). Labor exposure to climate risk, productivity loss, and capital deepening. *Available at SSRN 4475467*.

Xiao, Z., X. Zheng, and Y. Zheng (2023). The economic and financial impact of negative environmental and social practices: Evidence from consumers store visits. *Available at SSRN 4475050*.

Appendix A: Variable Definitions

Variables	Description
Dependent Variables	
Log(1+New Firms)	The natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level.
Log(1+Jobs Created by New Firms)	The natural logarithm of one plus the number of jobs created by new firms at the county-by-NAICS4 industry level.
Log(1+ New Establishments), Existing	The natural logarithm of one plus the number of new establishments created by existing firms at the county-by-NAICS4 industry level.
Log(1+ New Establishments), All	The natural logarithm of one plus the number of new establishments created by both new and existing firms at the county-by-NAICS4 industry level.
Log(Survival Years)	The natural logarithm of the average number of years that newly created firms survive until 2022 at the county-by-NAICS4 industry level.
Log(6-Year Jobs)	The natural logarithm of the average number of employment that newly created firms have six years after establishment at the county-by-NAICS4 industry level.
Log(Loan Amount)	The natural logarithm of the loan amount at the loan level.
Log(Loan Interest Rate)	The natural logarithm of the loan interest rate at the loan level.
Log(Total County Income)	The natural logarithm of the county-level total personal income from the BEA, in thousands of dollars.
Key Independent Variables	
Heat Shocks	An indicator that equals to one if heat shocks occur in the county, and zero otherwise, defined in Equation (1).
Labor Exposure	The NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2).
Other Independent Variables	
Log(Population)	The natural logarithm of the county's total population.
Log(Income per Capita)	The natural logarithm of the county's income per capita.
Unemployment Rate	The county's unemployment rate.
Log(SBA Loan Amount)	The natural logarithm of the loan amount guaranteed by the SBA.
Maturity	The natural logarithm of loan maturity in months.
Log(1+Jobs Supported)	The natural logarithm of one plus the number of jobs supported by the loan.
Credit Line	An indicator that equals to one if the loan is a revolving line of credit, and zero it it's a term loan.

Figures

Figure 1. Distribution of Newly Established Firms Across U.S. Counties

This figure presents the average annual number of newly established firms for each county in the continental U.S. during the period 1999 – 2019.

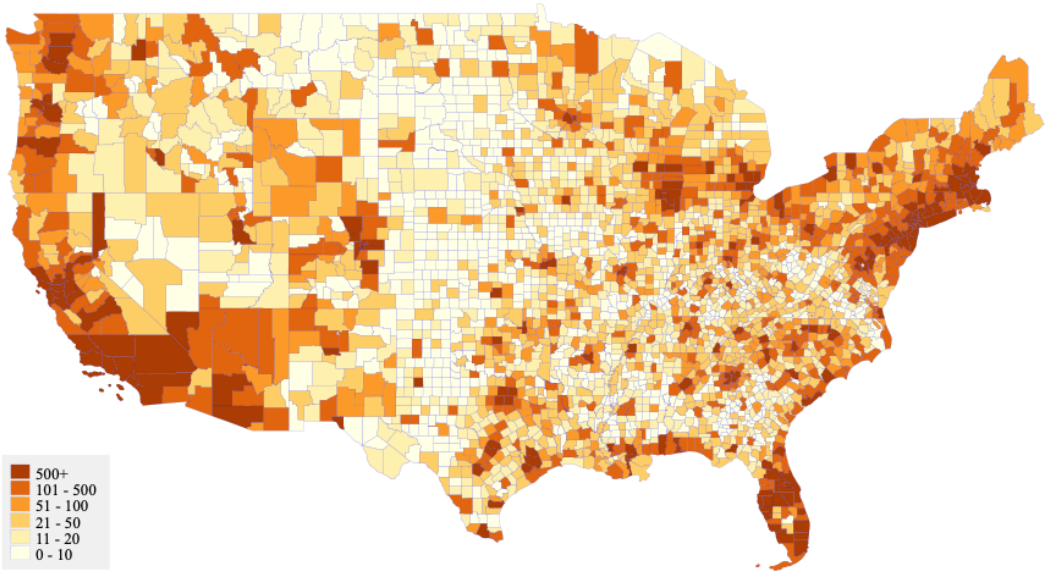
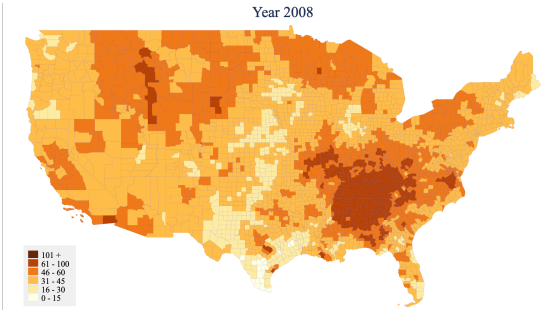


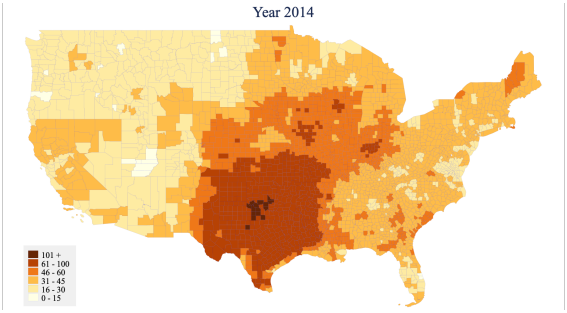
Figure 2. Distributions of Relative and Absolute High Temperatures Across U.S. Counties

These figures present distributions of relative and absolute high temperatures across counties in the continental U.S. Specifically, Figure (A) presents the number of summer days from 2005 to 2008 with temperatures above the rolling estimated 90^{th} percentile. Figure (B) presents the number of summer days from 2011 to 2014 with temperatures above the rolling estimated 90^{th} percentile. Figure (C) presents the number of summer days from 2005 to 2008 with temperatures above 30°C. Figure (D) presents the number of summer days from 2011 to 2014 with temperatures above 30°C. Refer to Equation (1) for detailed definitions of relative and absolute heat shocks.

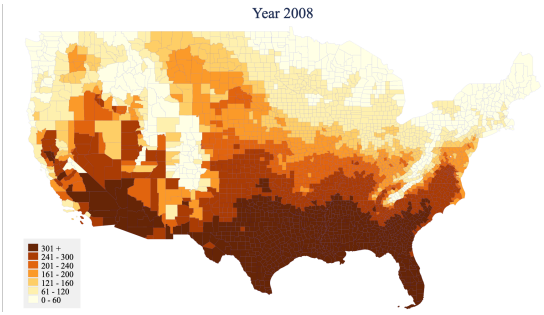
(A) No. Days Above the 90^{th} Percentile, 2008



(B) No. Days Above the 90^{th} Percentile, 2014



(C) No. Days Above 30°C, 2008



(D) No. Days Above 30°C, 2014

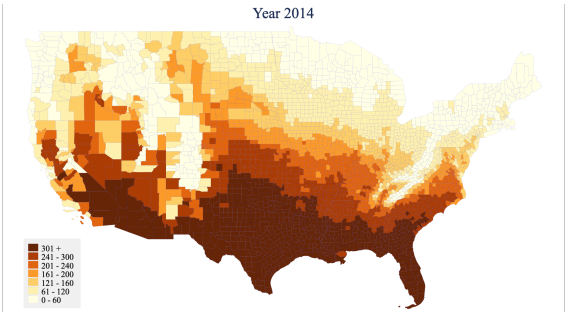
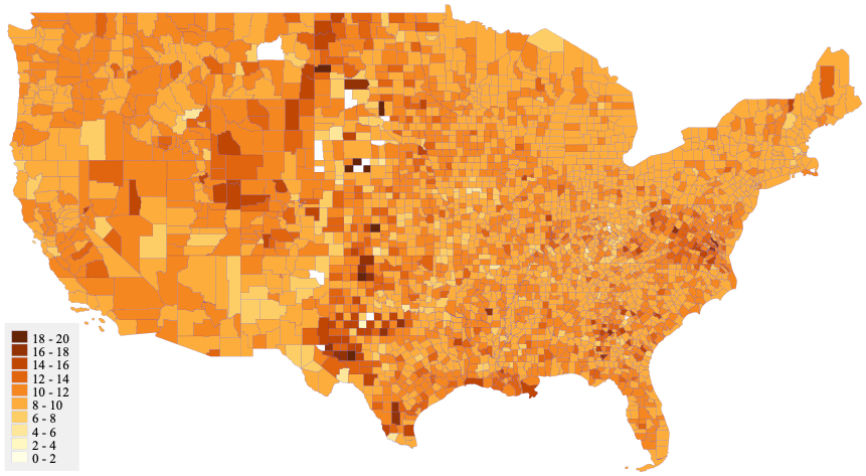


Figure 3. Distributions of the Labor Exposure Measure Across Counties and Sectors

These figures presents the distribution of the labor exposure measure across counties in the continental U.S. and across sectors. Specifically, Figure (A) presents the county-level labor exposure index, calculated as the employment-weighted average of the industry-level measure of labor exposure defined in Equation (2). The weight is the number of employees working in a NAICS4 industry and a county from the QCEW data. Figure (B) presents the distribution of the industry-level measure of labor exposure to climate risk (Equation (2) across NAICS2 sectors.

(A) Across Counties



(B) Across Sectors

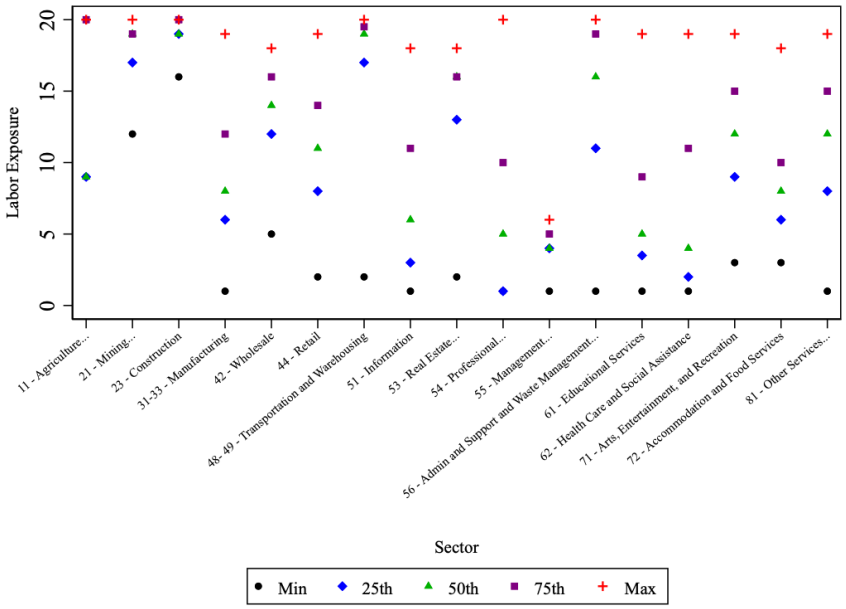
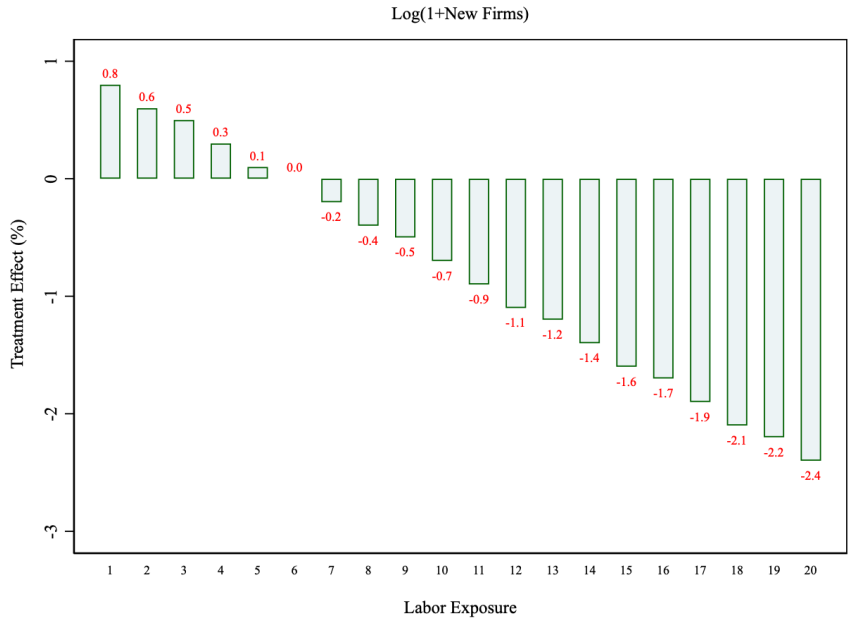


Figure 4. Heat Shocks and Entrepreneurship: Firm and Job Creation

These figures present the treatment effects of heat shocks on entrepreneurship by labor exposure category (1 to 20). Figure (A) presents the creation of new firms at the county-by-NAICS4 industry level, based on the estimation in Table 2 column (4). Figure (B) presents the number of jobs created by new firms at the county-by-NAICS4 industry level, based on the estimation in Table 3 column (4).

(A) Firm Creation



(B) Job Creation

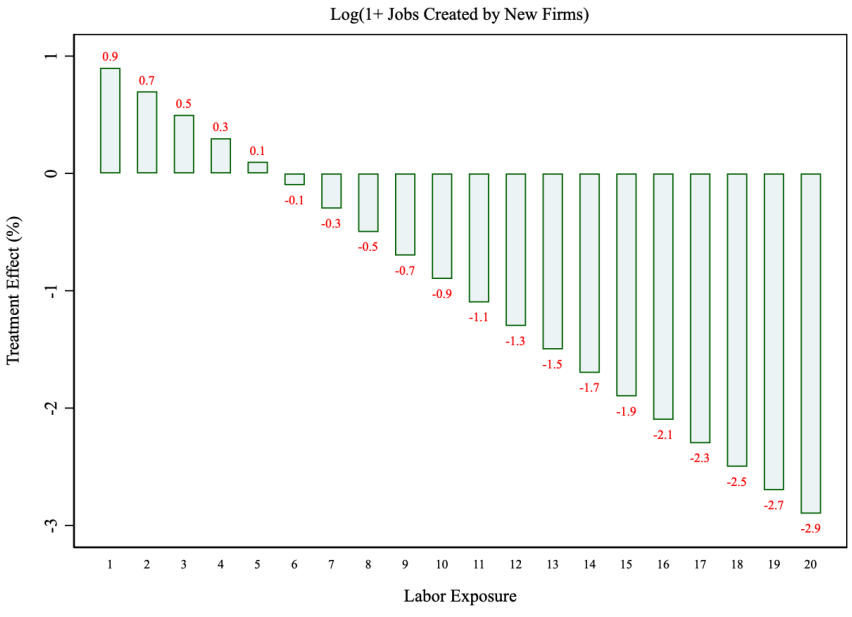


Figure 5. Heat Shocks and Entrepreneurship: Dynamic Effects

This figure presents the dynamic treatment effects of past, present, and future heat shocks on present entrepreneurship at the county-by-NAICS4 industry level. *T-3*, *T-2*, *T-1*, *T*, *T+1*, *T+2*, and *T+3* represent heat shocks occurring in years T-3, T-2, T-1, T, T+1, T+2, and T+3, respectively. The regression results are presented in column (6) of Table 4.

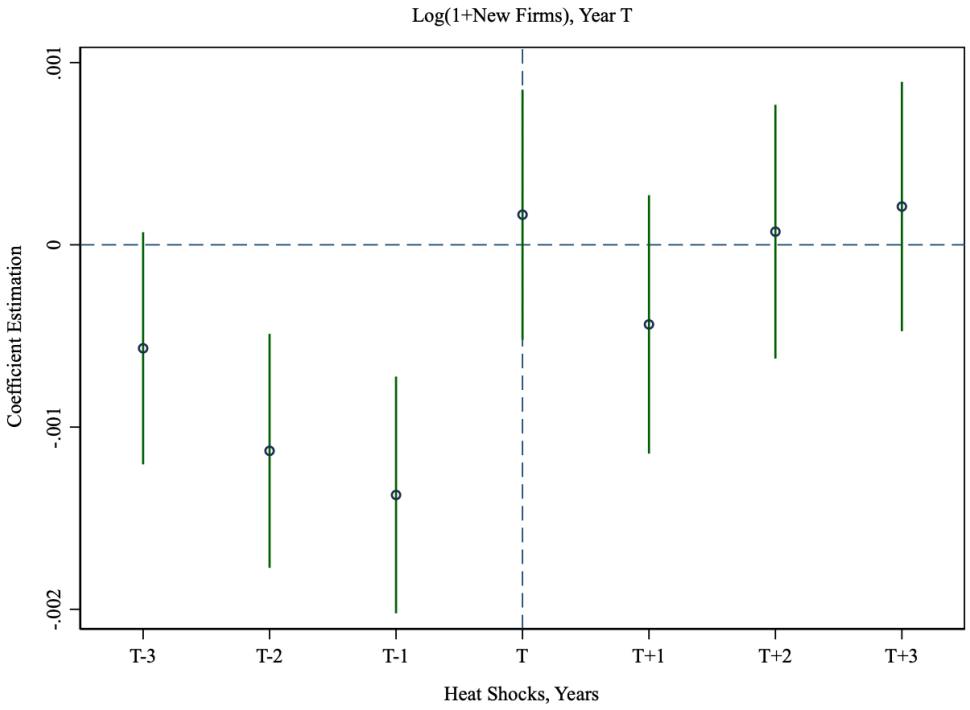
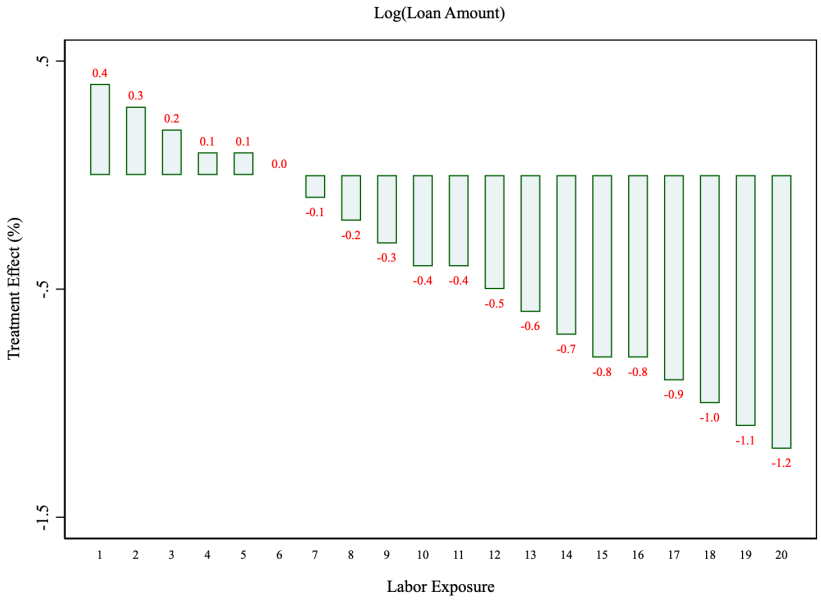


Figure 6. Heat Shocks and Credit Access

Figure (A) presents the treatment effects of heat shocks on small business loan amount by labor exposure category (1 to 20), based on the estimation in column (5) of Table 6 Panel A. Figure (B) presents the treatment effects of heat shocks on small business loan interest rate by labor exposure category (1 to 20), based on the estimation in column (5) of Table 6 Panel B.

(A) Loan Amount



(B) Loan Interest Rate

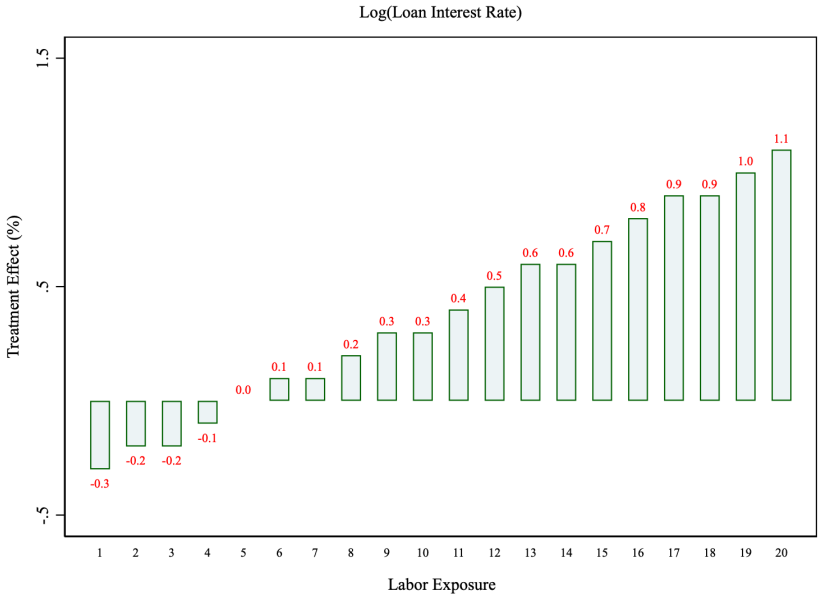
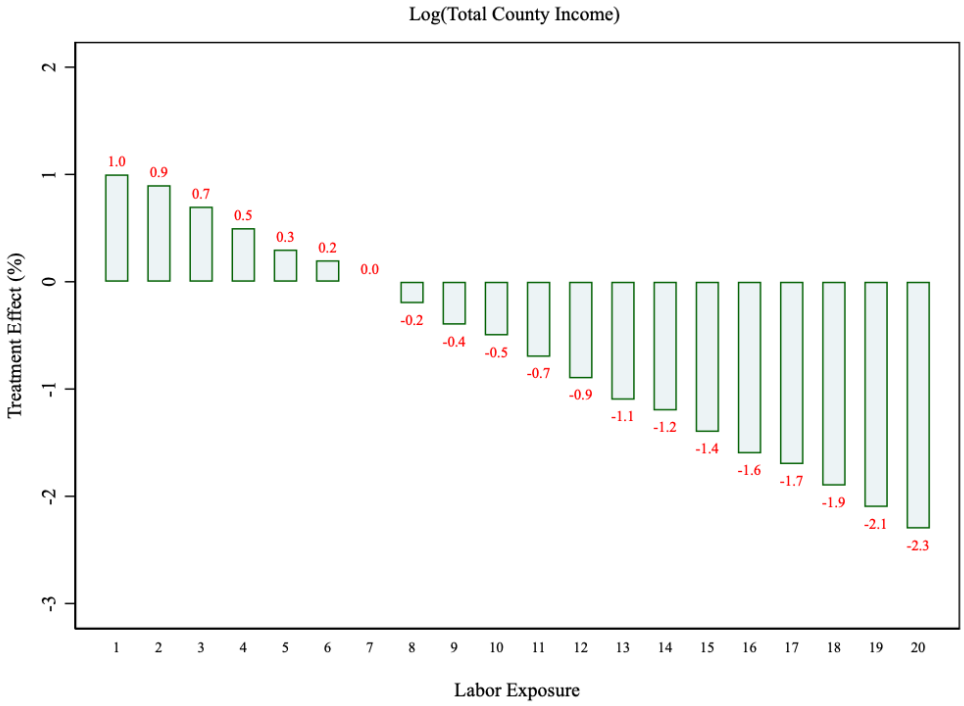


Figure 7. Macroeconomic Effects of Heat Shocks on Total County Income

This figure presents the macroeconomic effects of heat shocks on county-level total personal income by labor exposure category (1 to 20), based on the estimation in column (4) of Table 10.



Tables

Table 1. Summary Statistics

This table presents summary statistics of variables used in empirical analyses. *New Firms* is the number of new firms created at the county-by-NAICS4 industry level. *Log(1+New Firms)* is the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. *Jobs Created by New Firms* is the number of jobs created by new firms at the county-by-NAICS4 industry level. *Log(1+Jobs Created by New Firms)* is the natural logarithm of one plus the number of jobs created by new firms at the county-by-NAICS4 industry level. *New Establishments, Existing* is the number of new establishments created by existing firms at the county-by-NAICS4 industry level. *Log(1+ New Establishments), Existing* is the natural logarithm of one plus the number of new establishments created by existing firms at the county-by-NAICS4 industry level. *New Establishments, All* is the number of new establishments created by both new and existing firms at the county-by-NAICS4 industry level. *Log(1+ New Establishments), All* is the natural logarithm of one plus the number of new establishments created by both new and existing firms at the county-by-NAICS4 industry level. *Log(Survival Years)* is the natural logarithm of the average number of years that newly created firms survive until 2022, measured at the county-by-NAICS4 industry level. *Log(6-Year Jobs)* is the natural logarithm of the average number of employment that newly created firms have six years after establishment, measured at the county-by-NAICS4 industry level. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). *Log(Population)* is the natural logarithm of the county's total population. *Log(Income per Capita)* is the natural logarithm of the county's income per capita. *Unemployment Rate* is the county's unemployment rate. The sample period is from 1999 to 2019.

	N	Mean	P25	Median	P75	SD
New Firms	1,263,051	5.655	0	0	2	20.762
Log(1+New Firms)	1,263,051	0.791	0	0	1.099	1.128
Jobs Created by New Firms	1,263,051	32.213	0	0	13	109.283
Log(1+ Jobs Created by New Firms)	1,263,051	1.436	0	0	2.639	1.812
New Establishments, Existing	1,263,051	0.381	0	0	0	1.737
Log(1+New Establishments), Existing	1,263,051	0.148	0	0	0	0.437
New Establishments, All	1,263,051	6.035	0	0	3	21.64
Log(1+New Establishments), All	1,263,051	0.832	0	0	1.386	1.148
Log(Survival Years)	601,758	1.771	1.386	1.842	2.197	0.643
Log(6-Year Jobs)	601,758	0.936	0	0.811	1.427	0.988
Heat Shocks	1,263,051	0.174	0	0	0	0.379
Labor Exposure	1,263,051	9.858	4	9	15	6.17
Log(Population)	1,263,051	10.287	9.347	10.168	11.115	1.445
Log(Income per Capita)	1,263,051	10.378	10.163	10.37	10.576	0.307
Unemployment Rate	1,263,051	5.946	4	5.4	7.3	2.683

Table 2. Heat Shocks and Entrepreneurship: Firm Creation

This table presents the treatment effects of heat shocks on the creation of new firms. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks*, *Labor Exposure*, and the interaction term of the two (*Heat Shocks* × *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(1+New Firms)						
Heat Shocks	-0.007*	-0.008**	-0.008**	0.010**			
	(0.004)	(0.004)	(0.004)	(0.004)			
Heat Shocks × Labor Exposure				-0.002***	-0.002***	-0.001***	-0.001***
				(0.000)	(0.000)	(0.000)	(0.000)
Labor Exposure				-0.002***	-0.002***	-0.005***	
				(0.000)	(0.000)	(0.000)	
Log(Population)	0.678***	0.669***	0.645***	0.680***			
	(0.027)	(0.027)	(0.026)	(0.027)			
Log(Income per Capita)	0.050***	0.052***	0.057***	0.050***			
	(0.013)	(0.012)	(0.012)	(0.012)			
Unemployment Rate	0.000	0.000	0.000	0.000			
	(0.001)	(0.001)	(0.001)	(0.001)			
Observations	1,243,296	1,243,274	1,243,177	1,243,296	1,243,296	1,243,274	1,243,177
State x Year FE	Yes	Yes	Yes	Yes	No	No	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	No	No	Yes	Yes	No	No
NAICS3 x Year FE	No	Yes	No	No	No	Yes	No
NAICS4 x Year FE	No	No	Yes	No	No	No	Yes
County x Year FE	No	No	No	No	Yes	Yes	Yes
Adjusted R^2	0.848	0.853	0.860	0.848	0.864	0.869	0.877
Treatment Effects							
Labor Exposure=15				-1.6***			
				(0.004)			
Labor Exposure=16				-1.7***			
				(0.004)			
Labor Exposure=17				-1.9***			
				(0.004)			
Labor Exposure=18				-2.1***			
				(0.004)			
Labor Exposure=19				-2.2***			
				(0.005)			
Labor Exposure=20				-2.4***			
				(0.005)			

Table 3. Heat Shocks and Entrepreneurship: Jobs Created by New Firms

This table presents the treatment effects of heat shocks on the creation of jobs by new firms. The dependent variable is *Log(1+Jobs Created by New Firms)*, the natural logarithm of one plus the number of jobs created by new firms at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks*, *Labor Exposure*, and the interaction term of the two (*Heat Shocks* $\times$ *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(1+ Jobs Created by New Firms)						
Heat Shocks	-0.009	-0.010	-0.009	0.011			
	(0.007)	(0.007)	(0.007)	(0.009)			
Heat Shocks $\times$ Labor Exposure				-0.002***	-0.002***	-0.002***	-0.002***
				(0.001)	(0.001)	(0.001)	(0.001)
Labor Exposure				-0.004***	-0.004***	-0.011***	
				(0.001)	(0.001)	(0.001)	
Log(Population)	0.890***	0.880***	0.860***	0.893***			
	(0.037)	(0.037)	(0.036)	(0.037)			
Log(Income per Capita)	0.140***	0.143***	0.150***	0.139***			
	(0.022)	(0.021)	(0.021)	(0.022)			
Unemployment Rate	0.003	0.003*	0.003*	0.003			
	(0.002)	(0.002)	(0.002)	(0.002)			
Observations	1,243,296	1,243,274	1,243,177	1,243,296	1,243,296	1,243,274	1,243,177
State x Year FE	Yes	Yes	Yes	Yes	No	No	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	No	No	Yes	Yes	No	No
NAICS3 x Year FE	No	Yes	No	No	No	Yes	No
NAICS4 x Year FE	No	No	Yes	No	No	No	Yes
County x Year FE	No	No	No	No	Yes	Yes	Yes
Adjusted R^2	0.697	0.701	0.705	0.697	0.714	0.718	0.722
Treatment Effects							
Labor Exposure=15				-1.9***			
				(0.007)			
Labor Exposure=16				-2.1***			
				(0.008)			
Labor Exposure=17				-2.3***			
				(0.008)			
Labor Exposure=18				-2.5***			
				(0.008)			
Labor Exposure=19				-2.7***			
				(0.008)			
Labor Exposure=20				-2.9***			
				(0.008)			

Table 4. Heat Shocks and Entrepreneurship: Dynamic Effects

This table presents the dynamic treatment effects of past, present, and future heat shocks on present entrepreneurship at the county-by-NAICS4 industry level. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level in year t. The key independent variables are the interaction terms between *Labor Exposure* and indicators of heat shocks for the respective years from $t-3$ to $t+3$. *Heat Shocks (T-3)*, *Heat Shocks (T-2)*, *Heat Shocks (T-1)*, *Heat Shocks (T)*, *Heat Shocks (T+1)*, *Heat Shocks (T+2)*, *Heat Shocks (T+3)* represent heat shocks occurring in years *t-3*, *t-2*, *t-1*, *t*, *t+1*, *t+2*, and *t+3*, respectively. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include heat shocks in each year, *Labor Exposure*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+New Firms)					
Heat Shocks (T-3) × Labor Exposure	-0.001***				-0.001***	-0.001*
	(0.000)				(0.000)	(0.000)
Heat Shocks (T-2) × Labor Exposure		-0.001***			-0.001***	-0.001***
		(0.000)			(0.000)	(0.000)
Heat Shocks (T-1) × Labor Exposure			-0.002***		-0.002***	-0.001***
			(0.000)		(0.000)	(0.000)
Heat Shocks (T) × Labor Exposure				-0.001***	-0.001**	0.000
				(0.000)	(0.000)	(0.000)
Heat Shocks (T+1) × Labor Exposure						-0.000
						(0.000)
Heat Shocks (T+2) × Labor Exposure						0.000
						(0.000)
Heat Shocks (T+3) × Labor Exposure						0.000
						(0.000)
Observations	770,865	882,942	1,026,625	1,243,296	770,865	537,187
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.882	0.881	0.874	0.864	0.882	0.883

Table 5. Heat Shocks and Entrepreneurship: Labor Utilization in Production

This table presents the treatment effects of heat shocks on entrepreneurship conditional on labor utilization in production. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks*, *Heat Shocks* × *Labor Exposure*, and *Heat Shocks* × *Labor Exposure* × *High K/L*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). *High K/L* is an indicator that equals to one if the NAICS4 industry's capital-labor ratio (*K/L*) is above the sample median, and zero otherwise. The industry-level *K/L* is calculated as the median firm's property, plant, and equipment (PPENT) per employee within each NAICS4 industry. The data on firm-level PPENT and employment is from Compustat. Controls include *Labor Exposure*, *High K/L*, other two-way interactions, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	Log(1+New Firms)			
Heat Shocks	0.010**		0.016***	
	(0.005)		(0.005)	
Heat Shocks × Labor Exposure	-0.002***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Heat Shocks × Labor Exposure × High K/L			0.002***	0.001**
			(0.001)	(0.001)
Observations	700,141	700,124	700,141	700,124
Controls	Yes	Yes	Yes	Yes
State x Year FE	Yes	No	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes
Adjusted R^2	0.846	0.862	0.846	0.862

Table 6. Heat Shocks and Entrepreneurship: Credit Access

This table presents the treatment effects of heat shocks on credit access using the origination of small business loans in the SBA 7(a) loan program. The dependent variable in Panel A is *Log(Loan Amount)*, the natural logarithm of the loan amount. The dependent variable in Panel B is *Log(Loan Interest Rate)*, the natural logarithm of the loan interest rate. The key independent variables are *Heat Shocks* and the interaction term (*Heat Shocks* × *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, the natural logarithm of the loan amount guaranteed by the SBA (*Log(SBA Loan Amount)*), the natural logarithm of loan maturity in months (*Log(Maturity)*), the natural logarithm of one plus the number of jobs supported by the loan (*Log(1+Jobs Supported)*), an indicator that equals to one if the loan is a revolving line of credit and zero if it's a term loan (*Credit Line*), the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). Panel B further controls for the natural logarithm of the loan amount (*Log(Loan Amount)*). The sample period is from 1999 to 2019 in Panel A, and from 2008 to 2019 in Panel B. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Loan Amount

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log(Loan Amount)									
Heat Shocks	-0.0038**	-0.0041**	-0.0041**	-0.0031**	0.0047*	0.0014	0.0013	0.0015		
	(0.0020)	(0.0019)	(0.0019)	(0.0015)	(0.0026)	(0.0024)	(0.0024)	(0.0018)		
Heat Shocks × Labor Exposure					-0.0008***	-0.0005***	-0.0005***	-0.0004***	-0.0004***	-0.0003***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,138,122	1,138,122	1,138,120	1,137,644	1,138,122	1,138,122	1,138,120	1,137,644	1,127,738	1,127,575
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
SBA Office FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Bank FE	No	No	No	Yes	No	No	No	Yes	Yes	Yes
County x Year FE	No	No	No	No	No	No	No	No	Yes	Yes
NAICS4 x Year FE	No	No	No	No	No	No	No	No	No	Yes
Adjusted R^2	0.988	0.988	0.988	0.990	0.988	0.988	0.988	0.990	0.991	0.991
Treatment Effects										
Labor Exposure=15					-0.008***	-0.006***	-0.006***	-0.005***		
					(0.002)	(0.002)	(0.002)	(0.002)		
Labor Exposure=20					-0.012***	-0.009***	-0.009***	-0.007***		
					(0.002)	(0.002)	(0.002)	(0.002)		

Panel B. Loan Interest Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log(Loan Interest Rate)									
Heat Shocks	0.0038	0.0039*	0.0039*	0.0036*	-0.0039	-0.0044	-0.0045	-0.0025		
	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0031)	(0.0030)	(0.0030)	(0.0030)		
Heat Shocks × Labor Exposure					0.0007***	0.0008***	0.0008***	0.0006***	0.0006***	0.0005***
					(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	557,370	557,370	557,370	556,958	557,370	557,370	557,370	556,958	551,603	551,482
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
SBA Office FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Bank FE	No	No	No	Yes	No	No	No	Yes	Yes	Yes
County x Year FE	No	No	No	No	No	No	No	No	Yes	Yes
NAICS4 x Year FE	No	No	No	No	No	No	No	No	No	Yes
Adjusted R^2	0.436	0.439	0.439	0.507	0.436	0.439	0.439	0.507	0.513	0.516
Treatment Effects										
Labor Exposure=15					0.007***	0.008***	0.008***	0.006***		
					(0.002)	(0.002)	(0.002)	(0.002)		
Labor Exposure=20					0.011***	0.012***	0.012***	0.009***		
					(0.003)	(0.003)	(0.003)	(0.002)		

Table 7. Heat Shocks and Entrepreneurship: Expected Heat Risks

This table presents the treatment effects of heat shocks on entrepreneurship conditional on expected heat risks. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks* $\times$ *Labor Exposure*, *Heat Shocks* $\times$ *Labor Exposure* $\times$ *High Projection*, and *Heat Shocks* $\times$ *Labor Exposure* $\times$ *Projection*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). *Projection* is the projected differences in extreme heat days as compared to the historical period, scaled to one-tenth. *High Projection* is an indicator that equals to one if a county's projected temperature increase is above the sample median, and zero otherwise. Controls include *Labor Exposure*, *High Projection* (column (1)), *Projection* (column (2)), and other two-way interactions. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)
	Log(1+New Firms)	
Heat Shocks $\times$ Labor Exposure	-0.001	0.000
	(0.001)	(0.001)
Heat Shocks $\times$ Labor Exposure x High Projection	-0.002**	
	(0.001)	
Heat Shocks $\times$ Labor Exposure x Projection		-0.001*
		(0.001)
Observations	1,242,894	1,242,894
Controls	Yes	Yes
County x NAICS4 FE	Yes	Yes
NAICS2 x Year FE	Yes	Yes
County x Year FE	Yes	Yes
Adjusted R^2	0.864	0.864

Table 8. Long-term Survival of New Entrant Firms in Heat-Exposed Industries

This table presents the analysis of the long-term survival of new entrant firms following heat shocks. The dependent variable is *Log(Survival Years)* in columns (1) - (3), the natural logarithm of the average number of years that newly created firms survive until 2022, measured at the county-by-NAICS4 industry level. The dependent variable is *Log(6-Year Jobs)* in columns (4) - (6), the natural logarithm of the average number of employment that newly created firms have six years after founding, measured at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks* and the interaction term (*Heat Shocks* $\times$ *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Survival Years)			Log(6-Year Jobs)		
Heat Shocks	0.007*	-0.004		0.014**	0.001	
	(0.004)	(0.005)		(0.007)	(0.009)	
Heat Shocks $\times$ Labor Exposure		0.001***	0.001***		0.001**	0.002***
		(0.000)	(0.000)		(0.001)	(0.001)
Observations	573,074	573,074	570,136	573,074	573,074	570,136
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	Yes	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.376	0.377	0.402	0.360	0.360	0.371
Treatment Effects						
Labor Exposure=15		0.012***			0.020***	
		(0.004)			(0.007)	
Labor Exposure=20		0.018***			0.027***	
		(0.006)			(0.009)	

Table 9. New Establishments Created by Existing Firms

This table presents the treatment effects of heat shocks on the creation of new establishments by existing firms and overall establishment creation. The dependent variable is *Log(1+ New Establishments), Existing* in columns (1) - (3), the natural logarithm of one plus the number of new establishments created by existing firms at the county-by-NAICS4 industry level. The dependent variable is *Log(1+ New Establishments), All* in columns (4) - (6), the natural logarithm of one plus the number of new establishments created by both new and existing firms at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks* and the interaction term (*Heat Shocks* $\times$ *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+New Establishments), Existing			Log(1+New Establishments), All		
Heat Shocks	-0.001	-0.007***		-0.007*	0.006	
	(0.002)	(0.002)		(0.004)	(0.004)	
Heat Shocks $\times$ Labor Exposure		0.001***	0.001***		-0.001***	-0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
Observations	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	Yes	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.663	0.663	0.679	0.849	0.849	0.865
Treatment Effects						
Labor Exposure=15		0.002			-0.014***	
		(0.002)			(0.004)	
Labor Exposure=20		0.005**			-0.021***	
		(0.002)			(0.005)	

Table 10. Macroeconomic Effects of Heat Shocks on Total County Income

This table presents the macroeconomic effects of heat shocks on county-level total personal income. The dependent variable is *Log(Total County Income)*, the natural logarithm of the county-level total personal income from the BEA. The key independent variables are *Heat Shocks* and the interaction term *Heat Shocks* $\times$ *Labor Exposure*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes a county's exposure to climate risks through the labor channel. The county-level exposure variable is calculated as the employment-weighted average of the industry-level measure of labor exposure defined in Equation (2). The weight is the number of employees working in a NAICS4 industry and a county from QCEW. Controls include *Labor Exposure* and the natural logarithm of the county's total population (*Log(Population)*). NAICS2 and NAICS4 industry codes denote the leading industries at the two-digit and four-digit NAICS code levels in a county, respectively. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Total County Income)					
Heat Shocks	-0.005***	-0.006***	-0.003*	0.012	0.018**	0.017*
	(0.001)	(0.001)	(0.002)	(0.009)	(0.009)	(0.009)
Heat Shocks $\times$ Labor Exposure				-0.002**	-0.002**	-0.002**
				(0.001)	(0.001)	(0.001)
Observations	62,827	62,814	62,814	62,814	62,814	62,094
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No
NAICS2 x Year FE	No	Yes	Yes	Yes	Yes	No
NAICS4 x Year FE	No	No	No	No	No	Yes
Region x Year FE	No	No	Yes	No	Yes	Yes
Adjusted R^2	0.998	0.998	0.998	0.998	0.998	0.998
Treatment Effects						
Labor Exposure=15				-0.014***	-0.012***	-0.010**
				(0.004)	(0.004)	(0.004)
Labor Exposure=20				-0.023***	-0.021***	-0.019**
				(0.008)	(0.008)	(0.009)

Internet Appendix to

"How Does Climate Change Reshape U.S. Entrepreneurship? A Labor Channel"

Zhanbing Xiao

Sep 2024

A Anecdotal Evidence on the Impact of Extreme Heat on Small Businesses

In this section, I present several pieces of anecdotal evidence from various sources that highlight the significant heat-related risks and costs faced small businesses due to climate change.

[1] Heat Wave 2012 Taking Toll On Small Businesses, Physically And Financially

Janean Chun, *The Huffington Post*, 2012

[2] Record-Breaking Heat Waves Impact Small Businesses and Employees

Editorial, *SmallBizTechnology*, 2023

[3] The Impact of Extreme Heat on Small Businesses and the Economy

Becca Williams, *SmallBizTechnology*, 2023

[4] Weeks of Extreme Heat Strain Small Businesses and Economy

Scott Patterson, Jennifer Hiller, and Alyssa Lukpat, *The Wall Street Journal*, 2023

[5] Working Hours Drop as Temperatures Rise Nationwide

Luke Pardue, *Gusto*, 2023

[6] 'You Feel Death at Your Doorstep but Have No Choice': Extreme Heat Takes Toll on Outdoor Workers

Alicia Wallace, *CNN*, 2024

[7] First There Was the Derecho, Now Heat Is Hurting Texas Small Businesses

Erica Grieder, *Houston Chronicle*, 2024

B Robustness of Results in Table 2

In this section, I present additional analyses to demonstrate the robustness of the results in Table 2 on heat shocks and firm creation.

B.1 Alternative Definitions of Heat Shocks

In the main analysis, heat shocks are defined as cases where a county has at least 45 summer days with temperatures exceeding the rolling 90^{th} percentile and at least 240 summer days with temperatures above 30°C. In Table B.1, I use alternative thresholds to define heat shocks. In particular, Panel A tests different thresholds for defining relative heat shocks. In columns (1) - (2), heat shocks are redefined as instances where the county has at least 40 summer days with temperatures exceeding the rolling 90^{th} percentile, and at least 240 summer days with temperatures above 30°C. Columns (3) - (4) increase the threshold from 40 to 45 days, while maintaining the requirement of 240 absolute hot days. Columns (5) - (6) increase the threshold to 50 days, and columns (7) - (8) increase the threshold to 60 days. As shown, the coefficient estimate for the interaction term *Heat Shocks* $\times$ *Labor Exposure* remains negative and statistically significant. The economic magnitude increases from -1.7% in column (1) to -2.4% in column (3) as the threshold rises from 40 to 45 days, then stabilizes at around -2%.

Meanwhile, Panel B tests different thresholds for defining absolute heat shocks. In columns (1) - (2), heat shocks are redefined as instances where the county has at least 45 summer days with temperatures exceeding the rolling 90^{th} percentile, and at least 120 summer days with temperatures above 30°C. Columns (3) - (4) increase the threshold from 120 to 160 days, while maintaining the requirement of 45 relative hot days. Columns (5) - (6) increase the threshold to 200 days, and columns (7) - (8) increase the threshold to 240 days. The analysis shows that the results hold, with the economic magnitude increasing from -1.3% in column (1) to -2.4% in column (7) as the threshold rises from 120

to 240 days.

B.2 Alternative Sample Constructions

In the main analysis, I focus on the top 20 industries in a county based on total employment, as industries outside the top 20 contribute, on average, only 0.3% to the county's employment. In Table B.2, I reconstruct the sample using alternative methods to demonstrate the robustness of the results. In column (1), I repeat the analysis by including only the top 10 industries in a county. Columns (2), (3), and (4) differ by including the top 15, 25, and 30 industries, respectively. Furthermore, beyond constructing samples based on industry employment ranks, I include industries that account for more than 1% of total employment in a county in column (5), and those contributing more than 3% in column (6). The coefficient estimate for the interaction term *Heat Shocks* $\times$ *Labor Exposure* remains negative and statistically significant across all six columns.

B.3 Alternative Empirical Specifications

I also employ alternative empirical specifications to address concerns over the log form of the dependent variable (Cohn et al., 2022). The results are reported in Table B.3. Columns (1) - (2) use a linear regression model and the dependent variable is the number of new firms created at the county-by-NAICS4 industry level. Column (3) - (4) use a linear regression model and the dependent variable is a dummy indicating that at least one new firm is created at the county-by-NAICS4 industry level. Column (5) - (6) use a linear regression model and the dependent variable is the number of new firms created scaled by the number of existing establishments in the same NAICS4 industry and county from the previous year. Column (7) - (8) use the fixed effects Poisson model and the dependent variable is the number of new firms created at the county-by-NAICS4 industry level. The results hold across all columns and the economic magnitude in column (8) is even larger than that in column (4) of Table 2 (*-0.004 vs. -0.002*).

B.4 Sector Breakdowns and Excluding Alternative Channels

In addition to the labor channel, heat risks could discourage entrepreneurship through a consumer demand channel. That is, extreme heat may push consumers toward indoor activities, reducing visits to stores and restaurants and resulting in lower sales (Addoum et al., 2023). Moreover, heat risks could harm crop yields, thereby deterring the formation of new firms in the agricultural sector. I exclude these alternative channels in Table B.4 and B.5.

Specifically, in Table B.4 column (1), I repeat the analysis in Table 2 by excluding the agriculture, mining, oil, and gas sectors (*NAICS2 11 & 21*). Column (2) further excludes consumer-oriented industries (*NAICS2 44, 45, 61, 62, 71, & 72*). The results hold in both columns and the economic magnitudes are the same as in column (4) of Table 2. This evidences suggests that my findings are not likely driven by lower agricultural outputs or consumer demand. Furthermore, I split the remaining industries into two categories in columns (3) and (4): those engaged in real activities (*NAICS2 23, 31-33, 42, & 48 - 49*) and those in non-consumer-oriented service sectors (*NAICS2 51, 53, 54, 56, & 81*). I find that the negative effect of heat shocks on entrepreneurship exists in both categories. Interestingly, the economic effect is larger in service sectors compared to real activity sectors (*-0.003 in column (4) vs. -0.002 in column (3)*). This finding is consistent with Xiao (2021), which documents that service sectors suffer larger heat-related losses in labor productivity relative to real activity sectors.

To provide further evidence excluding the consumer demand channel, I repeat the analysis by excluding non-tradable industries in columns (1) - (2) of Table B.5, following the classification method in Mian and Sufi (2014). The results hold and the economic magnitudes are the same as in column (4) of Table 2. The results also hold in columns (3) - (6) after excluding construction industries.

B.5 Controlling for Other Climate Events

By construction, the labor exposure measure (*Labor Exposure*) captures a NAICS4 industry's exposure to climate events other than extreme heat, such as extreme cold and precipitation. To avoid biases introduced by other climate events, I control for each NAICS4 industry's exposure to cold shocks and precipitation in Table B.6 columns (1) - (3). I also control for each NAICS4 industry's exposure to all non-heat-related climate events covered by SHELDUS in column (4). The significance of *Heat Shocks* $\times$ *Labor Exposure* remains and the economic magnitude is the same as that in column (4) of Table 2.

B.6 Alternative Data on County-level Entrepreneurship

In addition to YTS, I also measure entrepreneurship using business registration data provided by Fazio et al. (2019).[1] A limitation of this data, compared to YTS, is that it is only available at the county level and lacks detailed breakdowns at the NAICS4 industry level. Consequently, my analysis using the data is conducted at the county level.

Table B.7 presents the results. The dependent variable is *Log(1+New Business Registrants)*, the natural logarithm of one plus the quantity of new business registrants within a given population at the county level. The variable *Labor Exposure* denotes a county's exposure to climate risks through the labor channel. The county-level exposure variable is calculated as the employment-weighted average of the industry-level measure of labor exposure defined in Equation (2). The weight is the number of employees working in a NAICS4 industry and a county from QCEW. The NAICS2 and NAICS4 industry codes used in fixed effects denote the leading industries based on total employment at the two-digit and four-digit code levels in a county, respectively.

As shown, the analysis yields consistent findings with those in Table 2. In columns (1) - (3), heat shocks negatively affect on county-wide new firm creation. In column (3), the

[1]The data can be accessed from "THE STARTUP CARTOGRAPHY PROJECT." Refer to Fazio et al. (2019) for more detailed information.

average county's entrepreneurship drops by 1.5% following heat shocks. Importantly, the coefficient estimate of the interaction term *Heat Shocks* $\times$ *Labor Exposure* is also negative and statistically significant, suggesting that the decline in new firm creation is primarily concentrated in counties highly exposed to heat through the labor channel. The economic impacts are even more substantial than those reported in 2. For counties at the 75^{th} percentile of heat exposure, entrepreneurial activities drop by 3.7% following heat shocks, while those with the highest exposure experience a 6.2% drop. Overall, this evidence further supports the findings in the main analyses.

Table B.1. Heat Shocks and Entrepreneurship: Alternative Definitions of Heat Shocks

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms by using alternative definitions of heat shocks. In Panel A columns (1) - (2), heat shocks are defined as instances where the county has at least 40 summer days with temperatures exceeding the rolling 90^{th} percentile, and at least 240 summer days with temperatures above 30°C. Columns (3) - (4) increase the threshold from 40 to 45 days, while maintaining the requirement of 240 absolute hot days. Columns (5) - (6) increase the threshold to 50 days, and columns (7) - (8) increase the threshold to 60 days. In Panel B columns (1) - (2), heat shocks are redefined as instances where the county has at least 45 summer days with temperatures exceeding the rolling 90^{th} percentile, and at least 120 summer days with temperatures above 30°C. Columns (3) - (4) increase the threshold from 120 to 160 days, while maintaining the requirement of 45 relative hot days. Columns (5) - (6) increase the threshold to 200 days, and columns (7) - (8) increase the threshold to 240 days. In both panels, the dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables are *Heat Shocks* and and the interaction term (*Heat Shocks* × *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Adjustments in Defining Relative Heat Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(1+New Firms)							
	40		45		50		60	
Heat Shocks	0.011**		0.010**		0.009**		0.011**	
	(0.004)		(0.004)		(0.004)		(0.005)	
Heat Shocks × Labor Exposure	-0.001***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.848	0.864	0.848	0.864	0.848	0.864	0.848	0.864
Treatment Effects								
Labor Exposure=15	-1.0**		-1.6***		-1.4***		-1.2***	
	(0.004)		(0.004)		(0.004)		(0.004)	
Labor Exposure=20	-1.7***		-2.4***		-2.1***		-2.0***	
	(0.005)		(0.005)		(0.005)		(0.005)	

Panel B. Adjustments in Defining Absolute Heat Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(1+New Firms)							
	120		160		200		240	
Heat Shocks	0.002		0.002		0.006		0.010**	
	(0.003)		(0.004)		(0.004)		(0.004)	
Heat Shocks × Labor Exposure	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296	1,243,296
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.848	0.864	0.848	0.864	0.848	0.864	0.848	0.864
Treatment Effects								
Labor Exposure=15	-0.9***		-1.0***		-1.0***		-1.6***	
	(0.003)		(0.003)		(0.004)		(0.004)	
Labor Exposure=20	-1.3***		-1.5***		-1.5***		-2.4***	
	(0.003)		(0.004)		(0.004)		(0.005)	

Table B.2. Heat Shocks and Entrepreneurship: Alternative Sample Constructions

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms by using alternative methods of sample construction. Columns (1), (2), (3), and (4) reconstruct the sample by including the top 10, 15, 25, and 30 industries in a county, respectively. The sample in column (5) includes industries that account for more than 1% of total employment in a county, while in column (6) includes those contributing more than 3% of total employment. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables is the interaction term *Heat Shocks* $\times$ *Labor Exposure*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, *Heat Shocks*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+New Firms)					
	Top Industries				Employment Share	
	Top 10	Top 15	Top 25	Top 30	1%	3%
Heat Shocks x Labor Exposure	-0.002***	-0.002***	-0.001***	-0.001***	-0.002***	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	618,330	929,978	1,557,442	1,870,875	1,413,161	397,799
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.877	0.870	0.858	0.852	0.865	0.869

Table B.3. Heat Shocks and Entrepreneurship: Alternative Empirical Specifications

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms by using alternative empirical specifications. Columns (1) - (2) use a linear regression model and the dependent variable is the number of new firms created at the county-by-NAICS4 industry level. Column (3) - (4) use a linear regression model and the dependent variable is a dummy indicating that at least one new firm is created at the county-by-NAICS4 industry level. Column (5) - (6) use a linear regression model and the dependent variable is the number of new firms created scaled by the number of existing establishments in the same NAICS4 industry and county from the previous year. Column (7) - (8) use the fixed effects Poisson model and the dependent variable is the number of new firms created at the county-by-NAICS4 industry level. The key independent variables is the interaction term *Heat Shocks* $\times$ *Labor Exposure*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, *Heat Shocks*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear						Possion	
	No. New Firms		No. New Firms>0		New Firm Creation Rate		No. New Firms	
Heat Shocks $\times$ Labor Exposure	-0.021***	-0.031***	-0.001***	-0.001***	-0.046***	-0.044***	-0.004***	-0.004***
	(0.008)	(0.006)	(0.000)	(0.000)	(0.007)	(0.007)	(0.001)	(0.001)
Observations	1,243,296	1,243,296	1,243,296	1,243,296	1,167,011	1,167,011	1,074,282	1,057,350
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.773	0.839	0.511	0.524	0.197	0.217	0.868	0.880

Table B.4. Heat Shocks and Entrepreneurship: Sector Breakdowns

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms using sector-based subsamples. Columns (1) excludes the agriculture, mining, oil, and gas sectors (*NAICS2 11 & 21*). Column (2) further excludes consumer-oriented industries (*NAICS2 44, 45, 61, 62, 71, & 72*). Columns (3) and (4) further split the remaining industries into two categories: those conducting real activities (*NAICS2 23, 31-33, 42, & 48 - 49*) and those in non-consumer-oriented service sectors (*NAICS2 51, 53, 54, 56, & 81*). The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables is the interaction term *Heat Shocks* $\times$ *Labor Exposure*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, *Heat Shocks*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	Log(1+New Firms)			
	Industries Excluded		Industries Included	
	Agriculture/Mining/Oil/Gas	Consumer-oriented	Real Activities	Services
Heat Shocks $\times$ Labor Exposure	-0.002***	-0.002***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	1,216,466	510,132	343,262	147,887
Controls	Yes	Yes	Yes	Yes
County x NAICS4 FE	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.867	0.896	0.852	0.913

Table B.5. Heat Shocks and Entrepreneurship: Excluding Non-Tradable and Construction Industries

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms by excluding non-tradable and construction industries. Columns (1) and (2) exclude non-tradable industries. Columns (3) and (4) exclude construction industries. Columns (5) and (6) exclude non-tradable and construction industries. The classification method of tradable and non-tradable industries is from Mian and Sufi (2014). The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables is the interaction term *Heat Shocks* $\times$ *Labor Exposure*. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, *Heat Shocks*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+New Firms)					
	Non-tradable Industries		Construction Industries		Non-tradable and Construction Industries	
Heat Shocks $\times$ Labor Exposure	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	950,620	950,611	860,402	860,386	756,204	756,186
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	No	Yes	No	Yes	No
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.853	0.869	0.843	0.858	0.851	0.865

Table B.6. Heat Shocks and Entrepreneurship: Controlling for Other Climate Events

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms by controlling for exposures to other climate events. Columns (1) and (2) control for cold shocks. Column (3) controls for cold shocks and total precipitation. Column (4) controls for all non-heat-related climate events covered by SHELDUS. The dependent variable is *Log(1+New Firms)*, the natural logarithm of one plus the number of new firms created at the county-by-NAICS4 industry level. The key independent variables are the interaction terms. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). Controls include *Labor Exposure*, *Heat Shocks*, *Cold Shocks*, *Precipitation*, *Non-Heat Climate Events*, *Labor Exposure*, the natural logarithm of the county's total population (*Log(Population)*), the natural logarithm of the county's income per capita (*Log(Income per Capita)*), and the county's unemployment rate (*Unemployment Rate*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	Log(1+New Firms)			
Heat Shocks × Labor Exposure	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Cold Shocks × Labor Exposure	-0.001***	-0.001***	-0.001***	
	(0.000)	(0.000)	(0.000)	
Precipitation × Labor Exposure			-0.001*	
			(0.000)	
Non-Heat Climate Events × Labor Exposure				0.001
				(0.096)
Observations	1,243,296	1,243,296	1,243,296	1,243,296
State x Year FE	Yes	No	No	No
County x NAICS4 FE	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes
County x Year FE	No	Yes	Yes	Yes
Adjusted R^2	0.847	0.864	0.864	0.864

Table B.7. Heat Shocks and Entrepreneurship: New Business Registrants

This table presents robustness checks of the treatment effects of heat shocks on the creation of new firms using alternative data on entrepreneurship, provided by Fazio et al. (2019). The dependent variable is *Log(1+New Business Formation Rate)*, the natural logarithm of one plus the quantity of new business registrants within a given population at the county level. The key independent variables are *Heat Shocks*, *Labor Exposure*, and the interaction term of the two (*Heat Shocks* $\times$ *Labor Exposure*). *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes a county's exposure to climate risks through the labor channel. The county-level exposure variable is calculated as the employment-weighted average of the industry-level measure of labor exposure defined in Equation (2). The weight is the number of employees working in a NAICS4 industry and a county from QCEW. NAICS2 and NAICS4 industry codes denote the leading industries at the two-digit and four-digit NAICS code levels in a county, respectively. The sample period is from 1999 to 2016. Numbers in parentheses are standard errors. Standard errors are clustered at the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+New Business Formation Rate)					
Heat Shocks	-0.083***	-0.012**	-0.015**	0.153*	0.032	0.037
	(0.031)	(0.006)	(0.006)	(0.083)	(0.026)	(0.028)
Heat Shocks $\times$ Labor Exposure				-0.023***	-0.004*	-0.005*
				(0.007)	(0.002)	(0.003)
Labor Exposure				0.021***	0.006***	0.008***
				(0.006)	(0.002)	(0.002)
Observations	53,612	52,575	51,933	52,594	52,575	51,933
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes
NAICS2 x Year FE	No	Yes	No	No	Yes	No
NAICS4 x Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.754	0.970	0.970	0.748	0.970	0.970
Treatment Effects						
Labor Exposure=15				-0.195***	-0.032**	-0.037***
				(0.043)	(0.013)	(0.014)
Labor Exposure=20				-0.310***	-0.053**	-0.062**
				(0.072)	(0.025)	(0.026)

C Supplementary Figures, Tables, and Analyses

In this section, I provide additional figures, tables, and analyses to complement and further extend the findings presented in the main part of this paper.

C.1 Treatment Effects of Heat Shocks on Labor Productivity: Xiao (2021)

Figure C.1, drawn from Xiao (2021), presents the treatment effects of heat shocks on firm-level labor productivity across labor exposure categories (*Labor Exposure = 1 to 20*). The figure demonstrates that extreme heat significantly reduces firm-level labor productivity, but only among firms employing a large number of heat-exposed workers in production. Specifically, labor productivity for firms at the 75^{th} percentile of heat exposure drops by 1.9% following heat shocks, while firms with the highest exposure experience a decline of 3%. Given that labor costs are sticky, this figure supports the conjecture that extreme heat increases labor costs per unit of output, thereby discouraging entrepreneurship when heat risks materialize.

C.2 Summary Statistics: Table 6

Table C.1 presents summary statistics for variables used in empirical analysis in Table 6. The loan data is from the SBA 7(a) loan program.

Figure C.1. Treatment Effects of Heat Shocks on Labor Productivity: Xiao (2021)

This figure presents the treatment effects of heat shocks on firm-level labor productivity across labor exposure categories (*Labor Exposure = 1 to 20*), as drawn from Xiao (2021).

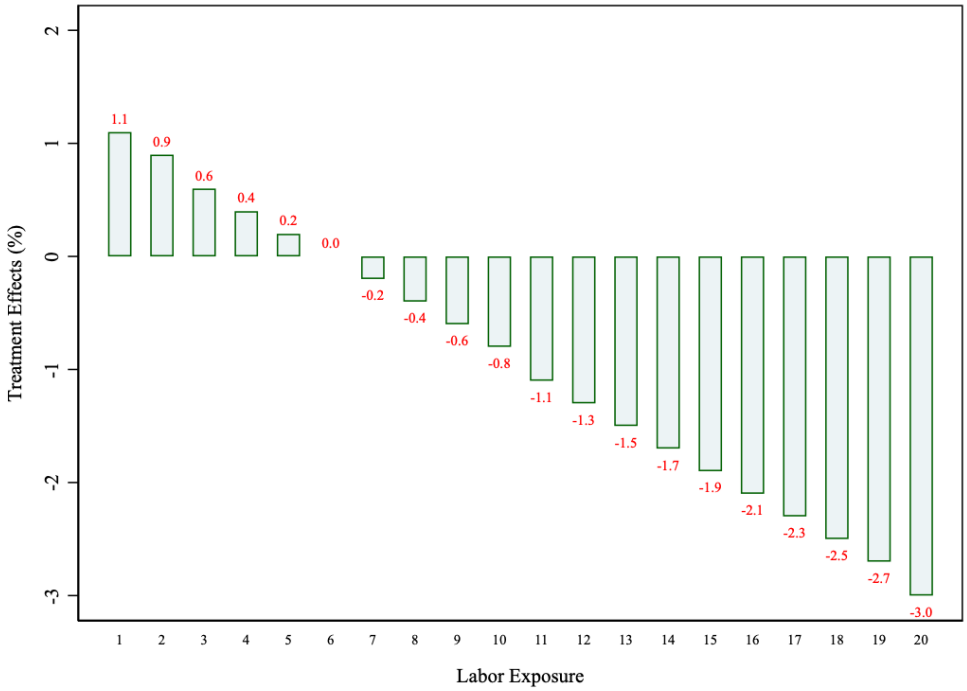


Table C.1. Summary Statistics: Table 6

This table presents summary statistics for variables used in empirical analyses in Table 6. *Log(Loan Amount)* is the natural logarithm of the loan amount. *Log(Loan Interest Rate)* is the natural logarithm of the loan interest rate. *Heat Shocks* is an indicator that equals to one if heat shocks defined in Equation (1) occur in the county, and zero otherwise. *Labor Exposure* denotes the NAICS4 industry's exposure to climate risks through the labor channel, defined in Equation (2). *Log(SBA Loan Amount)* is the natural logarithm of the loan amount guaranteed by the SBA. *Log(Maturity)* is the natural logarithm of loan maturity in months. *Log(1+Jobs Supported)* is the natural logarithm of one plus the number of jobs supported by the loan. *Credit Line* is an indicator that equals to one if the loan is a revolving line of credit and zero it it's a term loan. *Log(Population)* is the natural logarithm of the county's total population. *Log(Income per Capita)* is the natural logarithm of the county's income per capita. *Unemployment Rate* is the county's unemployment rate. The sample period is from 1999 to 2019, except that *Log(Loan Interest Rate)* is available for 2008 - 2019.

	N	**Mean**	**P25**	**Median**	**P75**	**SD**
Log(Loan Amount)	1,138,184	11.433	10.309	11.415	12.506	1.475
Log(Interest Rate)	557,488	1.853	1.705	1.792	2.015	0.222
Heat Shocks	1,138,184	0.103	0	0	0	0.304
Labor Exposure	1,138,184	10.483	5	10	17	6.433
Log(SBA Amount)	1,138,184	10.961	9.616	10.82	12.142	1.606
Maturity	1,138,184	110.088	63	84	120	75.167
Log(1+Jobs Supported)	1,138,184	1.624	0.693	1.609	2.398	1.114
Credit Line	1,138,184	0.313	0	0	1	0.464
Log(Population)	1,138,184	13.117	12.115	13.285	14.124	1.518
Log(Income per Capita)	1,138,184	10.637	10.431	10.615	10.821	0.31
Unemployment Rate	1,138,184	5.525	4	5	7	2.168

References

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

Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146*(2), 529–551.

Fazio, C., S. Stern, J. Guzman, Y. Liu, and R. Andrews (2019). The startup cartography project: Measuring and mapping entrepreneurial ecosystems. *Research Policy*.

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

Xiao, Z. (2021). Labor exposure to climate risk, productivity loss, and capital deepening. *Available at SSRN 4475467*.