IMPACT OF LOCAL TEMPERATURE SHOCKS ON SMALL BUSINESSES IN THE U.S. *

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Abstract

Using sales data from a major payment processor for 15 million small businesses with \$10,250 monthly median sales, we analyze how temperature shocks in the local area impact small business sales, store visits, and closures. Through event study regressions using weekly sales during 2021-2022, we document a 2% decrease in weekly sales revenue when the average daily maximum temperature during the week exceeds 100°F and a 10% decrease when the average daily minimum temperature falls below 32°F. Using monthly sales data during 2006–2023, we find that small businesses experience a 7.2 (11.6) percentage point reduction in sales per median impacted day during historically unusual heat (cold) shocks. Aggregating to the county-industry-month level, we find lost sales of 12.8% per median impacted day for heat shocks, suggesting that some of the sales, especially discretionary spending, don't transfer to normal days. A one standard deviation increase in hot days (8.4 days) increases the small business exit rate by 4.7%. Our results show how heat and cold shocks can significantly negatively affect small business sales, particularly for small, young establishments in discretionary sectors. Our findings highlight the need for targeted policies to enhance the climate resilience of small businesses.

Keywords: Small Business, Financial Distress, Climate Change

JEL Classification: G33, G38, J30

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1 Introduction

Since 1979, the average surface temperature across the contiguous United States has been increasing at an accelerated rate of between 0.32°F and 0.55°F per decade, compared to 0.17°F per decade from 1900s to 1970s (NOAA (2023), see Figure 1 and Figure 2). The Intergovernmental Panel on Climate Change (IPCC, 2023) reports similar trends on a global scale, noting that average temperatures are rising globally, and their volatility has increased, leading to a higher frequency of temperature shock events. According to climate scientists, the trend of heat waves in the U.S. is predicted to continue. It is projected that by the mid-twenty-first century, the frequency of heat waves could increase fivefold, their duration could double, and the total number of hot days could increase sixfold (Meehl and Tebaldi, 2004; Lau and Nath, 2012). For instance, Phoenix hit 110°F on 54 days in 2023, setting a new record and severely impacting sales of small businesses.[1]

Our study aims to understand the impact of temperature shocks on small businesses in the United States. Small businesses are a crucial part of the US economy, making up more than 90% of all businesses and contributing nearly 50% of non-farm GDP, according to the Bureau of Labor Statistics. The Small Business Administration (SBA) reports that small businesses employ 46% of the private workforce and contribute approximately 40% of the total payroll. Small businesses are more vulnerable to the adverse effects of extreme weather conditions. For instance, the hospitality industry may experience a decline in tourism due to extreme heat, resulting in a loss of revenue. Reduced productivity or work stoppages can also cause small businesses to turn away customers or delay orders, leading to further revenue and profit losses. However, organizations that have invested in cooling systems for their workplaces or have the ability to generate online sales can be better equipped to handle extreme weather events and minimize their impact. Furthermore, some small businesses in specific sectors may experience increased revenue, such as those offering air conditioning repair or indoor recreation services. Therefore, it is unclear whether temperature shocks will impact sales for small businesses.

We provide the first evidence of the impact of temperature shock events on the weekly sales of small businesses.[2] We utilize an establishment-level weekly sales dataset from one of the largest payment processors in the country, which covers over 15 million small busi-

[1]See WSJ Report here: `https://tinyurl.com/mr2vthes`

[2]Recent studies focusing on larger-sized businesses, such as Addoum, Ng, and Ortiz-Bobea (2020), found no significant impact of temperature shocks on sales for businesses owned by publicly listed firms. Later, Addoum, Ng, and Ortiz-Bobea (2023), find the bi-directional effects of temperature shocks on publicly listed firms, where some industries are harmed while others are benefited. Our study not only complements previous research but also provides compelling evidence from the revenue side. The previous research results show that the increased costs are linked to energy costs.

nesses. The data's extensive coverage allows us to analyze weekly temperature variations at the county level where establishments are located. We consider these weekly temperature shocks as random "weather" events from the climate distribution for a given geographical area. This enables us to examine the exogenous impact of temperature shocks on small business revenues, store visits, and exit rates.

We start our analysis by employing event-based regressions, defining a temperature shock as a week when the daily average maximum (minimum) temperature exceeds 100°F (below 32°F). We find that for heat shocks, there is a 2% decline in weekly sales revenue, and it takes four weeks for in-person sales to recover. For cold shocks, there is an almost 10% decline in sales, which takes two weeks to recover. It's worth noting that not all businesses are negatively impacted. For example, businesses providing air-conditioning repair services see an increase in sales following heat shocks. Similarly, auto-repair businesses and indoor recreation activities, such as bowling, experience a rise in sales after heat shocks. Drinking places, which typically generate most of their sales later in the day, also show a slight overall increase in sales, though the overall restaurant sector experiences negative impacts. Conversely, during cold shocks, dining restaurants experience a 10% decline in sales, and beauty salons suffer almost a 20% loss in weekly revenue when the temperature drops below 32°F. However, their sales recover within two weeks. During heat shocks, consistent evidence indicates that people travel less, leading to gas stations experiencing nearly a 10% loss in revenue over the subsequent four weeks after the daily average maximum temperature exceeds 100°F.

To examine longer-term impacts, we define two types of temperature exposure based on Visual Crossing's US historical weather data. The first type, following previous studies (Dell, Jones, and Olken, 2012; Addoum, Ng, and Ortiz-Bobea, 2020; Pankratz, Bauer, and Derwall, 2023), is an absolute temperature threshold. We create a dummy variable that is set to 1 if at least one day in the month experiences a daily average maximum (minimum) temperature exceeding 100°F (below 32°F). We keep track of the number of extremely hot or cold days that meet specific temperature thresholds within a month. The other type, which tries to capture the "historically-unusual" days, takes into account the variations in geographical location and defines extreme exposure as when the temperature exceeds (or falls below) 100°F (32°F) and is 1.5 standard deviations away from the maximum (minimum) monthly temperature average of the past five years during that month for that county. Similar measures are constructed for both a dummy and the count of days.

Our monthly empirical analysis commences with estimating a panel regression at the establishment-month level to assess the impact of temperature exposure on monthly sales and visitor frequency at individual establishments. Consistent with recent studies on the evidence of temperature shock fluctuations on firm performance (Addoum, Ng, and Ortiz-Bobea, 2020), as well as foundational work in climate economics (Dell, Jones, and Olken, 2012), we regress the natural logarithm of sales and the number of visits on various temperature exposure metrics, incorporating controls for precipitation over the fiscal period. By including merchant-calendar-month fixed effects, we exploit yearly variation within the same merchant and season (e.g., January). Additionally, NAICS3-year-month fixed effects are employed to account for time-varying, unobserved industry-specific shocks. By leveraging the random and exogenous nature of temperature shocks, this methodological approach enables us to isolate the causal effects of temperature exposure.

In our establishment-level study examining the impact of temperature shocks on small business performance across the US, we identified significant negative effects, particularly pronounced in small businesses. Our analysis encompasses both monthly and quarterly data, underscoring the vulnerability of these enterprises to climate variations. Our findings reveal that during months with extreme heat—defined as days with temperatures exceeding 100°F—small businesses experience a reduction in sales of up to 3.7 percentage points per median impacted day, with a median event length of 4 days. For a typical heat event, based on local historical temperatures, the impact is even more severe, with sales decreasing by 7.2% per impacted day, with a median event length of 2 days. Similarly, cold shocks result in comparable sales declines. Beyond sales, the number of transactions also decreases significantly, ranging from a 5.2% decline per median impacted day in hot conditions to a 12.7% decline per median impacted day in historically unusual cold conditions. This suggests that temperature shocks not only affect revenue but also influence consumer behavior, leading to reduced foot traffic and potentially increasing ticket size per purchase. The negative impacts are particularly concerning given that small businesses typically operate with very thin margins.

Further analysis at the county-NAICS3-year level, based on this annually-aggregated data from the entire 15 million small businesses, reinforces these findings. The results suggest that temperature shock events can lead to significant and sustained economic impacts at the local level, with annual sales losses reaching up to 0.122% (0.052%) per additional unusual hot (cold) day that is 1.5 standard deviation away from its historical records within the same year. This underscores the importance of accounting for geographical and climatic variances in business planning and risk assessment. Moreover, our study highlights the particular vulnerability of young merchants, those in operation for less than a year, who face even more severe impacts from temperature extremes. These young establishments report a marked reduction in sales and transactions, with decreases significantly outpacing those experienced by more established firms. Finally, we also show that our results are not driven by COVID-related factors by removing the period from our sample.

In examining the impact of temperature shocks on business exit decisions, our study identifies a nuanced response pattern. While immediate exit responses to temperature shock days within the current month are not significant, we observe that decisions to exit are influenced by accumulated temperature extremes over time. Specifically, our analysis indicates that roughly 71 additional days above 100°F in the past 3 to 6 months correlating with a 1 percentage point increase in the probability of an establishment closing within that month or a 40% increase to the mean exit rate—an economically meaningful effect given that the average monthly exit rate in our sample is about 2.5%. In other words, 17.9 extreme days respond to a 10% rise in the exit rate. A one standard deviation increase, equivalent to 8.4 hot days, will raise the rate by 4.7%. This trend is mirrored in the response to cold shocks, where 50 additional cold days similarly increase the exit probability by 1 percentage point. These results emphasize the critical role of extended exposure to adverse weather conditions in influencing the sustainability and operational decisions of small businesses.

In our detailed analysis of how different types of temperature shock events affect small business performance, we explore the impact of temperature shocks occurring during weekends versus weekdays, as well as the influence of prolonged temperature events, referred to as *Spells*. Our findings indicate that temperature shocks over weekends have a more pronounced negative impact on sales compared to weekdays. This is probably due to the fact that work hours are substantially higher during weekdays (Bhat and Misra (1999)). Specifically, extreme heat events during weekends lead to a reduction in sales by approximately 4% per median impacted day for the heat dummy, while the effect is statistically non-significant during weekdays. Similarly, cold shocks during weekends result in a more substantial decline in sales of 14.7% per median impacted day for the historically-unusual cold dummy, nearly double the decrease of -8.8% observed during non-weekend days. This suggests that consumer behavior, likely more flexible during weekends, responds more sensitively to temperature extremes when typical work or educational commitments are absent and do more spending on weekends (Gorski, Adam (2023)).

Furthermore, when examining multi-day temperature shock events, or *Spells*, we observe that prolonged exposure to cold temperatures has a more severe negative impact on business operations than shorter cold events, with a significant 1.1% decrease in monthly sales during *Spells* lasting three days or more. Conversely, shorter spells of extreme heat are associated with greater declines in customer visits than longer spells, indicating a nuanced dynamic where the duration of exposure influences the economic impact. These variations might be attributed to the additional challenges posed by hazardous weather accompanying these events, such as snow or ice during cold spells, which hinder consumer mobility more than extended heatwaves, which may discourage but not physically prevent shopping activities.

Our analysis delves into the varied impacts of temperature shock events across different industries and establishment sizes, revealing significant heterogeneity in vulnerability. Particularly, discretionary industries such as retail and entertainment, which are more dependent on consumer discretionary spending, exhibit a heightened sensitivity to temperature shocks, with sales declining by 4.5% per median impacted day on months seeing days exceeding 100°F. This susceptibility is contrasted starkly with non-discretionary sectors, where changes are negligible. Further emphasizing the influence of operational environment, outdoor industries like construction and commercial sports report even more drastic impacts, with transaction decreases as severe as 26.7% per median impacted day under similar conditions. Additionally, our findings indicate that smaller establishments, characterized by lower average monthly sales, and those with high sales volatility face more pronounced negative effects from temperature extremes, suggesting that financial robustness and scale may play critical roles in mitigating the adverse effects of such climatic challenges. This nuanced understanding underscores the importance of tailoring strategies for risk management and operational planning to the specific characteristics and vulnerabilities of different sectors and business sizes.

We contribute to a growing body of literature that enhances our understanding of how temperature shocks affect both firm-level and establishment-level performance. This study aims to provide direct evidence on how exposure to temperature shocks affects the performance of U.S. small businesses. Due to data collection constraints, it is inherently challenging to track or collect information on smaller businesses. To date, little is known about how temperature shocks impact the performance of small businesses in the U.S., and the impacts seem to be unclear. Prior research primarily centered on larger firms, as highlighted by Addoum, Ng, and Ortiz-Bobea (2020) and Jin, Li, and Zhang (2021), reported mixed impacts of temperature shocks on business outcomes such as sales and employment. Later, Addoum, Ng, and Ortiz-Bobea (2023), find the bi-directional effects of temperature shocks on publicly listed firms, where some industries are harmed while others are benefited. Complementing these studies focusing on larger businesses, as one of the initial inquiries into this critical area, our findings reveal more adverse effects on small businesses, including decreased sales, reduced customer visits, and increased business closures. This suggests a differentiated vulnerability and response capacity in small versus large enterprises. Our study not only complements prior research but also provides compelling evidence from the revenue perspective. Previous research findings indicate that increased costs are associated with energy expenses. Supporting our findings, recent studies by Acharya, Bhardwaj, and Tomunen (2023) and Ponticelli, Xu, and Zeume (2023) delve deeper into the dynamics of employment and plant size, respectively, illustrating how firms' responses to climate shocks vary by size and geographical diversity. Griffin, Lont, and Lubberink (2023) further our understanding by documenting financial performance deteriorations in EU-UK firms, while Peillex and et al. (2021) and Pankratz et al. (2023) explore broader economic indicators such as market trading volumes and firm revenues under varying temperature conditions. Chen and Lee (2023) add a nuanced layer by examining the nonlinear responses of industrial output to temperature changes in China, suggesting regional disparities in the impacts of temperature extremes. Collectively, these studies frame a complex picture of economic resilience and adaptation to climatic extremes, within which our research on small businesses offers new insights into the sector-specific challenges posed by climate change.

Building on existing research, our study also contributes a group of literature on small business vulnerability and constraints during negative shocks by examining the impacts of temperature shock events on them. While prior work focuses on economic shocks and financial crises (Caglio, Darst, and Kalemli-Özcan (2021)), we explore how climate-related shocks exacerbate potentially financially constrained small businesses. Our findings highlight the heightened sensitivity of small businesses to environmental shocks. Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton (2020) documents a significant shortage of cash flow for small businesses during the early Pandemic. Moreover, Chava, Oettl, and Singh (2023) has found that small establishments experience higher financial stress when facing increased costs due to new minimum wage laws. By connecting climatic impacts with financial fragility, our research suggests an urgent need for tailored strategies to enhance small business resilience, offering insights that could guide policymakers and business leaders in fostering sustainable business practices and climate adaptation.[3]

[3]Our study also makes a contribution to the scientific and economic literature on the impact of temperature shocks on diverse economic and social outcomes. Extending the foundational work of Dell, Jones, and Olken (2012), Hsiang (2010), and Dell, Jones, and Olken (2014), which demonstrates significant negative effects of temperature fluctuations on economic productivity and output, our research narrows the focus to the specific vulnerabilities and adaptive responses of small businesses. Further Burke, Hsiang, and Miguel (2015) document the nonlinear effects of temperature on overall economic production, emphasizing the profound influence of climate on economic structures. Moreover, emerging studies, such as those by Salas, Burke, Phelan, Wellenius, Orav, and Jha (2024) and Gould, Heft-Neal, Heaney, Bendavid, Callahan, Kiang, Graff Zivin, and Burke (2024), have furthered our understanding by linking health-related impacts of extreme weather to economic stability and resilience. Our work

2 Identification Challenges and Empirical Specifications

2.1 Empirical methodology

We start our analysis by using a nine-week staggered event study model, where we utilize weekly sales data provided by Fiserv.[4] The first affected week is labeled as week 0 in our weekly sample. This model is designed to measure how merchants immediately respond to temperature shocks by looking at both total and physical store sales. The weekly event study model is specified as follows:

$$y_{i,c,e,w} = \alpha + \sum_{w=-4}^{w=4} \theta_w \times EventWeek_{c,e,w} + \beta \times Precipitation_{c,w} + \rho_{i,e} + \epsilon_{i,c,e,w} \quad (1)$$

where $y_{i,c,e,w}$ represents the natural log of sales for establishment i in county c during event e in week w, and θ_w is our coefficient of interest. The variable $EventWeek_{c,e,w}$ is defined as the event week e where the county-level mean daily maximum (minimum) temperature exceeds 100°F (falls below 32°F), with w marking the number of weeks within the nine-week window. To avoid potential pre-trend issues, we include only those events that do not overlap with events in the four weeks prior to week 0. This ensures that the first event week within each nine-week window is consistently set at week 0. Additionally, we restrict the sample to merchants that remain in operation throughout the entire nine-week window to reduce noise and prevent sudden jumps in data. $Precipitation_{c,w}$ controls for the exposure of establishment i located in county c during week w. We include fixed effects $\rho_{i,e}$ for each business i and event e to control for potential establishment heterogeneity and event-time-varying impacts. These fixed effects enable us to compare the impacts of temperature shocks within the same establishment and during the same event. The model is fully saturated with one week before the event as the omitted category. We clustered our standard errors at the county level.

Our monthly analysis aims to quantify the impact of temperature shocks on merchant activity by regressing transaction amounts and counts at the establishment level against variables representing temperature shocks. Consistent with finance literature on temper-

synthesizes these insights to explore the specific challenges and strategies for small businesses in the face of climatic extremities, thereby enhancing our understanding of how local economic activities are intertwined with broader climate dynamics in the context of financial decision-making and economic policy.

[4] Fiserv is one of the leading payment processors and finance infrastructure providers servicing over 10,000 financial institutions and collects real-time, establishment-level transaction data continuously. See the data section for more details.

ature effects (e.g., Addoum, Ng, and Ortiz-Bobea (2020)) and the economic literature on climate impacts (e.g., Dell, Jones, and Olken (2012), Dell, Jones, and Olken (2014)), we employ the following regression equation, using an establishment-level monthly panel with fixed effects:

$$y_{i,t} = \alpha + \beta_1 \times TempExpo_{i,t} + \beta_2 \times Precipitation_{i,t} + \mu_{i,m} + \kappa_{j,t} + \epsilon_{i,t} \tag{2}$$

where $y_{i,t}$ denotes the natural log of sales for establishment i in year-month t, and β_1 is our coefficient of interest. The variables $TempExpo_{i,t}$ and $Precipitation_{i,t}$ represent the exposure of establishment i to temperature shocks and precipitation during year-month t, respectively. We include fixed effects $\mu_{i,m}$ for each establishment i by calendar month m to control for potential seasonal variations in merchant performance. These fixed effects also control for unobserved heterogeneity that is stable over time at the merchant level, allowing for consistent comparisons across the same merchant-month in different years. Further details on exposure measures are discussed in Section 3. Additionally, we control for broader, time-varying industry-level shocks through NAICS3-year-month fixed effects, denoted as $\kappa_{j,t}$. We clustered our standard errors at the county level.

In a similar vein, we conduct establishment-level performance regressions aggregated quarterly. By employing an *at least one extreme day* exposure metric, we assess whether merchant performance is affected over longer periods. The quarterly model is specified as follows:

$$y_{i,t} = \alpha + \beta_1 \times TempExpo_{i,t} + \beta_2 \times Precipitation_{i,t} + \mu_{i,q} + \kappa_{j,t} + \epsilon_{i,t} \tag{3}$$

where subscripts i, t, j, q index establishments, year-quarters, industries, and calendar-quarters, respectively. The dependent variable $y_{i,t}$ represents aggregated establishment-level performance for year-quarter t. The variables $TempExpo_{i,t}$ and $Precipitation_{i,t}$ quantify the temperature shocks and precipitation exposures at the merchant location during year-quarter t. The fixed effect $\mu_{i,q}$ captures stable, entity-specific characteristics over time, while $\kappa_{j,t}$ accounts for industry-specific fluctuations at the NAICS3 level each quarter.

To further explore the broader economic losses experienced by local businesses, we aggregate merchant sales and transaction counts at the county-NAICS3-year-month and county-NAICS3-year level for all 15 million small businesses in the merchant sales dataset. The regression model for this aggregation is:

$$y_{c,j,t} = \alpha + \beta_1 \times TempExpo_{c,t} + \beta_2 \times Precipitation_{c,t} + \mu_c + \kappa_{j,t} + \epsilon_{c,j,t} \tag{4}$$

where c, j, t indicate the county, NAICS3, and time, respectively. The variables $TempExpo_{c,t}$ and $Precipitation_{c,t}$ are our measures of extreme weather and precipitation during time t. To eliminate country-level time-stable heterogeneities, we included county-level fixed effects μ_c. To capture the time-varying NAICS3-level industry shocks, we have incorporated fixed effects, given by $\kappa_{j,t}$, for NAICS3 code j during time t. Aggregating at the county-industry level provides two important benefits that complement the establishment-level regressions. First, it mitigates the substitution effects arising from merchant entries and exits during the period. Second, it avoids the survivorship bias associated with establishment-calendar-month fixed effects, which would automatically exclude merchants with fewer than 12 months of records as singleton values.

3 Data and Descriptive Statistics

3.1 Data Sources and Sample Selection

To examine the impact of temperature shock events on small business outcomes in the United States, we utilize data from Fiserv, the leading payment processor globally. In 2023, Fiserv processed approximately one-fourth of all card transactions in the U.S., processing 90 billion transactions with a total value of $4 trillion, and served nearly 10,000 financial institution clients worldwide. This dataset offers two levels of granularity: a weekly perspective, available primarily during the post-Covid period from January 2021 to October 2022, and a historical monthly overview spanning from July 2006 to July 2023. It encompasses sales information, transaction counts, merchant industry classifications, and location details for a diverse array of establishments, each identified by unique hashed IDs across the nation. Furthermore, the weekly dataset enables observation of in-person physical store sales and foot traffic. Notably, attributes related to in-person transactions have been captured in recent years in order to reflect the evolving trend of alternative payment methods, including online transactions, QR code payments, buy-now-pay-later services, and others.

The historical monthly dataset initially spans approximately 16 million North American businesses. After refining our focus to U.S.-based firms within the 50 states and eliminating territories, our study encompasses around 15.5 million entities. Among these merchants, approximately 15 million are categorized as small businesses with annual sales below $5 million[5] between the period from July 2006 to July 2023. This dataset's

[5]The revenue threshold is derived from the "Executive Summary of the Small Business Lending Rule" by the Consumer Financial Protection Bureau (CFPB). This definition aligns with the Small Business Administration's (SBA) general criteria, which classify a business as small if it has less than $7.5 million

primary strength is its comprehensive coverage of small businesses, captured through real-world transactions and across geographical levels (Aladangady, Aron-Dine, Dunn, Feiveson, Lengermann, and Sahm (2021)). Unlike other datasets derived from public sources or surveys, which often miss smaller businesses, this dataset includes them, offering a rare insight. The median monthly sales in our study, which can be converted to about $123,000 in annual sales (see Table 1), are significantly lower than those reported in other establishment-level studies. For instance, the natural log of annual sales is 14.24 of median annual sales in Addoum, Ng, and Ortiz-Bobea (2020) studying establishments owned by publicly-listed firms, compared to 11.72 (converted from natural log of $123,000). This difference is crucial as previous literature has not found significant sales impacts from temperature shocks in establishments owned by publicly traded firms. Additionally, the database's complete transaction records for all customers help avoid potential survivorship bias. Last, our comparison with Census surveys shows no significant differences in geographical merchant coverage at the county level.

3.2 Summary Statistics

In Table 1, we present summary statistics for our weather and establishment datasets. We begin by outlining our methods for tracking temperature shocks, which involve setting absolute temperature thresholds and analyzing deviations from historical temperatures. Next, we present statistics based on a historical monthly dataset. Finally, we provide details on the quarterly aggregated merchant-level sample and the county-NAICS3 level aggregated sample with both monthly and annual frequencies.

3.2.1 Historical Weather Data

We use historical daily weather data from Visual Crossing Weather. This dataset, offering global coverage, employs a "centroid-distance-weighted" method to compile readings from the nearest stations into a daily weather dataset at the geographical level. To create our county-year-week/month level weather dataset, we started with 39058 ZIP codes in the US from 2001 to August 2023. To ensure consistency of the readings through the period, we further restrained to ZIP codes with stations that were recorded non-stop since 2001 (which resulted in 35041 ZIP codes and 3211 counties).

To explore the longer-term relationship between temperature shocks and establishment performance, we developed several weather exposure metrics for each county monthly. Initially, we calculated a straightforward absolute temperature dummy, indicating if any

in annual revenue or fewer than 500 employees.

day's maximum (minimum) temperature exceeded 100°F (fell below 32°F). Heat advisories or warnings are usually defined locally at the county level, 100°F is a general threshold for local governments issuing such hazard advisories. We believe this approach might underestimate effects due to continuous temperature variation. In Figure 3, we graphically show for each county the percentage of years that a given county was exposed to such temperature shocks in our sample. Second, inspired by recent studies (Jin, Li, and Zhang (2021) and Griffin, Lont, and Lubberink (2023)), we incorporated historical weather patterns with absolute extremes to create a measure based on each county-calendar-month's historical weather. By calculating the mean maximum (minimum) temperature for county-calendar-month, we defined an extreme heat (cold) measure if the day was above (below) 100°F (32°F) and 1.5 standard deviations away [6] from its past-five year historical mean maximum (minimum) monthly temperature. This method helps avoid biases toward traditionally warm or cool areas and captures "abnormal" extremes more accurately. Like other studies (Addoum, Ng, and Ortiz-Bobea (2023), Peillex and et al. (2021), Acharya, Bhardwaj, and Tomunen (2023)), we also counted the number of such extreme days for our analyses, utilizing the annual and quarterly aggregated samples.

3.2.2 Establishment Characteristics

For our main sample, we randomly selected 5% of merchants from the entire Fiserv merchant universe by their ID and collected their historical records. This approach yielded approximately 22 million merchant-year-month records for around 0.75 million merchants from mid-2006 to mid-2023. The statistics of the random sample mirror those of the entire dataset. To ensure data quality, we winsorized monthly sales and transaction counts at the 1st and 99th percentiles. The median monthly sales of our final merchant-level sample are $10,250 (Table 1), significantly lower than those in other establishment-level studies (Addoum, Ng, and Ortiz-Bobea (2020), Addoum, Ng, and Ortiz-Bobea (2023)). Besides NAICS3, the dataset's MCC industry code, used by all payment brands and applied specifically for merchants, includes 289 detailed categories.[7] This allows us to precisely categorize businesses in discretionary and outdoor industries for sub-sample analyses.

In addition to the main monthly sample, the dataset includes a weekly frequency

[6] Similar to Figure 3, we present the county level percentage of exposed years for these measures in Appendix Figure A.1.

[7] MCC has a total of 625 unique codes. However, some codes have been renamed to protect commercial secrets, as they correspond to specific hotel, rental car, or airline brands.

version, containing additional in-person store sales and visit information[8] from July 2019 to October 2022. To mitigate the impact of Covid-19, which caused significant disruptions to small business sales due to lockdowns and shifts in consumer demand, we focused on post-2020 data. This approach allows us to capture the trends in online shopping and merchant adoption of online ordering, resulting in a sample of approximately 3 million merchants. Utilizing these two years of data, we created staggered event study panels to analyze heat and cold shocks at the establishment level. For each merchant-event, we included the week of the event and the four weeks preceding and following it, resulting in a total of nine weeks per event. The event week is defined as the week where the mean daily maximum (minimum) temperature exceeds 100°F (falls below 32°F). As outlined in the empirical design section, we retained only those merchants with a complete series of nine weeks of records. We also excluded overlapping events that occurred within the four-week pre-event period to ensure that the first event in the nine-week window always starts from week 0. Similar to the monthly sample, we winsorized the weekly total and in-person sales and number of visits at the 1st and 99th percentiles to ensure data quality.

4 Results

4.1 Do Temperature Shocks Affect Small Business Sales and Number of Visits?

Firstly, we present our weekly staggered event study results in Section 4.1.1 for Equation (1). We examine our monthly baseline establishment performance results in Section 4.1.2 for Equation (2). Next, we document the impact of temperature shocks on merchant performance throughout the quarter (see Section 4.1.3 for Equation (3)). Additionally, we explore the aggregated sales losses at the county level over monthly and annual periods in Section 4.1.4 using Equation (4). After that, we test the impact on younger merchants, discussed in Section 4.1.5. We further explore business closures in Section 4.1.6. Finally, in Section 4.1.7, we provide robustness of our results.

4.1.1 Event Study Results - Weekly Frequency

We commence our analysis by examining whether temperature shocks significantly impact small business performance in the U.S.. Prior studies, such as Addoum, Ng, and

[8] In-person payment methods generally include any payment methods involving a physical POS machine in the store, such as card-swiping or card-tapping, and account for approximately one-fourth of total sales.

Ortiz-Bobea (2020) and Jin, Li, and Zhang (2021), have noted no significant impacts of abnormal temperatures over the previous year or quarter on establishment performance using commonly used datasets. These datasets typically focus on larger merchants that are part of publicly listed firms in the U.S.. While these studies provide valuable insights, they may not fully capture the experiences of smaller merchants who are more vulnerable to negative shocks and lack the support of a parent firm. We explore the effects on the immediate, short-term, and longer-term performance of small businesses by studying weekly, monthly, quarterly, and annual samples.

In Table 2, we conduct a staggered event study for both heat and cold shocks to assess immediate small business responses to temperature shocks based on the post-Covid weekly sample. In Columns (1) and (2), we regress establishment total and physical store sales on extreme heat events, controlling for precipitation. By incorporating establishment-event fixed effects, we can identify variations within the same merchant and the same shock. Column (1) reports a total sales decrease of approximately 1.5% for the week. Conversely, physical store sales experience an additional 0.1% decrease, with recovery observed within about four weeks, as shown in Figure 4. For cold shocks, Column (3) reports an initial sales reduction of about 10% for the impacted week, with most of the loss recovered within the next two weeks.

In Figure 5, we subsample our weekly data by merchant categories to study the heterogeneous impacts using the same specification. For heat shocks, a clear decreasing trend is observed in categories with lower levels of travel. For instance, gas stations experience a 5-10% decrease over the next four weeks. Similarly, parking lots are also negatively impacted. Retailers, such as furniture, swimming pool sales and service stores and clothing stores that conduct most of their business during the daytime, also experience lower sales. Interestingly, not all industries are negatively impacted; there are disparate impacts of temperature shocks across various industries. Notably, heat events have varying effects, with significant gains observed in air conditioning repair and auto repair services. Increased usage and the temperature difference between outdoor and indoor environments likely lead to higher failure rates of AC compressors, affecting both home and auto units. Furthermore, while the amusement and recreation sector experiences negative impacts, indoor recreation activities, such as bowling and bookstores, see positive impacts. Similarly, although overall fast-food and dining restaurants experience a decreasing trend, drinking places exhibit a reversed overall trend, likely due to their nightly nature. Notably, industries such as religious, political, and insurance, which do not depend on physical sales, show no obvious impacts.

Conversely, cold weather, as shown in Figure 6, presents a distinct pattern, with beneficiaries including merchants that help consumers stay warmer, such as fuel oil, wood, coal, and liquid petroleum dealers, along with heating and air conditioning repair services. On the other hand, beauty stores, retail outlets, hotels, restaurants, gas stations, parking lots, taxi services, grocery stores, and other retailers emerge as losers during cold spells, possibly due to consumers' reluctance to go outside. Interestingly, while clothing stores overall experience a 10-30% sales reduction during the shocked week and the following four weeks, fur stores are not impacted during the initial shocks. Moreover, "stock-up" effects might influence sales in sectors such as grocery stores, clothing stores, and beer, wine, and liquor stores. Notably, beer, wine, and liquor stores observe an almost 10% sales increase in the week right before the cold shocks, which might be attributed to some degree of addiction. Unlike heat shocks, the insurance sector experiences only a slight decrease during the impacted week, followed by a significant 10% increase in revenue in the subsequent weeks, possibly due to increased claims from snowstorms or ice-related property damage. Political organizations, once again, are not impacted.

4.1.2 Baseline Results - Establishment Level - Monthly Frequency

Although we have observed immediate negative impacts on small business performance due to temperature shocks, these losses may be fully recovered over the long term, potentially masking their effects. To examine the longer-term "sales loss" impacts, Table 3 investigates the effects of temperature shocks on small business performance using a historical monthly dataset spanning from 2006 to 2023.

Panel A presents the regression estimates for the natural logarithm of establishment sales based on Equation (2). Columns (1) through (4) estimate the regression for establishment-level sales incorporating merchant, industry, and time-fixed effects separately. Columns (5) through (8) report results that control for precipitation and include a comprehensive set of fixed effect controls.

Our preferred specification, presented in Columns (5) through (8), estimates the impacts within the same merchant-calendar-month across years, controlling for time-varying industry heterogeneity. In Column (5), we regress establishment sales on an extreme heat dummy, defined as at least one day in the month experiencing a maximum temperature exceeding 100°F. The resulting -0.5 percentage point estimate suggests that merchants in a county experiencing at least one such hot day would see an average reduction in monthly sales of several percentage points compared to the same stores and the same month in other years. Assuming that most of the monthly negative impacts occurred during the impacted days, this translates to a -3.7% (-0.495%/(4/30 days)) per impacted day, with a median event length of 4 days. In Column (6), we test the simple extreme cold measure, which also shows a similar monthly transaction amount decrease of 0.47 percentage points.

In Columns (7) and (8), we employ a refined metric of temperature shock exposure that integrates local historical climatic data. This measure, analyzed by regressing it against the natural logarithm of sales, captures infrequent climatic anomalies at the county level. We anticipate that its impact will be commensurate with, if not exceed, the effects observed with our absolute threshold measures in Columns (5) and (6). Indeed, the analysis reveals a stronger coefficient for unusual extreme heat events considering local historical temperatures in Column (7) at -7.2% (0.478%/(2/30 days)) per impacted day, with a median event length of 2 days. For unusual extreme cold events, the impact is more pronounced in Column (8), with a point estimate of -0.78% compared to -0.47% in Column (6). The impact is much stronger at 11.6% per median impacted day for historically unusual events, especially considering that the median event length is 2 days compared to 11 days for cold events in Column (6).

In Table 3, Panel B shifts our analysis to the number of transactions. Columns (5) through (8) present our preferred specifications, indicating adverse effects on establishment performance. Specifically, the reductions are 5.2% (0.69%/(4/30 days)) per median impacted day for the 100°F measure and 8.4% (0.562%/(2/30 days)) for unusual heat events, relative to 3.7% and 7.2% in Panel A, respectively. The magnitude of these coefficients suggests a stronger impact on transaction volumes than on sales, possibly because consumers tend to decrease their visitation frequency while increasing their expenditure per visit to minimize exposure to temperature shocks. Establishments experiencing uncommonly severe cold conditions, based on historical weather patterns for the month, also exhibit markedly negative effects.

4.1.3 Establishment Level - Quarterly Frequency

To further examine if the establishment-level losses are sustained over a longer period, Table 4 investigates the effects of temperature shocks on financial performance at a quarterly frequency, as outlined in Equation (3). As discussed in Section 2.1, the quarterly aggregated sample helps mitigate survivorship bias. For instance, while a merchant exit in June may not be captured in July for the monthly study, it will be included in the quarterly aggregation. Therefore, we expect stronger coefficients in the quarterly regressions.

Panel A of the table examines variations in weather across the establishments' calendar quarters to assess the prolonged impacts of temperature shocks. Given that initial adverse effects on performance may be temporary—consumers might delay rather than forego purchases—we continue to employ our exposure dummies for at least one day of extreme conditions. These specifications determine whether there are enduring sales losses associated with minimal occurrences of extreme events. In Columns (1) through (4), we regress the natural logarithm of transaction amounts and observe that extreme heat events indeed show stronger negative impacts per median impacted day, ranging from -17.9% (-0.796%/(4/90 days)) to -24.8% (-0.825%/(3/90 days)).[9] Similarly, the number of visits shows larger declines due to heat, with estimates of -22.8% (-1.015%/(4/90 days)) to -29.2% (-0.973%/(3/90 days)).[10] Conversely, we find no sustained sales reductions for extreme cold events.

In Table 4, Panel B, our analysis parallels the approach in Addoum et al. (2020). While the existing literature, which predominantly examines larger establishments owned by publicly traded firms, reports no significant effects of temperature shocks at the merchant-quarter level, our findings differ. Inspired by additional studies (Peillex and et al. (2021), Acharya et al. (2023), and Pankratz et al. (2023)), which quantify exposure by counting the number of extreme days, we identify negative impacts on performance from both heat and cold shocks. Comparing the use of the number of days with the dummies, we believe each model has its strengths and weaknesses. The former might overweight areas that frequently experience temperature shocks, underestimating impacts on areas that unusually experience such events. Conversely, using dummy-style regressors assigns equal weight to all events, avoiding overweighting "usual" extreme events. However, this approach makes it harder to interpret results over longer periods, as "unusual" events might be temporary and easily masked.

In Column (1), each additional day with temperatures exceeding 100°F is correlated with a statistically significant reduction in quarterly sales and the number of visits by -0.042% and -0.044%, or -3.78% (-0.042%/(1/90 days)) and -3.96% (-0.044%/(1/90 days)) per median impacted day, respectively. Similarly, an extra day of extreme cold correlates with a 0.032% and 0.035% decrease in sales and visits, or 2.88% and 3.15% per median impacted day, respectively. Echoing findings from Table 3, we note that an increase in the number of anomalously hot days (exceeding 1.5 standard deviations from the historical mean) exacerbates the negative impacts, with a decrement of 0.067% of quarterly loss per additional hot day, translating to a 6.03% loss per impacted day. The divergence in results from earlier studies may stem from the significantly larger size of the establishments they analyzed, which likely experience more stable revenue streams compared to the predominantly smaller businesses in our sample. Evidence supporting the influence of

[9] -0.8% to -0.83% at the quarterly level in Columns (1) and (3)

[10] -1.02% and -0.97% in Columns (5) and (7)

size on vulnerability to temperature extremes is further corroborated in Table 15, where smaller establishments within our dataset are specifically analyzed.

4.1.4 Lost Sales - County Level - Monthly and Annual Frequencies

To elucidate the long-term economic impacts at the local level, we aggregated transaction amounts and counts from the establishment-year-month level to the county-NAICS3-year-month and county-NAICS3-year level. In this part of the study, we analyzed data from the entire cohort of 15 million small businesses, as opposed to the 5% random sample previously utilized. As previously discussed, aggregating at the county-industry level mitigates substitution effects from merchant entries and exits and avoids the survivorship bias of establishment-calendar-month fixed effects. Employing regression analysis as specified in Equation (4), Table 5 for monthly frequency and Table 6 for annual frequency, Panel A, presents the results using our most basic measure of temperature shock exposure: the at-least-one-extreme-day-in-a-year dummy. This dummy assumes a value of one if at least one day of extreme hot or cold temperature was recorded in the county during the month or year. We postulate that this measure may potentially underestimate the true effects.

For both monthly and annual tables, Columns (1)-(4) explore the impact of temperature shocks on total county sales. Columns (5)-(8) assess the potential losses in transaction count within a county. By avoiding the survivorship bias due to the fixed effects in establishment-level regressions, we expect to see stronger negative impacts by studying county-level aggregation. In Table 5 Column (1), we observe a significant monthly county sales loss of at least -1.7% (-12.8% per median impacted day), compared to -3.7% per median impacted day in the monthly establishment-level regressions. The historically unusual extreme heat events in Column (3) present a -1.62% (-24.3% per median heat day) sales loss, compared to -7.2% per median impacted day for the establishment study in Table 3 Column (7). Similarly, extreme cold measures in Columns (2) and (4) report stronger impacts as well.

In Table 6, we continue our study on lost sales for the annual frequency. In Column (1), the annual county sales loss of at least -2.54% appears unrecoverable within the same year for a year with a median event of 5 hot days above 100°F. Employing the historical extreme heat measure, similar to the 100°F absolute threshold, results in a -2.37% reduction in annual sales with a median event length of 3 days. However, consistent with the quarterly frequency merchant-level results, no sustained loss was observed for days with temperatures below 32°F. Analysis of the potential impacts on the number of visits in Columns (5) and (7) indicates slightly stronger negative effects, reinforcing merchant-level findings that consumers reduce visits to potentially avoid commuting under temperature shock conditions.

4.1.5 Young Merchants

Our analysis framework, defined in Equation (2), allows for comparisons of the same merchant-calendar-month across different years. However, a significant limitation of this model is that it requires each merchant to have operated for at least two years to enable a self-comparison. Consequently, this regression approach excludes all young firms in business for less than 12 months as singletons, potentially omitting a critical group of merchants that may be particularly susceptible to financial shocks due to their nascent operational status. Literature on small business behaviors, such as Chava et al. (2023), highlights the importance of including such vulnerable groups in analyses.

In Table 7, Panel A, we bifurcate our sample: one subset includes only young merchants with 12 months or fewer of operational records in the Fiserv database; the other comprises establishments with more than one year of operational history. Columns (1), (3), (5), and (7) present findings exclusively for the young merchant sample, employing a modified version of Equation (2) labeled as Equation (5):

$$y_{i,t} = \alpha + \beta_1 \times TempExpo_{i,t} + \beta_2 \times Precipitation_{i,t} + \mu_i + \kappa_{j,t} + \epsilon_{i,t} \tag{5}$$

Equation (5) adapts the analysis by introducing merchant fixed effects due to their less-than-one-year tenure, in contrast to the merchant-calendar-month fixed effects, which require at least one year of operation to avoid exclusion as a singleton.

Table 7, Panel A reveals that young merchants suffer disproportionately larger negative impacts from extreme weather events. In Column (1), establishments with fewer than 12 months' lifespan experienced a -3.46%-percentage-point reduction in monthly sales that can be converted to -26% sales loss per median impacted day, compared to a -0.50% monthly loss (-3.7% per median impacted day) for merchants with more than one year's experience. Similar patterns emerge in Columns (3) and (4), where young merchants faced an average -4% reduction in transaction amount, significantly more severe than the nearly tenfold smaller -0.49% sales decrease observed in their more established counterparts. These findings are echoed in Table 7, Panel B, which shows similar trends with amplified impacts on transaction count losses.

4.1.6 Exit

Building upon our findings regarding the contemporaneous effects of temperature shock on merchant sales and transactions, we now explore the potential for these conditions to influence business exit decisions. Previous research, such as that by Bartik et al. (2020), indicates that a majority of small businesses encountered cash flow shortages during the Pandemic, often relying on revenue as collateral (Caglio et al. (2021)). Given the negative impacts on sales documented earlier in our study, we hypothesize that temperature shocks may contribute to forcing some small enterprises out of business due to their constraints and vulnerability to negative shocks.

We adopt the exit definition from Ponticelli et al. (2023), defining exit at the establishment level in year-month t as a dummy variable set to 1 if establishment i registers positive sales in year-month t but records no sales in year-month t+1 and beyond. This approach allows us to capture the contemporaneous relationship between temperature shocks and exit decisions accurately. To address the potential lag in the impact of weather conditions, inspired by Jin et al. (2021), we introduce a measure that counts the number of temperature shock days an establishment has experienced in the 3, 6, and 12 months prior to exit. This method recognizes that decisions to exit the market may not be immediate and are likely influenced by the accumulation of multiple adverse events over time.

Our empirical results, presented in Table 8, reveal no significant immediate exit responses to the number of temperature shock days within the current month. However, we find evidence suggesting that exit decisions are responsive to accumulated temperature shock exposures in prior months. Specifically, Column (2) indicates a 0.014% increase in the probability of exit for each additional extreme hot day experienced in the past three months. This effect translates to approximately 71 additional days above 100°F correlating with a 1 percentage point increase in the probability of establishment closure or a 40% increase to the mean exit rate within that month—an economically substantial effect given the average exit rate in our sample is 2.5%. In other words, 17.9 extreme days respond to a 10% raise in the exit rate. A one standard deviation increase of 8.4 hot days will raise the exit rate by 4.7%. Similarly, Columns (5)-(8) present findings for cold shocks, showing a comparable, albeit slightly greater, impact, whereby a roughly additional 50 cold days within the same time frames increase the exit probability by 1 percentage point, or 11.9 days for a 10% increase in the exit rate. Panel B further explores the impacts using historical definitions of extreme days, affirming the robustness of our results. These findings underscore the importance of considering accumulated exposure to temperature shocks in understanding the dynamics of small business sustainability.

4.1.7 Robustness - Remove Covid Period

In the robustness analysis, we investigate the potential confounding effects of the COVID-19 pandemic by re-evaluating our baseline regression models, excluding data from the period after January 2020. This approach allows us to assess whether the significant impacts of temperature shock events on small business sales and transaction numbers, observed in our main analysis, might have been influenced by the unique economic disruptions during the pandemic. The results of this robustness check are presented in the robustness Table 9, which replicates the earlier regression specifications without including the pandemic period. Remarkably, the exclusion of this anomalous period does not alter our findings, as the coefficients for both extreme heat and cold events remain consistent with those reported in the main analysis. This consistency underscores the robustness of our results, indicating that the negative impacts of temperature shocks on small business performance are not driven by the extraordinary economic conditions induced by COVID-19. This finding lends further credence to the argument that temperature shock events pose a genuine and persistent risk to small businesses, independent of the pandemic's transient economic effects.

4.2 How Do Various Types of Temperature Shock Events Differ in Their Impacts?

This subsection aims to dissect the relationship between temperature shocks and establishment performance by exploring different types of temperature shock events. We analyze the impact of extreme events occurring on weekends in Section 4.2.1 and specify the analysis framework in Equation (2). We further investigate the implications of extreme weather *Spells*—periods characterized by several consecutive days of very hot or cold temperatures—in Section 4.2.2.

4.2.1 Weekend Events

We categorize extreme events into *weekend* and *non-weekend* groups. Notably, work hours during weekdays are substantially higher than weekends (Bhat and Misra (1999)), with most individuals engaged in non-work activities during the latter. Consequently, we hypothesize that consumer behavior in response to temperature impacts might be more flexible during weekends. To analyze this, we define a weekend dummy as *at least one extreme day on weekend* and a non-weekend dummy as *at least one extreme day but none of the days are on weekend* within a given month.

In Table 10, we assess the differential impacts of weekend versus non-weekend temperature events. Utilizing Equation (2), Column (1) regresses the natural logarithm of sales against both dummies. The results indicate that the majority of negative monthly sales impacts, specifically *at least one day above 100˚F*, predominantly occur during weekends, with an estimated reduction of -0.53% (-4% per median impacted day). Conversely, the non-weekend dummy shows a statistically non-significant effect. The analysis of cold shocks in Column (4) reveals a significant discrepancy; the weekend dummy shows a decline of -0.98% (-14.7% per median impact day with a median event length of 2 days), nearly double the effect compared to the -0.59% (-8.8% per median impacted day) for non-weekend events. A similar trend is observed in Columns (5)-(8), where the negative impacts on the number of visits are significantly more pronounced for weekend events.

4.2.2 ***Spells***—Multiday Events

Table 7 investigates the effects of multiday temperature shock events, or *Spells*, based on Equation (2). Meteorological studies define heatwaves typically as lasting two to three days (Lau and Nath (2012), Meehl and Tebaldi (2004)). To discern the impacts of short-term versus prolonged temperature spikes, we divide extreme events into *1-2 day shocks* and *3+ day Spells*.

Columns (1)-(4) of Table 11 report regression results focusing on transaction amounts, while Columns (5)-(8) present findings on transaction counts. Contrary to expectations, prolonged cold *Spells* are associated with more severe negative impacts on establishment performance, with a -1.1% decrease in monthly sales for 32˚F shocks, significantly exceeding the -0.4% decrease observed for shorter-duration shocks in Column (3). Conversely, short-duration extreme heat events tend to have more pronounced negative effects. For instance, *3+ day Spells* of 100˚F heat result in a -0.71% decrease in the monthly number of visits, compared to a -0.62-percentage-point reduction for shorter spells.

Currently, there is no definitive explanation for these observations. However, it is posited that accompanying hazardous weather conditions significantly influence these outcomes. Cold shocks, often accompanied by snow or ice, effectively impede consumer mobility and shopping activity, whereas extended heatwaves, typically associated with drought conditions, discourage but do not physically prevent commuting. Therefore, more frequent short-term heat events might exert stronger negative impacts on merchants.

4.3 How Does the Impact of Temperature Shocks Vary Across Industries and Establishments?

This subsection explores the heterogeneity in the impacts of temperature shock events across different merchants, industries, and geographic regions in the U.S. We particularly examine variations in these impacts based on the industry's sensitivity to temperature, market conditions, size, and geographical location of the establishment.

4.3.1 Discretionary vs. Non-discretionary Industries

While Jin et al. (2021) did not observe immediate responses to temperature shocks, they highlighted a local demand channel by examining the differential responses between non-tradable and tradable sectors. In a related study, Garmaise et al. (2020) found that households tend to reduce their discretionary spending when confronted with adverse news. Motivated by these findings, we conduct an industry-level analysis to delve deeper into the demand channel and assess the differential impacts of temperature shocks on discretionary and non-discretionary industries. It is hypothesized that discretionary consumption would be more severely affected during periods of temperature shocks.

Discretionary spending is often the first to be curtailed under financial duress. To categorize industries, we employ Merchant Category Codes (MCCs) used across the U.S. payment system to classify merchants by the nature of goods or services they provide. These codes are utilized by payment brands, issuers, and acquirers to manage transactions, for tax reporting, interchange promotion, and analyzing cardholder purchasing behaviors. Although our regressions control for industry effects using mapped NAICS3 codes, MCCs offer a more precise categorization, which is instrumental in assessing specific industry vulnerabilities to temperature extremes.

The dataset comprises approximately 289 MCC categories. Based on card payment industry routines[11], in Table 12, we categorize industries into discretionary sectors, including restaurants, lodging, most retail, entertainment, travel-related, and other non-essential services. Non-discretionary sectors include grocery, medical or health services, pharmacy, supermarkets, postal services, utilities, education, tolls, fees, and wholesale clubs. Other industries such as gas stations, publishing, financial services, insurance, government-related services, tax, fines, bail, bond payments, and court costs are classified as "other". These classifications and their corresponding MCC details are listed in Appendix Table A.2.

Results from Table 13 display a pattern across subsample analyses from Panel A to

[11] See "Fiserv SpendTrend Monthly Report" and "Visa Business and Economic Insights".

Panel D, showing that merchants in discretionary industries experience more substantial negative impacts relative to those in non-discretionary and other categories. For example, Panel A, Column (1) indicates a 0.6% (4.5% per median impacted day) decline in monthly sales for discretionary merchants experiencing at least one day above 100°F during the month, as opposed to an insignificant change in non-discretionary industries and a slightly positive coefficient for the "other" category. This trend suggests that discretionary sectors are particularly sensitive to extreme weather conditions. Similarly, the pattern of visitor numbers in Columns (4)-(6) also mirrors this trend, further corroborating the impact of temperature extremes on consumer behavior.

4.3.2 Climate Sensitive - Outdoor Industries

Temperature shocks pose significant economic losses and present severe risks to human health, particularly for workers exposed to the elements. Gubernot et al. (2015) reported an occupational heat-related death rate of 0.22 per million workers from 2000 to 2010, markedly higher than the 0.02 rate for all U.S. civilian workers. Guidance from the recently established Heat.gov (National Integrated Heat Health Information System (2024)) identifies groups particularly at risk from extreme heat, prompting our focus on outdoor industries. More recent literature, such as Xiao (2021), examines that extreme heat wave might reduce labor productivity. We specifically consider sporting-related workers (e.g., golf, commercial sports) and those in construction (e.g., roofing, landscaping) or other outdoor services (e.g., amusement parks, tourist attractions) who lack access to air conditioning and are thus more susceptible to heat-related illnesses and injuries.

Table 14 delineates the impact of temperature shocks on these outdoor industries, revealing significantly stronger negative effects. For instance, Column (1) shows a substantial decrease of 3.57% (26.7% per median impacted day) in monthly transactions for at least one day at or above 100°F, compared to an unconditional -0.5% (-3.7% per median impacted day) observed in the baseline model (Table 3, Panel A, Column (1)). This pattern persists across various extreme exposure measures, with Column (5) documenting a significant 4.6-percentage-point reduction in transaction count.

4.3.3 Establishment Size and Sales Volatility

This subsection explores how the impact of temperature shock events varies with establishment size and sales volatility, reflecting a business's capacity to absorb weather-related shocks. We test this hypothesis using our baseline model and present the findings in Table 15. Several previous studies, such as Chava, Oettl, and Singh (2023), have documented that smaller-sized enterprises might be more vulnerable when facing negative economic shocks. Studies focusing on temperature shocks and datasets centered on publicly-listed-firm-owned businesses that are typically larger in size report no significant results, whereas we have found negative impacts for small businesses, indicating that merchant size indeed affects a business's resilience. Similarly, Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton (2020) documents a significant shortage of cash flow for small businesses during the early pandemic, suggesting that unstable sales volumes could also impact small merchants' ability to absorb negative weather-related shocks.

We define establishments as *Small* if their average monthly sales over the months $t-1$ and $t-13$ fall within the lowest quantile for their industry in month $t-1$. To be included, each merchant must have at least 12 months of recorded data. This requirement introduces a potential survivorship bias, which may understate the negative impacts. Results for these smaller establishments, particularly in response to heat events, are presented in Columns (1), (3), (5), and (7) of Table 15. Columns (1) through (4) examine the impacts of temperature shocks on sales, while Columns (5) through (8) assess the impacts on foot traffic. Notably, we observe a significant increase in the negative impact due to heat shocks, with a -3.3% (-24.8% per median impacted day) additional decline in monthly sales for small establishments. In contrast, cold shocks also have a stronger negative impact on merchants with bottom quantile revenue in their category, though the difference is less pronounced, ranging from 0.9% to 1.5% monthly losses.

An interesting observation is that historically-unusual exposure generally has stronger negative impacts in earlier tables but shows weaker coefficients for smaller merchants. This is likely because absolute threshold exposure usually lasts longer (e.g., the median event length for 32°F is 11 days), making it costly for smaller establishments to adjust their energy spending or invest in climate-adjustment equipment. In contrast, the historical measure (32°F*1.5 stdev) typically lasts only 2 days, which may not impose as significant a financial constraint on energy costs. However, despite the shorter duration, the 1.5 stdev events still have stronger negative impacts on sales per event.

In Table 16, we introduce the *High Sales Volatility* measure. This variable is assigned a value of 1 for merchants whose sales volatility during the past 12 months ranks in the highest quantile of their industry and 0 otherwise. Sales volatility is calculated as the standard deviation of sales from month $t-1$ to $t-13$, normalized by the average monthly sales during the same period. This measure allows for a comparison of volatility effects across different merchant sizes. The results, particularly in Column (1), illustrate a significant negative impact due to heat shocks, with a 2.4-percentage-point monthly revenue reduction attributed to high volatility in sales. Similar to the establishment size study, this analysis also has a potential survivorship bias, as it requires at least 12 months of data for each merchant to calculate its normalized revenue standard deviation.

5 Conclusion

In conclusion, our study adds a significant layer to the existing literature on the impact of climate change on economic activities by focusing on the specific vulnerabilities of small businesses to temperature shock events. Through a comprehensive analysis of over 15 million establishment-level weekly and monthly records from one of the largest payment processors in the U.S., we reveal that small businesses suffer disproportionately during periods of extreme heat and cold. The increased frequency and intensity of these events, as predicted by climate models, pose a critical threat to the sustainability and profitability of small enterprises, which are already under significant financial strain. Our findings underscore the necessity of incorporating climate risk into the strategic planning and operational resilience frameworks of small businesses. Moreover, the pronounced impact on transaction volumes and the frequency of business exits highlight the broader economic implications of climate change, emphasizing the need for targeted policy interventions that support small businesses in enhancing their adaptive capacities.

Furthermore, our research contributes to a nuanced understanding of how geographical and industry-specific factors influence the resilience of small businesses to climatic extremes. By differentiating between discretionary and non-discretionary sectors, as well as examining the effects of temperature shocks on different types of business operations, we provide detailed insights that can inform more customized climate adaptation strategies. The evidence of significant economic disruption underscores the urgent need for policies that bolster the economic resilience of the most vulnerable sectors and regions. As climate change continues to shape economic landscapes, this study calls for an integrated approach that combines economic, environmental, and policy perspectives to support the critical role that small businesses play in the broader economy. This approach is essential not only for mitigating the impacts of current climate variability but also for preparing these economic actors for future climatic challenges.

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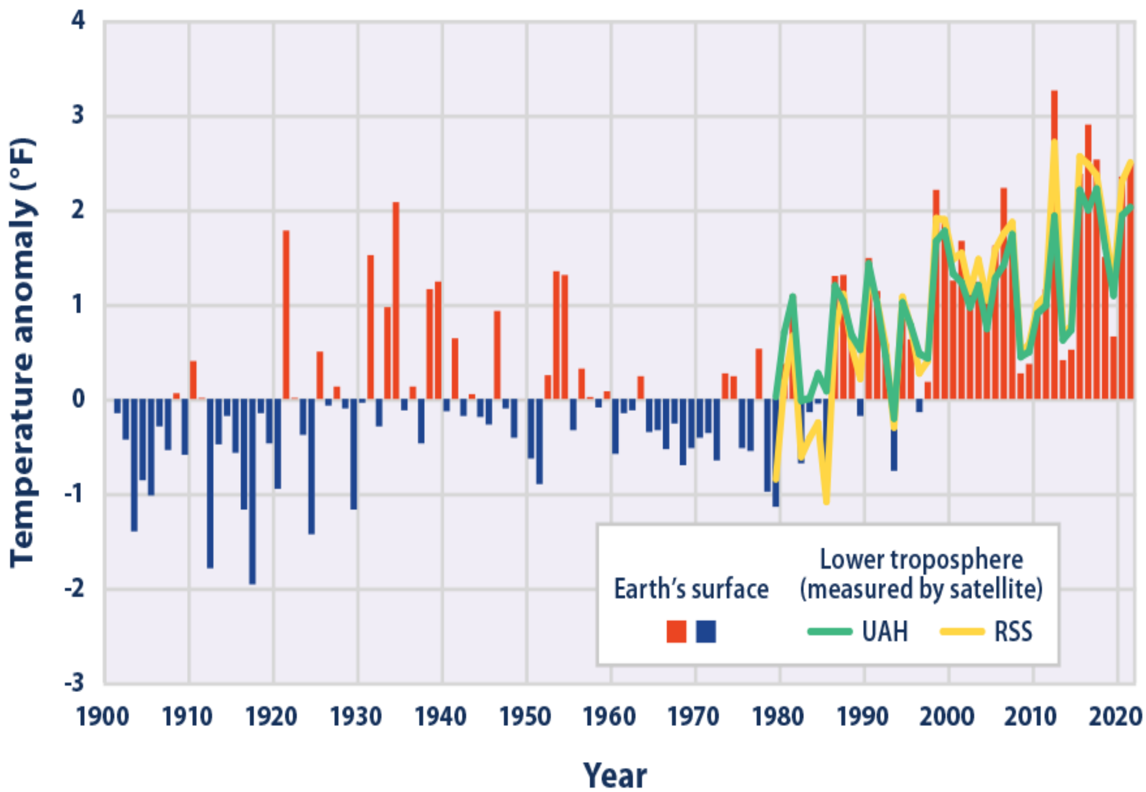


Data source: NOAA (National Oceanic and Atmospheric Administration). 2022. Climate at a glance. Accessed March 2022. www.ncdc.noaa.gov/cag.

For more information, visit U.S. EPA's "Climate Change Indicators in the United States" at www.epa.gov/climate-indicators.

Figure 1: Temperatures - Contiguous 48 States, 1901-2021

This figure shows how annual average temperatures in the contiguous 48 states have changed since 1901. Surface data come from land-based weather stations. Satellite measurements cover the lower troposphere, which is the lowest level of the Earth's atmosphere. "UAH" and "RSS" represent two different methods of analyzing the original satellite measurements. This graph uses the 1901–2000 average as a baseline for depicting change. Choosing a different baseline period would not change the shape of the data over time.

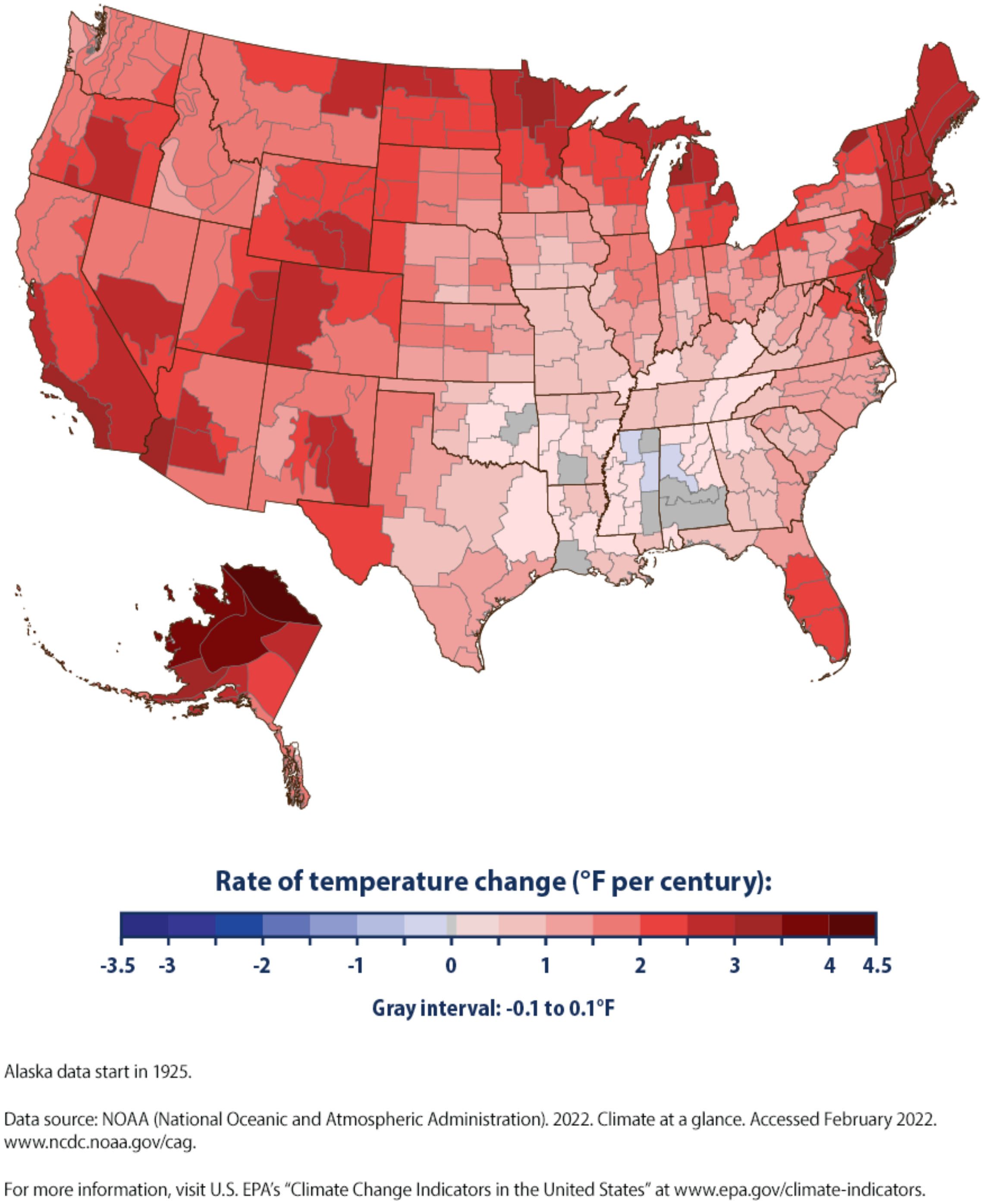


Figure 2: Rate of Temperature Change, 1901-2021

This figure shows how annual average air temperatures have changed in different parts of the United States since the early 20th century (since 1901 for the contiguous 48 states and 1925 for Alaska). The data are shown for climate divisions, as defined by the National Oceanic and Atmospheric Administration.

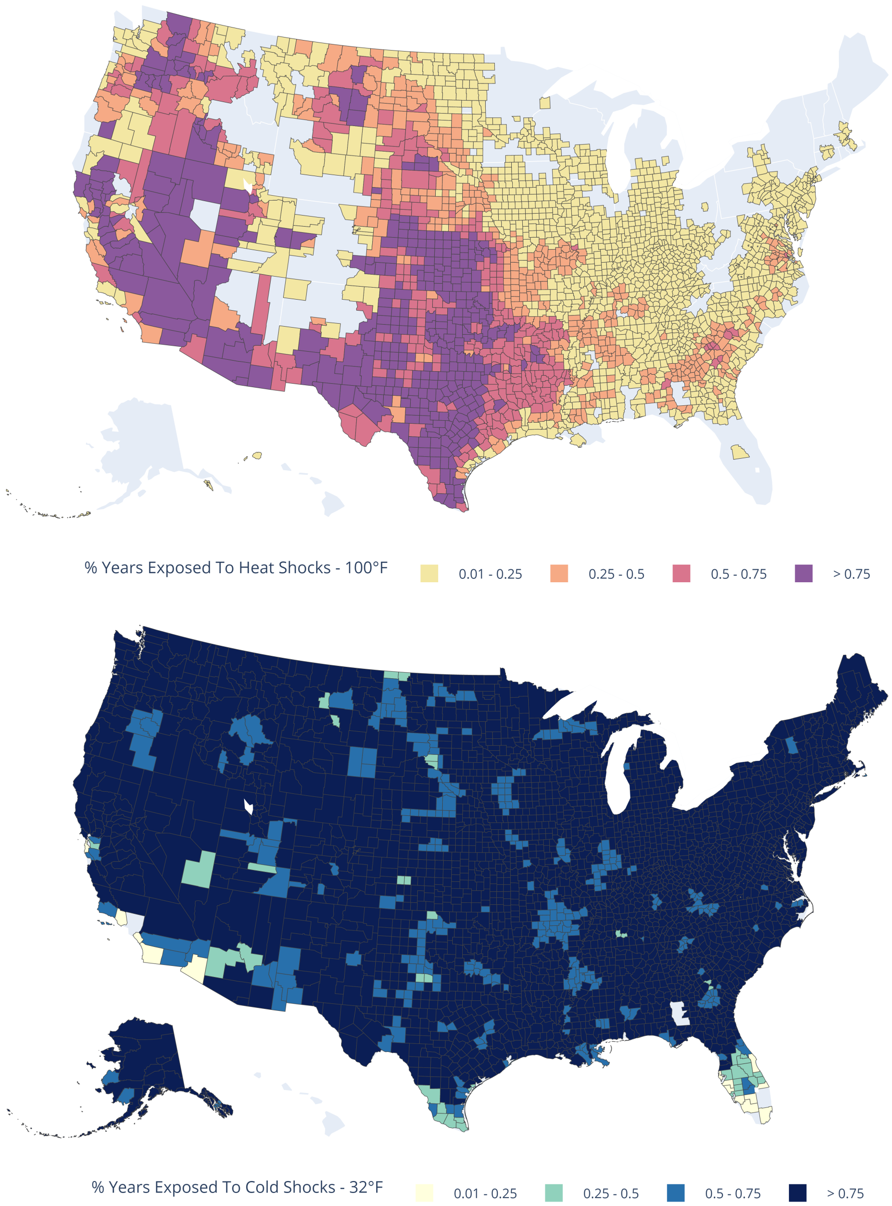


Figure 3: Heat and Cold Shocks from 2006 to 2023 at U.S. County Level

This figure illustrates the percentage of years during 2006-2023 a given county has exposed to extreme weather events. The top panel shows counties that experienced extreme heat events, defined as days with temperatures exceeding 100°F, while the bottom panel displays counties affected by extreme cold events, defined as days with temperatures below 32°F. The grey areas are not exposed to extreme events during the period. The maps highlight the regional patterns and frequency of these temperature shock events at annual level over the specified period.

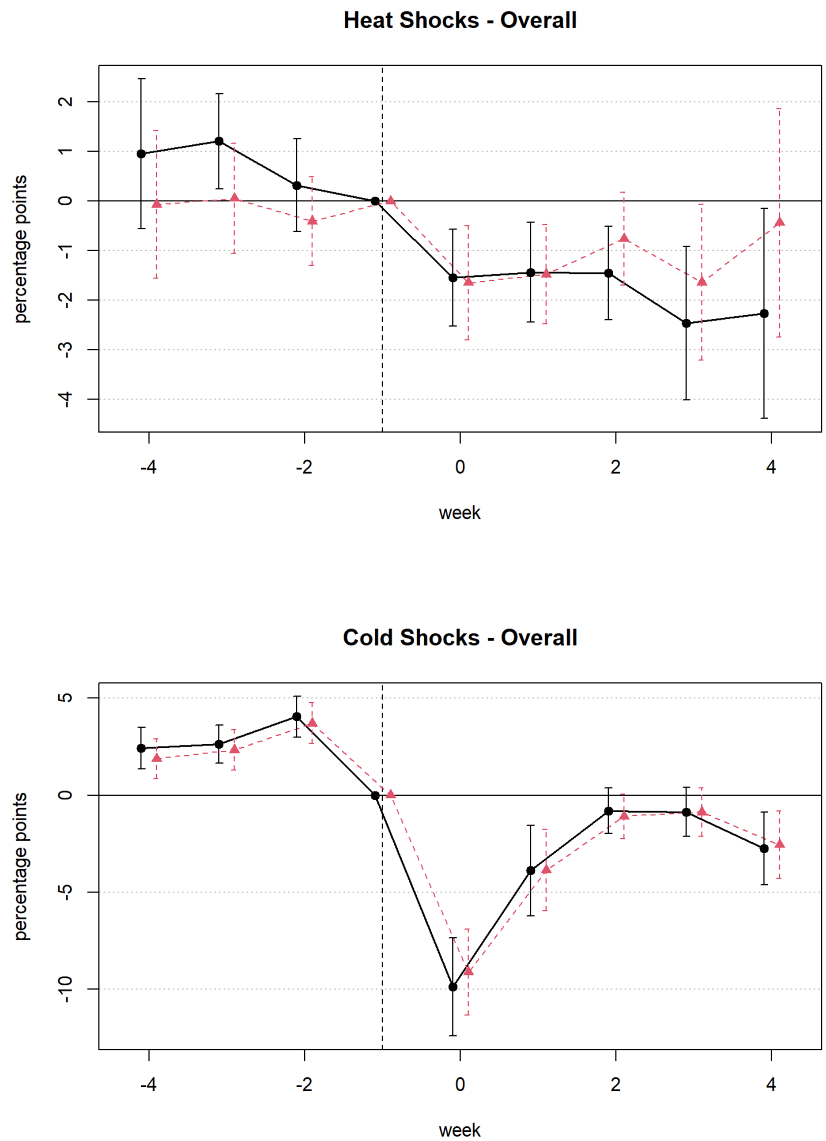
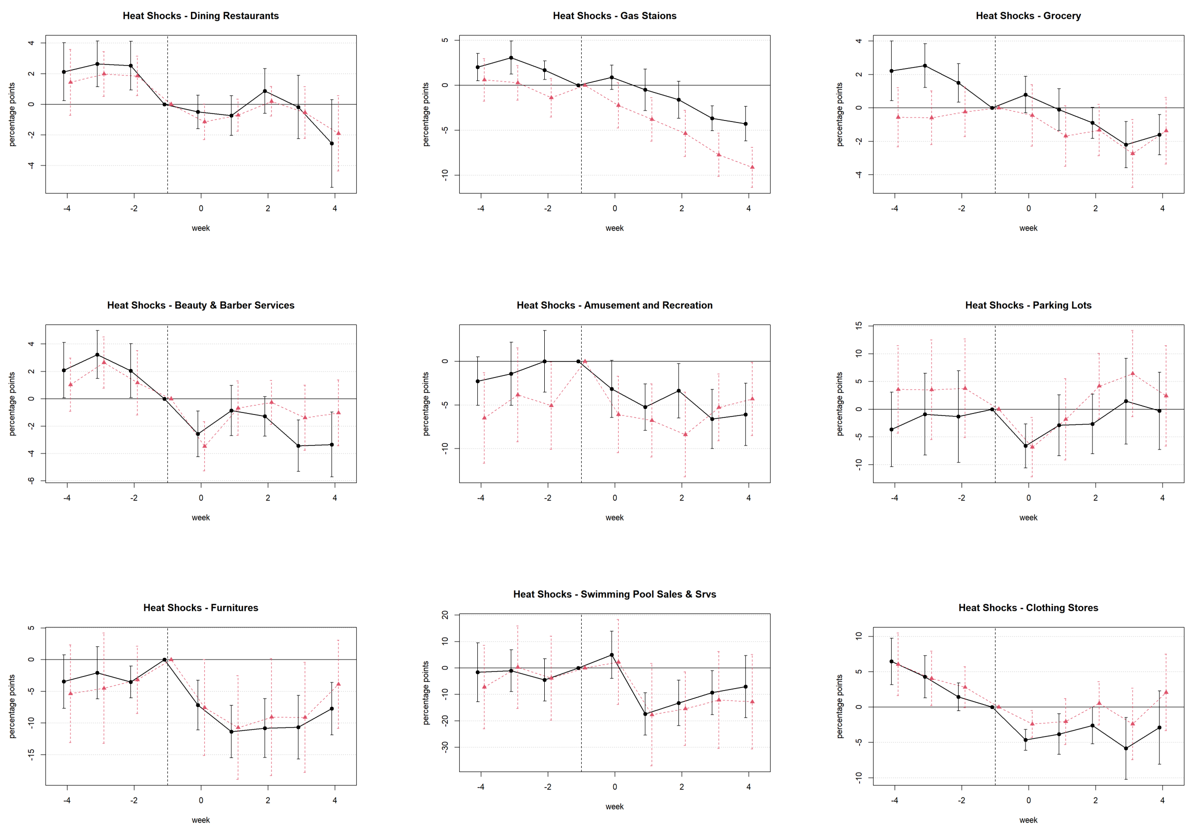
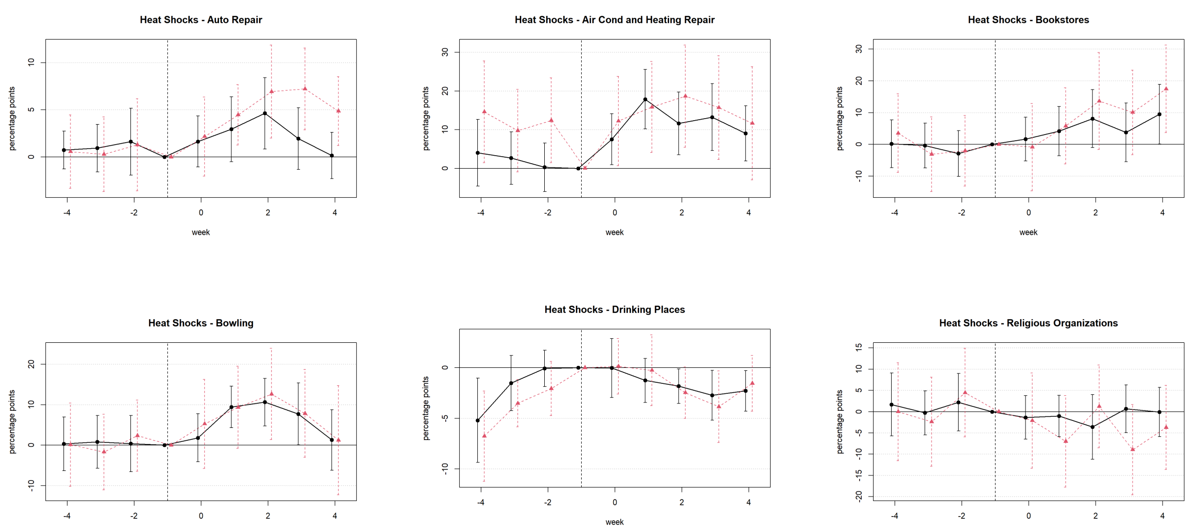


Figure 4: Heat and Cold Shocks Impacts - Overall

This figure illustrates the impact of temperature shocks on small business total and in-person sales during a nine-week event window, based on the regression specified in Equation (1). The solid black line represents total sales, while the dashed red line shows the coefficients for in-person sales. Each event spans nine weeks, with the first affected week labeled as week 0. Heat shocks are defined as a weekly maximum temperature above 100°F, while cold shocks are defined as a weekly minimum temperature below 32°F. The corresponding coefficients are reported in Table 2.



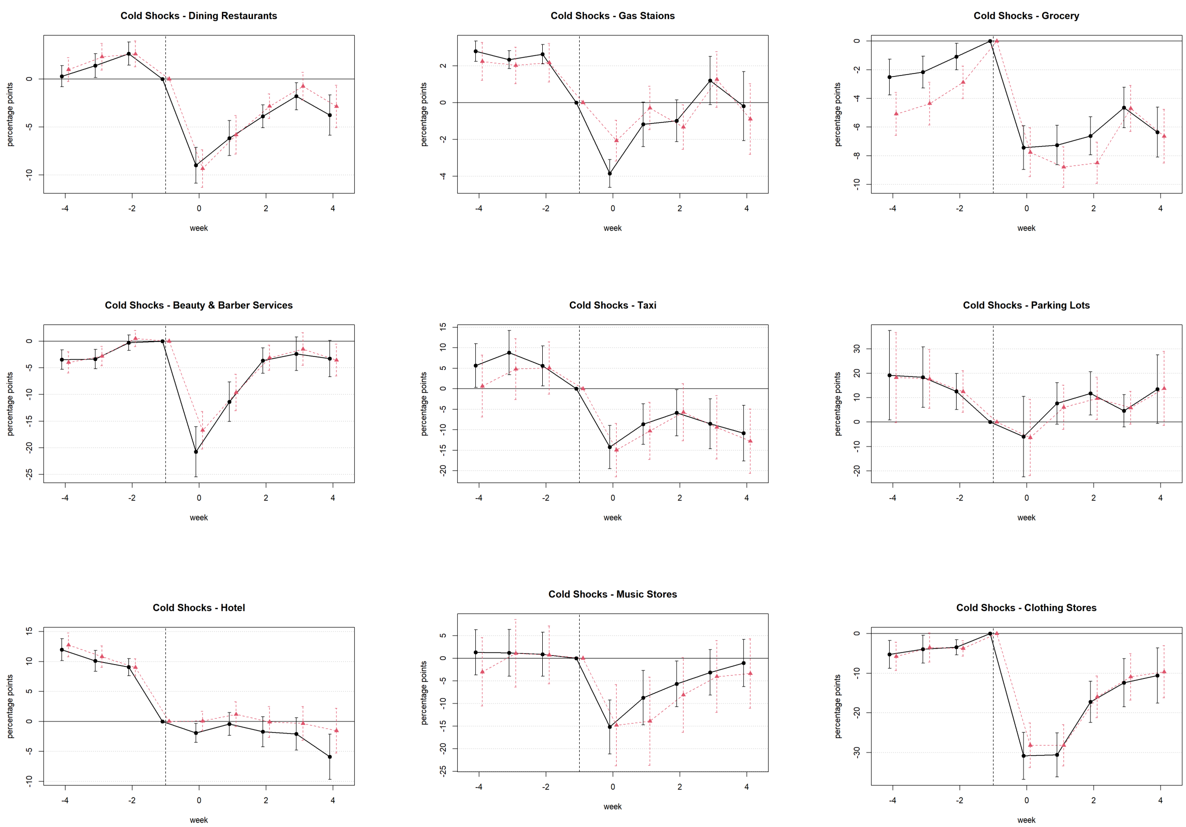
(a) Negative Impacts



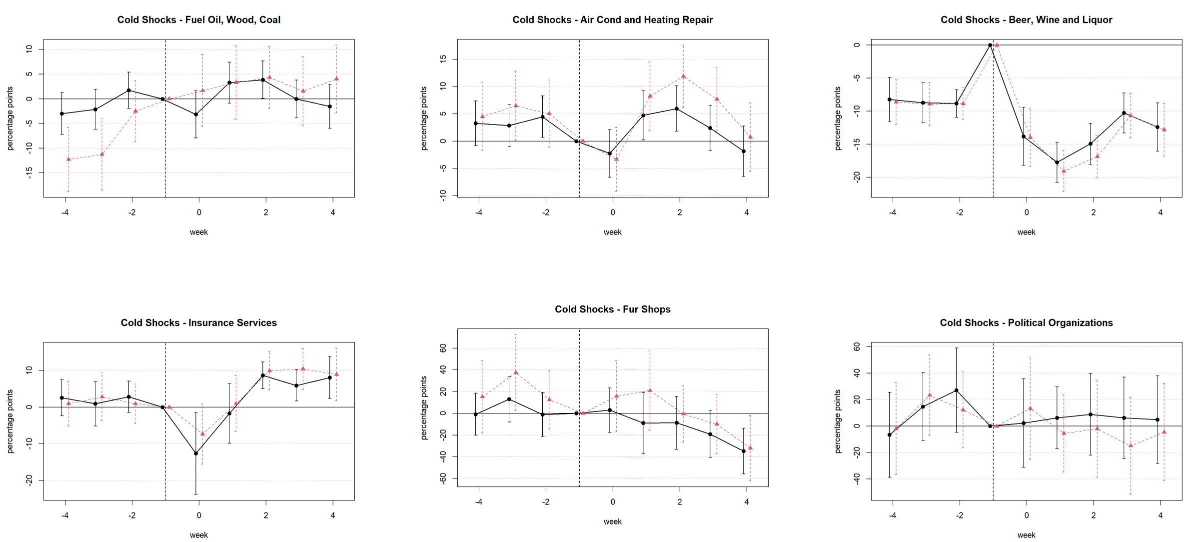
(b) Mixed Impacts

Figure 5: Heat Shocks Impacts - By Merchant Category

This figure illustrates the impact of extreme heat (defined as a weekly maximum temperature above 100°F) on small business total and in-person sales, categorized by business type, during a nine-week event window based on the regression specified in Equation (1). The solid black line represents total sales, while the dashed red line shows the coefficients for in-person sales. Each event spans nine weeks, with the first affected week labeled as week 0.



(a) Negative Impacts



(b) Mixed Impacts

Figure 6: Cold Shocks Impacts - By Merchant Category

This figure illustrates the impact of extreme cold (defined as a weekly minimum temperature below 32°F) on small business total and in-person sales, categorized by business type, during a nine-week event window based on the regression specified in Equation (1). The solid black line represents total sales, while the dashed red line shows the coefficients for in-person sales. Each event spans nine weeks, with the first affected week labeled as week 0.

Table 1: Summary Statistics

This table provides the summary statistics for key variables used in the analysis. Panel A reports the summary statistics of weekly establishment data from January 2021 to October 2022, covering about 3 million small businesses. Detailed summary statistics for staggered event samples are provided in Appendix Table A.1. Panel B reports summary statistics for a 5% randomly selected sample of monthly establishment data from July 2016 to July 2023, encompassing approximately 750,000 merchants. Panel C reports summary statistics for a 5% randomly selected sample of quarterly establishment data from July 2016 to July 2023, aggregated from the monthly establishment data for the entire sample period. Panel D reports summary statistics for a county-NAICS3-Year aggregated sample based on the complete dataset of 15 million small businesses, covering the entire sample period, unlike the 5% sample used for monthly and quarterly data. Sales in Panel D have been converted to thousands before taking the natural log. All sales and transaction count variables are winsorized at the 1st and 99th percentiles. Mean daily precipitation is calculated based on county and period. Section 3.2.1 defines the temperature variables. Temperatures are reported in degrees Fahrenheit, and daily precipitation is reported in inches.

	Mean	SD	1st Qu.	Median	3rd Qu.
Panel A. Merchant*YearWeek Frequency					
(3 Million Merchants - Post 2020)					
Sales	12,261	18,162	1,225	4,749	15,024
Transaction count	282	584	8	41	228
In-person sales	2,581	5,927	0	200	2,187
In-person transaction count	43	119	0	2	20
Log(sales)	8.24	1.84	7.11	8.47	9.62
Log(transaction count)	3.76	2.17	2.08	3.71	5.43
Log(in-person sales)	7.18	1.79	6.03	7.35	8.48
Log(in-person transaction count)	2.72	1.84	1.10	2.56	4.09
Mean daily precipitation (inch)	0.09	0.12	0.00	0.04	0.12
Panel B. Merchant*YearMonth Frequency					
(0.75 Million Merchants - 5% Randomly Selected)					
Sales	33,865	59,648	2,505	10,250	35,483
Transaction count	802	1,855	15	88	537
Log(sales)	9.02	2.02	7.83	9.24	10.48
Log(transaction count)	4.49	2.38	2.71	4.48	6.29
Number of days above 100°F	0.43	2.65	0	0	0
Number of days below 32°F	4.76	8.32	0	0	6
Number of days above 100°F*1.5stdev	0.14	0.93	0	0	0
Number of days below 32°F*1.5stdev	0.83	1.92	0	0	1
Dummy above 100°F	0.05	0.22	0	0	0
Dummy below 32°F	0.38	0.49	0	0	1
Dummy above 100°F*1.5stdev	0.04	0.20	0	0	0
Dummy below 32°F*1.5stdev	0.27	0.44	0	0	1
Number of weekend days above 100°F	0.12	0.78	0	0	0
Number of weekend days below 32°F	1.39	2.47	0	0	2
Number of weekend days above 100°F*1.5stdev	0.04	0.30	0	0	0
Number of weekend days below 32°F*1.5stdev	0.23	0.64	0	0	0
Mean daily precipitation (inch)	0.09	0.09	0.03	0.07	0.13

Table 1: (Continued) Summary Statistics

	Mean	SD	1st Qu.	Median	3rd Qu.
Panel C. Merchant*YearQuarter Frequency					
(0.75 Million Merchants - 5% Randomly Selected)					
Log(sales)	9.90	2.17	8.67	10.15	11.45
Log(transaction count)	5.30	2.55	3.50	5.35	7.21
Number of days above 100°F	1.28	6.71	0	0	0
Number of days below 32°F	14.18	22.09	0	1	22
Number of days above 100°F*1.5stdev	0.41	2.02	0	0	0
Number of days below 32°F*1.5stdev	2.47	4.25	0	0	4
Dummy above 100°F	0.10	0.30	0	0	0
Dummy below 32°F	0.52	0.50	0	1	1
Dummy above 100°F*1.5stdev	0.09	0.29	0	0	0
Dummy below 32°F*1.5stdev	0.46	0.50	0	0	1
Mean daily precipitation (inch)	0.09	0.07	0.04	0.08	0.13
Panel D. County*NAICS3*YearMonth Frequency					
(15 Million Merchants)					
Log(sales)	18.00	2.53	16.31	18.07	19.79
Log(transaction count)	6.45	2.87	4.43	6.45	8.48
Number of days above 100°F	0.25	1.72	0	0	0
Number of days below 32°F	6.58	9.46	0	0	12
Number of days above 100°F*1.5stdev	0.13	0.94	0	0	0
Number of days below 32°F*1.5stdev	1.08	2.11	0	0	1
Dummy above 100°F	0.04	0.21	0	0	0
Dummy below 32°F	0.49	0.50	0	0	1
Dummy above 100°F*1.5stdev	0.04	0.19	0	0	0
Dummy below 32°F*1.5stdev	0.35	0.48	0	0	1
Mean daily precipitation (inch)	0.09	0.18	0.03	0.07	0.12
Panel E. County*NAICS3*Year Frequency					
(15 Million Merchants)					
Log(sales - in thousands)	6.34	2.75	4.60	6.48	8.27
Log(transaction count)	8.55	3.12	6.50	8.65	10.75
Number of days above 100°F	2.86	9.60	0	0	1
Number of days below 32°F	77.68	49.71	35	76	115
Number of days above 100°F*1.5stdev	1.49	4.58	0	0	0
Number of days below 32°F*1.5stdev	12.59	9.02	6	11	17
Dummy above 100°F	0.26	0.44	0	0	1
Dummy below 32°F	0.98	0.15	1	1	1
Dummy above 100°F*1.5stdev	0.24	0.43	0	0	0
Dummy below 32°F*1.5stdev	0.97	0.18	1	1	1
Mean daily precipitation (inch)	0.09	0.09	0.06	0.09	0.12

Table 2: Effects of Temperature Shocks on Small Businesses - Weekly

This table presents results from our staggered event study regression, Equation (1), estimating the differential effect of temperature shocks on an establishment's weekly sales and in-person sales. Columns (1) and (2) report estimates for establishments in counties experiencing a weekly maximum temperature above 100°F, while Columns (3) and (4) report results for cold shocks, defined as establishments in counties experiencing a weekly minimum temperature below 32°F. The dependent variable in Columns (1) and (3) is the natural logarithm of total weekly sales, whereas in Columns (2) and (4), it is the natural logarithm of total in-person (physical store) weekly sales. Each event spans nine weeks, with the first affected week labeled as week 0. The model is fully saturated, with one week prior to the event (Event Week = -1) serving as the omitted category. The independent variables represent the remaining eight weeks within the nine-week event window, each corresponding to a specific week number. All regressions include event-establishment fixed effects, with events defined as either heat or cold shocks. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering on the county level.

Shock Type:	Heat - 100°F		Cold - 32°F	
Dependent Variables:	Log (Sales)	Log (In-Person Sales)	Log (Sales)	Log (In-Person Sales)
Model:	(1)	(2)	(3)	(4)
Variables				
Event Week = -4	0.00955	-0.00065	0.02426***	0.01880***
	(1.23890)	(-0.08588)	(4.42614)	(3.57440)
Event Week = -3	0.01214**	0.00055	0.02628***	0.02341***
	(2.48028)	(0.09707)	(5.22870)	(4.39694)
Event Week = -2	0.00323	-0.00401	0.04046***	0.03706***
	(0.67856)	(-0.87978)	(7.61397)	(6.88272)
Event Week = 0	-0.01543***	-0.01643***	-0.09876***	-0.09119***
	(-3.09057)	(-2.79549)	(-7.67879)	(-8.07063)
Event Week = 1	-0.01433***	-0.01470***	-0.03872***	-0.03858***
	(-2.79696)	(-2.87652)	(-3.25423)	(-3.62000)
Event Week = 2	-0.01449***	-0.00756	-0.00802	-0.01094*
	(-3.00568)	(-1.57759)	(-1.33550)	(-1.86893)
Event Week = 3	-0.02461***	-0.01632**	-0.00857	-0.00869
	(-3.11103)	(-2.03746)	(-1.34180)	(-1.36491)
Event Week = 4	-0.02262**	-0.00433	-0.02745***	-0.02556***
	(-2.09508)	(-0.36831)	(-2.86483)	(-2.88816)
Precipitation	0.01119	0.02972	-0.07712***	-0.06884***
	(0.53508)	(0.91649)	(-4.97915)	(-4.65853)
Fixed-effects				
Event*Merchant	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.90005	0.85888	0.88059	0.84736
Observations	2,888,559	1,799,695	12,633,725	7,648,641

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Effect of Temperature Shocks on Small Businesses - Monthly

This table presents establishment-level monthly sales and number of visits regressions as specified in Equation (2). The sample consists of 5% randomly selected merchants from a total of 15 million. The dependent variable in all specifications has been taken the natural log. Panel A presents the estimated results for total sales, while Panel B reports the coefficients using transaction count as the dependent variable. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. Columns (1) - (4) include establishment, industry, and time fixed effects, with industries defined using 3-digit NAICS codes mapped from Merchant Category Codes (MCC). Columns (5) - (8) employ our preferred specification in Equation (2), which includes establishment-calendar-month and industry-year-month fixed effects. In parentheses under the independent variables, we also provide the median event length for each type of temperature exposure in days. The event length is calculated as the total number of extreme days within the time period. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: Sales

Dependent Variable:	Log(sales)							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.03147***				-0.00495**			
(Median event length: 4 days)	(-4.51551)				(-2.06952)			
Dummy below 32°F		-0.04308***				-0.00471***		
(Median event length: 11 days)		(-9.40988)				(-2.69645)		
Dummy above 100°F*1.5stdev			-0.02368***				-0.00478**	
(Median event length: 2 days)			(-5.35689)				(-2.24614)	
Dummy below 32°F*1.5stdev				-0.02296***				-0.00775***
(Median event length: 2 days)				(-7.90319)				(-6.90914)
Precipitation	-0.06665***	-0.06029***	-0.06421***	-0.06094***	-0.03201***	-0.03176***	-0.03202***	-0.03221***
	(-4.20821)	(-4.54710)	(-4.12994)	(-4.18378)	(-4.51670)	(-4.51993)	(-4.52031)	(-4.53314)
Fixed-effects								
Merchant	Yes	Yes	Yes	Yes				
NAICS3	Yes	Yes	Yes	Yes				
Year-Month	Yes	Yes	Yes	Yes				
Merchant*Calendar-Month					Yes	Yes	Yes	Yes
NAICS3*Year-Month					Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.78555	0.78557	0.78554	0.78555	0.84199	0.84199	0.84199	0.84199
Observations	22,008,356	22,008,356	22,008,356	22,008,356	19,801,409	19,801,409	19,801,409	19,801,409

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Number of Visits

Dependent Variable:	Log(transaction count)							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.03259***				-0.00690***			
(Median event length: 4 days)	(-5.15588)				(-2.95040)			
Dummy below 32°F		-0.04201***				-0.00591***		
(Median event length: 11 days)		(-10.16941)				(-3.98820)		
Dummy above 100°F*1.5stdev			-0.02457***				-0.00562**	
(Median event length: 2 days)			(-6.30622)				(-2.46777)	
Dummy below 32°F*1.5stdev				-0.02272***				-0.00851***
(Median event length: 2 days)				(-8.36961)				(-8.78213)
Precipitation	-0.06092***	-0.05430***	-0.05840***	-0.05495***	-0.03348***	-0.03308***	-0.03337***	-0.03353***
	(-4.18283)	(-4.59370)	(-4.09965)	(-4.17302)	(-4.82081)	(-4.82840)	(-4.82153)	(-4.83810)
Fixed-effects								
Merchant	Yes	Yes	Yes	Yes				
NAICS3	Yes	Yes	Yes	Yes				
Year-Month	Yes	Yes	Yes	Yes				
Merchant*Calendar-Month					Yes	Yes	Yes	Yes
NAICS3*Year-Month					Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.89604	0.89606	0.89604	0.89605	0.92497	0.92497	0.92497	0.92497
Observations	22,008,356	22,008,356	22,008,356	22,008,356	19,801,409	19,801,409	19,801,409	19,801,409

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Effect of Temperature Shocks on Small Businesses - Quarterly

This table presents establishment-level quarterly sales and number of visits regressions as specified in Equation (3). The sample is aggregated from the monthly sample that comprises 5% randomly selected merchants from a total of 15 million. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. Panel A presents results using extreme exposure dummies as independent variables. Panel B reports coefficients using the number of extreme days in the quarter as independent variables. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-quarter and industry-year-quarter fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: Dummy - *At Least One Day during the Quarter*

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.00796**				-0.01015***			
(Median event length: 4 days)	(-2.42746)				(-3.52913)			
Dummy below 32°F		0.00178				0.00247		
(Median event length: 21 days)		(0.56673)				(0.94146)		
Dummy above 100°F*1.5stdev			-0.00825***				-0.00973***	
(Median event length: 3 days)			(-2.76111)				(-3.71138)	
Dummy below 32°F*1.5stdev				-0.00140				-0.00094
(Median event length: 4 days)				(-0.69619)				(-0.54302)
Precipitation	-0.02252**	-0.02022**	-0.02276**	-0.02059**	-0.02071**	-0.01777**	-0.02079**	-0.01811**
	(-2.34612)	(-2.16578)	(-2.38257)	(-2.19247)	(-2.50455)	(-2.22406)	(-2.53005)	(-2.25022)
Fixed-effects								
Merchant*Calendar-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.82736	0.82736	0.82736	0.82736	0.91018	0.91018	0.91018	0.91018
Observations	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Number of Extreme Days

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Number of days above 100°F	-0.00042*				-0.00044**			
	(-1.75959)				(-2.32533)			
Number of days below 32°F		-0.00032**				-0.00035***		
		(-2.47216)				(-3.03540)		
Number of days above 100°F*1.5stdev			-0.00067**				-0.00061**	
			(-2.13091)				(-2.43192)	
Number of days below 32°F*1.5stdev				-0.00056***				-0.00065***
				(-2.80079)				(-3.85887)
Precipitation	-0.02184**	-0.02067**	-0.02206**	-0.02107**	-0.01952**	-0.01830**	-0.01948**	-0.01879**
	(-2.33446)	(-2.20387)	(-2.34395)	(-2.24801)	(-2.44595)	(-2.28415)	(-2.42824)	(-2.34774)
Fixed-effects								
Merchant*Calendar-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.82736	0.82736	0.82736	0.82736	0.91018	0.91018	0.91018	0.91018
Observations	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213	7,291,213

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: ***Lost Sales*** - Monthly Aggregated County*NAICS3 Level

This table presents county-industry level monthly aggregated sales and number of visits regressions as specified in Equation (4), with industries defined using 3-digit NAICS codes. The sample is aggregated from the entire monthly sample that contains information for 15 million merchants. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. Panel A presents results using extreme exposure dummies as independent variables. Panel B reports coefficients using the number of extreme days in the year as independent variables. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include county-industry-calendar-month and industry-year-month fixed effects. The *t*-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: Dummy - *At Least One Day during the year*

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.01700***				-0.02103***			
(Median event length: 4 days)	(-5.78442)				(-6.91339)			
Dummy below 32°F		-0.00595***				-0.00501***		
(Median event length: 11 days)		(-3.63320)				(-3.00730)		
Dummy above 100°F*1.5stdev			-0.01624***				-0.01913***	
(Median event length: 2 days)			(-6.05682)				(-6.81141)	
Dummy below 32°F*1.5stdev				-0.00817***				-0.00830***
(Median event length: 2 days)				(-7.99039)				(-7.92965)
Precipitation	0.00038	0.00068	0.00039	0.00053	-0.00017	0.00024	-0.00014	0.00007
	(0.12708)	(0.23756)	(0.13098)	(0.18051)	(-0.04453)	(0.06432)	(-0.03529)	(0.01775)
Fixed-effects								
County*NAICS3*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.86319	0.86319	0.86319	0.86319	0.88902	0.88902	0.88902	0.88902
Observations	17,020,437	17,020,437	17,020,437	17,020,437	17,027,259	17,027,259	17,027,259	17,027,259

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Number of Extreme Days

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Number of days above 100°F	-0.00090**				-0.00150***			
	(-2.04812)				(-3.27739)			
Number of days below 32°F		-0.00144***				-0.00170***		
		(-7.22680)				(-8.25886)		
Number of days above 100°F*1.5stdev			-0.00244***				-0.00299***	
			(-4.97702)				(-5.84504)	
Number of days below 32°F*1.5stdev				-0.00129***				-0.00148***
				(-5.47296)				(-6.03197)
Precipitation	0.00063	0.00031	0.00048	0.00053	0.00008	-0.00023	-0.00004	0.00004
	(0.21686)	(0.10318)	(0.16509)	(0.18273)	(0.02054)	(-0.05894)	(-0.00944)	(0.01136)
Fixed-effects								
County*NAICS3*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.86319	0.86319	0.86319	0.86319	0.88902	0.88902	0.88902	0.88902
Observations	17,020,437	17,020,437	17,020,437	17,020,437	17,027,259	17,027,259	17,027,259	17,027,259

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: *Lost Sales* - Annually Aggregated County*NAICS3 Level

This table presents county-industry level annually aggregated sales and number of visits regressions as specified in Equation (4), with industries defined using 3-digit NAICS codes. The sample is aggregated from the entire monthly sample that contains information for 15 million merchants. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. Panel A presents results using extreme exposure dummies as independent variables. Panel B reports coefficients using the number of extreme days in the year as independent variables. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include county-industry and industry-year fixed effects. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: Dummy - *At Least One Day during the year*

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.02535***				-0.02656***			
(Median event length: 5 days)	(-6.11160)				(-6.09983)			
Dummy below 32°F		0.01856				0.01775		
(Median event length: 77 days)		(1.45261)				(1.26700)		
Dummy above 100°F*1.5stdev			-0.02373***				-0.02465***	
(Median event length: 3 days)			(-6.19028)				(-6.07630)	
Dummy below 32°F*1.5stdev				-0.00606				-0.00595
(Median event length: 11 days)				(-0.66528)				(-0.61429)
Precipitation	0.03051**	0.03364**	0.03000**	0.03360**	0.03004**	0.03330**	0.02954**	0.03327**
	(2.11589)	(2.13579)	(2.11198)	(2.13457)	(2.49903)	(2.51785)	(2.49376)	(2.51625)
Fixed-effects								
County*NAICS3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.85060	0.85059	0.85060	0.85059	0.87544	0.87543	0.87544	0.87543
Observations	1,607,052	1,607,052	1,607,052	1,607,052	1,607,761	1,607,761	1,607,761	1,607,761

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Number of Extreme Days

Dependent Variables:	Log(sales)				log_txn_cnt			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Number of days above 100°F	-0.00043*				-0.00070***			
	(-1.79435)				(-2.74873)			
Number of days below 32°F		0.00006				-0.00005		
		(0.47415)				(-0.36902)		
Number of days above 100°F*1.5stdev			-0.00122***				-0.00141***	
			(-4.01932)				(-4.46235)	
Number of days below 32°F*1.5stdev				-0.00052***				-0.00062***
				(-2.64123)				(-2.97103)
Precipitation	0.03249**	0.03381**	0.03117**	0.03271**	0.03144**	0.03316**	0.03046**	0.03220**
	(2.13163)	(2.13544)	(2.12629)	(2.12343)	(2.51483)	(2.51293)	(2.50832)	(2.50144)
Fixed-effects								
County*NAICS3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.85059	0.85059	0.85059	0.85059	0.87543	0.87543	0.87543	0.87543
Observations	1,607,052	1,607,052	1,607,052	1,607,052	1,607,761	1,607,761	1,607,761	1,607,761

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Effect on Young Merchants

This table presents establishment-level monthly sales and number of visits regressions. The sample consists of 5% randomly selected merchants from a total of 15 million. The dependent variable in all specifications has been taken the natural log. Panel A presents the estimated results for total sales, while Panel B reports the coefficients using transaction count as the dependent variable. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. Columns "$<= 12mo$" include establishments with at most 12 months' observations in our sample. Columns "$> 12mo$" are the establishments that we could observe at least 12 months' records in our sample. "$<= 12mo$" regressions include establishment fixed effects, while the rest employ Equation (2) that includes establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: Sales

Dependent Variable:	Log(sales)							
Model:	$<= 12mo$	$> 12mo$	$<= 12mo$	$> 12mo$	$<= 12mo$	$> 12mo$	$<= 12mo$	$> 12mo$
Variables								
Dummy above 100°F	-0.03462**	-0.00495**						
	(-2.54401)	(-2.04086)						
Dummy below 32°F			-0.03993***	-0.00485***				
			(-6.35710)	(-2.78004)				
Dummy above 100°F*1.5stdev					-0.02511***	-0.00489**		
					(-2.73910)	(-2.28049)		
Dummy below 32°F*1.5stdev							-0.02034***	-0.00780***
							(-4.08255)	(-6.96363)
Precipitation	-0.07330***	-0.03175***	-0.05998**	-0.03150***	-0.06933**	-0.03177***	-0.06316**	-0.03195***
	(-2.70589)	(-4.49034)	(-2.34749)	(-4.49221)	(-2.57289)	(-4.49495)	(-2.39741)	(-4.50586)
Fixed-effects								
Merchant	Yes		Yes		Yes		Yes	
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Merchant*Calendar-Month		Yes		Yes		Yes		Yes
Fit statistics								
R^2	0.72633	0.84124	0.72634	0.84124	0.72633	0.84124	0.72633	0.84124
Observations	1,545,180	19,708,641	1,545,180	19,708,641	1,545,180	19,708,641	1,545,180	19,708,641

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Number of Visits

Dependent Variable:	Log(transaction count)							
Model:	<= 12mo	> 12mo	<= 12mo	> 12mo	<= 12mo	> 12mo	<= 12mo	> 12mo
Variables								
Dummy above 100°F	-0.03375***	-0.00687***						
	(-3.10898)	(-2.91970)						
Dummy below 32°F			-0.03822***	-0.00604***				
			(-7.34223)	(-4.09437)				
Dummy above 100°F*1.5stdev					-0.02533***	-0.00565**		
					(-3.36263)	(-2.47786)		
Dummy below 32°F*1.5stdev							-0.01982***	-0.00855***
							(-4.80334)	(-8.85726)
Precipitation	-0.06938***	-0.03353***	-0.05646***	-0.03315***	-0.06572***	-0.03343***	-0.05950***	-0.03359***
	(-3.05657)	(-4.81059)	(-2.71609)	(-4.81766)	(-2.90389)	(-4.81183)	(-2.71881)	(-4.82725)
Fixed-effects								
Merchant	Yes		Yes		Yes		Yes	
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Merchant*Calendar-Month		Yes		Yes		Yes		Yes
Fit statistics								
R^2	0.86062	0.92462	0.86063	0.92462	0.86061	0.92462	0.86062	0.92462
Observations	1,545,180	19,708,641	1,545,180	19,708,641	1,545,180	19,708,641	1,545,180	19,708,641

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Exit - Merchant Closure

This table presents establishment-level monthly sales and number of visits regressions. The sample consists of 5% randomly selected merchants from a total of 15 million. The dependent variable in all specifications is an exit dummy variable, set to 1 for year-month t if the establishment registers positive sales in year-month t but records no sales in year-month $t+1$ and beyond. Panel A presents the estimated results for extreme days using the absolute threshold, while Panel B reports the coefficients using historical measures described in Section 3.2.1. The independent variables are cumulative exposure measures calculated by counting all the corresponding types of extreme days in the past 1, 3, 6, and 12 months. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: 100°F & 32°F

Dependent Variable:	Exit							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Number of days above 100°F	0.00000							
	(0.15818)							
Number of days above 100°F - pre 3mo		0.00014***						
		(4.43644)						
Number of days above 100°F - pre 6mo			0.00015***					
			(6.03164)					
Number of days above 100°F - pre 12mo				0.00020***				
				(18.84442)				
Number of days below 32°F					-0.00002			
					(-0.91899)			
Number of days below 32°F - pre 3mo						0.00020***		
						(23.15332)		
Number of days below 32°F - pre 6mo							0.00022***	
							(44.46245)	
Number of days below 32°F - pre 12mo								0.00020***
								(44.99786)
Precipitation	0.00000	0.00015	0.00010	0.00001	-0.00001	0.00009	-0.00009	-0.00017
	(0.00692)	(0.52648)	(0.33517)	(0.02409)	(-0.05239)	(0.32927)	(-0.30743)	(-0.55488)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.31751	0.31751	0.31752	0.31759	0.31751	0.31755	0.31773	0.31827
Observations	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: 100°F*1.5 Standard Deviation & 32°F*1.5 Standard Deviation

Dependent Variable:	Exit							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Number of days above 100°F*1.5stdev	0.00002							
	(0.61942)							
Number of days above 100°F*1.5stdev - pre 3mo		0.00012^{***}						
		(5.23222)						
Number of days above 100°F*1.5stdev - pre 6mo			0.00013^{***}					
			(7.32915)					
Number of days above 100°F*1.5stdev - pre 12mo				0.00021^{***}				
				(10.11807)				
Number of days below 32°F*1.5stdev					-0.00004^{**}			
					(-1.96841)			
Number of days below 32°F*1.5stdev - pre 3mo						0.00011^{***}		
						(8.40301)		
Number of days below 32°F*1.5stdev - pre 6mo							0.00025^{***}	
							(21.19883)	
Number of days below 32°F*1.5stdev - pre 12mo								0.00039^{***}
								(26.94751)
Precipitation	0.00001	0.00009	0.00006	0.00004	-0.00003	0.00004	0.00010	0.00025
	(0.03856)	(0.33507)	(0.21957)	(0.13420)	(-0.09258)	(0.13116)	(0.34333)	(0.88502)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.31751	0.31751	0.31751	0.31753	0.31751	0.31751	0.31755	0.31777
Observations	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539	21,621,539

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Robustness - Remove Covid Period

This table presents establishment-level monthly sales and number of visits regressions as specified in Equation (2). To mitigate potential COVID-19 impacts, we have excluded observations from 2020 onward from our 5% randomly selected monthly sample. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.00446**				-0.00551***			
	(-2.09554)				(-2.73144)			
Dummy below 32°F		-0.00461***				-0.00440***		
		(-2.60832)				(-2.95721)		
Dummy above 100°F*1.5stdev			-0.00506***				-0.00549***	
			(-2.58841)				(-3.03948)	
Dummy below 32°F*1.5stdev				-0.00788***				-0.00819***
				(-6.59549)				(-8.19896)
Precipitation	-0.03325***	-0.03302***	-0.03332***	-0.03348***	-0.03533***	-0.03498***	-0.03533***	-0.03547***
	(-4.26189)	(-4.27004)	(-4.26207)	(-4.27568)	(-4.43192)	(-4.44578)	(-4.43244)	(-4.45038)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.85642	0.85642	0.85642	0.85642	0.93351	0.93351	0.93351	0.93351
Observations	15,668,421	15,668,421	15,668,421	15,668,421	15,668,421	15,668,421	15,668,421	15,668,421

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Weekend vs. Non-weekend

This table presents establishment-level monthly sales and number of visits regressions as specified in Equation (2). We further distinguish all monthly temperature shock dummies into two types: *weekend* and *non-weekend*. The *weekend* is defined as an impacted month if at least one extreme day within the month falls on a weekend (Saturday or Sunday), and *non-weekend* otherwise. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F - weekend	-0.00533*				-0.00815***			
	(-1.78917)				(-2.75295)			
Dummy above 100°F - non-weekend	-0.00435				-0.00542**			
	(-1.54255)				(-2.12560)			
Dummy below 32°F - weekend		-0.00606***				-0.00718***		
		(-3.10676)				(-4.52712)		
Dummy below 32°F - non-weekend		-0.00355*				-0.00478***		
		(-1.66094)				(-2.60789)		
Dummy above 100°F*1.5stdev - weekend			-0.00582**				-0.00710***	
			(-2.25688)				(-2.59516)	
Dummy above 100°F*1.5stdev - non-weekend			-0.00341				-0.00378	
			(-1.12069)				(-1.32763)	
Dummy below 32°F*1.5stdev - weekend				-0.00980***				-0.01024***
				(-7.77713)				(-9.77562)
Dummy below 32°F*1.5stdev - non-weekend				-0.00585***				-0.00691***
				(-4.50060)				(-6.13215)
Precipitation	-0.03223***	-0.03203***	-0.03224***	-0.03249***	-0.03367***	-0.03330***	-0.03355***	-0.03375***
	(-4.52452)	(-4.52842)	(-4.52927)	(-4.54499)	(-4.82162)	(-4.83227)	(-4.82525)	(-4.84447)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.84191	0.84191	0.84191	0.84191	0.92491	0.92491	0.92491	0.92491
Observations	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: *Spells* - Multiday Events

This table presents establishment-level monthly sales and number of visits regressions as specified in Equation (2). We further distinguish all monthly temperature shock dummies into two types: "$\geq$ 3-day event" and "$<$ 3-day event". The "$\geq$ 3-day event" is defined as an impacted month if the longest event lasts at least 3 days, and "$<$ 3-day event" otherwise. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F - $\geq$ 3-day event	-0.00440				-0.00618*			
	(-1.21192)				(-1.80247)			
Dummy above 100°F - $<$ 3-day event	-0.00504**				-0.00708***			
	(-1.98025)				(-2.96768)			
Dummy above 100°F*1.5stdev - $\geq$ 3-day event		-0.00380				-0.00452		
		(-1.24514)				(-1.53448)		
Dummy above 100°F*1.5stdev - $<$ 3-day event		-0.00512**				-0.00604**		
		(-2.16325)				(-2.45135)		
Dummy below 32°F - $\geq$ 3-day event			-0.01061***				-0.01223***	
			(-4.39442)				(-6.09976)	
Dummy below 32°F - $<$ 3-day event			-0.00399**				-0.00511***	
			(-2.30626)				(-3.45490)	
Dummy below 32°F*1.5stdev - $\geq$ 3-day event				-0.01352***				-0.01446***
				(-7.33407)				(-8.77959)
Dummy below 32°F*1.5stdev - $<$ 3-day event				-0.00654***				-0.00726***
				(-5.85881)				(-7.69045)
Precipitation	-0.03220***	-0.03220***	-0.03242***	-0.03282***	-0.03361***	-0.03350***	-0.03373***	-0.03411***
	(-4.53070)	(-4.53003)	(-4.53283)	(-4.55185)	(-4.82938)	(-4.82685)	(-4.83396)	(-4.84733)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.84191	0.84191	0.84191	0.84191	0.92491	0.92491	0.92491	0.92491
Observations	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099	19,806,099

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Merchant Categorization

This table provides the broad definitions for discretionary, non-discretionary, other, and outdoor merchants based on Merchant Category Codes (MCC). Discretionary merchants include categories such as dining, entertainment, and specialty retail stores. Non-discretionary merchants encompass essential services and goods such as groceries, utilities, and healthcare services. The "other" category includes merchants that do not distinctly fall into discretionary or non-discretionary categories, such as financial services and government services. Outdoor merchants refer to businesses primarily operating in outdoor environments, including recreational facilities and outdoor contractors. These classifications are used to analyze the differential impact of temperature shock events on various types of merchants. Detailed MCC codes are available in Appendix Table A.2 and Table A.3.

Category Name	Type	Category Name	Type
Discretionary, Non-discretionary, and Other Merchant Categories			
Restaurants & bars	Discretionary	Professional services	Discretionary
Airlines	Discretionary	Spa/beauty services	Discretionary
Lodging	Discretionary	Telecommunication	Discretionary
Auto rental	Discretionary	Charity	Discretionary
Appliance retail	Discretionary	Direct marketing	Discretionary
Computer retail	Discretionary	Clubs	Discretionary
Fashion retail	Discretionary	Grocery (food retail)	Non-discretionary
Florist	Discretionary	Medical/health services	Non-discretionary
General department store	Discretionary	Pharmacy	Non-discretionary
Home goods retail	Discretionary	Supermarkets	Non-discretionary
Leisure goods retail	Discretionary	Postal/courier	Non-discretionary
Luxury goods retail	Discretionary	Utilities	Non-discretionary
Repurposed goods retail	Discretionary	Education	Non-discretionary
Sporting goods retail	Discretionary	Tolls/fees	Non-discretionary
Attractions & amusements	Discretionary	Wholesale	Non-discretionary
Duty free	Discretionary	Gas stations	Other
Entertainment	Discretionary	Non-store retailers	Other
Gambling	Discretionary	Publishing	Other
Marina services	Discretionary	Finance services	Other
Sport & recreation	Discretionary	Insurance services	Other
Transportation	Discretionary	Counseling services	Other
Travel agencies	Discretionary	Government services	Other
Construction services	Discretionary	Tax payments	Other
Electric goods repair	Discretionary	Fines	Other
Home repair services	Discretionary	Bail and bond payments	Other
Personal services	Discretionary	Court costs	Other
Outdoor Merchant Categories			
Roofing and siding	Outdoor	Tourist attractions	Outdoor
Landscaping and horticultural	Outdoor	Amusement parks	Outdoor
Golf courses	Outdoor	Trailer parks and camp sites	Outdoor
Commercial sports	Outdoor	Tent and awning shops	Outdoor
Sporting and recreation camps	Outdoor	Car washes	Outdoor

Table 13: Discretionary vs. Non-discretionary

This table presents establishment-level monthly sales and number of visits regressions as specified in Equation (2). We have divided our 5% randomly selected monthly sample into three subsamples based on merchant categorizations in Table 12, including *discretionary*, *non-discretionary*, and *other*. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (3), the dependent variable is sales, while Columns (4) through (6) examine the number of visits. Panels A, B, C, and D represent results for *Dummy above 100°F*, *Dummy below 32°F*, *Dummy above 100°F*1.5 stdev*, and *Dummy below 32°F*1.5 stdev*, respectively. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Panel A: 100°F

Dependent Variables:	Log(sales)			Log(transaction count)		
Model:	Discretionary	Non-Discretionary	Other	Discretionary	Non-Discretionary	Other
Variables						
Dummy above 100°F	-0.00599**	-0.00688	0.00368	-0.00854***	-0.00695*	0.00307
	(-2.20865)	(-1.50106)	(0.64610)	(-3.34745)	(-1.72041)	(0.60631)
Precipitation	-0.03613***	-0.02765***	-0.02556**	-0.03946***	-0.03510***	-0.01910**
	(-3.81577)	(-3.12449)	(-2.41707)	(-4.51063)	(-3.82919)	(-2.18305)
Fixed-effects						
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.83881	0.84296	0.85629	0.92642	0.90569	0.93820
Observations	13,158,253	3,819,570	2,787,392	13,158,253	3,819,570	2,787,392

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: 32°F

Dependent Variables:	Log(sales)			Log(transaction count)		
Model:	Discretionary	Non-Discretionary	Other	Discretionary	Non-Discretionary	Other
Variables						
Dummy below 32°F	-0.00539**	-0.00580*	-0.00033	-0.00610***	-0.00578**	-0.00356
	(-2.46180)	(-1.88950)	(-0.08029)	(-3.23258)	(-2.16282)	(-1.03753)
Precipitation	-0.03574***	-0.02721***	-0.02580**	-0.03880***	-0.03465***	-0.01942**
	(-3.79613)	(-3.10374)	(-2.43347)	(-4.48785)	(-3.82586)	(-2.21235)
Fixed-effects						
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.83881	0.84296	0.85629	0.92642	0.90569	0.93820
Observations	13,158,253	3,819,570	2,787,392	13,158,253	3,819,570	2,787,392

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: (Continuted) Discretionary vs. Non-discretionary

Panel C: 100°F*1.5 Standard Deviation

Dependent Variables:	Log(sales)			Log(transaction count)		
Model:	Discretionary	Non-Discretionary	Other	Discretionary	Non-Discretionary	Other
Variables						
Dummy above 100°F*1.5stdev	-0.00655***	-0.00480	0.00459	-0.00761***	-0.00436	0.00428
	(-2.83390)	(-0.98597)	(0.73392)	(-3.56762)	(-0.91905)	(0.76175)
Precipitation	-0.03624***	-0.02742***	-0.02549**	-0.03939***	-0.03480***	-0.01901**
	(-3.82146)	(-3.11421)	(-2.41605)	(-4.50829)	(-3.82277)	(-2.17944)
Fixed-effects						
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.83881	0.84296	0.85629	0.92642	0.90569	0.93820
Observations	13,158,253	3,819,570	2,787,392	13,158,253	3,819,570	2,787,392

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel D: 32°F*1.5 Standard Deviation

Dependent Variables:	Log(sales)			Log(transaction count)		
Model:	Discretionary	Non-Discretionary	Other	Discretionary	Non-Discretionary	Other
Variables						
Dummy below 32°F*1.5stdev	-0.00914***	-0.00802***	-0.00114	-0.00962***	-0.00756***	-0.00430*
	(-7.11007)	(-3.87020)	(-0.45666)	(-8.81903)	(-4.23930)	(-1.95203)
Precipitation	-0.03637***	-0.02765***	-0.02585**	-0.03943***	-0.03504***	-0.01953**
	(-3.82242)	(-3.14237)	(-2.43608)	(-4.50938)	(-3.85468)	(-2.22109)
Fixed-effects						
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.83881	0.84296	0.85629	0.92642	0.90569	0.93820
Observations	13,158,253	3,819,570	2,787,392	13,158,253	3,819,570	2,787,392

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14: Outdoor Merchants

This table presents establishment-level monthly sales and number of visits regressions as specified in Equation (2). The sample contains only *outdoor* establishments based on their merchant categories as described in Table 12. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The t-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F	-0.03566**				-0.04597***			
	(-2.12908)				(-3.27486)			
Dummy below 32°F		-0.02576**				-0.01132		
		(-1.97385)				(-1.03361)		
Dummy above 100°F*1.5stdev			-0.04342***				-0.04600***	
			(-2.62064)				(-3.41305)	
Dummy below 32°F*1.5stdev				-0.02811***				-0.02366***
				(-3.11755)				(-3.07274)
Precipitation	-0.41753***	-0.41351***	-0.41912***	-0.41507***	-0.39079***	-0.38340***	-0.39096***	-0.38576***
	(-7.19051)	(-7.15742)	(-7.22152)	(-7.15197)	(-7.80515)	(-7.69299)	(-7.81635)	(-7.69721)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.83058	0.83058	0.83058	0.83059	0.92964	0.92963	0.92964	0.92964
Observations	163,525	163,525	163,525	163,525	163,525	163,525	163,525	163,525

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 15: Merchant Size

This table presents establishment-level monthly sales and number of visits regressions. The sample consists of 5% randomly selected merchants from a total of 15 million. The dependent variable in all specifications is the natural log of total sales. We define *Small* as an indicator variable equal to 1 if an establishment's lagged past-12-month mean monthly sales is within the bottom quantile for its industry (3-digit NAICS) in the month. We run Equation (2) using the interaction of *Small* and *Temperature Exposure*. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The *t*-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F × Small	-0.03310***				-0.02723***			
	(-4.66558)				(-3.87292)			
Dummy below 32°F × Small		-0.00912*				-0.01534***		
		(-1.82125)				(-3.39091)		
Dummy above 100°F*1.5stdev × Small			-0.02605***				-0.02199***	
			(-3.64408)				(-3.16067)	
Dummy below 32°F*1.5stdev × Small				-0.00050				-0.00324
				(-0.18366)				(-1.33479)
Small	-0.82690***	-0.82517***	-0.82760***	-0.82850***	-0.72065***	-0.71626***	-0.72120***	-0.72122***
	(-115.09025)	(-118.44577)	(-115.50587)	(-117.42711)	(-104.59917)	(-110.27439)	(-105.13630)	(-107.39450)
Dummy above 100°F	0.00260				-0.00049			
	(0.90193)				(-0.19543)			
Dummy below 32°F		-0.00276				-0.00243		
		(-1.27982)				(-1.28287)		
Dummy above 100°F*1.5stdev			0.00151				-0.00031	
			(0.54824)				(-0.12241)	
Dummy below 32°F*1.5stdev				-0.00717***				-0.00753***
				(-5.71440)				(-6.79524)
Precipitation	-0.02487***	-0.02466***	-0.02484***	-0.02501***	-0.02934***	-0.02903***	-0.02924***	-0.02940***
	(-3.91995)	(-3.90434)	(-3.92071)	(-3.91528)	(-4.29991)	(-4.29519)	(-4.30235)	(-4.29972)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.86645	0.86644	0.86644	0.86644	0.93864	0.93864	0.93864	0.93864
Observations	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 16: Sales Volatility

This table presents establishment-level monthly sales and number of visits regressions. The sample consists of 5% randomly selected merchants from a total of 15 million. The dependent variable in all specifications is the natural log of total sales. We define *High sales volatility* as an indicator variable equal to 1, if an establishment's lagged past-12-month standard deviation of its monthly sales normalized by the average monthly sales in the same period, is within the bottom quantile for its industry (3-digit NAICS) in the month. We run Equation (2) using the interaction of *High sales volatility* and *Temperature Exposure*. The dependent variable in all specifications is the natural logarithm. In Columns (1) through (4), the dependent variable is sales, while Columns (5) through (8) examine the number of visits. The independent variables include various temperature shock exposure measurements described in Section 3.2.1. All regressions include establishment-calendar-month and industry-year-month fixed effects, with industries defined using 3-digit NAICS codes. The *t*-statistics, reported below the coefficient estimates, are calculated using standard errors adjusted for clustering at the county level.

Dependent Variables:	Log(sales)				Log(transaction count)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dummy above 100°F × High sales volatility	-0.02382***				-0.01875***			
	(-3.25793)				(-2.67833)			
Dummy below 32°F × High sales volatility		0.00123				0.00038		
		(0.19649)				(0.06776)		
Dummy above 100°F*1.5stdev × High sales volatility			-0.02298***				-0.01826**	
			(-3.04918)				(-2.50437)	
Dummy below 32°F*1.5stdev × High sales volatility				0.00299				0.00157
				(0.74356)				(0.45594)
High sales volatility	-0.43425***	-0.43596***	-0.43458***	-0.43627***	-0.41801***	-0.41913***	-0.41827***	-0.41940***
	(-71.67210)	(-61.41166)	(-71.82378)	(-67.97944)	(-74.40007)	(-65.00202)	(-74.62648)	(-71.35023)
Dummy above 100°F	0.00089				-0.00202			
	(0.29820)				(-0.72583)			
Dummy below 32°F		-0.00514**				-0.00603***		
		(-2.33841)				(-3.03146)		
Dummy above 100°F*1.5stdev			0.00101				-0.00094	
			(0.38287)				(-0.36251)	
Dummy below 32°F*1.5stdev				-0.00838***				-0.00898***
				(-5.56298)				(-6.56003)
Precipitation	-0.02613***	-0.02599***	-0.02612***	-0.02638***	-0.03052***	-0.03026***	-0.03043***	-0.03067***
	(-3.84896)	(-3.83851)	(-3.85180)	(-3.85179)	(-4.18290)	(-4.17970)	(-4.18582)	(-4.18673)
Fixed-effects								
Merchant*Calendar-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3*Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.86352	0.86352	0.86352	0.86352	0.93754	0.93754	0.93754	0.93754
Observations	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040	13,938,040

Clustered (county) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A Appendix

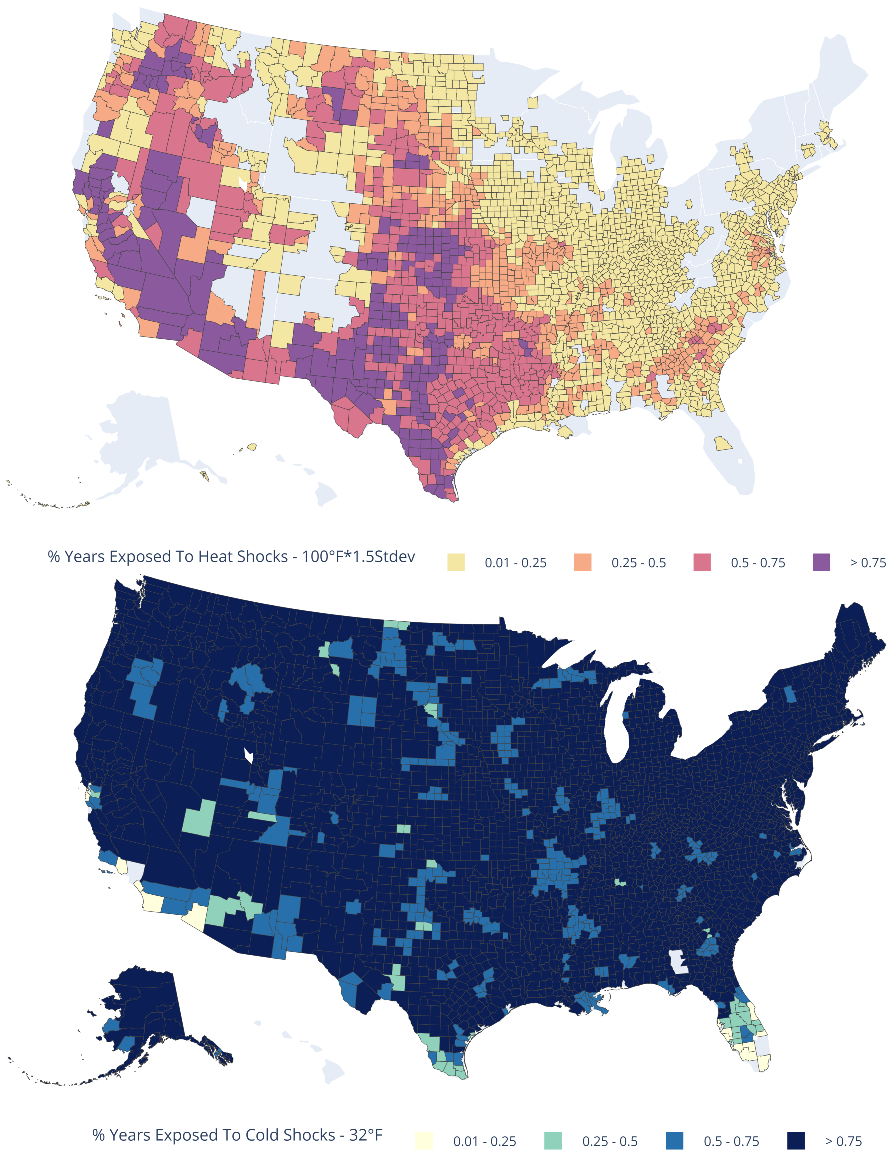


Figure A.1: Heat and Cold Shocks from 2006 to 2023 at U.S. County Level - 1.5 Stdev

This figure illustrates the percentage of years during 2006-2023 a given county has exposed to extreme weather events. The top panel shows counties that experienced extreme heat events, defined as days with temperatures exceeding 100˚F*1.5stdev, while the bottom panel displays counties affected by extreme cold events, defined as days with temperatures below 32˚F*1.5stdev. The grey areas are not exposed to extreme events during the period. The maps highlight the regional patterns and frequency of these temperature shock events at annual level over the specified period.

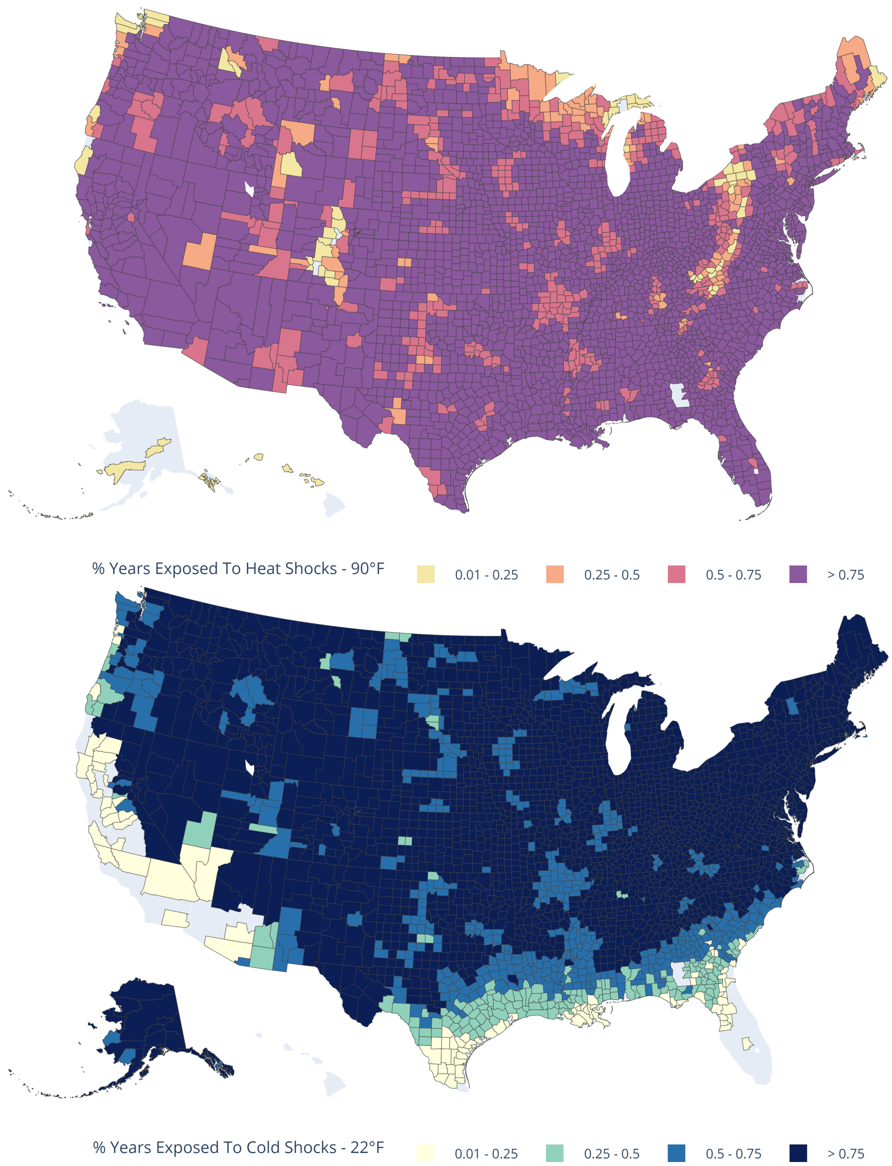


Figure A.2: Heat and Cold Shocks from 2006 to 2023 at U.S. County Level - 90°F and 22°F

This figure illustrates the percentage of years during 2006-2023 a given county has exposed to extreme weather events. The top panel shows counties that experienced extreme heat events, defined as days with temperatures exceeding 90°F, while the bottom panel displays counties affected by extreme cold events, defined as days with temperatures below 22°F. The grey areas are not exposed to extreme events during the period. The maps highlight the regional patterns and frequency of these temperature shock events at annual level over the specified period.

Table A.1: Summary Statistics - Staggered Event Sample

This table provides the summary statistics for key variables used in the analysis. Panel A reports the summary statistics of staggered event study sample for 100°F heat shocks from January 2021 to October 2022, covering about 3 million small businesses. Panel B reports summary statistics of staggered event study sample for 32°F cold shocks. All sales and transaction count variables are winsorized at the 1st and 99th percentiles. Mean daily precipitation is calculated based on county and period. Section 3.2.1 defines the temperature variables. Daily precipitation is reported in inches.

	Mean	SD	1st Qu.	Median	3rd Qu.
Panel A. Staggered Event Sample - Heat *(3 Million Merchants - Post 2020)*					
Sales	15,397.05	20,319.17	2,138	7,025.25	19,870.16
Transaction count	357.70	648.76	18	75	351
In-person sales	2,889.75	6,257.14	0	346.50	2,678.20
In-person transaction count	50.69	128.73	0	4	30
Log(sales)	8.69	1.61	7.67	8.86	9.90
Log(transaction count)	4.36	1.93	2.89	4.32	5.86
Log(in-person sales)	7.30	1.72	6.19	7.46	8.54
Log(in-person transaction count)	2.96	1.79	1.61	2.89	4.32
Mean daily precipitation (inch)	0.02	0.06	0	0	0
Panel B. Staggered Event Sample - Cold *(3 Million Merchants - Post 2020)*					
Sales	13,645.70	18,345.66	1,927.31	6,325.06	17,404.06
Transaction count	342.12	625.63	17	70	330
In-person sales	2,837.22	6,138.89	0	313	2,655
In-person transaction count	51.97	132.00	0	3	30
Log(sales)	8.57	1.61	7.56	8.75	9.76
Log(transaction count)	4.31	1.92	2.83	4.25	5.80
Log(in-person sales)	7.34	1.71	6.25	7.51	8.57
Log(in-person transaction count)	3.03	1.78	1.61	2.94	4.37
Mean daily precipitation (inch)	0.07	0.10	0	0.03	0.10

Table A.2: Merchant Categorization

This table presents all 625 Merchant Category Codes (MCCs). All categories are classified as either *Discretionary*, *Non-discretionary*, or *Other*.

Category	MCC Code	Category	MCC Code	Category	MCC Code
		Discretionary			
Veterinary services	742	Landscaping and horticultural	780	General contractors	1520
Heating- plumbing	1711	Masonry- stonework	1740	Carpentry	1750
Roofing and siding	1761	Contractors-concrete work	1771	Special trade contractors	1799
Typesetting-plate making- and related srvs	2791	Specialty cleaning-polishing-sanitation	2842	Airlines	3000-3299
Car rental	3351-3441	Branded hotels	3501-3836	Local passenger trans.	4111
Passenger railways	4112	Taxicabs/limousines	4121	Bus lines-including charter	4131
Steamship/cruise lines	4411	Boat rentals and leases	4457	Marinas- marine service	4468
Air transportation	4511	Airports-flying fields-terminals	4582	Travel agencies	4722
Travel services mail	4761	Transportation services- not elsewhere	4789	Telephone service/equipment	4812-4813
Telephone service/mag stripe calls	4814	Visaphone	4815	Computer network/information services	4816
Telegraph services	4821	Cable television services	4899	Motor vehicle suppplies and new parts	5013
Commercial furniture	5021	Offc-photogrphic-photocopy-microfilm eq	5044	Computers-peripheral equip-sftwre	5045
Commercial eqpmnt not elsewh classified	5046	Electrical parts and equipment	5065	Industrial supplies not elsewh clssified	5085
Precious stones-metals-watches-jewelry	5094	Durable goods not elsewhere classified	5099	Stationery-offc supplies-printing-wr ppr	5111
Piece goods-notions-and other dry goods	5131	Florist supplies-nursery stk-flowers	5193	Nondurable goods not elsewhere classifd	5199
Home supply warehouse stores	5200	Lumber and building materials	5211	Glass- paint- and wallpaper stores	5231
Hardware stores	5251	Lawn and garden supply stores	5261	Mobile home dealers	5271
Wholesale club	5300	Duty free stores	5309	Discount stores	5310
Department stores	5311	Variety stores	5331	Miscellaneous general merchandise	5399
Automobile and truck new/used svc parts	5511	Automobile and truck dealers used only	5521	Auto and home supply stores	5531
Automotive tire stores	5532	Automotive parts-accessories stores	5533	Boat dealers	5551
Recreational and utility trailers	5561	Motorcycle dealers	5571	Motor homes dealers	5592
Snowmobile dealers	5598	Miscellaneous automotive dealers-not els	5599	Mens and boys clothing	5611
Womens ready-to-wear stores	5621	Womens accessory and specialty shops	5631	Childrens and infants wear	5641
Family clothing stores	5651	Sports apparel- riding apparel stores	5655	Shoe stores	5661
Furriers and fur shops	5681	Mens womens clothing stores	5691	Tailors-seamstresses- mending	5697
Wig and toupee stores	5698	Miscellaneous apparel	5699	Furniture-home furnishings	5712
Floor covering stores	5713	Drapery-windowcovering-upholstery	5714	Fireplace-fireplace screens	5718
Miscellaneous home furnishing	5719	Household appliance stores	5722	Radio-television- and stero	5732
Music stores- musical instruments	5733	Computer software stores	5734	Record shops	5735
Caterers	5811	Eating places- rest. except express pay	5812	Drinking places	5813
Fast food restaurants	5814	Used merchandise stores	5931	Antique shops	5932
Pawn shops	5933	Wrecking and salvage yards	5935	Antique reproductions	5937
Bicycle shops-sales and service	5940	Sporting goods stores	5941	Book stores	5942
Stationery stores	5943	Jewelry stores	5944	Hobby toy and game shops	5945
Camera and photographic supply	5946	Gift- card- novelty	5947	Luggage and leather goods	5948
Sewing needlework	5949	Glassware/crystal stores	5950	Direct marketing insurance srvs	5960
Telemarketing travel-related	5962	Artists supply and craft shops	5970	Art dealers and galleries	5971, 8411
Stamp and coin stores	5972	Religious goods stores	5973	Rubber stamp stores	5974
Hearing aids- sales- service	5975	Cosmetic stores	5977	Typewriter store-sales- rentals- service	5978
Florists	5992	Cigar stores and stands	5993	News dealers and newsstands	5994
Pet shops- pet foods	5995	Swimming pools- sales and service	5996	Electric razor stores	5997
Tent and awning shops	5998	Miscellaneous and specialty retail	5999	RE agents- brokers- mgrs	6513
Central reservation services	7011	Timeshares	7012	Sporting and recreational camps	7032
Trailer parks and camp sites	7033	Laundry- cleaning- and garment services	7210	Laundries-family and commercial	7211-7212
Dry cleaners	7216	Carpet and upholstery cleaning	7217	Photographic studios-portraits	7221
Beauty shops- barber shops	7230-7231	Shoe repair shops-shoe shine parlors	7251	Funeral service and crematories	7261
Dating and escort services	7273	Tax preparation service	7276	Clothing-rental- costumes	7296
Massage parlors	7297	Health and beauty spas	7298	Miscellaneous personal services	7299
Advertising services	7311	Consumer credit reporting agencies	7321-7332	Commercial photography	7333
Quick copy and reproduction services	7338	Stenographic services	7339, 7341	Disinfecting and exterminating services	7342
Cleaning and maintenance	7349	Employement agencies	7361	Computer and data processing services	7372
Information retrieval srvs	7375	Computer maint-repair-srvs not classfied	7379	Management- consulting	7392
Dectective agencies	7393	Equipment rental and leasing services	7394	Photofinishing laboratories	7395
Business services- not elsewhere	7399	Auto rentals and leasing	7512	Truck and utility trailer rentals	7513
Motor home and rec vehicles rental	7519	Parking lots and garages	7523	Automotive top and body repair	7531
Tire retreading and repair	7534	Paint shops-automotive	7535	Automotive repair shops-non-dealer	7538-7539
Car washes	7542	Radio-television and stero repair	7622	Air conditioning and refrigeration repair	7623
Electrical and small appliance repair	7629	Watch- clock and jewelry repair	7631	Reupholstery and furniture repair	7641
Welding	7692	Miscellaneous repair shops	7699	Motion picture the. except exp pay	7832
Video tape rental stores	7841	Dance halls-studios/schools	7911	Theatrical producers	7922
Bands- orchestras-	7929	Billard and pool establishments	7932	Bowling alleys	7933
Commercial sports-	7941	Tourist attractions and exhibits	7991	Golf courses-public	7992
Video amusement game supplies	7993	Video game arcades	7994	Gambling transactions	7995
Amusement parks	7996	Membership clubs	7997	Aquariums- seaquariums	7998
Recreation services	7999	Opticians, optical goods, and eyeglasses	8044	Legal services- attorneys	8111
Charitable and social service organization	8398	Civic- social- and fraternal assoc.	8641	Political organizations	8651
Religious organizations	8661	Automobile associations	8675	Membership organizations-not elsewhere	8699
Testing lab (non-medical)	8734	Architectural- engineering	8911	Accountants- auditors	8931
Professional services- not elsewhere	8999				

Table A.2: (Continuted) Merchant Categorization

Category	MCC Code	Category	MCC Code	Category	MCC Code
		Non-discretionary			
Ambulance services	4119	Motor freight carriers	4214	Courier services	4215
Public warehousing	4225	Toll and bridge fees	4784	Utilities-electric-gas-water	4900
Construction materials	5039	Lab/med/dental/ophthalmic hosp eq and supply	5047	Metal service center	5051
Hardware equipmnt and supplies	5072	Plumbing and heating equipmnt	5074	Drugs-drug proprieties-druggist sundries	5122
Mens-womens-childrens uniforms-comm clth	5137, 5139	Chemicals and allied products not elsewhere	5169	Books-periodicals- and newspapers	5192
Paint-varnishes-supplies	5198	Grocery stores-supermarkets	5411	Freezer and locker meat provisioners	5422-5423
Candy-nut- and confectionery stores	5441	Dairy products stores	5451	Bakeries	5462
Miscellaneous food stores-specialty	5499	Drug stores and pharmacies	5912	Package stores - beer- wine and liquor	5921
Orthopedic goods	5976	Babysitting services	7295	Towing services	7549
Doctors- physicians	8011	Dentists- orthodontists	8021	Osteopaths	8031
Chiropractors	8041	Optometrists- ophthalmologists	8042	Opticians	8043
Chiropodists- podiatrists	8049	Convalescent homes/nursing	8050	Hospitals	8062
Medical dental laboratories	8071	Medical services and health practitioners	8099	Elementary and secondary schools	8211
Colleges- universities-	8220-8221	Correspondence schools	8241	Business and secretarial schools	8244
Vocational and trade schools	8249	Schools and educational svcs-not elsw.	8299	Child day care services	8351
		Other			
Agricultural co-operative	763	Miscellaneous publishing and printing	2741	Money transfer-merchant	4829
Petroleum and petroleum products	5172	Service stations	5541	Automated gasoline dispensers	5542
Electric vehicle charging	5552	Mail order catalog	5961	Direct selling establishments	5963
Catalog merchant	5964	Comb catalog and retail merch.	5965	High risk mccs.	5966-5967
Continuity/subscription merch.	5968	Direct marketers-not elsewhere class.	5969	Fuel oil dealers-wood-coal-lpg	5983
Member fncl.inst.manual cash dsbrsmnt.	6010	Member fncl.inst.automated cash dsbrsmnt	6011	Member fincl.inst.merchandise and services	6012
Quasi cash-member fincl/institution	6050	Quasi cash-merchant	6051	Security brokers/dealers	6211
Insurance sales and underwriting	6300, 6399	Insurance premiums	6381	Counseling service	7277
Buying/shopping services- clubs	7278	Truck stop	7511	Motion picture and video tape prod and distribtn	7829
Court costs/alimony-child supp.	9211	Fines	9222	Bail and bond payments	9223
Tax payments	9311	Government services- not elsewhere	9399	Postage stamps	9402
U.S. federal government agencies or dept	9405				

Table A.3: Outdoor Merchants

Category	MCC Code
Landscaping and horticultural	780
Roofing and siding	1761
Tent and awning shops	5998
Sporting and recreation camps	7032
Trailer parks and camp sites	7033
Car washes	7542
Commercial sports	7941
Tourist attractions	7991
Golf courses	7992
Amusement parks	7996