The Value of Nature-Based Adaptation: Evidence that Tree Cover Protects Urban Revenue from Heat

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Abstract

Climate change is increasing the frequency and intensity of extreme heat events, particularly in cities. This paper estimates the causal effect of temperature on daily revenue using over 15,000 consumer-facing storefronts in the 49 largest U.S. cities between 2019 and 2023. Above 35 °C (95 °F), revenue falls steeply, averaging 9 percent lower on days above 37.5 °C (99.5 °F) days than on 20 °C (68 °F) days. Consumption smoothing across days mitigates some damage from an extreme heat event, but a 1.3 percent revenue drop persists for two weeks following a hot day. Therefore, I estimate how effective urban green space is as a climate adaptation strategy that can prevent revenue losses caused by extreme heat. I find that a one percent increase in tree cover surrounding a storefront increases revenue by 0.94 percent on hot days ($\geq$ 37.5 °C). A 10 percent increase in surrounding tree cover eliminates revenue losses at 37.5 °C and reduces them by half at 40 °C, relative to areas without canopy. Storefronts located in the Southwest and South have the most to gain from urban tree cover. On average, businesses in this region can cover the cost of moving to a 10 percent tree cover scenario in four years with the avoided revenue losses. This length of time shortens under projected climate scenarios. These results suggest that green infrastructure can improve firm resilience to heat, providing evidence of a private incentive to finance urban green space that could simultaneously provide a positive externality.

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1 Introduction

Climate change is increasing the frequency and severity of extreme heat events, creating an urgent need for cost-effective adaptation strategies (Calvin et al., 2023). Cities, which house 80 percent of the U.S. population (US Census Bureau, 2022), are particularly vulnerable because the urban heat island effect amplifies heat waves (Perkins-Kirkpatrick and Lewis, 2020; Mohajerani, 2017). Extreme heat damages physical and mental health (Gould et al., 2024; Carleton et al., 2022; Heutel et al., 2021; He et al., 2025; Janzen, 2025), lowers welfare (Kuruc et al., 2025), slows economic growth (Nordhaus, 2017; Tol, 2018; Dell et al., 2012), reduces labor productivity (Dasgupta et al., 2024; Park, 2022), and dampens consumer demand (Lee and Zheng, 2025; Berg et al., 2025; Lai et al., 2022).

Urban green space offers a promising nature-based adaptation solution to the increasing severity of heat. Vegetation cools surrounding areas by creating a microclimate (Wong et al., 2021), while also providing a wide range of ecological and social benefits (Cook et al., 2025). The cooler microclimate created by urban green space counteracts the urban heat island effect, a phenomenon where urban environments experience higher surface temperatures due to the low albedo of asphalt and concrete (Mohajerani, 2017). Despite green space's promise, several distinct market frictions hinder the efficient financing of nature-based solutions to climate change. First, there is imperfect information on the economic benefits of nature-based adaptation, partially because most research has emphasized ecological benefits (Diep and McPhearson, 2025; McPhearson et al., 2025). Additionally, green space is often provisioned publicly, creating an incentive for stakeholders who benefit to free ride and under provision. Furthermore, budget-limited city governments that typically own the property right to locations that could be converted to green space face coordination frictions with private firms that may have an incentive and ability to finance nature-based adaptation strategies (Toxopeus and Polzin, 2021).

This paper asks how extreme heat affects the revenue collected by brick-and-mortar storefronts in the service industry, and how urban tree cover can mitigate losses caused by heat. I use daily credit and debit card transactions from more than 15,000 storefronts across the 49 largest U.S. metropolitan areas between 2019 and 2023, combined with high-resolution temperature and tree canopy cover data. The storefronts included are primarily restaurants and retail stores. Cold weather leads to less economic activity, and revenue rises with temperature, peaking around 32.5 °C. Revenue begins to decline once maximum daily temperature exceeds 35 °C. By 40 °C, revenue falls nearly 9 percent relative to a mild 20 °C day. This result reveals that extreme heat imposes a cost on cities' businesses due to unrealized revenue earnings.

This paper also considers whether adaptive behavior can mitigate revenue losses caused by a heat event. Specifically, I estimate whether total revenue in the two-week period after a hot day (defined as $\geq$ 37.5 °C) recovers the initial loss, and whether spending rebounds when a pleasant day follows heat. Temporal substitution can partially mitigate the revenue losses from extreme heat, but a 1.3 percent cumulative revenue decrease is persistent two weeks after a hot day. This result is consistent with prior work on retail consumption in the U.S. (Lee and Zheng, 2025). Adaptive infrastructure that can mitigate economic losses from extreme heat ex ante is needed because behavior adaptation, like consumption smoothing, only partially offsets revenue losses from extreme heat events ex post.

Urban tree canopy cover (hereafter tree cover) substantially reduces the revenue losses caused by extreme heat without increasing losses from cold weather. A one-percent increase in nearby tree cover raises storefront revenue by 0.94 percent on hot days through its cooling effect. When comparing a high-tree-cover scenario with 10 percent canopy to a zero-cover scenario, the cooling effect fully offsets the revenue loss at 37.5 °C and halves the loss at 40 °C. It is this ameliorating benefit of tree cover that prevents revenue loss that would otherwise be suffered on hot days, not additional consumption that may be restricted by consumers' budget constraints. These results illustrate tree cover's effectiveness as a strategy for urban businesses seeking to adapt to increases in extreme heat due to climate change. The results are robust to a wide range of alternative specifications and placebo tests, including varying the buffer used to calculate tree canopy cover, dropping dates affected by the COVID-19 pandemic, dropping observations in the hottest city (Phoenix, AZ), and showing green space does not have a beneficial effect on storefronts located inside of malls.

A potential concern may be that urban green space is correlated with income or other neighborhood characteristics that may affect storefront spending (Sims et al., 2022; Nardone et al., 2021; Zhou and Kim, 2013), making it difficult to observe the necessary exogenous variation in tree cover to identify its effect on storefront revenue. I partially address this concern with a rich fixed effect identification strategy that is feasible due to observing daily revenue at thousands of storefronts. An additional fact that supports my identification strategy is that the correlation between a storefront's surrounding tree cover and the median income of its customers is near zero. This means people experience a more equitable distribution of tree cover where they shop than where they live. Therefore, spatial disparities in income are unlikely to bias the estimates presented in this paper.

Finally, after establishing that tree cover protects firms from heat-related revenue losses, I quantify the financial returns from investing in this adaptation strategy. Using the estimated effects of heat and tree cover, I calculate how quickly prevented revenue losses from additional tree cover exceed the cost of expanding canopy. Businesses in the Southwest and South (California to Mississippi) experience the greatest benefit from a tree cover intervention due to current low tree cover and already experiencing frequent hot days. In this southern region, the increased revenue from mitigating extreme heat would offset the cost of moving from a low- to high-tree-cover scenario in four years. This is a conservative estimate because it excludes the general amenity value of additional trees in order to isolate tree cover's role as a nature-based climate adaptation strategy. Under warmer climate scenarios, the payback period shortens further, implying that green infrastructure can provide private adaptation benefits that increase in value with the frequency of extremely hot days.

If a private incentive exists, the question of why firms have not already planted more tree cover arises. As previously discussed, there is imperfect information on local benefits, an incentive to free ride exists, and city governments typically have the property right to sidewalks and parks, creating coordination frictions with storefronts. I provide a longer discussion in Section 7 of how cities can navigate these frictions to provide more optimal allocations of urban green space.

This paper fills a central gap in the climate-adaptation literature identified by Carleton et al. (2024): the lack of evidence on the private returns to climate change adaptation investments outside agriculture, health and labor. I show that urban tree cover – a nature-based, local form of capital – reduces the revenue losses that retail storefronts and restaurants experience during extreme heat. By quantifying how the financial return to this investment varies across regions and under warmer scenarios, this paper provides evidence on where adaptation is currently most valuable, and how its benefits scale with climate change. These results demonstrate a clear private incentive for firms to invest in tree cover for its climate-regulating effect, addressing the call for empirical evidence that links specific adaptation mechanisms to their economic returns.

This paper also contributes to the literature on nature-based solutions to climate change. Most existing work focuses on nature-based mitigation (Barbier and Burgess, 2025; Brumberg et al., 2025). Unlike mitigation, the gains from adaptation accrue locally. As a result, financing relies on coordination mechanisms between entities who own the property rights to the land where a nature-based solution can be implemented and stakeholders with a positive willingness to pay for that intervention. The ecosystem-services and biodiversity literature has provided evidence that public-private partnerships are one mechanism to overcome these coordination frictions and deliver efficient levels of nature-based solutions (Flammer et al., 2025; Plantinga et al., 2024). By documenting that storefronts experience measurable revenue gains from nearby tree cover, this paper identifies a private return that can support such partnerships. In doing so, it frames urban tree cover not only as a local public good but also as an asset that generates private economic value, exemplifying tree cover's potential to mobilize private capital toward climate resilience.

Additionally, this paper provides evidence that heat shocks disrupt the service economy, demonstrating that the surrounding climate of restaurants and retail stores complements the private goods sold and may be affected by climate change. The effect of heat on the service sector is relatively understudied compared to agriculture, health, and outdoor labor. Recent work shows that temperature shocks alter consumption and firm behavior: consumers use delivery services to order from restaurants more during extreme heat events (Papp, 2024); extreme temperatures reduce retail spending in China and the United States (Lai et al., 2022; Lee and Zheng, 2025); the willingness to pay for baseball games decreases on very hot and cold days (Kuruc et al., 2025); and the performance of the service sector, in addition to manufacturing, is affected by rising temperatures (Berg et al., 2025). This paper extends this literature by using daily, storefront-level data to estimate a causal relationship between extreme heat and the revenue of storefronts in the service industry. Because of my rich dataset, the only assumption required for my effect to be considered causal is that the variation in temperature within a firm is exogenous. The negative effect caused by heat incentives firms to adapt.

Finally, this paper contributes to estimating the economic benefit of urban green space. Economists have primarily valued urban green space through its capitalization into housing prices (Klaiber et al., 2017; Netusil et al., 2010; Sander et al., 2010) and through its cost-saving effect of lowering the energy required to cool buildings (Han et al., 2024; Heris et al., 2021). This paper demonstrates that the value of tree cover extends beyond residential amenities and cost minimization to the service sector. Salazar Miranda et al. (2021) used people's commuting behavior to document a revealed preference for tree-lined streets throughout city landscapes. I show that brick-and-mortar storefronts capitalize on this preference for urban tree cover through higher daily revenue during extreme heat events. Because many of the goods and services sold in these storefronts are non-durables and purchased regularly, this is evidence that tree cover contributes directly to day-to-day economic activity. In this way, urban vegetation functions as a shared natural capital asset for firms and the public, sustaining commercial performance during extreme heat events while delivering broader social and ecological benefits.

The paper proceeds in the following way. Section 2 presents a conceptual framework that defines the mechanisms through which heat and tree cover can affect storefront revenue. I summarize the multiple datasets I use to identify the effect of heat and tree cover on revenue in Section 3. Section 4 outlines my identification strategy. Section 5 provides the results, including temporal substitution's effect and various robustness checks. Section 6, presents a back-of-the-envelope calculation of the benefits from adopting additional tree cover for various regions in the U.S. under various climate scenarios. Finally, Section 7 offers a brief discussion and conclusion.

2 Conceptual Framework

This section develops a conceptual framework linking extreme heat, urban tree cover, and storefront revenue. The goal is to clarify the mechanisms through which environmental conditions influence consumer behavior and firm performance, and to motivate the empirical specifications that follow. By formalizing how temperature shocks and tree cover jointly affect demand for in-person services, this framework provides testable predictions about how extreme heat reduces revenue, how tree cover mitigates those losses through microclimate regulation, and how firms' location choices may reflect anticipated exposure to heat and tree cover.

Consider a setting where extreme heat and tree cover affect storefront revenue through consumers' preferences for pleasant shopping and dining experiences. Consumers are more likely to shop in greener, more comfortable environments because tree cover improves aesthetic quality, offers recreational and mental health benefits, and reduces exposure to extreme heat. These two channels (general amenity value and microclimate regulation) suggest that tree cover can be capitalized into storefront revenue. This framework considers how (1) heat shocks may reduce revenue because they create a less pleasant shopping experience, (2) businesses may capitalize on the ability of tree cover to mitigate those losses because of tree cover's ability to regulate the microclimate, and (3) businesses may anticipate these effects when choosing locations, leading brands to have a shared citing strategy that is not exogenous to tree cover.

A shopping or dining experience can be thought of as a composite good $(\mathbf{x}, H, G)$ comprised of a vector of private attributes specific to the storefront $\mathbf{x}$ and environmental attributes such as temperature H and tree cover G that augment the private characteristics. Below in Section 4, I outline how the empirical strategy decomposes revenue into these same attributes.

2.1 The Effect of Heat on Revenue

Let revenue be the demand for the composite good multiplied by a fixed price,

$$R(\mathbf{x}, H, G) = p \times d(\mathbf{x}, H, G).$$

This framework assumes fixed prices in the short run. Prior empirical work has found that retail and supermarket prices do not respond to daily changes in demand due to weather shocks (Lee and Zheng, 2025; Gagnon and López-Salido, 2020). Therefore, changes in revenue are driven by changes in demand. Assume markets clear, and thus the quantity supplied is equal to the quantity demanded.

A threshold temperature exists H^* such that an increase past it leads to a decrease in demand for the composite good,

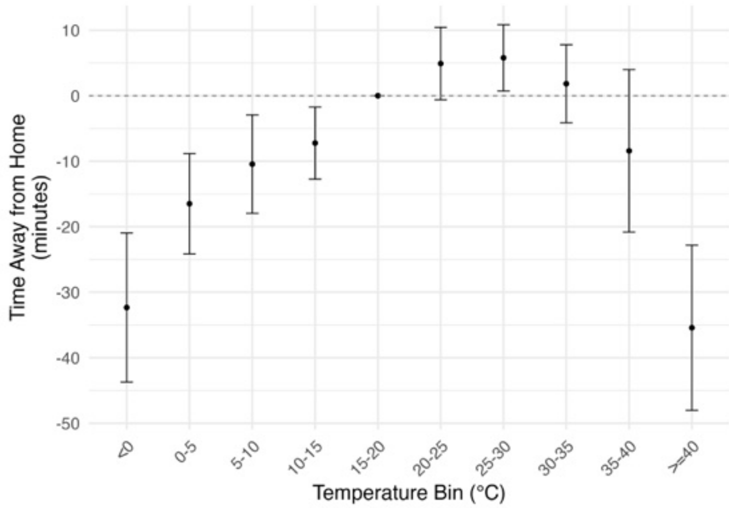
$$\frac{\partial d(\mathbf{x}, H, G)}{\partial H} < 0 : H > H^*.$$

This assumption is supported by evidence that Americans place the most value on temperatures around 18 °C (65 °F) and dislike marginal increases in heat more than they dislike the temperature becoming marginally cooler (Albouy et al., 2016). A decrease in revenue follows directly from the decrease in demand on days above H^*,

$$\frac{\partial R(\mathbf{x}, \mathbf{q})}{\partial H} < 0 : H > H^*.$$

This mechanism is consistent with evidence from the American Time Use Survey, which shows that individuals spend more time at home on hot days (Figure 1). This shift in time use highlights why extreme heat reduces demand for storefront goods and services (see Appendix B for details).

Figure 1: Effect of Daily Maximum Temperature on Time Spent Away from Home



Notes: Coefficients and 95% confidence intervals from regression of daily minutes spent away from home on 5°C temperature bins (reference = 15-20 °C), estimated with ATUS microdata. Models control for state, year, and day-of-week fixed effects, as well as rural residence, hourly worker status, gender, and holiday indicators. Results show that time away from home peaks at mild temperatures and declines sharply above 35 °C.

2.2 The Effect of Heat and Tree Cover on Revenue

Tree cover reduces the severity of heat that customers experience during extreme heat events because it regulates the microclimate. This increases the threshold temperature where heat begins to decrease business revenue by $h(G)$ degrees,

$$\frac{\partial R(\mathbf{x}, H, G)}{\partial H} < 0 : H > H^* + h(G)$$
$$\text{where } \frac{\partial h(G)}{\partial G} > 0.$$

Tree cover is a natural asset to businesses because it mitigates the damage to revenue caused by heat, and thus enables customers to continue experiencing a pleasant shopping experience during a heat event. Tree cover's climate regulation provides a flow of benefits to these businesses during extreme heat events by mitigating the revenue losses driven by decreased demand.

In addition to preventing losses from extreme heat, tree cover also provides a general amenity effect. Therefore, an increase in tree cover surrounding a business may lead to an increase in revenue through its increase in consumer demand,

$$\frac{\partial R(\mathbf{x}, H, G)}{\partial G} > 0.$$

Therefore, there are two channels that tree cover can provide benefit through: its own main effect (general amenity value) and its interaction with temperature (microclimate regulation). This paper focuses on identifying tree covers ability to mitigate revenue losses by regulating the microclimate, but the genearal amenity value is estimated as a benchmark.

2.3 Siting for Tree Cover

If tree cover raises revenue both directly and by mitigating heat, firms may anticipate these effects when choosing locations. Evidence from the housing market shows that households are willing to pay for access to tree cover and to avoid extreme heat (Klaiber et al., 2017; Han et al., 2024; Netusil et al., 2010; Sander et al., 2010), and urban trees reduce energy expenditures and storm water management costs (Heris et al., 2021). These findings suggest that businesses may consider environmental amenities when selecting sites, particularly when those amenities influence customer demand or operating costs. As a result, storefronts belonging to the same brand may share siting strategies, consistently choosing to site in greener or cooler parts of a city.

3 Data and Motivating Statistics

This section describes the data used to estimate how extreme temperatures affect storefront revenue and the benefits provided by green space. The analysis relies on a novel dataset that combines daily credit and debit card transactions, storefront characteristics, daily temperature records, and satellite data on tree canopy cover.

3.1 Storefront Revenue

The SafeGraph Spend dataset is used to measure daily storefront revenue. This dataset collects daily credit and debit card transactions at individual places of interest, hereafter referred to as storefronts (SafeGraph, 2025b). The SafeGraph Spend data closely track earnings reported by companies (see validation), supporting its use for observing revenue at the storefront level.

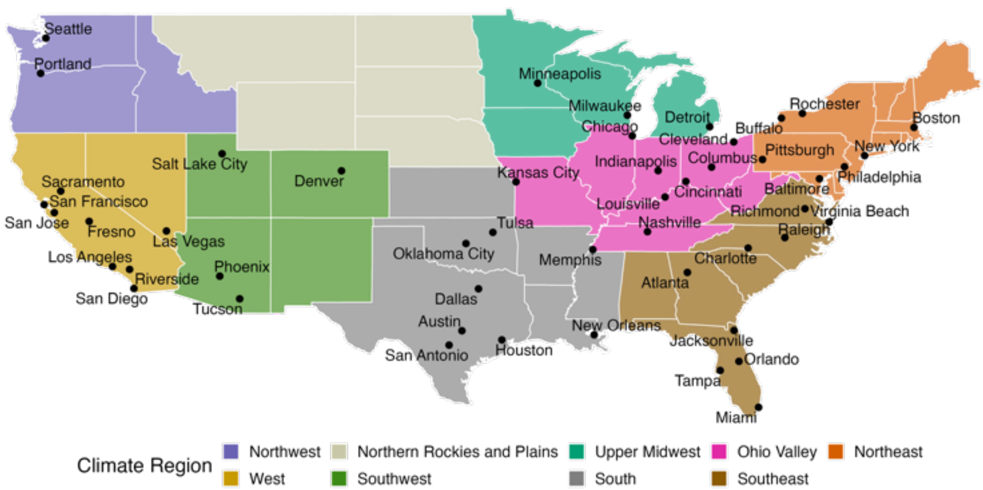
The SafeGraph Spend dataset is available from 2019 onward. This paper uses data from 2019 through 2023, and includes robustness checks that consider the COVID-19 pandemic. Because the focus is on the effects of urban heat and tree cover, the analysis is restricted to U.S. metropolitan statistical areas with populations over one million in 2020 (Figure 2). Only storefronts located within city limits are included, ensuring that the analysis reflects the effects of urban, rather than suburban, heat and tree cover.

The sample is further restricted to industries that sell goods and services directly to consumers. To be included, an industry must contain at least 200 businesses across the sample cities. These are primarily restaurants and retail stores. A full list of included industries is provided in Table A1.

The SafeGraph Spend dataset also provides information on the income distribution of customers. Each month, the number of customers visiting a storefront is observed in seven annual income brackets: $<$ 25K, 25–45K, 45–60K, 60–75K, 75–100K, 100–150K, and $>$ 150K. SafeGraph classifies customers into these income bins using a proprietary model based on their transaction and spending behavior.

In robustness checks, the SafeGraph Spend dataset is also used to examine the share of spending that occurs at the storefront's physical location versus online, through transaction intermediaries such as DoorDash or GrubHub. This analysis tests whether delivery services enable customers to adapt to heat events by staying home while still consuming their preferred bundle of goods.

Figure 2: The 49 Cities in the Dataset



Finally, storefront characteristics are obtained from SafeGraph's Global Places (POI) & Geometry dataset (SafeGraph, 2025a). This dataset provides information on the size of each storefront, brand affiliation, latitude and longitude coordinates, North American Industry Classification System (NAICS) codes, the presence of an associated parking lot, and whether the business is part of a shopping mall or shared plaza.

3.2 Daily Temperature

Daily weather conditions are measured using the nClimGrid-Daily dataset provided by the National Oceanic and Atmospheric Administration (NOAA) (Durre et al., 2022). This dataset contains interpolated daily values of maximum and minimum temperature, precipitation, and other weather variables across the contiguous United States, with a gridded spatial resolution of approximately 5 kilometers. NOAA aggregates these data to the census tract level by calculating the spatial mean of daily maximum temperature across all grid cells intersecting each tract. The analysis uses these aggregated tract-level values. Figure 3 shows the distribution of heat observation.

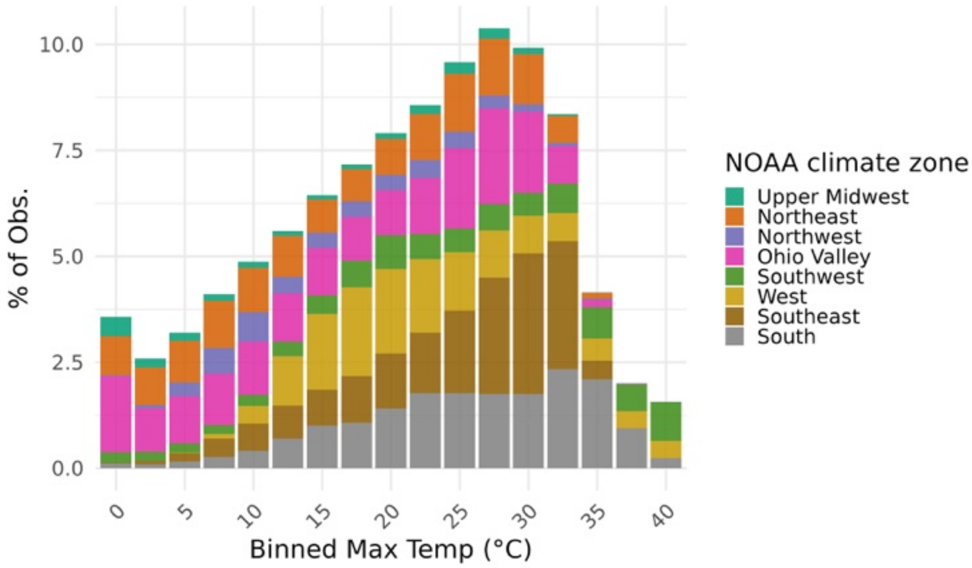
3.3 Urban Tree Cover

Urban tree cover is measured using the Tree Canopy Cover (TCC) dataset from the National Land Cover Database (NLCD), developed by the U.S. Forest Service (Housman et al., 2023). This dataset provides annual, 30-meter resolution estimates of percent tree canopy cover from 2011 to 2023, derived from Landsat and Sentinel-2 satellite imagery. The TCC product covers the conterminous United States, allowing spatial variation in urban tree canopy to be observed and providing some temporal variation.

Tree canopy cover is assigned to each storefront by drawing a buffer with a fixed radius around the storefront's latitude-longitude location and calculating the average canopy cover within that buffer. The buffer radius is 200 meters in the preferred specification, capturing immediate surrounding tree cover. Alternative buffer sizes are tested in robustness checks to assess sensitivity.

The suitability of the TCC dataset for measuring urban tree cover is validated by comparing it with

Figure 3: Distribution of Temperature Observations



two alternative datasets. First, the U.S. Forest Service's TCC product is compared to other layers in the National Land Cover Database (NLCD), provided by the U.S. Geological Survey (Dewitz, 2023). Second, for a subset of cities, the TCC data are compared to a volumetric green space index derived from Google Street View imagery provided by Arianna Salazar-Miranda's Livable City's Lab.[1]

Using the NLCD impervious surface layer, average tree canopy cover near a business is found to be highly negatively correlated with impervious surface, with a correlation coefficient of approximately 60 percent. Using the Google Street View index, tree canopy cover is 70 percent correlated with the volumetric measure of green space. In contrast, the Google Street View and NLCD measures are only 44 percent correlated with each other. The TCC dataset is used as the preferred measure of urban green space because it is strongly correlated with both alternatives and because tree canopy plays a key role in shaping local microclimates.

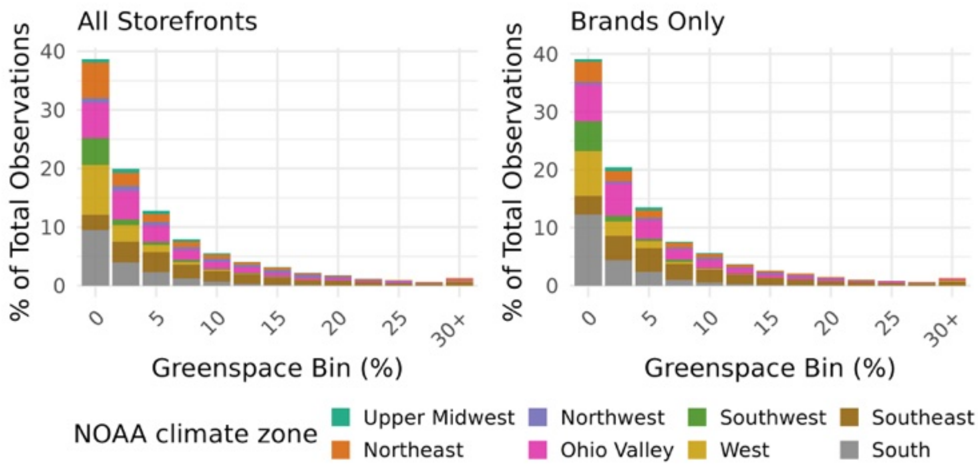
Two groups of storefronts are the focus of the primary analyses. The first includes all storefronts with at least 350 daily observations. The second is a subset of these businesses that are affiliated with a brand, and further restricted to brands with at least five storefronts located within the same city. This restriction enables using spatial variation within brand-city-month clusters to identify the effect of tree cover on revenue.

The distribution of tree cover surrounding storefronts is shown in Figure 4. Panel A displays the distribution for all storefronts and only storefronts that are a part of a brand. Panel B provides a visual example of storefronts located in low, medium, and high tree cover environments. The median amount of tree cover surrounding businesses also varies greatly by city. For instance, the median surrounding tree cover in Portland, OR is 14 percent, the highest of any city in the dataset, while the median in Tucson, AZ is less than one percent, the lowest. Median values for climate regions are presented in Table 1, and results for all cities are presented in Appendix A2.

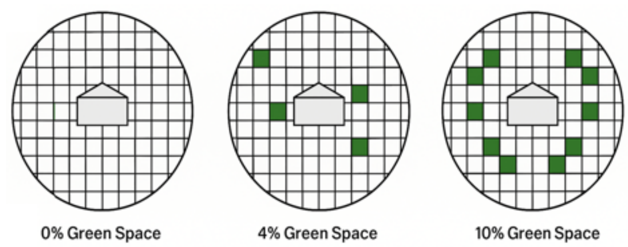
[1] The dataset provided by the Livable City's Lab is similar to that used by Falchetta and Hammad (2025).

Figure 4: The distribution of tree cover across all businesses and brands

(A) Distribution of Tree Cover



(B) Visual representation of low, medium and high tree cover scenarios



4 Empirical Strategy

This paper estimates the effect of extreme heat and urban tree cover on revenue using the combined panel data on daily storefront-level revenue, daily maximum temperature, and annual tree canopy cover. The empirical strategy exploits plausibly exogenous day-to-day variation in local maximum temperature at a specific storefront, as well as cross-sectional variation in tree cover across firms that follow similar siting strategies (*i.e.,* businesses that are part of the same brand in the same city).

4.1 Estimating the Effect of Heat on Revenue

Specification (1) estimates how temperature affects daily revenue at storefronts,

$$\ln(R_{it}) = \boldsymbol{\beta_H} \sum_{h=0}^{40} \mathbb{I}(H_{it} = h) + \boldsymbol{\beta_I} \mathbf{I}_{im} + \alpha_i + \tau_t + \epsilon_{it}, \tag{1}$$

where R_{it} is revenue at storefront i on day t, and $\mathbb{I}(H_{it} = h)$ denotes a set of indicator variables for daily maximum temperature, binned in 2.5 °C increments. The 20–22.5 °C bin is excluded and serves as the reference level. $\mathbf{I}_{im}$ is a vector of controls for the monthly m distribution of customer income, measured as the share of monthly customers in seven income bins. Storefront fixed effects α_i control for all time-

Table 1: Median Surrounding Tree Cover

Climate Region	Median Green Space	Average Temp (°C)
Northwest	10.62	17.60
Southeast	9.09	24.93
Upper Midwest	5.96	17.15
Ohio Valley	5.42	19.02
Northeast	5.22	18.35
South	3.78	26.27
West	2.60	23.01
Southwest	2.11	24.23

invariant characteristics of each location, while temporal fixed effects τ_t capture day-of-week, city-by-month, and year effects, accounting for weekly, seasonal, and annual variation in revenue. The key identifying assumption required to interpret the results causally is that daily variation in temperature is exogenous to other unobserved determinants of revenue within a given storefront after controlling for broad temporal trends captured in the fixed effects.

Specification (1) is this paper's preferred model for estimating the effect of heat on revenue. However, a modified version of Specification (1) that includes an interaction between the temperature bins and the average maximum temperature in a city is estimated, along with a specification where heat's effect on revenue follows a second-order functional form, to understand whether significant regional adaptation to heat occurs within my sample. These modified specifications test whether regional adaptation has a significant effect on how heat effects revenue within the U.S. (see Appendix C for details).

4.2 Temporal Substitution

Before testing whether tree cover mitigates the damage caused by extreme heat, I examine whether temporal substitution offsets revenue losses with two approaches. This is important for understanding if consumer behavior can mitigate any revenue losses experienced.

The first evaluates how total revenue over a period responds to the occurrence of an extreme heat event. The second estimates how much revenue rebounds when a "pleasant" day (20–35 °C) follows an extremely hot day (above 37.5 °C). The first approach speaks to the overall economic relevance of substitution by considering the magnitude of potential rebound and the frequency with which such opportunities arise. The second directly tests whether a rebound effect occurs when favorable weather follows extreme heat.

To test whether revenue rebounds within a period of $k \in \{1, \ldots, 14\}$ days, Specification (2) estimates the effect of an extreme heat event on total revenue in that period. An indicator variable, $\texttt{preceded\_by\_hot}_{it}^{k}$, equals one if at least one of the previous k days at storefront i on day t had a maximum temperature above 37.5 °C. The estimating equation is

$$\ln\left(\sum_{\nu=1}^{k} R_{i\nu}\right) = \boldsymbol{\beta_I}\mathbf{I}_{im} + \theta_k \cdot \texttt{preceded\_by\_hot}_{it}^{k} + \alpha_i + \tau_t + \epsilon_{it}, \tag{2}$$

where $R_{i\nu}$ is the revenue at storefront i on day v of the period k. $\mathbf{I}_{im}$, α_i, and τ_t are defined as in Specification (1). The coefficient θ_k captures the semi-elasticity of total revenue in a k-day period with respect to an extreme heat event. A negative θ_k indicates that revenue has not fully rebounded within k days, while a coefficient close to zero implies that losses are recovered through temporal substitution.

To test whether substitution occurs specifically when pleasant weather follows extreme heat, Specification (3) estimates the effect of a pleasant day occurring exactly k days after a hot day. The indicator $\texttt{pleasant\_post\_hot}_{it}^{k}$ equals one if day t is pleasant and was preceded exactly k days earlier by a day with maximum temperature ≥ 37.5 °C. The specification is

$$\ln(R_{it}) = \boldsymbol{\beta_I} \mathbf{I}_{it} + \zeta_k \cdot \texttt{pleasant\_post\_hot}_{it}^{k} + \alpha_i + \tau_t + \epsilon_{it}. \tag{3}$$

The coefficient ζ_k captures the semi-elasticity of revenue with respect to a pleasant day that follows extreme heat at lag k. A positive ζ_k indicates a rebound effect, while small or insignificant values suggest limited or no substitution.

4.3 Identifying Heat's Interaction with Urban Tree Cover

To identify how urban tree cover moderates revenue changes from extreme heat, Specification (1) is modified to include tree cover and its interaction with temperature

$$\begin{aligned} \ln(R_{it}) = \boldsymbol{\beta_H} \sum_h \mathbb{I}(H_{it} = h) + \boldsymbol{\beta_{GH}} \left(G_{iy} \times \sum_h \mathbb{I}(H_{it} = h) \right) + \beta_G G_{iy} \\ + \boldsymbol{\beta_I} \mathbf{I}_{im} + \beta_s s_i + \beta_l \texttt{Lot}_i + \alpha_{bcm} + \tau_t + \epsilon_{ibctmy}. \end{aligned} \tag{4}$$

G_{iy} measures percent tree canopy cover within a designated buffer of storefront i in year y, s is the size of storefront i and $\texttt{Lot}$ indicates whether the storefront has an associated parking lot. The fixed effects α_{bcm} are brand-by-city-by-month, absorbing shared demand shocks at the brand-city-month level. The fixed effects τ_t capture day-of-week and year-specific spending patterns. The preferred specification uses a 200-meter buffer to measure tree cover around each storefront. Robustness checks vary the buffer radius to assess sensitivity.

Because this paper focuses on identifying the effects of temperature β_H and tree cover's moderating interaction effect β_{GH} (rather than the main effect of tree cover β_G) one might consider including storefront fixed effects (which would absorb the main effect) and exploiting daily variation in the interaction term $G_{iy} \times \sum_h \mathbb{I}(H_{it} = h)$ to estimate β_{GH}. This specification, however, would yield weak identification of the parameters of interest. The interaction term varies almost entirely through temperature because G_{iy} changes little between a year. Following, a specification that includes a storefront fixed effect results in high collinearity between the interaction and the main heat term $\sum_h \mathbb{I}(H_{it} = h)$. Consequently, the model would rely on within-store temperature variation to identify β_H and β_{GH}, inflating standard errors and attenuating the estimated effects.

Therefore, fitting Specification (4) requires a different fixed effect specification than Specification (1). I choose to limit the analysis to storefronts that are a part of a brand[2] and include the brand-by-city-by-month fixed effect α_{bcm}. This allows me to use the spatial variation in tree cover across storefronts of the same brand in the same city and month to aid in identifying β_{GH}. Specification (4) also controls for observable storefront characteristics ($\mathbf{I}_{im}$, s_i, and $\texttt{Lot}_i$). Under the assumption that stores belonging to the same brand in a given city share a siting strategy (See Section 2.3), this variation in surrounding tree cover is plausibly exogenous to unobserved determinants of revenue. This holds true even if tree cover is correlated with other amenities that a business may sort on, if all storefronts that are a part of the brand are sited with the same strategy.

[2]The datatset contains 3,005 brand-affiliated storefronts across 58 brands, with 3.6 million observations.

4.4 Benchmarking the Interaction Effect by Recovering the Main Effect

The brand-by-city-by-month fixed effect identification strategy carries the risk that part of the revenue increase attributable to tree cover's amenity effect (*i.e.* tree cover's main effect) will be absorbed by the brand-by-city-by-month fixed effects. This is not a threat to identifying this paper's primary effects of interest, which are the main effect of heat and heat's interaction with three cover. However, it is useful to estimate the main effect of green space as a benchmark for the interaction effect between green space and heat.

The coefficient β_G in Specification (4) may understate the true main effect of tree cover if a brand systematically locates its storefronts in greener areas because the brand-by-city-by-month fixed effect will control for this systematic siting. Brands may systematically site near green space if their goods or services are consistently complemented by tree cover (See Section 2.3). The average effect of tree cover across a brand that has systematically sited locations will be controlled for in α_{bcm}. Therefore, the fine-scale fixed effects can lead to a downward bias the in estimate of tree cover's main effect (Abbott and Klaiber, 2011).

To address the possibility that part of the main effect of tree cover is absorbed by the brand-by-city-by-month fixed effects, I adopt two strategies. First, I used the coefficients estimated in Specification (4) to calculate a lower-bound estimates of the elasticity of revenue with respect to tree cover. While the coefficient β_G may be biased downward by the fixed effect structure, the interaction terms $\boldsymbol{\beta_{GH}}$ is not. The lower-bound elasticity of revenue with respect to tree cover is therefore defined as

$$\frac{\partial \ln(R)}{\partial G} = \beta_G + \beta_{GH} H, \tag{5}$$

where the elasticity is conditioned on a realized temperature H because of the interaction effect between temperature and tree cover. This is the preferred specification for the elasticity of revenue with respect to tree cover because it measures tree cover's ability to moderate termpature.

As a second strategy, this paper implements a two-stage approach to recover the portion of the tree cover effect absorbed by the brand-by-city-by-month fixed effects. In the second stage, the estimated fixed effects α_{bcm} from Specification (4) are regressed on a brand's average surrounding tree cover,

$$\alpha_{bcm} = f(\overline{G}_{bcy}) + \gamma_2 \texttt{Ind}_b + \epsilon_{bcm}, \tag{6}$$

where $\overline{G}_{bcy}$ is the average tree cover for brand b in city c in year y, $f(\cdot)$ is the functional form chosen to model the main effect of tree cover on revenue (linear, logged, second-order and third-order polynomial), and $\texttt{Ind}_b$ is a categorical variable denoting the six-digit NAICS industry of brand b. This second-stage regression recovers the main effect of tree cover on revenue that is otherwise absorbed by the fixed effects. The approach is inspired by methods in Zhang and Smith (2011), adapted here to the context of urban storefronts. The full elasticity of revenue with respect to tree cover can then include the recovered main effect of tree cover and be expressed as

$$\frac{\partial \ln(R)}{\partial G} = f'(G) + \beta_G + \beta_{GH} H^*. \tag{7}$$

This paper presents Equation 5 as the preferred specification for measuring the elasticity of revenue to tree cover because it is a conservative estimate that carefully captures tree cover's role as a regulator of extreme heat. However, $f'(G)$ is presented as the recovered amenity effect of tree cover as a benchmark for

Equation 5. The benchmark is useful for understanding how tree cover's ability to regulate heat compares to its general amenity value.

4.5 Considering the Correlation of Amenities and Income

A potential threat to identifying the effect of tree cover on storefront revenue is the correlation between tree cover and demographic characteristics that shape consumer spending. Prior research shows that green space is distributed unequally. Redlined neighborhoods in the U.S. (Nardone et al., 2021), communities of color in Illinois (Zhou and Kim, 2013), and low-income communities in the Northeast (Sims et al., 2022) all tend to have less surrounding vegetation. This raises the concern that businesses serving lower-income customers, and therefore generating less revenue, may also be systematically located in areas with less green space.

This paper address this concern by examining the correlation between green space and measures of income. The correlation between the median income of the census tract in which a storefront is located, and its surrounding tree cover is positive but small (correlation coefficient: 0.02, p-value: 0.01). In contrast, the correlation between a storefront's surrounding tree cover and the median income of its customers is near zero (correlation coefficient: -0.002, p-value: 0.001). These results suggest that people encounter a more equitable distribution of tree cover in the places where they shop than in the neighborhoods where they live, and that spatial disparities in income are unlikely to bias the estimates presented in this paper.

5 Empirical Results

This section presents the main empirical findings. First, I present how extreme temperatures affect storefront revenue, documenting the nonlinear effects of heat and cold. Second, I show whether temporal substitution offsets these losses by shifting spending to subsequent days. Next, I present how urban tree cover affects revenue by mitigating the damage from extreme heat. Finally, I present various placebo and robustness analyses.

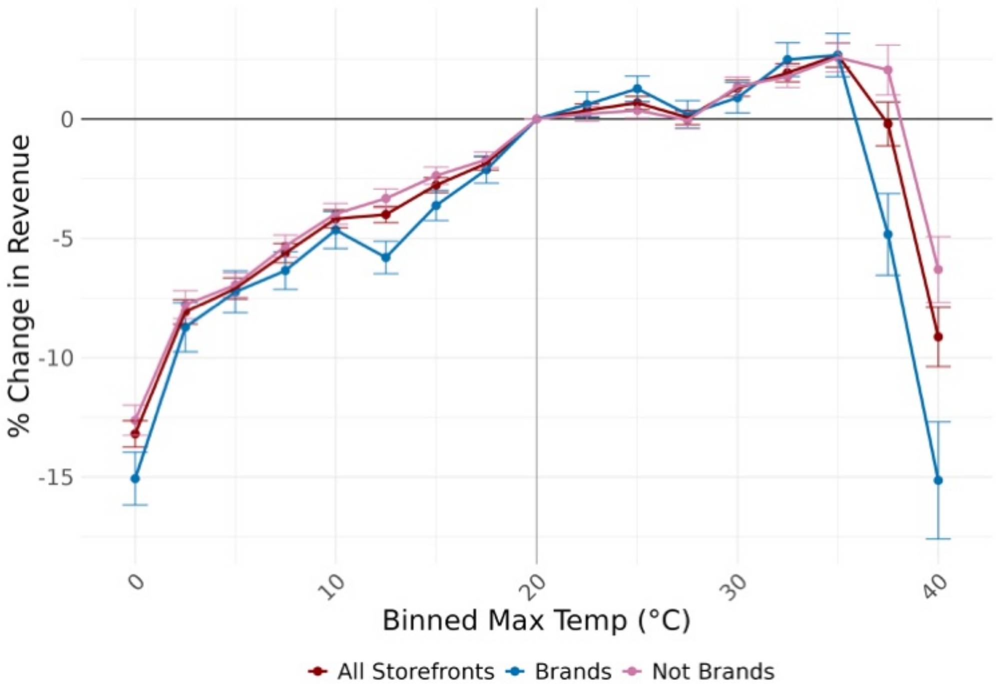
5.1 Heat on Revenue

The regression results from Specification (1) are presented graphically in Figure 5. Once temperatures exceed 35 °C, revenue begins to decline. The drop is particularly sharp beyond 37.5 °C, where revenue falls by 9 percent on average for all storefronts. On days above 40 °C, average revenue is comparable to that on a 2.5 °C day. Revenue increases steadily as temperature rises from below 0 °C up to 35 °C. Full regression results are reported in Appendix Table A3.

Although extremely hot and cold days are relatively rare (Figure 3), the analysis contains approximately half a million observations of business-days for each due to the large sample size. Observations of extremely hot days are spread across thirty-three cities, and observations of extremely cold days are found in thirty-eight.

Tests for regional adaptation provide little evidence that U.S. storefronts respond differently to extreme heat across heterogeneous climates (Appendix C). While warmer regions appear more sensitive to hot days, this pattern is likely driven by the concentration of extremely hot observations in the South and Southwest, whereas cooler regions experience fewer extreme heat events. As a result, estimates of adaptation in cooler regions are imprecise and rely heavily on extrapolation. Fitting Specification (1) to data from each NOAA climate zone also does not provide supportive evidence of adaptation, but these results are also imprecise.

Figure 5: The Effect of Heat on Revenue



The coefficients from Specification (1) are plotted, which regresses the logarithm of daily revenue on 2.5 °C temperature bins, with 20-22.5 °C as the reference category. The model controls for storefront fixed effects, city-by-month seasonal effects, year effects, day-of-week effects, and the monthly distribution of customer income. Revenue rises steadily from cold temperatures up to about 35 °C, then declines sharply. Beyond 37.5 °C, revenue falls by nearly 10 percent on average for all storefronts. The damage of extreme heat on revenue is more severe for brand affiliated storefronts, and less so for non-brands.

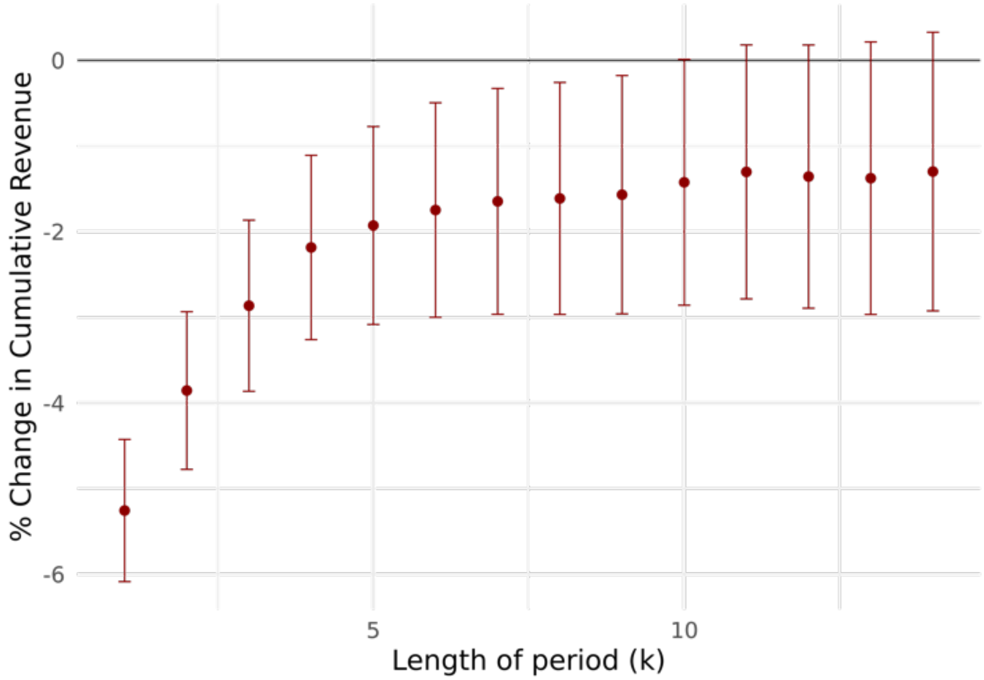
Given the data limitation of few observations of hot days in cool regions, the main analysis proceeds without interacting daily temperature with long-run regional climate. The underlying assumption is that hot days in already hot regions are the best predictor of how hot days in currently cool regions will affect revenue.

5.2 Temporal Substitution

Figure 6 plots the coefficients estimated from Specification (2) and shows that cumulative revenue does not recover from the negative effects of an extreme heat event within a two-week period. On average, a day at or above 37.5 °C leads to a more than 5 percent decline in revenue on the day of the heat event. In the days that follow, cumulative revenue remains persistently lower. Total revenue over a week decreases by nearly 2 percent if an extreme heat event occurs at the beginning of the week, and over a two-week period, revenue is down by more than 1 percent. The results are statistically significant at the 95 percent confidence level through day 10, and remain significant at the 90 percent level until day 14. Regression results are reported in Appendix Table A4.

Results from Specification (3) shows that consumers may shift spending to pleasant days (defined as days with a maximum temperature between 20 °C and 35 °C) that follow extremely hot days (above 37.5 °C). On average, revenue is about 2.5 percent higher on pleasant days than on an average day. When a pleasant day occurs one to five days after an extremely hot day, revenue is significantly higher than the average pleasant day. After five days, however, the pattern becomes less clear. Overall, these results show that consumers

Figure 6: Revenue Summed Over K Days, following a Heat Event Within k Days



Specification (2) coefficients are plotted, which regresses the logarithm of cumulative revenue over k days on an indicator for whether the day at the beginning of the k day long period was at or above 37.5 °C. The specification includes storefront fixed effects, city-by-month seasonal effects, year effects, day-of-week effects, and controls for the monthly distribution of customer income. A day at or above 37.5 °C reduces revenue by more than 5 percent on impact, and cumulative revenue remains depressed for up to two weeks. Standard errors are clustered at the storefront level. Days 10 through 11 are significantly different from zero at the $\alpha = 0.90$ level.

do shift some spending to pleasant days following extremely hot days. Nevertheless, because a pleasant day does not always follow an extremely hot day, this substitution behavior is not sufficient to offset cumulative revenue losses over time, as shown in Figure 6. Regression results are plotted in Appendix Figure A1 and reported in Appendix Table A5.

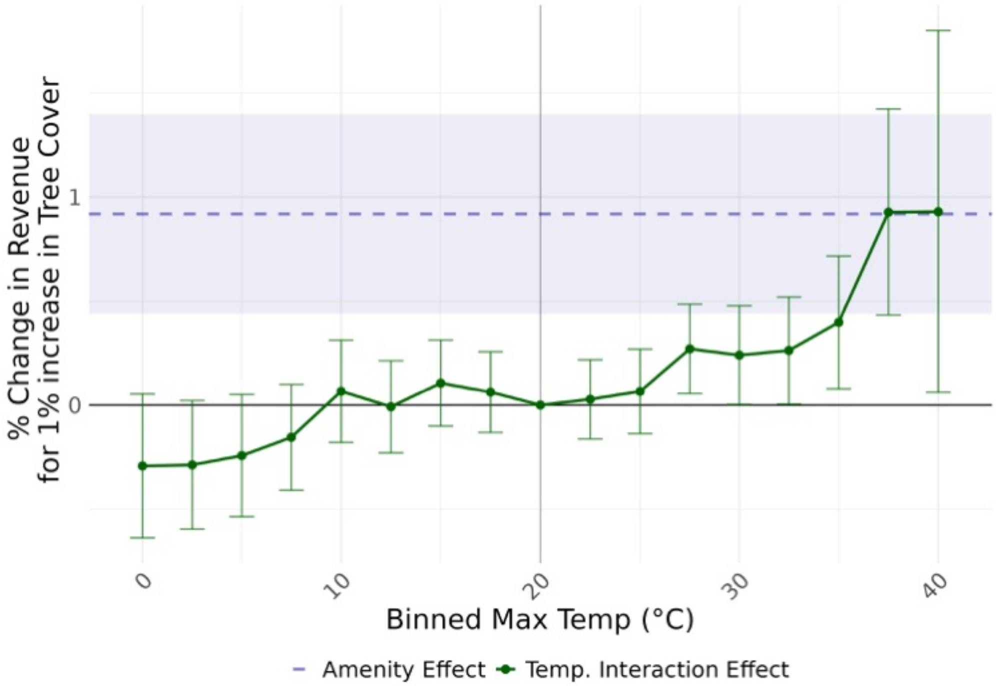
5.3 Tree Cover's Interaction Effect with Heat

Figure 7 shows that a one percent increase in surrounding tree cover increases revenue as temperature rises. The elasticities plotted are derived from the single-stage, lower bound estimation strategy described in Equation 5 using coefficients from Specification (4). The revenue increasing cooling effect from a marginal increase in tree cover becomes significantly different from zero at 27.5 °C, and increases revenue 0.94 percent when temperature increases past 35 °C. Regression results for Specification (4) are in Appendix Table A6.

The Amenity Effect line in Figure 7 plots the recovered main effect of tree cover defined by Equation 6 to benchmark the interaction effect of tree cover and temperature. Figure 7 uses a linear specification for $f(\overline{G})$ as the benchmark. Regression results for a linear, logged, second-, and third-order polynomial function forms of modeling $f(\overline{G})$ are reported in Appendix Table A7. Recovering the amenity value reveals that a one percent increase in average tree cover around a brand (within a given city and month) is associated with a 0.92 percent increase in revenue, regardless of the temperature.

Figure 8 illustrates how temperature affects revenue under high and low tree cover scenarios. A high

Figure 7: Elasticity of Revenue with Respect to Tree Cover



This figure plots the elasticity of revenue with respect to surrounding tree cover, conditional on temperature. The green line considers the interaction effect between heat and temperature and is derived from Specification (4) using the lower-bound strategy described by Equation 5. Results show that a one percent increase in tree cover has a growing positive effect on revenue as temperatures rise, becoming statistically significant at 27.5 °C and reaching nearly 1 percent at 37.5 °C. The Specification controls for storefront size, parking lot presence, and the monthly distribution of customer income, and has brand-by-city-by-month, year, and day of week fixed effects. Standard errors are clustered at the storefront level. The blue line labeled Amenity Effect plots the recovers the portion of the amenity effect that is absorbed by brand-by-city-by-month fixed effects, and later recovered using the two-stage approach defined in Equation 6. This figure plots a linear specification of how the amenity value of tree cover affects revenue.

tree cover environment can fully offset or substantially reduce the revenue losses associated with extreme heat. In the zero tree cover scenario, a 37.5 °C day results in a 10 percent decrease in revenue. In contrast, the same temperature in a high tree cover scenario (10 percent coverage) leads to a decline that is not statistically distinguishable from zero. On a 40 °C day, revenue falls by 20 percent in the low tree cover scenario, compared to only a 12 percent decline in this high tree cover scenario.

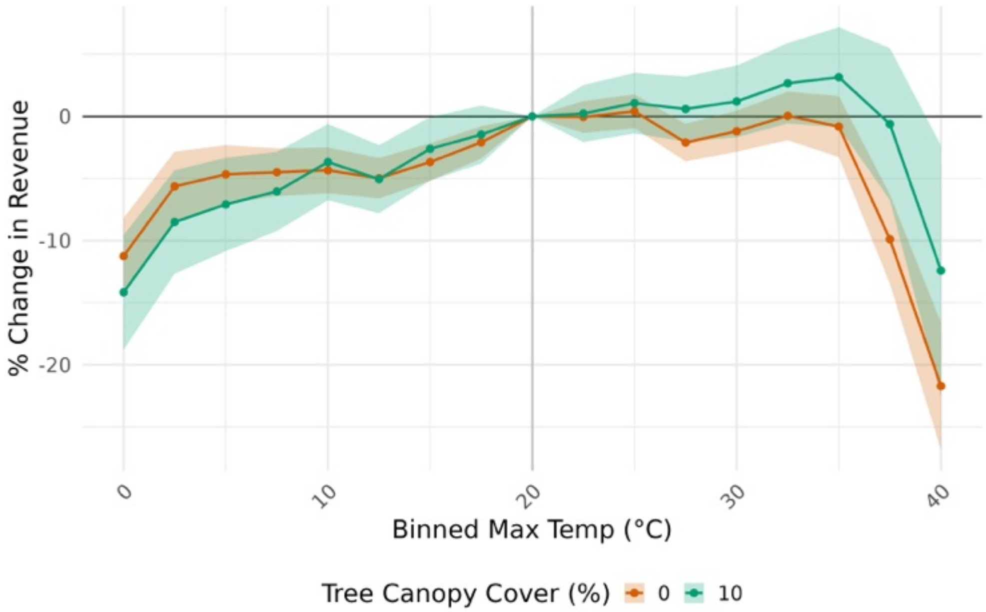
5.4 Robustness and Placebo Tests

I test the robustness and legitimacy of the results in multiple ways.

5.4.1 Robustness to radii measuring tree canopy cover

To test whether the main results are sensitive to how surrounding tree cover is measured, I re-estimate Specification (4) using alternative buffer radii of 50, 100, 400, and 800 meters around each storefront. For each buffer, tree canopy cover is recalculated as the mean percent canopy within the given radius. The estimated elasticities of revenue with respect to tree cover are fairly robust across buffer sizes. All specifications show that the effect of tree cover on revenue begins to spike upward at 32.5 °C and peaks at

Figure 8: Revenue Under High and Low Tree Cover Scenarios



This figure compares the effect of temperature on storefront revenue in low versus high tree cover scenarios. In the low tree cover scenario, revenue declines by about 10 percent at 37.5 °C and by 20 percent at 40 °C. In a high tree cover scenario, the decline at 37.5 °C is not significantly different from zero, and the loss at 40 °C is only 12 percent.

37.5 °C. Results for radii other than the 200 meter preferred specification are less precisely estimated for the 40 °C bin. Appendix Figure A4 and Table A8 summarize these findings, showing that the moderating effect of tree cover on heat-induced revenue losses is consistent across buffer specifications, although varying in precision.

5.4.2 Placebo test measuring tree cover effect on malls

As a placebo test, the data is subset to storefronts that are within a mall or other plaza center (*i.e.*, a Starbucks within a Target). While the effect of heat on these storefronts' revenue behaves extremely similar to the average effect on all storefronts, revenue is unresponsive to heat's interaction with urban tree cover (see Appendix Figure A2). This result is expected, because outdoor tree cover should not be complimented to storefronts entirely contained indoors.

5.4.3 Testing for adaptation through delivery services

To investigate other adaptation channels, I examine whether consumers respond to extreme heat by substituting in-person spending with online or delivery-based transactions. Using the SafeGraph Spend dataset, I test whether a higher share of extremely hot days within a month increases the amount of spending conducted through intermediaries such as DoorDash, Grubhub, or Shopify (see details in Appendix D). Across multiple specifications, there is no strong evidence that spending shifts toward these intermediaries in hotter months. While this suggests that adaptive consumer behavior is not captured within the aggregated transaction data used here, it does not imply that such adaptation does not occur. Papp (2024) finds strong evidence that some consumers do adapt to extreme heat by using delivery services more. My results indicate that any behavioral adaptation of this kind is either limited in scope or not well measured at the level of monthly-storefront revenue in this dataset.

5.4.4 Robustness to dropping COVID-19 pandemic

To investigate the robustness of the results to the COVID-19 pandemic, I drop transactions that occurred between the beginning of the COVID-19 pandemic and when the second Pfizer vaccine became largely available to Americans (March 2020 through April of 2021). My results are robust to these dates being dropped from the analysis (Appendix Figure A5). After dropping the pandemic dates, I find that temperature increases are beneficial until 35 °C, but temperature increases beyond are damaging to daily business revenue. A day above 37.5 °C decreases revenue by more than 6 percent. Tree cover is beneficial in mitigating damage from heat beginning on days at or above 27.5 °C, and particularly beneficial on days at or above 35 °C.

5.4.5 Robustness to dropping Phoenix, AZ

To ensure the findings are not driven by the hottest city in the sample, I re-estimate my primary results after dropping all observations from Phoenix, AZ. My results are robust to excluding Phoenix (Appendix Figure A6). The temperature-revenue relationship is effectively unchanged: revenue rises with temperature up to about 35 °C and then declines; days at or above 37.5 °C reduce revenue on the order of 8 percent. The moderating effect of surrounding tree cover remains positive and statistically significant beginning at 27.5 °C, with particularly strong benefits on days at or above 35 °C.

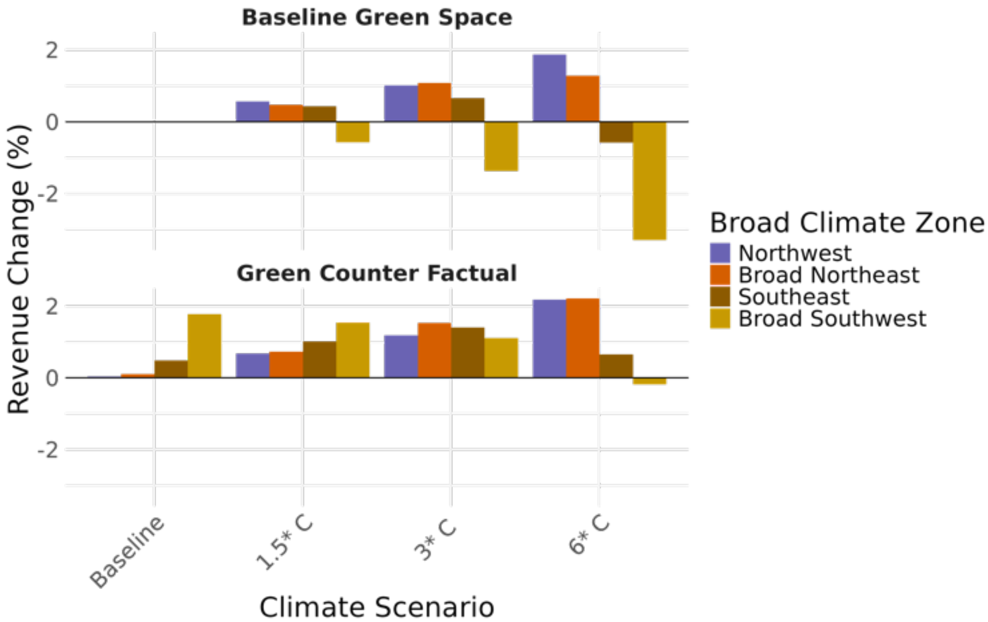
6 Back of the Envelope Climate Scenario

This section presents the projected annual revenue change for three back of the envelope climate scenarios where every temperature observation is shifted upward by 1.5, 3, or 6 °C. This exercise is equivalent to imposing a mean shift in the distribution of observed temperatures. The results from Specification (4) are used to project revenue under these counterfactual conditions. Total revenue in each climate scenario is then compared to baseline revenue modeled under current conditions. These climate scenarios are modeled at the baseline climate scenario and at a counterfactual high tree cover scenario (all storefronts surrounded by $\geq$10 percent tree cover).

Figure 9 presents the three climate scenarios projected in four broad climate regions, along with estimates of the same climate scenarios in a high tree cover scenario. The broad climate regions are grouped as regions with similar median tree cover and average temperature (see Table 1). I use the lower bound estimates of the elasticity of revenue with respect to tree cover (Equation 5) as the specification for the projected climate scenarios and corresponding finance questions to isolate tree cover's beneficial cooling service and present a conservative estimate of tree cover's benefit to businesses.

Storefronts in the Broad Southwest (West, Southwest and South NOAA climate regions) are the most vulnerable to heat increases, followed by the Southeast. Any amount of warming is damaging to the Broad Southwest, whereas all other regions see initial increases in revenue due to currently cool days moving toward warmer pleasant days. The most severe modeled scenario (6 °C of warming) leads to the Southeast experiencing a revenue loss, but the Northwest and Broad Northeast (Northeast, Ohio Valley and Upper Midwest climate regions) only experience revenue increases, regardless of the amount of warming. These projections assume people are able to substitute shopping and dining trips across seasons.

Figure 9: Projected Annual Revenue Change under Various Counterfactuals (Lower Bound Estimates)



This figure presents projected changes in annual storefront revenue under three back-of-the-envelope climate scenarios that shift all daily temperature observations upward by 1.5, 3, or 6 °C. Projections are based on Specification (4) and use the lower-bound elasticity of revenue with respect to tree cover (Equation 5). Results are shown for broad climate regions under baseline conditions and under a counterfactual high tree cover scenario in which all storefronts are surrounded by at least 10 percent canopy cover. The Broad Southwest experiences the largest losses under warming, but additional tree cover is able to completely or nearly eliminate these losses, even in the most severe warming scenario.

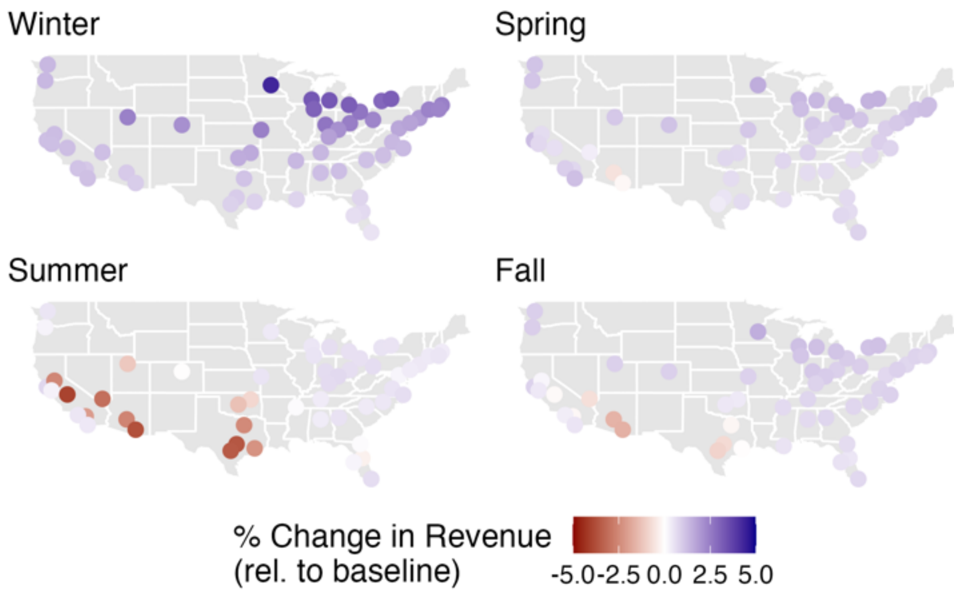
Temperature increases have different effects across seasons. Figure 10 plots the revenue change by city using Specification (1) under 3 °C of warming. The Southwest region experiences the most damage in the summer. Ten cities experience a more than 2 percent decrease in revenue during the summer, with Fresno, CA and Tuscon, AZ experiences the largest drop of approximately 4 percent.[3] These cities in the Broad Southwest would have the most to gain from using urban tree cover to mitigate the damage from extreme heat to storefronts' revenue.

Even when using the lower-bound estimate to model the elasticity of revenue with respect to tree cover, the Broad Southwest is able to mitigate all losses due to temperature increases by moving to a high tree cover scenario (Figure 9). In the baseline climate scenario, the average storefronts' revenue would increase by 1.85 percent annually solely due to the heat mitigating service tree cover provides. In the most severe warming scenario, the Broad Southwest only experiences a 0.12 percent loss of revenue under the high tree cover scenario. This is in comparison to a 3.25 percent loss that the region would experience in this severe scenario at its baseline tree cover. This region has the most to gain because it already experiences extreme heat and has relatively little urban tree cover (Table 1).

While the marginal effects of the amenity effect and cooling effect of tree cover on hot days are extremely similar, the increase in revenue from the amenity effect in a high green space scenario is much larger than the increase from cooling services. This is because the amenity effect is experienced daily. The annual revenue changes projected using a linear and logged recovered main effect specification from Equation 7 are plotted

[3] The cities that experience a 2 percent decrease are: Fresno, CA; Tucson, AZ; Austin, TX; San Antonio, TX; Las Vegas, NV; Phoenix, AZ; Sacramento, CA; Dallas, TX; Houston, TX; Riverside, CA.

Figure 10: Annual 3 °C Climate Scenario by City and Season



This figure projects revenue changes under a 3 °C warming scenario, disaggregated by city and season using Specification (1). Summer losses are concentrated in the Southwest, where ten cities experience revenue declines greater than 2 percent and Fresno, CA and Tucson, AZ see drops of about 4 percent. Other regions experience gains as cooler days shift toward more favorable temperatures.

in Appendix Figure A3. All regions experience more than a 10 percent increase in annual revenue under all climate scenarios when incorporating tree cover's amenity value.

6.1 Years to Cover Cost of High Tree Cover Scenario

This subsection presents the number of years it would take the cover the cost of moving from the baseline tree cover scenario to a high tree cover scenario ($\geq$ 10 percent). I present the result for the Southwest and Southern regions under the baseline climate scenario because California through Mississippi have the most to gain from adaptation.

When using the lower bound estimate of tree covers' value to storefronts (*i.e.,* not including the recovered amenity effect), moving to the high tree cover scenario for the average storefront in the Southwest would increase revenue 1.85 percent annually under the current, baseline climate scenario. The median surrounding tree cover in the Broad Southwest is around 2 percent. To move from 2 percent coverage to 10 at a single storefront would require planing approximately 10,000 meters squared of tree canopy cover, or 100 medium sized trees. A reasonable approximation of annual revenue at a restaurant, which the most represented storefront type in this paper's sample, is $1 million. The cost of planting a tree, including initial maintenance, is $750 (Murphy-Dunning, 2025).

Accordingly, the cost of moving to the high tree cover scenario is $75 thousand. The annual benefit is $18.5 thousand. Therefore, It would take 4.05 years for the businesses to recuperate the planting cost of the trees. For the Southwest and Southern regions, this length of time only becomes shorter under climate scenarios. This is because warmer scenarios monotonically increase the revenue gain of moving from the baseline tree cover scenario to the high tree cover counterfactual.

In the baseline climate scenario, other regions do not have as much to gain in terms of revenue increases from tree cover mitigating the effect of extreme heat. These regions currently do not experience as many extremely hot days that can to be mitigated by tree cover, and also already enjoy much higher levels of tree cover than the Southwest and Southern regions.

7 Conclusion and Discussion

This paper estimates the causal effect of extreme heat and urban tree cover on storefront revenue across the 49 largest U.S. metropolitan areas. Using high-frequency transaction data combined with detailed temperature records and satellite-based tree canopy measures, the analysis finds that daily maximum temperatures above 35 °C depress storefront revenue. Losses are the sharpest beyond 37.5 °C, where revenue declines by nearly 10 percent relative to a 20 °C day. These effects are not offset through temporal substitution. Spending fails to rebound within a two-week window following an extreme heat event.

Urban tree cover provides a valuable buffer against these damages. When temperatures exceed 35 °C, a one-percent increase in canopy corresponds to a near one-percent gain in revenue. This benefit is the same magnitude as the general amenity value of tree cover to storefront revenue. Together, these findings show that tree cover functions simultaneously as an amenity to storefronts every day and as natural infrastructure that regulates local microclimates on extremely hot days.

The climate scenario analysis underscores the uneven consequences of warming across U.S. regions. On average, annual revenue effects appear modest at the national scale, as losses from extreme heat are partially offset by gains from fewer extremely cold days. Yet seasonal and regional breakdowns reveal concentrated damages. In the Southwest, summer revenue losses can exceed four percent under a 3 °C warming scenario. By contrast, northern regions, which have both cooler baseline temperatures and higher canopy cover, see net gains. This heterogeneity highlights the importance of local conditions.

Cities' green space varies greatly and is changing in different ways. Some cities, such as Houston, expanded median canopy cover by 13 percent between 2016 and 2022, while others, such as Phoenix, lost 12 percent over the same period (Falchetta and Hammad, 2025). New York lost 2 percent but still maintains more canopy cover than many southern cities. Cities beginning with low levels of green space and high heat exposure stand to benefit the most from investment.

These results diverge from earlier work suggesting that temperature shocks have limited economic significance at the establishment level (Addoum et al., 2020). By leveraging high-frequency, daily transaction data and explicitly modeling extreme heat, this paper demonstrates economically meaningful losses that accumulate seasonally in hotter regions. Importantly, the analysis focuses on revenue rather than profit, and thus does not capture cost-side effects that may further amplify the negative consequences of extreme heat, such as increased cooling expenditures (Heris et al., 2021) or decreased labor productivity (Dasgupta et al., 2024; Park, 2022; Park et al., 2021).

My findings contribute to the growing literature on nature-based solutions to climate change. Most existing work and financing mechanisms have emphasized mitigation (*i.e.,* paying to sequester carbon or avoid emissions (Barbier and Burgess, 2025)). While co-benefits of nature-based climate solutions are often acknowledged, they are rarely the basis for investment, with limited exceptions in insurance markets (Beck et al., 2018; Schelske et al., 2021). The analysis here demonstrates a distinct adaptation channel. Urban tree cover reduces the private damages of extreme heat by protecting storefront revenue. This reframes green space not only as a public good but also as a commercially important asset. Because the benefits accrue directly to businesses, there is a private incentive to invest in green infrastructure as a form of climate adaptation.

These private incentives can complement public financing mechanisms. For example, municipal governments already issue bonds to finance infrastructure such as parks and streetscapes. If investments in green space raise storefront revenue, and thereby expand the local tax base, then municipalities could credibly leverage fiscal instruments to fund canopy expansion. Such effects have been observed. For example, bat presence has led to higher property tax revenue raised by increasing agricultural yields Nakhmurina et al. (2025). By aligning private benefits with public returns, urban tree cover emerges as a scalable, potentially self-financing adaptation strategy to the increasing severity of extreme heat caused by climate change.

In sum, this paper shows that extreme heat threatens storefront revenue, that urban tree cover provides both amenity and climate-regulating benefits, and that these benefits are strongest where the risks are highest. Tree cover therefore represents not just an environmental asset but a financial one that is capable of delivering resilience to climate change for private businesses while advancing urban livability for people.

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A Supplementary Results

Figure A1: Revenue on Nice Day Following Hot, as Compared to Avg. Nice Day

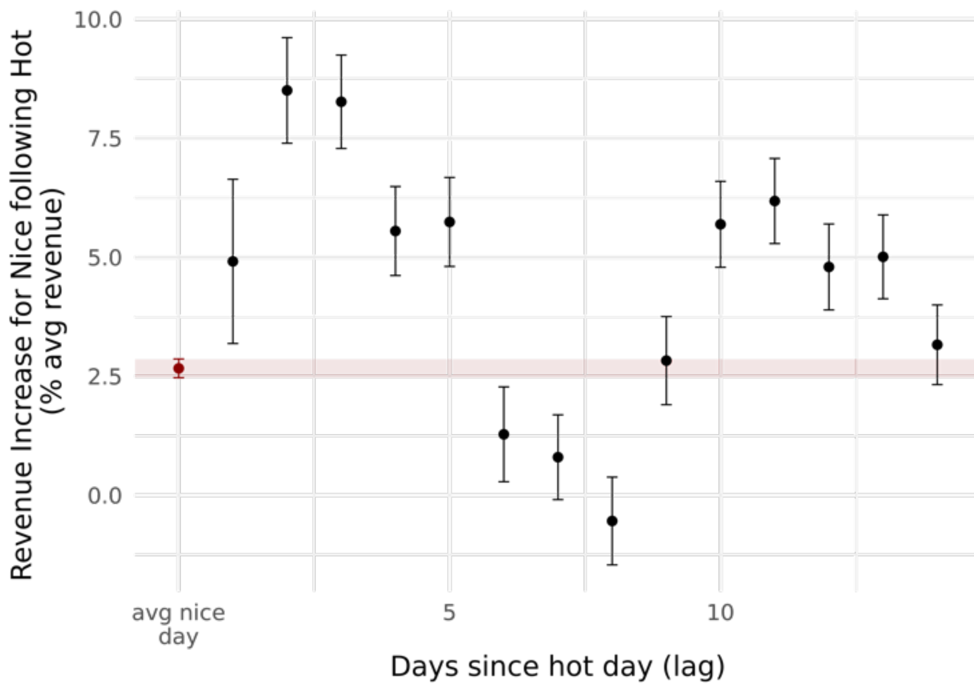

Figure A2: Placebo: No Evidence of Green Space Effect in Malls

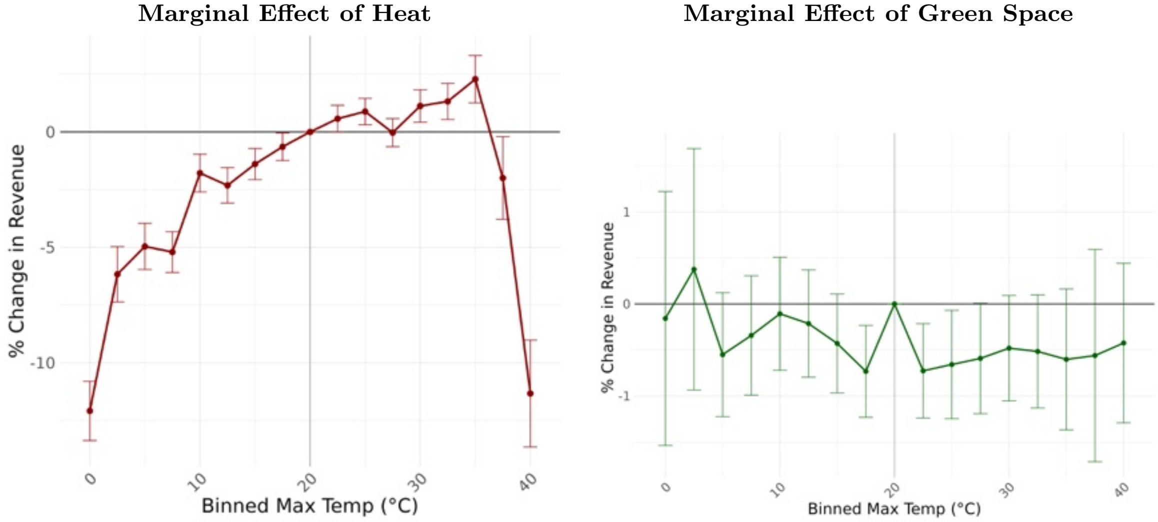

Figure A3: Projected Annual Revenue Change under Various Counterfactuals (Recovered Main Effects)

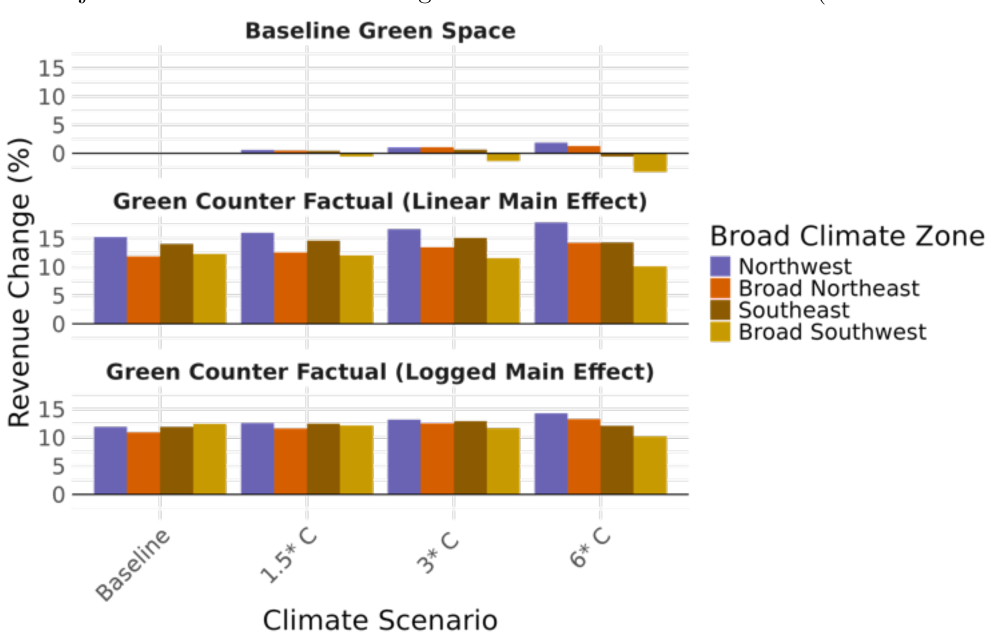

Figure A4: Robustness check to various radii for calculating tree canopy cover

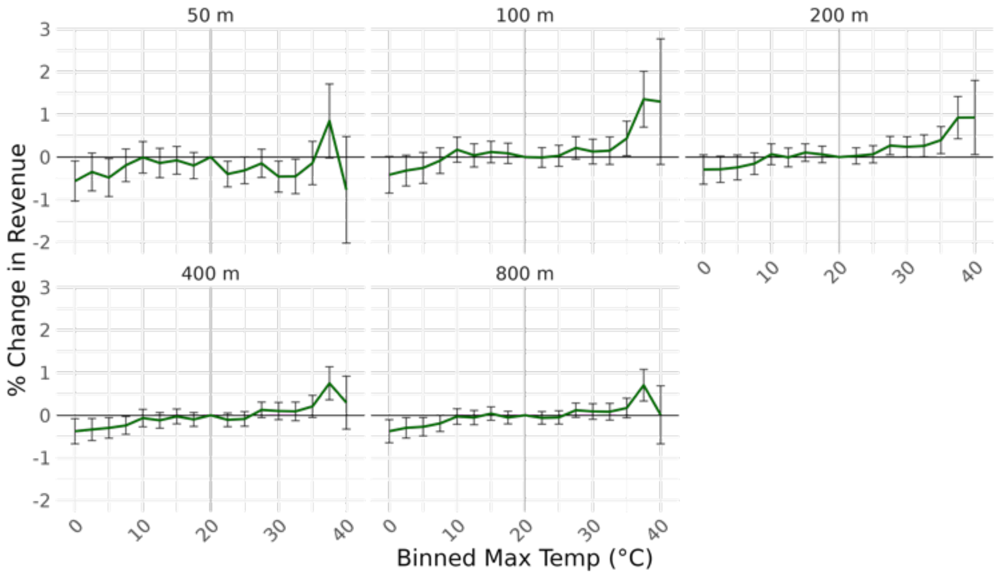

Figure A5: Robustness Check: Dropping Covid

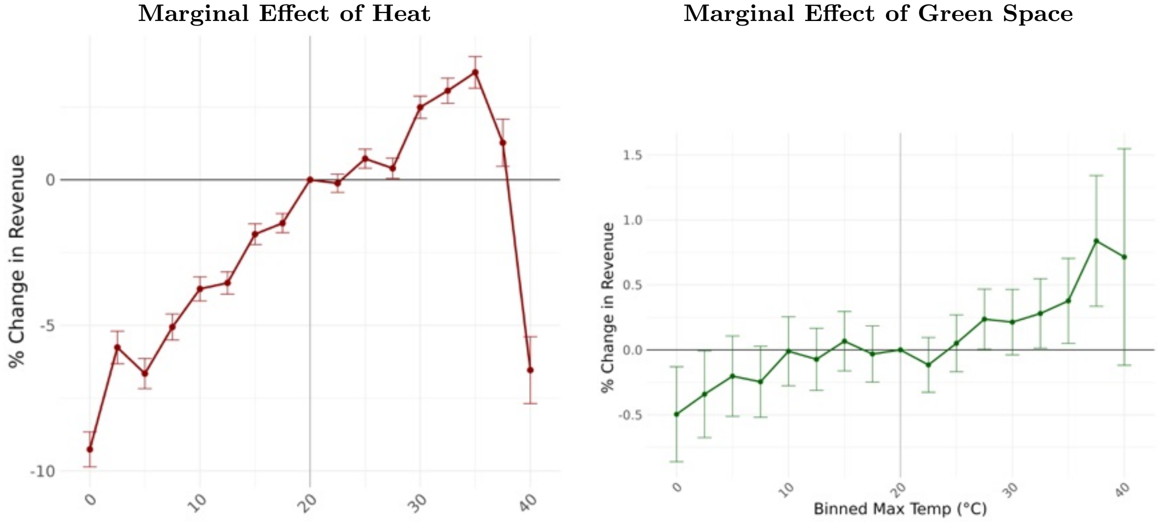

Figure A6: Robustness Check: Dropping Phoenix, AZ

Marginal Effect of Heat **Marginal Effect of Green Space**

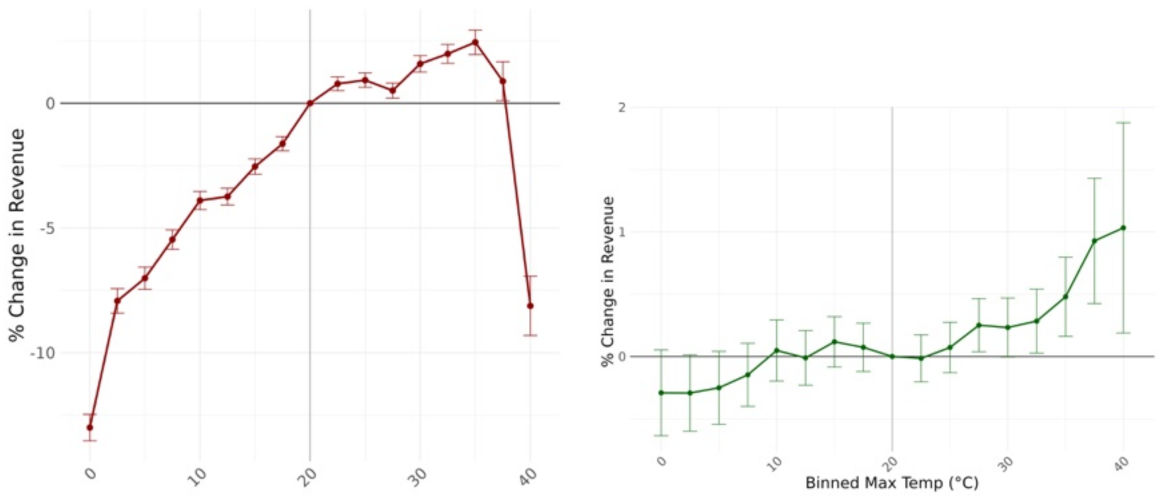

Table A1: Summary of Included Industries

NAICs Code	Industry Description	Storefront Count
722	Food services & drinking places	9524
445	Food & beverage stores	1226
812	Personal & laundry services	881
448	Clothing & accessories stores	736
446	Health & personal care stores	713
452	General merchandise stores	526
453	Misc. store retailers	418
441	Motor vehicle & parts dealers	340
451	Sporting goods, hobby & book stores	299
447	Gasoline stations	273
811	Repair & maintenance	209
–	Total	15145

Table A2: Summary of median surrounding green space by city, and average temperature

	City	Median Green Space	Average Temp (°C)
1	Portland, OR	14.34	18.25
2	Raleigh, NC	13.81	22.02
3	Pittsburgh, PA	13.02	18.00
4	Minneapolis, MN	12.31	17.90
5	Memphis, TN	12.30	22.71
6	Atlanta, GA	11.80	22.84
7	Charlotte, NC	11.62	22.41
8	Richmond, VA	10.82	21.12
9	Jacksonville, FL	9.83	26.74
10	Baltimore, MD	9.81	20.19
11	Tampa, FL	9.36	27.86
12	Nashville, TN	9.21	22.02
13	Milwaukee, WI	8.72	16.60
14	Kansas City, MO	8.53	20.30
15	Virginia Beach, VA	8.51	21.17
16	Rochester, NY	8.32	16.56
17	Buffalo, NY	7.97	16.25
18	Orlando, FL	7.22	28.20
19	Salt Lake City, UT	7.10	18.90
20	Cincinnati, OH	7.01	19.20
21	Seattle, WA	6.78	17.02
22	Louisville, KY	6.22	20.20
23	Miami, FL	5.26	29.07
24	Cleveland, OH	4.93	17.03
25	Indianapolis, IN	4.91	18.29
26	Detroit, MI	4.89	17.35
27	Denver, CO	4.48	19.71
28	Philadelphia, PA	4.46	19.16
29	San Jose, CA	3.98	23.32
30	Austin, TX	3.88	26.59
31	Columbus, OH	3.78	18.61
32	Houston, TX	3.58	27.06
33	New Orleans, LA	3.24	25.69
34	Sacramento, CA	3.10	24.81
35	Chicago, IL	3.01	17.34
36	Riverside, CA	2.71	25.86
37	San Antonio, TX	2.60	27.38
38	Fresno, CA	2.56	25.15
39	San Diego, CA	2.54	22.51
40	Dallas, TX	2.36	25.02
41	Boston, MA	2.35	17.27
42	New York, NY	1.81	18.22
43	Tulsa, OK	1.29	23.15
44	Los Angeles, CA	1.11	23.87
45	Oklahoma City, OK	0.79	22.97
46	Phoenix, AZ	0.54	27.22
47	Las Vegas, NV	0.50	24.68
48	San Francisco, CA	0.45	19.00
49	Tucson, AZ	0.37	27.65

Table A3: Heat only models

	reg_1	reg_2	reg_3	reg_4	reg_5	reg_preferred
Dependent Var.:	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend
Constant	4.715*** (0.0040)	4.620*** (0.0042)				
Share in 25–45K	0.1346*** (0.0068)	0.1241*** (0.0068)	0.2274*** (0.0179)	0.3040*** (0.0137)	0.3256*** (0.0137)	0.3465*** (0.0142)
Share in 45–60K	-0.5369*** (0.0071)	-0.4966*** (0.0071)	0.1037*** (0.0211)	0.1407*** (0.0146)	0.2631*** (0.0147)	0.2739*** (0.0153)
Share in 60–75K	-1.241*** (0.0079)	-1.160*** (0.0079)	-0.0705** (0.0226)	-0.0698*** (0.0157)	0.0510** (0.0158)	0.0464** (0.0163)
Share in 75–100K	-0.3510*** (0.0067)	-0.2585*** (0.0067)	0.2025*** (0.0245)	0.2446*** (0.0150)	0.2312*** (0.0150)	0.2623*** (0.0156)
Share in 100–150K	0.0598*** (0.0060)	0.1666*** (0.0061)	0.3362*** (0.0264)	0.3669*** (0.0147)	0.3353*** (0.0147)	0.3876*** (0.0153)
Share >150K	0.4824*** (0.0048)	0.5374*** (0.0048)	0.0688** (0.0262)	0.0143 (0.0139)	0.1716*** (0.0143)	0.2195*** (0.0148)
Bin: 0 °C		0.1813*** (0.0024)	-0.1235*** (0.0030)	-0.1376*** (0.0030)	-0.1712*** (0.0029)	-0.1313*** (0.0027)
Bin: 2.5 °C		0.2428*** (0.0027)	-0.0466*** (0.0029)	-0.0732*** (0.0027)	-0.0946*** (0.0027)	-0.0809*** (0.0025)
Bin: 5 °C		0.1890*** (0.0025)	-0.0366*** (0.0026)	-0.0625*** (0.0024)	-0.0789*** (0.0024)	-0.0719*** (0.0023)
Bin: 7.5 °C		0.1437*** (0.0023)	-0.0373*** (0.0023)	-0.0542*** (0.0021)	-0.0682*** (0.0021)	-0.0565*** (0.0020)
Bin: 10 °C		0.1025*** (0.0021)	-0.0164*** (0.0021)	-0.0285*** (0.0019)	-0.0370*** (0.0019)	-0.0423*** (0.0018)
Bin: 12.5 °C		0.0316*** (0.0021)	-0.0309*** (0.0019)	-0.0431*** (0.0018)	-0.0499*** (0.0018)	-0.0400*** (0.0017)
Bin: 15 °C		0.0028 (0.0020)	-0.0180*** (0.0017)	-0.0234*** (0.0017)	-0.0267*** (0.0016)	-0.0276*** (0.0016)
Bin: 17.5 °C		-0.0192*** (0.0019)	-0.0128*** (0.0015)	-0.0161*** (0.0015)	-0.0182*** (0.0015)	-0.0180*** (0.0014)
Bin: 22.5 °C		0.0326*** (0.0018)	0.0096*** (0.0015)	0.0096*** (0.0015)	0.0086*** (0.0015)	0.0034* (0.0014)
Bin: 25 °C		0.0635*** (0.0018)	0.0007 (0.0014)	0.0017 (0.0015)	0.0039** (0.0015)	0.0071*** (0.0014)
Bin: 27.5 °C		0.0592*** (0.0018)	-0.0107*** (0.0015)	-0.0092*** (0.0016)	-0.0059*** (0.0016)	0.0015 (0.0015)
Bin: 30 °C		0.0617*** (0.0018)	0.0018 (0.0017)	0.0057** (0.0018)	0.0074*** (0.0018)	0.0141*** (0.0017)
Bin: 32.5 °C		0.0022 (0.0018)	0.0136*** (0.0019)	0.0153*** (0.0020)	0.0150*** (0.0020)	0.0204*** (0.0019)
Bin: 35 °C		-0.0501*** (0.0023)	0.0179*** (0.0023)	0.0121*** (0.0025)	0.0205*** (0.0025)	0.0273*** (0.0025)
Bin: 37.5 °C		-0.0381*** (0.0029)	0.0038 (0.0035)	-0.0169*** (0.0038)	0.0150*** (0.0038)	-0.0041 (0.0037)
Bin: 40 °C		-0.1051*** (0.0033)	-0.0790*** (0.0048)	-0.1009*** (0.0054)	-0.0620*** (0.0053)	-0.0956*** (0.0053)
Fixed-Effects:	------------------	------------------	------------------	------------------	------------------	------------------
POI	No	No	Yes	No	No	No
POI x Month	No	No	No	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes
Year	No	No	No	No	Yes	Yes
Day of Week	No	No	No	No	No	Yes
------------------	------------------	------------------	------------------	------------------	------------------	------------------
S.E. type	IID	IID	by: POI	by: POI x Month	by: POI x Month	by: POI x Month
Observations	13,771,685	13,771,685	13,771,685	13,771,685	13,771,685	13,771,685
R2	0.00678	0.00909	0.39756	0.40944	0.41277	0.49596
Within R2	–	–	0.00102	0.00094	0.00083	0.00090

Table A4: Temporal Substitution in Response to Heat – Cumulative Effects

	k = 1	k = 2	k = 3	k = 4	k = 5	k = 6	k = 7
Dependent Var.:	log_tot	log_tot	log_tot	log_tot	log_tot	log_tot	log_tot
share_25_45	0.2518*** (0.0188)	0.2898*** (0.0250)	0.2929*** (0.0311)	0.2835*** (0.0369)	0.2574*** (0.0430)	0.2256*** (0.0512)	0.2112*** (0.0571)
share_45_60	0.1816*** (0.0227)	0.2619*** (0.0303)	0.3280*** (0.0376)	0.3806*** (0.0442)	0.4017*** (0.0511)	0.4112*** (0.0602)	0.4290*** (0.0668)
share_60_75	-0.0116 (0.0242)	0.0138 (0.0326)	0.0964* (0.0404)	0.1818*** (0.0474)	0.2429*** (0.0545)	0.3041*** (0.0639)	0.3571*** (0.0706)
share_75_100	0.1917*** (0.0255)	0.2585*** (0.0348)	0.3126*** (0.0433)	0.3432*** (0.0509)	0.3447*** (0.0587)	0.3257*** (0.0686)	0.3176*** (0.0758)
share_100_150	0.3225*** (0.0271)	0.3885*** (0.0377)	0.4260*** (0.0479)	0.4522*** (0.0575)	0.4501*** (0.0676)	0.4346*** (0.0801)	0.4323*** (0.0896)
share_more150	0.2143*** (0.0283)	0.1504*** (0.0381)	0.0622 (0.0476)	-0.0195 (0.0566)	-0.1094. (0.0659)	-0.2007** (0.0771)	-0.2589** (0.0857)
preceded_by_hotTRUE	-0.0526*** (0.0042)	-0.0386*** (0.0047)	-0.0286*** (0.0051)	-0.0218*** (0.0055)	-0.0193** (0.0059)	-0.0175** (0.0064)	-0.0165* (0.0067)
Fixed-Effects:							
placekey	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
city_month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
day_of_week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: placekey	by: placekey	by: placekey	by: placekey	by: placekey	by: placekey	by: placekey
Observations	13,993,732	10,393,616	8,316,375	6,924,102	5,887,223	5,058,251	4,538,509
R2	0.48784	0.62829	0.70170	0.74356	0.76988	0.79071	0.80551
Within R2	0.00043	0.00073	0.00115	0.00173	0.00236	0.00307	0.00378

	k = 8	k = 9	k = 10	k = 11	k = 12	k = 13	k = 14
Dependent Var.:	log_tot	log_tot	log_tot	log_tot	log_tot	log_tot	log_tot
share_25_45	0.2062*** (0.0607)	0.2040** (0.0639)	0.1994** (0.0672)	0.1923** (0.0706)	0.1843* (0.0742)	0.1757* (0.0781)	0.1674* (0.0815)
share_45_60	0.4417*** (0.0708)	0.4587*** (0.0744)	0.4697*** (0.0782)	0.4774*** (0.0822)	0.4799*** (0.0864)	0.4803*** (0.0910)	0.4776*** (0.0951)
share_60_75	0.4017*** (0.0747)	0.4388*** (0.0783)	0.4673*** (0.0820)	0.4868*** (0.0860)	0.5008*** (0.0901)	0.5105*** (0.0946)	0.5200*** (0.0986)
share_75_100	0.3207*** (0.0802)	0.3241*** (0.0841)	0.3264*** (0.0883)	0.3240*** (0.0926)	0.3161** (0.0970)	0.3026** (0.1017)	0.2948** (0.1058)
share_100_150	0.4362*** (0.0957)	0.4399*** (0.1011)	0.4395*** (0.1066)	0.4322*** (0.1121)	0.4216*** (0.1175)	0.4066*** (0.1233)	0.3942** (0.1281)
share_more150	-0.2880** (0.0915)	-0.3094** (0.0969)	-0.3344** (0.1023)	-0.3615*** (0.1079)	-0.3909*** (0.1135)	-0.4231*** (0.1195)	-0.4502*** (0.1248)
preceded_by_hotTRUE	-0.0161* (0.0069)	-0.0157* (0.0071)	-0.0142. (0.0073)	-0.0130. (0.0076)	-0.0136. (0.0078)	-0.0138. (0.0081)	-0.0130 (0.0083)
Fixed-Effects:							
placekey	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
city_month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
day_of_week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: placekey	by: placekey	by: placekey	by: placekey	by: placekey	by: placekey	by: placekey
Observations	4,218,416	3,954,703	3,716,767	3,500,193	3,302,872	3,120,808	2,968,778
R2	0.81323	0.81903	0.82445	0.82953	0.83435	0.83908	0.84306
Within R2	0.00425	0.00465	0.00506	0.00545	0.00583	0.00622	0.00657

Table A5: Temporal Substitution in Response to Heat – Substitution to Nice Days

	pleasant	post_hot1	post_hot2	post_hot3	post_hot4	post_hot5	post_hot6	post_hot7	post_hot8	post_hot9	post_hot10	post_hot11	post_hot12	post_hot13	post_hot14
Dependent Var.:	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend	log_spend
Share in 25–45K	0.2517*** (0.0188)	0.2752*** (0.0217)	0.2741*** (0.0219)	0.2799*** (0.0217)	0.2839*** (0.0218)	0.2808*** (0.0219)	0.2781*** (0.0217)	0.2792*** (0.0214)	0.2783*** (0.0217)	0.2764*** (0.0220)	0.2771*** (0.0218)	0.2881*** (0.0219)	0.2803*** (0.0220)	0.2778*** (0.0218)	0.2805*** (0.0215)
Share in 45–60K	0.1812*** (0.0227)	0.2231*** (0.0264)	0.2221*** (0.0265)	0.2212*** (0.0263)	0.2250*** (0.0263)	0.2190*** (0.0265)	0.2221*** (0.0263)	0.2158*** (0.0259)	0.2244*** (0.0263)	0.2250*** (0.0266)	0.2178*** (0.0264)	0.2289*** (0.0264)	0.2248*** (0.0265)	0.2174*** (0.0263)	0.2175*** (0.0260)
Share in 60–75K	-0.0114 (0.0242)	0.0002 (0.0282)	0.0077 (0.0283)	0.0031 (0.0280)	-0.0007 (0.0281)	0.0039 (0.0283)	0.0024 (0.0281)	-0.0085 (0.0278)	0.0066 (0.0281)	0.0093 (0.0283)	-0.0048 (0.0281)	0.0012 (0.0283)	0.0016 (0.0283)	-0.0011 (0.0282)	-0.0017 (0.0278)
Share in 75–100K	0.1913*** (0.0255)	0.2237*** (0.0297)	0.2284*** (0.0299)	0.2306*** (0.0297)	0.2255*** (0.0297)	0.2229*** (0.0299)	0.2249*** (0.0297)	0.2205*** (0.0294)	0.2235*** (0.0298)	0.2279*** (0.0300)	0.2268*** (0.0298)	0.2268*** (0.0298)	0.2167*** (0.0300)	0.2181*** (0.0298)	0.2166*** (0.0294)
Share in 100–150K	0.3232*** (0.0271)	0.3601*** (0.0318)	0.3678*** (0.0319)	0.3663*** (0.0317)	0.3606*** (0.0317)	0.3614*** (0.0319)	0.3590*** (0.0317)	0.3537*** (0.0312)	0.3626*** (0.0317)	0.3677*** (0.0320)	0.3581*** (0.0318)	0.3635*** (0.0318)	0.3570*** (0.0319)	0.3551*** (0.0318)	0.3492*** (0.0313)
Share >150K	0.2152*** (0.0283)	0.2082*** (0.0326)	0.2151*** (0.0327)	0.2088*** (0.0326)	0.2037*** (0.0326)	0.1992*** (0.0327)	0.2028*** (0.0326)	0.2025*** (0.0322)	0.2089*** (0.0326)	0.2115*** (0.0328)	0.2046*** (0.0327)	0.2078*** (0.0327)	0.1989*** (0.0328)	0.1976*** (0.0327)	0.2013*** (0.0323)
Tree Canopy Covery	-0.0146*** (0.0032)	-0.0152*** (0.0033)	-0.0155*** (0.0033)	-0.0153*** (0.0033)	-0.0154*** (0.0033)	-0.0153*** (0.0033)	-0.0154*** (0.0033)	-0.0155*** (0.0034)	-0.0154*** (0.0034)	-0.0156*** (0.0033)	-0.0155*** (0.0033)	-0.0155*** (0.0034)	-0.0154*** (0.0034)	-0.0154*** (0.0033)	-0.0155*** (0.0034)
Avg. nice day boost	0.0267*** (0.0010)														
Nice day, hot 1 day ago		0.0491*** (0.0088)													
Nice day, 2 days			0.0851*** (0.0057)												
Nice day, 3 days				0.0827*** (0.0050)											
Nice day, 4 days					0.0555*** (0.0048)										
Nice day, 5 days						0.0574*** (0.0048)									
Nice day, 6 days							0.0128* (0.0051)								
Nice day, 7 days								0.0080. (0.0045)							
Nice day, 8 days									-0.0054 (0.0047)						
Nice day, 9 days										0.0283*** (0.0047)					
Nice day, 10 days											0.0569*** (0.0046)				
Nice day, 11 days												0.0618*** (0.0046)			
Nice day, 12 days													0.0480*** (0.0046)		
Nice day, 13 days														0.0501*** (0.0045)	
Nice day, 14 days															0.0316*** (0.0043)
Fixed-Effects:															
POI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City x Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI	by: POI
Observations	13,993,732	12,071,939	11,868,959	11,898,808	11,871,528	11,790,182	11,972,091	12,250,378	11,921,958	11,700,327	11,728,267	11,711,944	11,638,248	11,823,766	12,102,727
R2	0.48790	0.49607	0.49905	0.49777	0.49541	0.49645	0.49547	0.49173	0.49420	0.49836	0.49735	0.49554	0.49666	0.49570	0.49248
Within R2	0.00056	0.00050	0.00052	0.00053	0.00051	0.00050	0.00049	0.00050	0.00050	0.00050	0.00051	0.00052	0.00050	0.00050	0.00050

Table A6: The Effect of Temperature on Revenue

	reg_g
Dependent Var.:	log_spend
Share in 25–45K	0.1649*** (0.0476)
Share in 45–60K	0.1101* (0.0534)
Share in 60–75K	-0.1921*** (0.0580)
Share in 75–100K	0.5085*** (0.0551)
Share in 100–150K	1.094*** (0.0595)
Share >150K	0.8024*** (0.0541)
Storefront Size (m2)	0.0001*** (1.74e-5)
Parking Lot	-0.1428*** (0.0369)
Bin: 0 °C	-0.1125*** (0.0157)
Bin: 2.5 °C	-0.0564*** (0.0143)
Bin: 5 °C	-0.0467*** (0.0120)
Bin: 7.5 °C	-0.0450*** (0.0098)
Bin: 10 °C	-0.0434*** (0.0094)
Bin: 12.5 °C	-0.0498*** (0.0083)
Bin: 15 °C	-0.0368*** (0.0077)
Bin: 17.5 °C	-0.0209** (0.0066)
Bin: 22.5 °C	-0.0005 (0.0066)
Bin: 25 °C	0.0040 (0.0069)
Bin: 27.5 °C	-0.0211** (0.0077)
Bin: 30 °C	-0.0120 (0.0084)
Bin: 32.5 °C	0.0004 (0.0100)
Bin: 35 °C	-0.0082 (0.0125)
Bin: 37.5 °C	-0.0989*** (0.0183)
Bin: 40 °C	-0.2171*** (0.0261)
Tree Canopy Covery	-0.0002 (0.0008)
Bin: 0 °C x Tree Canopy Covery	-0.0028. (0.0016)
Bin: 2.5 °C x Tree Canopy Covery	-0.0027* (0.0014)
Bin: 5 °C x Tree Canopy Covery	-0.0023. (0.0013)
Bin: 7.5 °C x Tree Canopy Covery	-0.0014 (0.0010)
Bin: 10 °C x Tree Canopy Covery	0.0008 (0.0010)
Bin: 12.5 °C x Tree Canopy Covery	8.5e-5 (0.0008)
Bin: 15 °C x Tree Canopy Covery	0.0012. (0.0007)
Bin: 17.5 °C x Tree Canopy Covery	0.0008 (0.0006)
Bin: 22.5 °C x Tree Canopy Covery	0.0004 (0.0006)
Bin: 25 °C x Tree Canopy Covery	0.0008 (0.0007)
Bin: 27.5 °C x Tree Canopy Covery	0.0029*** (0.0008)
Bin: 30 °C x Tree Canopy Covery	0.0026** (0.0009)
Bin: 32.5 °C x Tree Canopy Covery	0.0028** (0.0011)
Bin: 35 °C x Tree Canopy Covery	0.0041** (0.0014)
Bin: 37.5 °C x Tree Canopy Covery	0.0094*** (0.0024)
Bin: 40 °C x Tree Canopy Covery	0.0095* (0.0044)
Fixed-Effects:	———————-
Brand x City x Month	Yes
Year	Yes
Day of Week	Yes
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S.E.: Clustered	by: Brand x City ..
Observations	3,599,675
R2	0.39570
Within R2	0.00785

Table A7: The effect of avg. tree canopy cover on the brand X city X month fixed effect

	reg_main_g_1	reg_main_g_2	reg_main_g_3	reg_main_g_4	reg_main_g_5
Dependent Var.:	fe_value	fe_value	fe_value	fe_value	fe_value
Constant	4.271*** (0.0192)	4.138*** (0.0652)	4.137*** (0.0652)	4.084*** (0.0670)	4.082*** (0.0698)
Mean Tree Canopy (200 m)	-0.0041 (0.0026)	0.0092*** (0.0024)		0.0303*** (0.0067)	0.0320* (0.0142)
as.factor(naics_code)445120		0.1410. (0.0736)	0.1452* (0.0734)	0.1407. (0.0735)	0.1408. (0.0735)
Pharmacies & Drug Stores		0.5162*** (0.0727)	0.5116*** (0.0727)	0.5091*** (0.0726)	0.5090*** (0.0727)
Cosmetic & Beauty Supply Stores		0.1716 (0.2134)	0.1654 (0.2133)	0.1922 (0.2132)	0.1924 (0.2132)
Gas Stations w/ Conv. Stores		0.1535 (0.0970)	0.1747. (0.0966)	0.1796. (0.0972)	0.1795. (0.0972)
Hobby, Toy & Game Stores		0.9052*** (0.2134)	0.9002*** (0.2133)	0.9272*** (0.2132)	0.9275*** (0.2132)
All Other Gen. Merch. Stores		-0.7952*** (0.0755)	-0.7905*** (0.0753)	-0.7874*** (0.0754)	-0.7879*** (0.0755)
Full-Service Restaurants		0.4832*** (0.1114)	0.4913*** (0.1114)	0.4932*** (0.1113)	0.4944*** (0.1116)
Limited-Service Restaurants		0.1220. (0.0662)	0.1189. (0.0662)	0.1220. (0.0661)	0.1220. (0.0661)
Snack & Nonalc. Bev. Bars		-0.2003** (0.0708)	-0.2053** (0.0709)	-0.2061** (0.0707)	-0.2062** (0.0707)
Automotive Shops		1.173*** (0.1576)	1.155*** (0.1577)	1.146*** (0.1575)	1.145*** (0.1578)
Beauty Salons		0.4176** (0.1578)	0.4176** (0.1577)	0.4141** (0.1575)	0.4149** (0.1577)
log(Mean Tree Canopy)			0.0414*** (0.0108)		
Mean Canopy: Squared				-0.0012*** (0.0004)	-0.0014 (0.0016)
Mean Canopy: Cubed					7.3e-6 (5.15e-5)
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S.E. type	IID	IID	IID	IID	IID
Observations	3,795	3,795	3,795	3,795	3,795
R2	0.00066	0.18739	0.18750	0.18980	0.18981
Adj. R2	0.00040	0.18481	0.18493	0.18702	0.18681

Table A8: Robustness check for various radii buffer specifications for the effect of green space on revenue

		50	100	200	400	800
1	Dependent Var.:	log_spend	log_spend	log_spend	log_spend	log_spend
2						
3	Share in 25–45K	0.1661*** (0.0476)	0.1637*** (0.0476)	0.1649*** (0.0476)	0.1649*** (0.0476)	0.1648*** (0.0476)
4	Share in 45–60K	0.1106* (0.0533)	0.1088* (0.0534)	0.1101* (0.0534)	0.1103* (0.0533)	0.1099* (0.0533)
5	Share in 60–75K	-0.1877** (0.0580)	-0.1931*** (0.0581)	-0.1921*** (0.0580)	-0.1895** (0.0579)	-0.1901** (0.0580)
6	Share in 75–100K	0.5094*** (0.0551)	0.5080*** (0.0551)	0.5085*** (0.0551)	0.5106*** (0.0550)	0.5105*** (0.0550)
7	Share in 100–150K	1.101*** (0.0595)	1.095*** (0.0595)	1.094*** (0.0595)	1.099*** (0.0594)	1.098*** (0.0594)
8	Share >150K	0.8138*** (0.0541)	0.8040*** (0.0542)	0.8024*** (0.0541)	0.8102*** (0.0542)	0.8085*** (0.0541)
9	Storefront Size (m2)	0.0001*** (1.74e-5)	0.0001*** (1.74e-5)	0.0001*** (1.74e-5)	0.0001*** (1.74e-5)	0.0001*** (1.74e-5)
10	Parking Lot	-0.1396*** (0.0369)	-0.1435*** (0.0370)	-0.1428*** (0.0369)	-0.1421*** (0.0370)	-0.1428*** (0.0369)
11	Bin: 0 °C	-0.1244*** (0.0135)	-0.1150*** (0.0146)	-0.1125*** (0.0157)	-0.1113*** (0.0169)	-0.1006*** (0.0184)
12	Bin: 2.5 °C	-0.0726*** (0.0119)	-0.0620*** (0.0129)	-0.0564*** (0.0143)	-0.0582*** (0.0155)	-0.0520** (0.0170)
13	Bin: 5 °C	-0.0577*** (0.0099)	-0.0520*** (0.0108)	-0.0467*** (0.0120)	-0.0491*** (0.0131)	-0.0422** (0.0144)
14	Bin: 7.5 °C	-0.0575*** (0.0082)	-0.0520*** (0.0089)	-0.0450*** (0.0098)	-0.0471*** (0.0108)	-0.0444*** (0.0120)
15	Bin: 10 °C	-0.0458*** (0.0076)	-0.0467*** (0.0083)	-0.0434*** (0.0094)	-0.0477*** (0.0105)	-0.0488*** (0.0115)
16	Bin: 12.5 °C	-0.0535*** (0.0071)	-0.0521*** (0.0076)	-0.0498*** (0.0083)	-0.0539*** (0.0092)	-0.0570*** (0.0100)
17	Bin: 15 °C	-0.0355*** (0.0067)	-0.0356*** (0.0071)	-0.0368*** (0.0077)	-0.0421*** (0.0084)	-0.0478*** (0.0091)
18	Bin: 17.5 °C	-0.0197*** (0.0059)	-0.0210*** (0.0062)	-0.0209** (0.0066)	-0.0230** (0.0071)	-0.0245** (0.0076)
19	Bin: 22.5 °C	0.0025 (0.0059)	0.0006 (0.0062)	-0.0005 (0.0066)	-0.0038 (0.0070)	-0.0051 (0.0074)
20	Bin: 25 °C	0.0074 (0.0061)	0.0059 (0.0064)	0.0040 (0.0069)	0.0013 (0.0075)	0.0004 (0.0081)
21	Bin: 27.5 °C	-0.0100 (0.0067)	-0.0146* (0.0072)	-0.0211** (0.0077)	-0.0301*** (0.0084)	-0.0319*** (0.0092)
22	Bin: 30 °C	0.0042 (0.0073)	-0.0041 (0.0078)	-0.0120 (0.0084)	-0.0203* (0.0093)	-0.0210* (0.0102)
23	Bin: 32.5 °C	0.0176* (0.0085)	0.0086 (0.0092)	0.0004 (0.0100)	-0.0057 (0.0112)	-0.0064 (0.0121)
24	Bin: 35 °C	0.0101 (0.0108)	-0.0020 (0.0117)	-0.0082 (0.0125)	-0.0165 (0.0138)	-0.0175 (0.0149)
25	Bin: 37.5 °C	-0.0732*** (0.0170)	-0.0928*** (0.0177)	-0.0989*** (0.0183)	-0.1157*** (0.0189)	-0.1248*** (0.0203)
26	Bin: 40 °C	-0.1840*** (0.0255)	-0.2101*** (0.0262)	-0.2171*** (0.0261)	-0.2201*** (0.0256)	-0.2149*** (0.0274)
27	avg_canopy	-0.0035** (0.0012)	-0.0004 (0.0009)	-0.0002 (0.0008)	-0.0018** (0.0007)	-0.0013* (0.0006)
28	Bin: 0 °C x avg_canopy	-0.0021 (0.0021)	-0.0037. (0.0020)	-0.0028. (0.0016)	-0.0020 (0.0013)	-0.0025* (0.0012)
29	Bin: 2.5 °C x avg_canopy	2.57e-6 (0.0019)	-0.0028. (0.0016)	-0.0027* (0.0014)	-0.0016 (0.0011)	-0.0017 (0.0010)
30	Bin: 5 °C x avg_canopy	-0.0013 (0.0020)	-0.0021 (0.0016)	-0.0023. (0.0013)	-0.0012 (0.0010)	-0.0014 (0.0009)
31	Bin: 7.5 °C x avg_canopy	0.0016 (0.0016)	-0.0004 (0.0012)	-0.0014 (0.0010)	-0.0006 (0.0008)	-0.0006 (0.0007)
32	Bin: 10 °C x avg_canopy	0.0034* (0.0015)	0.0021. (0.0012)	0.0008 (0.0010)	0.0011 (0.0008)	0.0010 (0.0007)
33	Bin: 12.5 °C x avg_canopy	0.0021 (0.0013)	0.0008 (0.0010)	8.5e-5 (0.0008)	0.0006 (0.0007)	0.0007 (0.0006)
34	Bin: 15 °C x avg_canopy	0.0027* (0.0012)	0.0016. (0.0009)	0.0012. (0.0007)	0.0015* (0.0006)	0.0017*** (0.0005)
35	Bin: 17.5 °C x avg_canopy	0.0015 (0.0010)	0.0013 (0.0008)	0.0008 (0.0006)	0.0008 (0.0005)	0.0007. (0.0004)
36	Bin: 22.5 °C x avg_canopy	-0.0005 (0.0010)	0.0003 (0.0007)	0.0004 (0.0006)	0.0007 (0.0005)	0.0007 (0.0004)
37	Bin: 25 °C x avg_canopy	0.0004 (0.0011)	0.0007 (0.0009)	0.0008 (0.0007)	0.0009 (0.0006)	0.0008 (0.0005)
38	Bin: 27.5 °C x avg_canopy	0.0020 (0.0012)	0.0026** (0.0010)	0.0029*** (0.0008)	0.0030*** (0.0006)	0.0025*** (0.0006)
39	Bin: 30 °C x avg_canopy	-0.0011 (0.0015)	0.0017 (0.0012)	0.0026** (0.0009)	0.0028*** (0.0008)	0.0022** (0.0007)
40	Bin: 32.5 °C x avg_canopy	-0.0010 (0.0017)	0.0019 (0.0014)	0.0028** (0.0011)	0.0027** (0.0009)	0.0021** (0.0008)
41	Bin: 35 °C x avg_canopy	0.0021 (0.0023)	0.0048** (0.0019)	0.0041** (0.0014)	0.0039*** (0.0011)	0.0030** (0.0010)
42	Bin: 37.5 °C x avg_canopy	0.0120** (0.0043)	0.0140*** (0.0032)	0.0094*** (0.0024)	0.0093*** (0.0019)	0.0083*** (0.0018)
43	Bin: 40 °C x avg_canopy	-0.0042 (0.0063)	0.0134. (0.0075)	0.0095* (0.0044)	0.0047 (0.0031)	0.0014 (0.0034)
44	Fixed-Effects:	-------------------	-------------------	-------------------	-------------------	-------------------
45	Brand x City x Month	Yes	Yes	Yes	Yes	Yes
46	Year	Yes	Yes	Yes	Yes	Yes
47	Day of Week	Yes	Yes	Yes	Yes	Yes
48	-------------------------	-------------------	-------------------	-------------------	-------------------	-------------------
49	S.E.: Clustered	by: Brand x City ..	by: Brand x City ..	by: Brand x City ..	by: Brand x City ..	by: Brand x City ..
50	Observations	3,599,675	3,599,675	3,599,675	3,599,675	3,599,675
51	R2	0.39569	0.39568	0.39570	0.39569	0.39570
52	Within R2	0.00783	0.00782	0.00785	0.00784	0.00784

B Additional Evidence from the American Time Use Survey

To provide evidence on how heat affects consumer time use, I combine the American Time Use Survey (ATUS) with daily weather data. The outcome of interest is daily minutes spent away from home, defined as any activity that does not occur at home or in the respondent's own yard. This measure captures time available for activities such as shopping, dining, and recreation outside the home.

B.1 Sample and Variables

The ATUS microdata are merged with daily maximum temperatures from gridMET in the respondent's county. Daily maximum temperature is binned into 5 °C intervals: < 0, 0-5, $\ldots$, 35-40, and ≥ 40. The reference category is 15–20 °C, which corresponds to a comfortable outdoor temperature in prior work on climate amenities.

For each observation, I observe year, day of week that the respondent was interviewed, season, state of residence, and indicators for rural location, whether the respondent is an hourly worker, gender, and whether the diary date falls on a holiday.

B.2 Empirical Specification

I estimate the following model:

$$\text{TimeAway}_{it} = \sum_{h} \beta_h \, \mathbb{I}(T_{it} \in h) + \gamma X_{it} + \alpha_s + \alpha_d + \alpha_y + \varepsilon_{it}. \tag{8}$$

where TimeAway_{it} is minutes spent away from home by individual i on day t, T_{it} is maximum daily temperature, and $\mathbb{I}(T_{it} \in h)$ are indicator variables for the temperature bins h (reference = 15-20°C). X_{it} includes individual-level controls (rural residence, hourly worker, male, holiday), α_s are state fixed effects, α_d are day-of-week fixed effects, and α_y are year fixed effects.

B.3 Results

Estimates show that time away from home is maximized at mild temperatures and declines significantly on hotter days. In particular, when maximum temperature exceeds 35 °C, individuals spend over an additional half hour at home and less time away. These results are consistent with the mechanism in Section 2: extreme heat reduces demand for out-of-home activities, thereby lowering storefront revenue. Full regression results are reported in Table A9 and plotted in Figure 1.

Table A9: Regression Results – Effect of Temperature on Time Away from Home

	reg_1	reg_2	reg_3
Dependent Var.:	time_away	time_away	time_away
Constant	944.7*** (2.147)		
t_bin = <0	-29.41*** (4.790)	-31.18*** (5.776)	-32.33*** (5.642)
t_bin = 0-5	-17.52*** (3.880)	-15.26*** (3.857)	-16.49*** (3.797)
t_bin = 5-10	-13.75*** (3.531)	-10.43* (3.979)	-10.44** (3.724)
t_bin = 10-15	-10.45** (3.238)	-7.721* (3.008)	-7.224* (2.731)
t_bin = 20-25	4.769 (2.948)	4.877 (3.104)	4.914. (2.745)
t_bin = 25-30	3.473 (2.827)	5.204. (2.605)	5.788* (2.508)
t_bin = 30-35	-0.1778 (2.971)	1.209 (2.681)	1.827 (2.955)
t_bin = 35-40	-6.216 (4.931)	-7.403 (6.569)	-8.409 (6.156)
t_bin = >=40	-45.44*** (10.68)	-35.98*** (6.431)	-35.42*** (6.253)
rural			-21.28** (7.493)
hourly_worker			129.9*** (2.498)
male			35.64*** (2.429)
holiday			-34.77*** (5.151)
Fixed-Effects:	————	————	————
statefip	No	Yes	Yes
day_of_week	No	Yes	Yes
year	No	Yes	Yes
---------------	-----------------	-----------------	-----------------
S.E. type	IID	by: statefip	by: statefip
Observations	104,301	104,301	104,301
R2	0.00124	0.03824	0.09256
Within R2	–	0.00106	0.05748

C Testing Regional Adaptation to Heat

This appendix examines whether regional adaptation alters the estimated effect of heat on storefront revenue. Regional adaptation has been shown to be important in global analyses of temperature impacts, where long-run exposure to hotter climates dampens the effect of extreme heat (Carleton et al., 2022). To assess whether similar patterns are present within the United States, this paper estimates two alternative specifications that explicitly allow the effect of heat to interact with a city's average climate.

C.1 Methods

The first specification augments Model (1) by interacting the daily temperature-bin indicators with the city's long-run average maximum temperature:

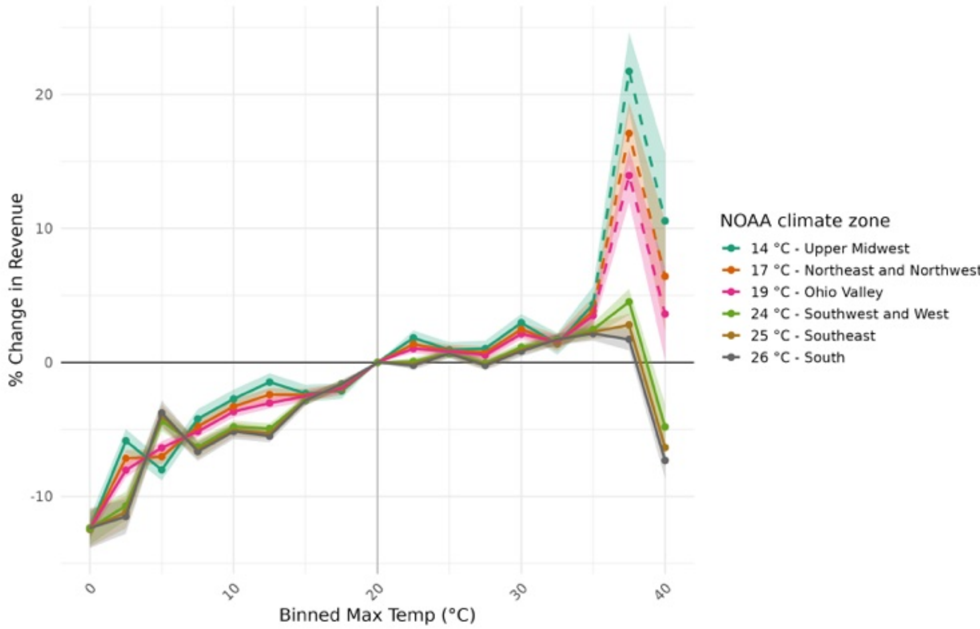
$$\ln(R_{it}) = \boldsymbol{\beta_I}\mathbf{I}_{it} + \sum_h \beta_h\,\mathbb{I}(H_{it} = h) + \sum_h \delta_h\,\mathbb{I}(H_{it} = h) \times \overline{T}_c + \alpha_i + \tau_t + \epsilon_{it}. \tag{9}$$

where $\overline{T}_c$ is the long-run average maximum temperature in city c. A main effect for average temperature is not included because the storefront fixed-effect α_i absorbs it.

The second specification models the effect of temperature using a quadratic functional form, interacted with the city's average temperature:

$$\ln(R_{it}) = \boldsymbol{\beta_I}\mathbf{I}_{it} + \theta_1 T_{it} + \theta_2 T_{it}^2 + \delta_1\overline{T}_c \times T_{it} + \delta_2\overline{T}_c \times T_{it}^2 + \beta_G G_{iy} + \alpha_i + \tau_t + \epsilon_{it}. \tag{10}$$

Figure A7: The Effect of Temperature in Different Regions



where T_{it} is the maximum daily temperature at storefront i on day t, and G_{iy} is the average tree canopy cover surrounding storefront i in year y. Both models include place-of-interest (storefront) fixed effects α_i, day-of-week effects, city-by-month seasonal effects, and year effects τ_t.

C.2 Results

Figure 3 shows the distribution of temperature observations by NOAA climate region. Extremely hot days (>37.5,°C) are concentrated in the South and Southwest, while such events are rare in cooler regions like the Northeast and Upper Midwest. As a result, estimates of adaptation for cooler regions rely heavily on extrapolation. Rather than impose additional structure that risks over-interpreting sparse data, the main analysis therefore uses the temperature-bin specification in Model (1) without interactions.

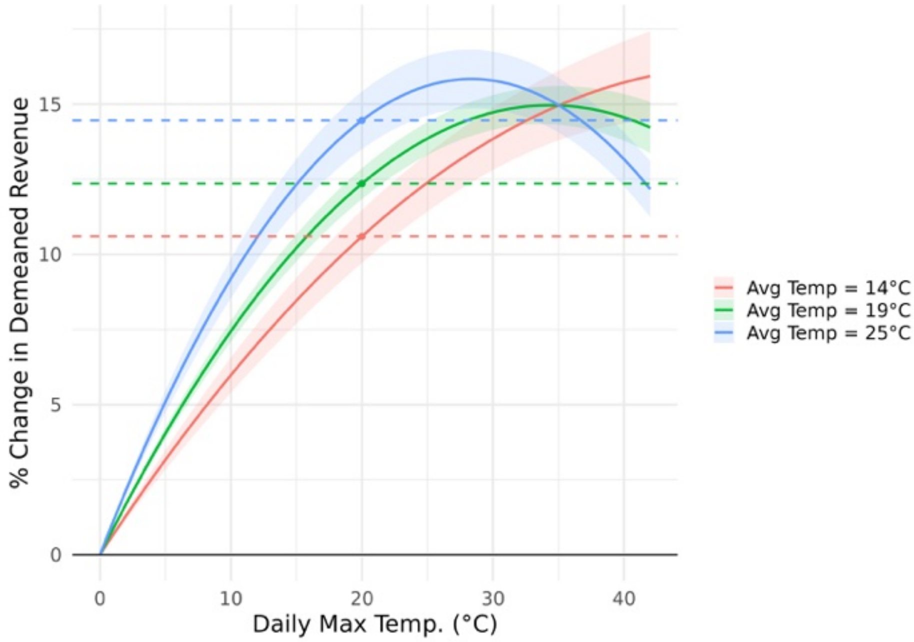
Figure A7 presents the results from the non-parametric interaction model. In warmer regions, revenue declines sharply at high temperatures, with losses exceeding 5 percent on days above 37.5,°C. In contrast, cooler regions show imprecisely estimated effects at these temperatures.

The parametric interaction model (Figure A8) produces a similar conclusion. Warmer regions appear more sensitive to extreme heat, but this likely reflects the limited number of very hot days observed in cooler regions, which constrains the model's ability to capture their true response. Note that the reference level for Figure A8 is a demeaned zero °C day, not a 20 °C which has been chosen as the reference level for the binned specifications. The dashed horizontal lines indicate when each modeled region's change in demeaned revenue crosses 20 °C to assist in orienting between figures. For example, the region with an average temperature of 25 °C experiences an approximate 2 percent revenue loss on a 40 °C day in comparison to a 20 °C day.

C.3 Interpretation

Together, these results suggest limited evidence of meaningful regional adaptation within the United States. The stronger negative responses in warm regions do not necessarily imply that businesses in cooler regions

Figure A8: The Effect of Temperature in Different Regions



are more resilient. Instead, they likely arise because cooler regions rarely experience extreme heat, leaving insufficient observations to identify how revenue responds to rare hot days. For this reason, the main empirical analyses in this paper rely on Model (1) without regional interactions, which provides more stable estimates across the full sample.

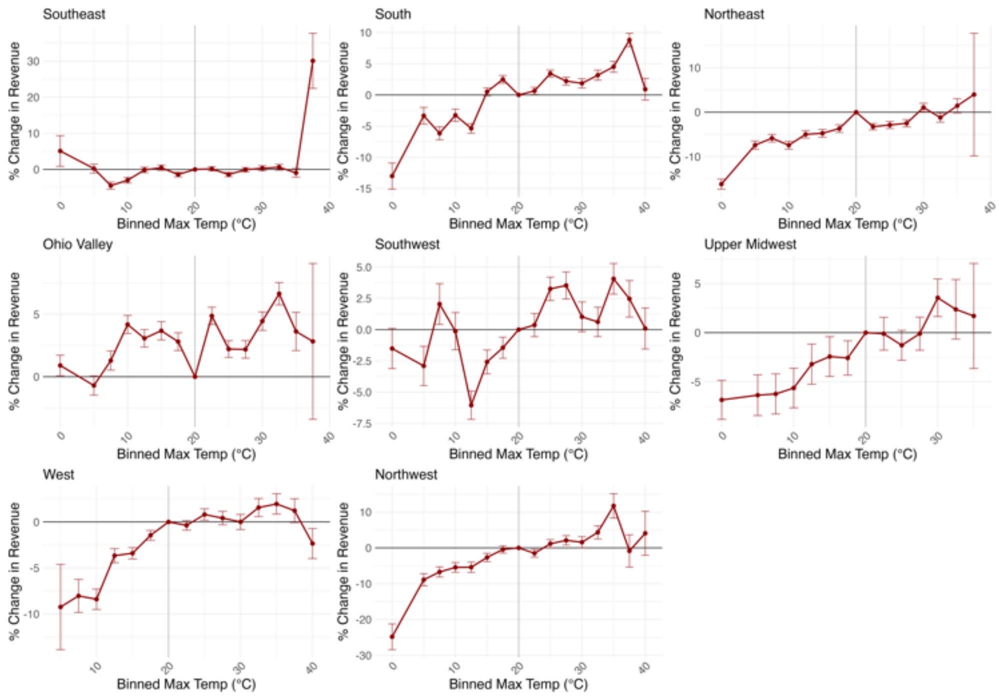
Overall, this exercise suggests that while regional adaptation may be important in global comparisons, within the United States the revenue response to extreme heat is relatively uniform across climate regions. The final section of this appendix explores this more closely.

C.4 NOAA Climate Regions

I fit Model (1) using data from each NOAA climate region, separately. Revenue peaks before 35 °C and then declines across most NOAA Climate Regions. The exceptions are the South, Southeast and Northeast. In the South, revenue peaks at 37.5 °C before declining. The Southeast is largely unresponsive to temperature, but shows a noisy response above 37 °C. The Northeast also exhibits a noisy response above 35 °C.

The resiliency of the Southeast may be explained by the region's high level of green space surrounding store fonts. The median surrounding green space in the Southeast is 9% (Table 1). The Northeast's behavior at high temperatures can be explained by a lack of power. Figure A9 shows the estimated effects.

Figure A9: The Effect of Temperature in Different Regions



D Appendix: Do Hotter Months Shift Spending to Intermediaries?

This appendix examines whether hotter months lead consumers to shift spending toward delivery and e-commerce intermediaries (e.g., UberEats/Grubhub/Shopify). The analysis examines if monthly storefront revenue collected through food delivery services are responsive to the share of hot days in the month. To benchmark results, I also include how total monthly spending at a storefront responds to the share days that month that are extremely hot (>37.5 °C). Ultimately, I do not find strong evidence that consumers switch to ordering through a food delivery service in response to hot days. However, the substitution behavior may take place, but be unobservable within the aggregated dataset used in this paper.

D.1 Data

The SafeGraph Spend dataset provides the total amount of monthly spending that occurred at a storefront through many intermediaries, as well as the number total number of transactions that used an intermediary. It does not provide this data at the daily level, like it does for total spending at a storefront. The intermediaries I use to measure spending and transactions through a delivery service are the following: DoorDash, Postmates, Shopify, Olo, Grubhub. Safegraph Spend also provides the total amount of spending, and that amount that required no intermediary.

I construct the share of extremely hot days as the number of days above 37.5 °C divided by the number of days a storefront was observed that month. Because the dataset is not a full panel, the denominator may be significantly smaller than the number of days in that month.

Only a small fraction (2 percent, $n = 16,194$) of storefront-months report positive spending through a delivery service. Ninety-three percent of the transactions that occur through delivery services occurred at chain restaurant (brand affiliated), indicating that intermediary reporting is more complete among branded chains than independents.

D.2 Empirical Specifications

Let $\ln S^*_{icm}$ denote the log of a spend measure ($* \in \{\text{total}, \text{delivery-service}\}$). The baseline specification relates the share of hot days to monthly spending with a robust fixed effect specification:

$$\ln S^*_{im} = \beta^* \text{share\_hot}_{im} + \alpha_i + \mu_m + \lambda_y + \gamma_c + \varepsilon_{icm}. \tag{11}$$

where α_i are storefront fixed effects, μ_m month fixed effects, λ_y year fixed effects, and γ_c city fixed effects. Standard errors are clustered at the storefront level. An alternative fixed effect specification uses $\alpha_{i \times m}$ (`poi_month`) in place of $\alpha_i + \mu_m$, with similar conclusions. An alternative model replaces the dependent variable with $\ln N^{\text{delivery}}_{im}$ to examine the number of transactions that used a delivery service N^{delivery}, rather than the total spending. Dining-focused regressions are estimated and restrict to NAICS 722 (Food service & drinking places) and 445 (Food & beverage stores) to observe the margin where delivery is most plausible.

D.3 Results Summary

Appendix Figure A10 plots coefficient estimates with 95% confidence intervals. Across storefront-months with nonzero total spend, estimates for Equation 11 indicate that a higher share of hot days is associated with lower $\ln S^{\text{total}}_{im}$, consistent with the daily panel results on heat suppressing revenue. By contrast, coefficients on $\ln S^{\text{delivery}}_{im}$ and $\ln N^{\text{delivery}}_{im}$ are not precisely estimated and do not show evidence of adaptive behavior. Within the dining subset (NAICS 722 & 445), signs are similar. However, inference should be tempered by limited coverage.

Only about 2% of storefront-months report positive spending through delivery services, and reporting is concentrated among branded chains. These two limitations qualify any conclusions. First, the SafeGraph Spend dataset does not observe all transactions conducted with delivery services, biasing against finding substitution behavior. Second, intermediary reporting appears more complete for large brands, limiting generalizability to independents. Therefore, other work on online ordering services should be deferred to (*e.g.*, Papp (2024)).

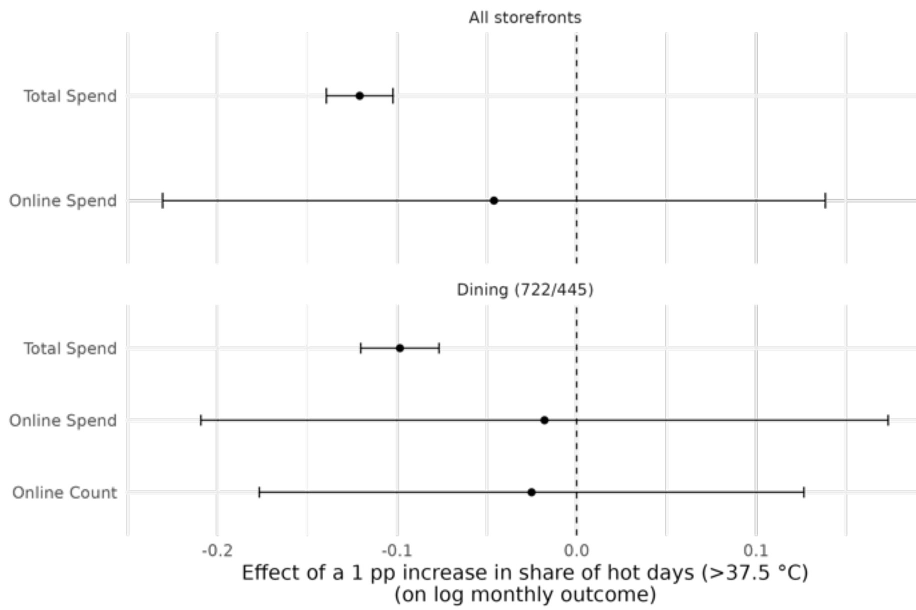


Figure A10: Effect of Hotter Months on Total Spending and Delivery Services

Notes: Points plot $\hat{\beta}^{\bullet}$ from Equation 11 with 95% confidence intervals.