Revenue Under Heat: The Value of Urban Green Space

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Abstract

Extreme heat is becoming more frequent and intense due to climate change, particularly in cities where the urban heat island effect amplifies high temperatures. This paper estimates the causal effect of temperature on daily revenue at over 15,000 consumer-facing storefronts in the 49 largest U.S. metro areas between 2019 and 2023, with a focus on how green space can mitigate revenue loss caused by extreme heat. I find that revenue begins to decline on days with a maximum temperature above 35 °C (95 °F) and drops by 9 percent on days above 37.5 °C (99.5 °F) relative to the average revenue on a 20 °C (68 °F) day. Substituting spending across days mitigates some damage from an extreme heat event, but a 1.3 percent revenue drop is persistent for two weeks following an extremely hot day. Because temporal substitution does not completely mitigate the negative effect of extreme heat, I examine the role of urban green space as a climate adaptation strategy. Using variation in greenery around storefronts belonging to the same brand within a city, I find that a one percent increase in surrounding green space raises revenue by 1.78 percent on extremely hot days: 0.96 percent from general amenity value and 0.82 percent from its cooling effect. These results suggest that green infrastructure can improve firm resilience to heat, providing evidence of a private incentive to finance public urban green space that could simultaneously provide a positive externality.

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 over half the world's population and generate 80 percent of global GDP (World Economic Forum, 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 adaptation strategy. 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). Nature-based solutions are, on average, 50 percent more cost-effective than traditional "grey" infrastructure (World Economic Forum, 2022). Yet despite their promise, financing urban green space

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remains a challenge. Practitioners face barriers to investment (Diep and McPhearson, 2025; Toxopeus and Polzin, 2021), and most research has emphasized ecological rather than economic benefits (McPhearson et al., 2025).

This paper estimates how extreme heat affects storefront revenue and how urban green space mitigates those losses. Using daily credit and debit card transactions from over 15,000 storefronts across the 49 largest U.S. metropolitan areas between 2019 and 2023, combined with high-resolution temperature and green space data, identifies the causal effect of heat on firm performance. Revenue begins to decline once daily maximum temperature exceeds 35 °C, falling by nearly 9 percent relative to a mild day when temperatures surpass 37.5 °C. Extremely cold days have comparable effects. A 40 °C day lowers revenue nearly as much as a 0 °C day.

Green space substantially reduces the losses from extreme heat without increasing losses from cold weather. By comparing storefronts of the same brand within the same city but with different surrounding vegetation, this paper finds that one percent increase in nearby green space raises revenue by 0.8 percent on hot days due to its cooling effect. Green space also provides a general amenity value. A one percent increase in green space increases revenue by 0.96 percent, regardless of temperature. On extremely hot days, these effects compound and revenue increases by 1.76 percent for a one percent increase in green space.

Using these heat and green space effect, this paper calculates how many years it would take for additional revenue to cover the cost of expanding green space. For the average storefront in the Broad Southwest (California to Mississippi), it would take less than three years for a business to recuperate the cost of moving from a low green space scenario to a high one. This calculation is an underestimate because it only considers the gains from green spaces' ability to regulate the microclimate, and does not include its general amenity value. The speed at which an investment in green space pays itself off only shortens under climate warming scenarios. These estimates characterize the private return to adaptation investments, because once the additional revenue from an increase in green space supersedes the cost of investment, the green space provides a continuous flow of benefits to private businesses.

This paper contributes to three strands of literature that together frame how climate shocks shape economic activity and how natural capital can serve as adaptation infrastructure.

First, it builds on the literature using weather shocks to anticipate how climate change will affect economic outcomes (Auffhammer et al., 2013). A growing subset of this work has moved beyond aggregate outcomes to examine how temperature influences specific goods and services. For example, Lai et al. (2022) show that extreme heat and cold reduce consumption in China, particularly at clothing and department stores, with regional adaptation strategies moderating losses under severe climate scenarios. Lee and Zheng (2025) find that extremely hot and cold days suppress retail spending in the United States, with little evidence of temporal substitution. Kuruc et al. (2025) show that willingness to pay for baseball games declines on very hot or cold days, while other work links temperature shocks to changes in demand for energy (Auffhammer, 2022; Manderson and Considine, 2025), air conditioners (He et al., 2022), and sugary drinks and desserts (He et al., 2025). Firm-level evidence is more limited. Berg et al. (2025) find that extreme temperatures depress earnings, but their use of annualized data masks short-run dynamics.

This paper advances this literature by showing that extreme temperature events reduce revenue at the daily level for over 15,000 storefronts across U.S. metropolitan areas. High-frequency microdata reveal the damage from the shock of an extreme heat, estimating an effect that average temperatures may miss in aggregate studies. Emerging evidence suggests that extreme weather events may be more disruptive to economic activity than long-run changes in average temperature (Akyapı et al., 2025), and the results here demonstrate how those shocks transmit through firm revenues. By leveraging within-firm temperature variation, this paper isolates the causal effect of daily heat shocks on business performance and provide evidence that private firms have an incentive to adapt. Having established the short-run revenue impacts of extreme heat, this paper considers how natural capital, specifically urban green space, can mitigate those losses.

This paper extends the literature valuing urban green space. The urban ecology and planning literatures document that vegetation reduces the urban heat island effect and delivers a wide array of co-benefits, including improved air quality, carbon sequestration, storm water management, and mental health benefits (Wong et al., 2021; Keeler et al., 2019). Individuals reveal demand for these amenities, for instance by choosing longer routes along tree-lined streets (Salazar Miranda et al., 2021). Economists have primarily valued urban green space through its capitalization into housing prices. Buyers in Phoenix and Toronto pay premiums both for access to vegetation and to avoid extreme heat (Klaiber et al., 2017; Han et al., 2024), while studies in Portland and Minnesota similarly find that proximity to tree cover raises property values (Netusil et al., 2010; Sander et al., 2010). Natural experiments, such as tree die-off from emerald ash borer, further confirm causal effects (Han et al., 2024). Work outside the housing market emphasizes cost savings, showing that urban trees provide at least $500 million annually in the U.S. in cooling energy savings and $400 million in storm water treatment costs (Heris et al., 2021).

This paper demonstrates that the value of green space extends beyond residential amenities and cost minimization to the commercial sector. Brick-and-mortar storefronts capitalize on nearby vegetation through higher daily revenue, particularly during extreme heat events. Because many of the goods and services sold in these settings are non-durables purchased regularly, this is evidence that green space contributes directly to day-to-day economic activity. In this way, urban green space functions as a natural capital asset for firms, sustaining commercial performance while delivering broader ecological benefits. Because green space generates both ecological benefits and measurable private returns, the final contribution examines how these findings inform financing.

This paper's final contribution is to the literature on financing nature-based adaptation. Much of the work on financing nature-based solutions has focused on mitigation, such as carbon sequestration, where global benefits enable participation in international markets (Barbier and Burgess, 2025; Brumberg et al., 2025). Adaptation, by contrast, generates primarily local benefits and therefore presents different economic incentives for investment and financing challenges. Because adaptation cannot be sold on a global market due to the flow of benefits only being experienced locally, it depends on local demand and institutions that support place-based investment. Recent research points to the promise of public-private partnerships, including payments for ecosystem services (Plantinga et al., 2024), but adaptation finance remains an underexplored element of nature-based climate solutions.

By documenting that storefronts directly benefit from surrounding green space through higher revenue, this paper identifies a measurable private return to adaptation investment. This evidence highlights that cost-sharing arrangements between municipalities and the businesses that gain from its cooling and amenity value is a potential mechanism for scaling urban green infrastructure. In doing so, this work frames urban green space not only as a public good but also as a provisioner of private economic benefits, offering a pathway to mobilize private capital toward climate resilience.

The paper proceeds in the following way. Section 2 discusses a conceptual framework that sets the stage for the empirical identification strategy. Section 3 summarizes the multiple datasets I use to identify the effect of heat and green space on revenue. Section 4 outlines the identification strategy, introducing three different models I use to identify the effect of heat on revenue, how heat interacts with green space, and how to recover the main effect of green space. Next, Section 5 presents the results, including temporal substitution and climate scenarios. Finally, Section 6 offers a brief discussion and conclusion.

2 Conceptual Framework

Consider a setting where extreme heat and green space affect storefront revenue through consumers' preferences for pleasant shopping and dining experiences. Consumers are more likely to shop in greener, more comfortable environments because green space improves aesthetic quality, offers recreational and mental health benefits, and reduces exposure to extreme heat. These two channels (general amenity value and microclimate regulation) mean that green space can be capitalized into storefront revenue. The goal of this section is to formalize this intuition and show how this paper's empirical models follow from the framework that (1) extreme heat shocks reduce revenue because it creates a less pleasant shopping experience, (2) businesses can capitalize on the ability of green space to mitigate those losses because of green space'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 green space.

A shopping or dining experience can be thought of as a composite good $(\mathbf{x}, \mathbf{q})$ comprised of a vector of private attributes specific to the storefront $\mathbf{x}$ and a vector of nearby environmental attributes $\mathbf{q}$ that complement the private characteristics. This paper's empirical strategy decompose revenue into various attributes of the storefront, including the temperature, surrounding green space, and their interaction to estimate how each affects revenue.

2.1 The Effect of Heat on Revenue

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

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

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 T^* such that an increase past it leads to a decrease in demand for the composite good,

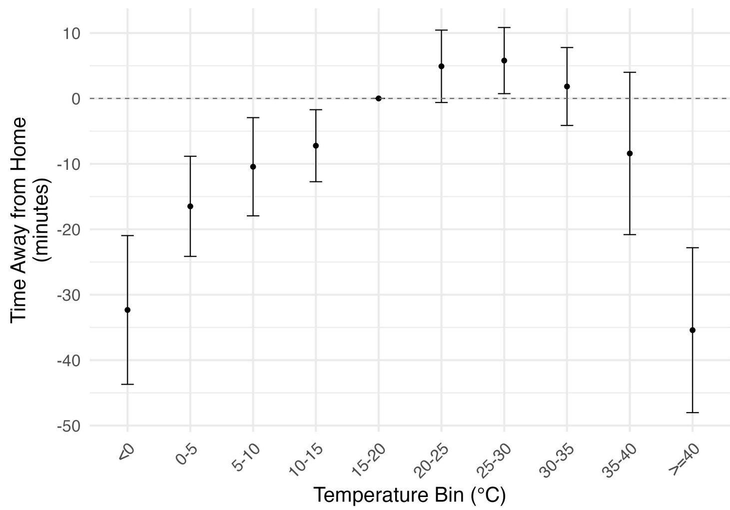
$$\frac{\partial d(\mathbf{x}, \mathbf{q})}{\partial q_T} < 0 : q_T > T^*.$$

This assumption is supported by evidence that Americans place the most value on temperatures around 18 °C (65 °F) and dislike marginal increase 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 T^*,

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

This mechanism is consistent with evidence from the American Time Use Survey, which shows that individuals spend more time at home 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 Green Space on Revenue

Now, recognize that green space has the ability to regulate the microclimate (Wong et al., 2021), reducing the heat that customers experience during extreme heat events. Assume that climate regulation occurs if the surrounding green space is a above a threshold, $q_G > G^*$. This increases the threshold temperature where heat becomes damaging to business revenue through its effect on consumer demand by τ degrees,

$$\frac{\partial R(\mathbf{x}, \mathbf{q})}{\partial q_T} < 0 : q_T > T^* + \tau$$
$$\text{and } q_G > G^*.$$

Green space 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. Green space'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, green space also provides a general amenity effect. Therefore, an increase in green space surrounding a business leads to an increase in revenue through its increase in consumer demand,

$$\frac{\partial R(\mathbf{x}, \mathbf{q})}{\partial q_G} > 0.$$

Therefore, there are two channels that green space can provide benefit through: its own main effect (general

Table 1: 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

amenity value) and its interaction with temperature (microclimate regulation).

2.3 Siting for Green Space

If green space 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 green space and to avoid extreme heat (Klaiber et al., 2017; Han et al., 2024; Netusil et al., 2010; Sander et al., 2010), while urban trees reduce energy expenditures and stormwater management costs (Heris et al., 2021). These findings suggest that businesses, like households, 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. In the empirics, this creates a challenge: brand-by-city fixed effects absorb part of the main effect of green space on revenue. A second-stage regression is therefore required to recover the portion of green space's effect that is otherwise lost when controlling for shared siting strategies.

3 Data and Motivating Statistics

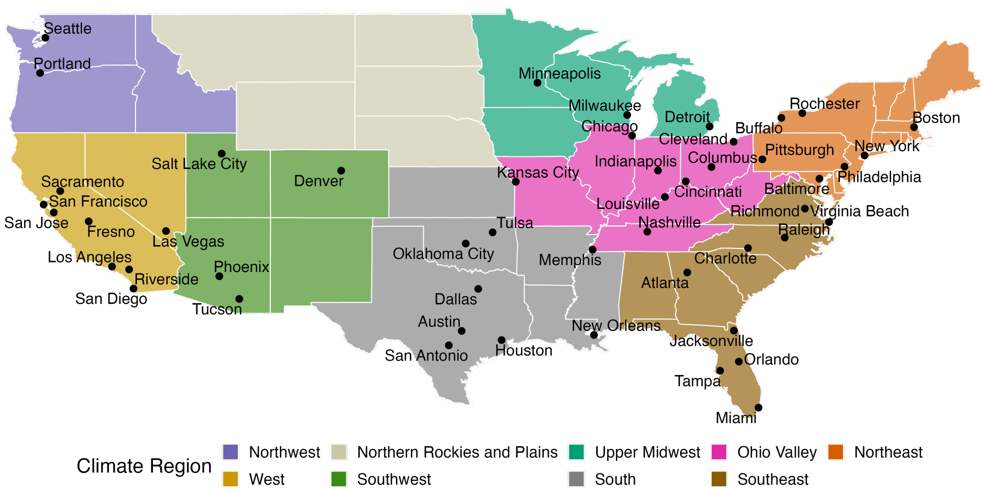
This section describes the data used to estimate how extreme temperatures affect storefront revenue and the benefits provided by green space. The analysis relies on a novel dataset that combines daily credit and debit card transactions, storefront characteristics, daily temperature records, and satellite 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. Because the focus is on the effects of urban heat and green space, the analysis is restricted to U.S. metropolitan statistical areas with populations over one million in 2020 (Figure 2). Only storefronts located

Figure 2: The 49 Cities in the Dataset



within city limits are included, ensuring that the analysis reflects the effects of urban, rather than suburban, heat and green space.

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 1.

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.

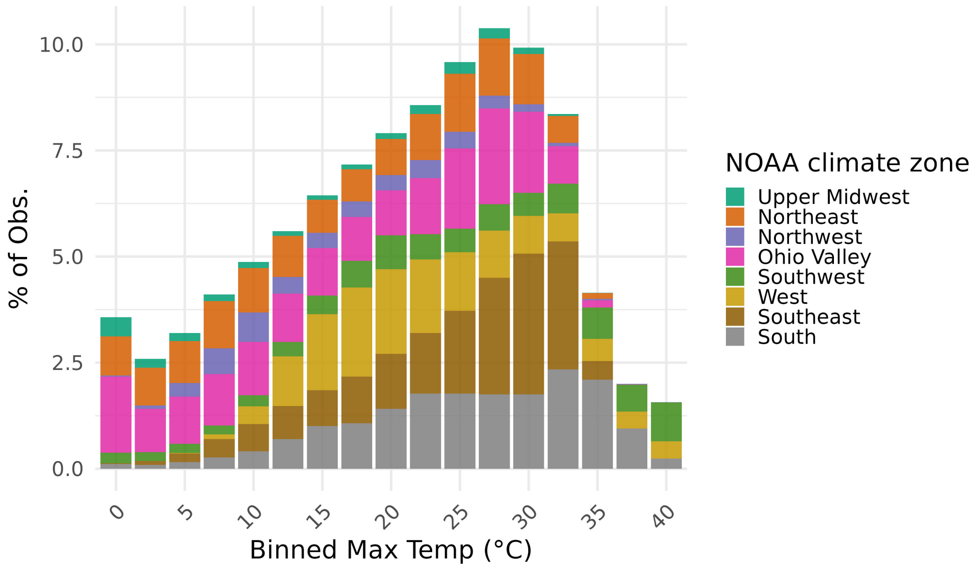
In robustness checks, the SafeGraph Spend dataset is also used to examine the share of spending that occurs at the storefront's physical location versus online, through transaction intermediaries such as UberEats or Square.

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.

Figure 3: Distribution of Temperature Observations



3.3 Urban Green Space

Urban green space 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. In the preferred specification, the buffer radius is 200 meters, capturing immediate surrounding green space. Alternative buffer sizes are tested in robustness checks to assess sensitivity.

The suitability of the TCC dataset for measuring urban green space is validated by comparing it with 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]

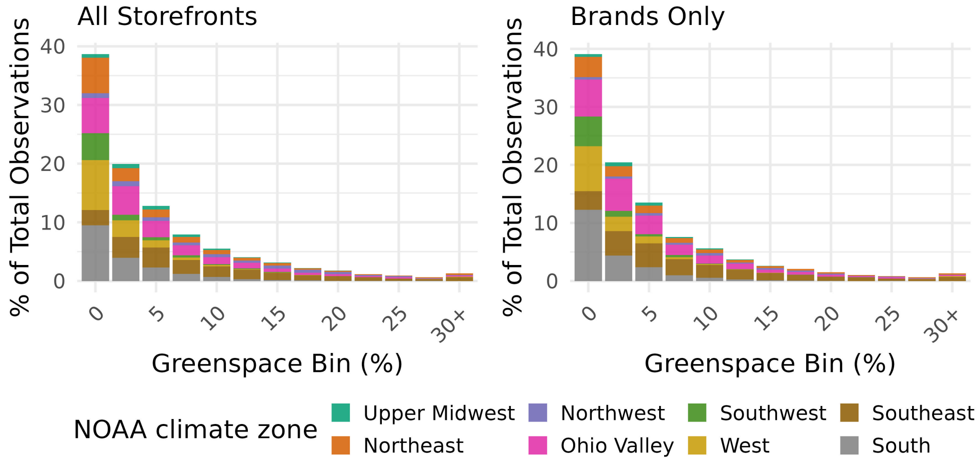
Using the NLCD impervious surface layer, average tree canopy cover near a business is found to be highly negatively correlated with impervious surface, with a correlation coefficient of approximately 60 percent. Using the Google Street View index, tree canopy cover is 70 percent correlated with the volumetric 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 not yet filtered out with at least 350 daily observations. The second is a subset of these businesses that are affiliated with a brand, further restricted to brands with at least five storefronts located within the same metropolitan

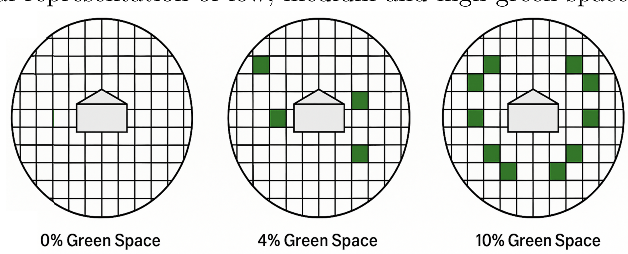
[1] The dataset provided by the Livable City's Lab is similar to that used by Falchetta and Hammad (2025).

Figure 4: The distribution of green space across all businesses and brands

(A) Distribution of Green Space



(B) Visual representation of low, medium and high green space scenarios



area. This restriction enables this paper's empirical models to use spatial variation within brand-city-month clusters to identify the effect of green space on revenue.

The distribution of green space 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 green space environments. The median amount of green space surrounding businesses also varies greatly by city. For instance, the median surrounding green space 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 2, and results for all cities are presented in Appendix A1.

4 Empirical Strategy

This paper estimates the effect of extreme heat and urban green space 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 green space across firms that follow similar siting strategies (*i.e.,* businesses that are part of the same brand in the same city). The analyses regress the logarithm of revenue on measures of temperature and green space while controlling for storefront characteristics. This

Table 2: Median Surrounding Green Space

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

approach identifies the semi-elasticity of revenue with respect to temperature, the elasticity of revenue with respect to green spaces. I estimate a second-stage model to the main effect of green space after accounting for brand-by-city fixed effects and separate green space's cooling effect from its general amenity effect.

4.1 Estimating the Effect of Heat on Revenue

Model (1) estimates how temperature affect daily revenue at storefronts,

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

where R_{it} is revenue at storefront i on day t, and $\mathbf{I}_{im}$ is a vector of controls for the monthly m distribution of customer income, measured as the share of monthly customers in seven income bins. The variable $\mathbb{I}(H_{it} = h)$ 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. Storefront fixed effects α_i control for all time-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.

To interpret the coefficients causally, this paper assumes that daily variation in temperature is exogenous to other unobserved determinants of revenue within a given storefront after controlling for broad temporal trends.

Model (1) is this paper's preferred model for estimating the effect of heat on revenue. However, a modified version of Model (1) that includes an interaction between the temperature bins and the average maximum temperature in a city is estimated, along with a model 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 models tests 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 green space mitigates the damage caused by extreme heat, this paper examines whether temporal substitution offsets revenue losses with two approaches. 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 both 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, Model (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_{it}, $\mathbf{I}_{im}$, α_i, and τ_t are defined as in Model (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, Model (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 Interaction with Urban Green Space

To identify how urban green space mitigates revenue losses from extreme heat that are not already offset by temporal substitution, Model (1) is extended to include green space and its interaction with temperature:

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

where s_i is the size of storefront i, $\texttt{Lot}_i$ indicates whether the storefront has an associated parking lot, and G_{iy} measures percent tree canopy cover within a designated buffer of storefront i in year y. 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_{ty} capture day-of-week and year-specific spending patterns.

Fitting Model (4) requires limiting the analysis to storefronts that are a part of a brand. After dropping observations of businesses with no brand affiliation, the dataset covers 3,005 storefronts that are affiliated with 58 different brands, and has 3.6 million observations. The preferred specification uses a 200-meter buffer to measure green space around each storefront. Robustness checks vary the buffer radius to assess sensitivity.

Because temporal variation in tree canopy is limited, identification relies on spatial variation across storefronts in the same city. As a result, Model (4) does not include storefront fixed effects, unlike Model

(1). Instead, the specification controls for observable storefront characteristics ($\mathbf{I}_{im}$, s_i, and $\texttt{Lot}_i$) and exploits variation across storefronts of the same brand in the same city and month, captured by α_{bcm}. 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 green space is plausibly exogenous to unobserved determinants of revenue. Even if green space is correlated with other amenities that a business may sort on, so long as all storefronts that are a part of the brand are sited with the same strategy, then the variation in green space within a brand in a city is plausibly exogenous.

The coefficients β_G and $\boldsymbol{\beta_{GH}}$ therefore capture, respectively, the main effect of green space and its moderating effect on heat shocks. To interpret the results causally, this paper assumes that after controlling for storefront characteristics and fixed effects, variation in green space within brand-city clusters is not correlated with other revenue determinants.

This identification strategy carries the risk that part of the revenue increase attributable to green space's amenity effect will be absorbed by the brand-by-city-by-month fixed effects. If a brand systematically locates its storefronts in greener areas because its goods or services are consistently complemented by green space, the average effect of green space across that brand's locations will be controlled for in α_{bcm}. As a result, the coefficient β_G may understate the true main effect of green space. Abbott and Klaiber (2011) provide an in-depth discussion of how fine-scale fixed effects can lead to downward bias in estimates of non-market goods' value.

To address the possibility that part of the main effect of green space is absorbed by the brand-by-city-by-month fixed effects, this paper adopts two strategies. First, all results from Equation (4) are presented as lower-bound estimates of the elasticity of revenue with respect to green space. 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 is therefore defined as

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

where the elasticity is conditioned temperature a realized temperature H^* because of temperature's interaction with green space, and β_{GH} is the corresponding coefficient.

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

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

where $\overline{G}_{bcy}$ is the average green space for brand b in city c in year y, $f(\cdot)$ is the functional form chosen to model the main effect of green space 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 green space 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 elasticity of revenue with respect to green space is then expressed as

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

This paper reports the semi-elasticities from both Equation 5 and Equation 7. Preferred specifications use Equation 7 because it includes the recovered part of the general amenity value of green space, in addition to its role as a regulator of extreme heat.

4.4 Threats to Identification

A potential threat to identifying the effect of green space on storefront revenue is the correlation between green space 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 green space is positive but small (correlation coefficient: 0.02, p-value: 0.01). In contrast, the correlation between a storefront's surrounding green space 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 green space 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 in seven parts. First, the presents how extreme temperatures affect storefront revenue, documenting the nonlinear effects of heat and cold. Second, it evaluates whether temporal substitution offsets these losses by shifting spending to subsequent days. Next, it evaluates how urban green space affects revenue by mitigating the damage from extreme heat and through recovered amenity value. Following, this section presents back-of-the-envelope climate scenarios to assess the aggregate consequences of future warming and the potential for green space to buffer these effects. Finally, this section presents various placebo and robustness analyses.

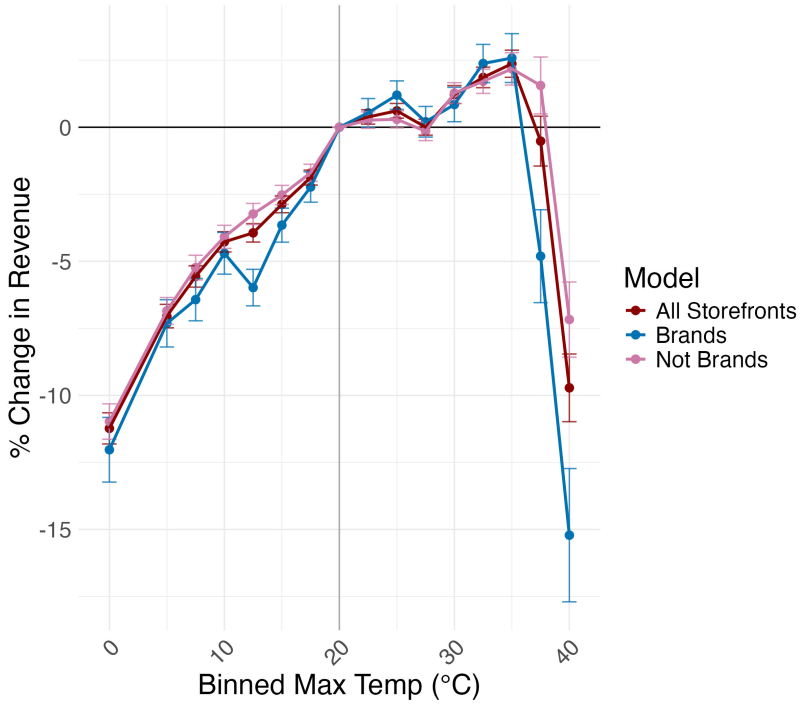
5.1 Heat on Revenue

The regression results from Model (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 0 °C day. Revenue increases steadily as temperature rises from below 0 °C up to 35 °C. Full regression results are reported in Appendix Table A2.

Although extremely hot and cold days are relatively rare (Figure 3), the analysis contains approximately half a million of each due to the large size of the sample. 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

Figure 5: The Effect of Heat on Revenue



The coefficients from Model (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-brand storefronts.

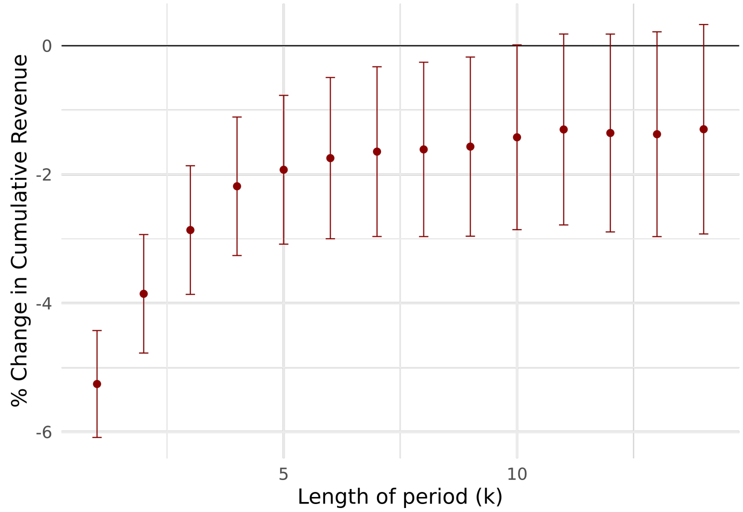
regions are imprecise and rely heavily on extrapolation. Fitting Model (1) for data from each NOAA climate zone also does not provide supportive evidence of adaptation, but these results are also imprecise. Given the data limitation of few observations of hot days in cool regions, the main analysis proceeds 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 affect revenue.

5.2 Temporal Substitution

Figure 6 plots the coefficients estimated from Model (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 through day 14. Regression results are reported in Appendix Table A3.

Results from Model (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

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



Model (2) coefficients are plotted, which regresses the logarithm of cumulative revenue over k days on an indicator for whether at least one of the previous k days was at or above 37.5 °C. All specifications include 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.

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 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 A4.

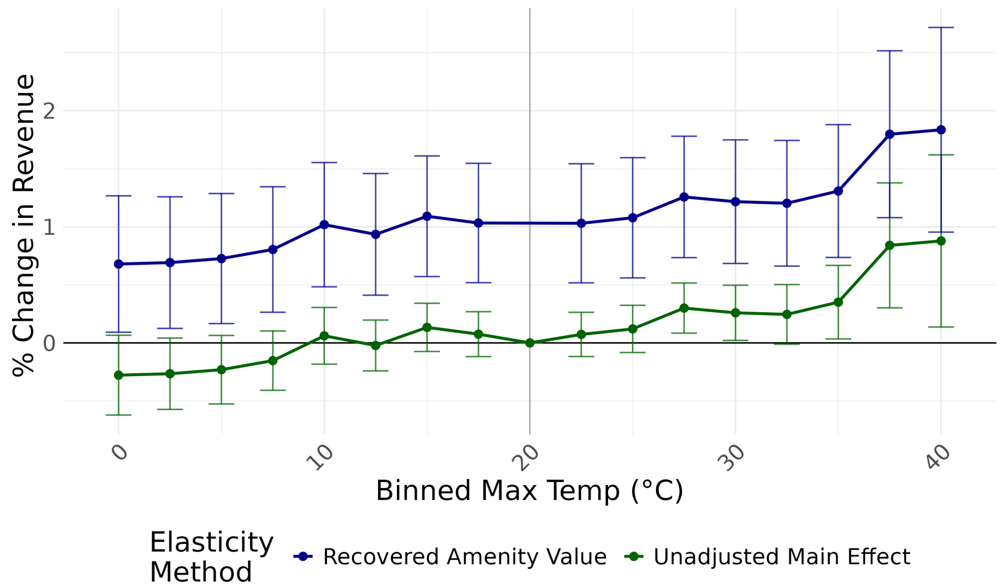
5.3 Green Space's Effect Mitigating Extreme Heat

Estimating the effect of green space on revenue requires limiting the sample to storefronts that are brand affiliated to use the brand by city by month fixed effect identification strategy. Brands are more susceptible to heat than the average storefront, but otherwise behave similarly (Figure 5).

Figure 7 shows that a 1 percent increase in surrounding green space increases revenue as temperature rises (see line labeled Unadjusted Main Effect). This effect becomes significantly different from zero at 27.5 °C, and increases to nearly 1 percent when temperature increases past 35 °C. The Unadjusted Main Effect line plots coefficients from Model (4), which depict the elasticity of revenue with respect to green space, conditional on temperature due to the interaction term. These elasticities are derived from the single-stage, lower bound estimation strategy described in Equation 5. Regression results for Model (4) are in Appendix Table A5.

Figure 8 illustrates how temperature affects revenue under high and low green space scenarios. A high green space environment can fully offset or substantially reduce the revenue losses associated with extreme heat. In the zero green space scenario, a 37.5 °C day results in an approximate 10 percent decrease in revenue. In contrast, the same temperature in the lower bound estimate of the high green space scenario leads to a decline that is not statistically distinguishable from zero (see line labeled Unadjusted Main Effect). On a

Figure 7: Elasticity of Revenue with Respect to Green Space, Unadjusted and Adjusted



This figure plots elasticities of revenue with respect to surrounding green space, conditional on temperature. The green line labeled Unadjusted Main Effect is derived from Model (4) using the single-stage, lower-bound strategy in Equation 5. Results show that a 1 percent increase in green space 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 blue line labeled Recovered Amenity Value reflects the two-stage approach in Equation 6, which recovers the portion of the amenity effect absorbed by brand-by-city-by-month fixed effects. This figure plots a linear specification of how the amenity value of green space affects revenue. Under this adjusted specification (Equation 7), the marginal benefit of green space is just under 1 percent at lower temperatures, rises to nearly 1.5 percent at 35 °C, and reaches about 2 percent on days above 35 °C. All models include controls for storefront size, parking lot presence, and the monthly distribution of customer income, as well as fixed effects for brand-by-city-by-month, year, and day of week. Standard errors are clustered at the storefront level.

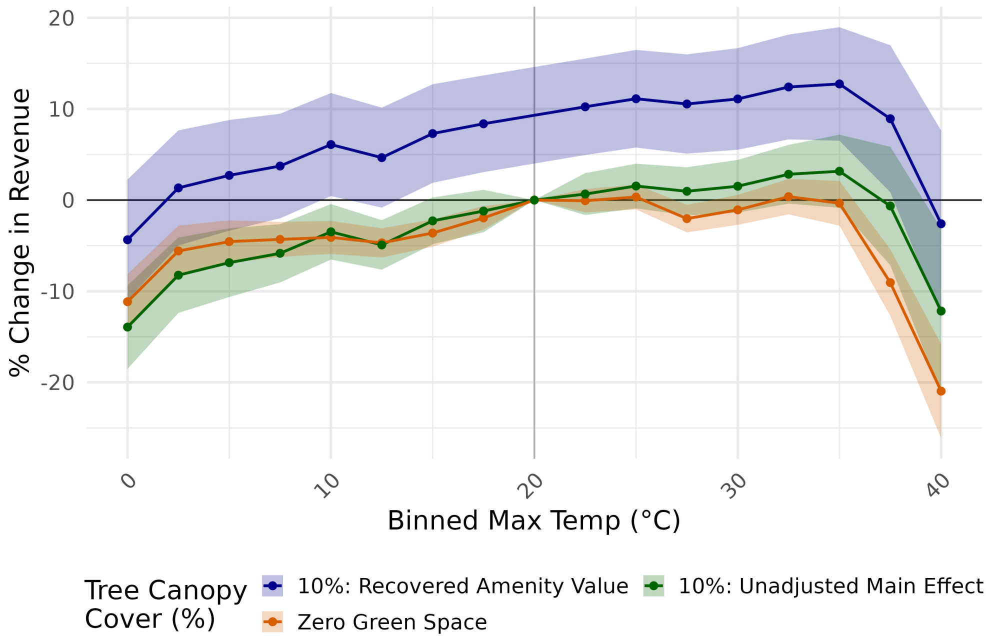
40 °C day, revenue falls by 20 percent in the low green space scenario, compared to only a 12 percent decline in this high green space scenario.

5.4 Recovering Green Space's Amenity Effect

Estimating Equation 6 recovers a portion of the amenity effect of surrounding green space, previously absorbed by the brand-by-city-by-month fixed effect. Regression results for a linear, logged, second-, and third-order polynomial function forms of modeling the main effect of green space on revenue are reported in Appendix Table A6. After controlling for the industry that a brand is a part of and using the linear specification as the preferred model of how the amenity value of green space affects revenue, a one percent increase in average green space around a brand (within a given city and month) is associated with a 0.96 percent increase in revenue. Because fixed effects serve as the intercept for each of these units, this recovered main effect implies that a one percent increase in surrounding green space shifts revenue upward by nearly an additional percent, as described in Equation 7.

After adjusting for this recovered main effect, the marginal effect of a one percent increase in green space is shown graphically in Figure 7 (see line labeled Recovered Amenity Value). At lower temperatures, the marginal benefit of green space is just under 1 percent, gradually rising to almost 1.5 percent at 35 °C. When temperatures exceed 35 °C, the marginal benefit of a 1 percent increase in green space jumps to nearly 2 percent.

Figure 8: Revenue Under High and Low Green Space Scenarios



This figure compares the effect of temperature on storefront revenue in low versus high green space environments. In the low green space scenario, revenue declines by about 10 percent at 37.5 °C and by 20 percent at 40 °C. In a lower bound estimate of the effect of a high green space scenario (Unadjusted Main Effect), the decline at 37.5 °C is not statistically significant, and the loss at 40 °C is only 12 percent. Incorporating the recovered amenity value of green space implies that high green space environments are consistently more beneficial: on a 20 °C day, storefronts in high green space areas earn about 10 percent more revenue than those in low green space areas, and by 40 °C this difference grows to 20 percent.

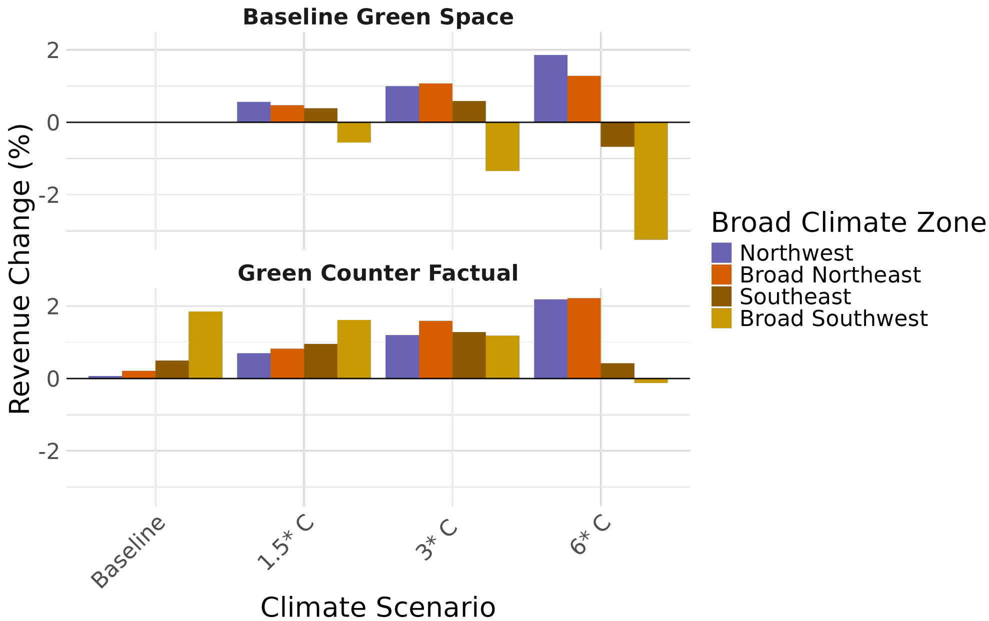
This recovered amenity value implies a high green space scenario is significantly more beneficial than low green space scenarios at any temperature, as illustrated in Figure 8 (see line labeled Recovered Amenity Value). On a 20 °C day, storefronts in high green space environments earn about 10 percent more revenue than those in low green space environments. On a 40 °C day, this difference increases to 20 percent.

5.5 Back of the Envelope Climate Scenario

This paper 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 Model (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 green space scenario (all storefronts surrounded by ≥10 percent green space).

Figure 9 presents the three climate scenarios projected in four broad climate regions, along with lower bound estimates of the same climate scenarios in a high green space scenario. The broad climate regions are grouped as regions with similar median green space and average temperature (see Table 2). This paper uses the lower bound estimates of the elasticity of revenue with respect to green space (Equation 5) as the specification for the projected climate scenarios and corresponding finance questions to isolate green space's

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 Model (4) and use the lower-bound elasticity of revenue with respect to green space (Equation 5). Results are shown for broad climate regions under baseline conditions and under a counterfactual high green space 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 green space is able to completely or nearly eliminate these losses, even in the most severe warming scenario.

beneficial cooling service and present a conservative estimate of green space's benefit to businesses.

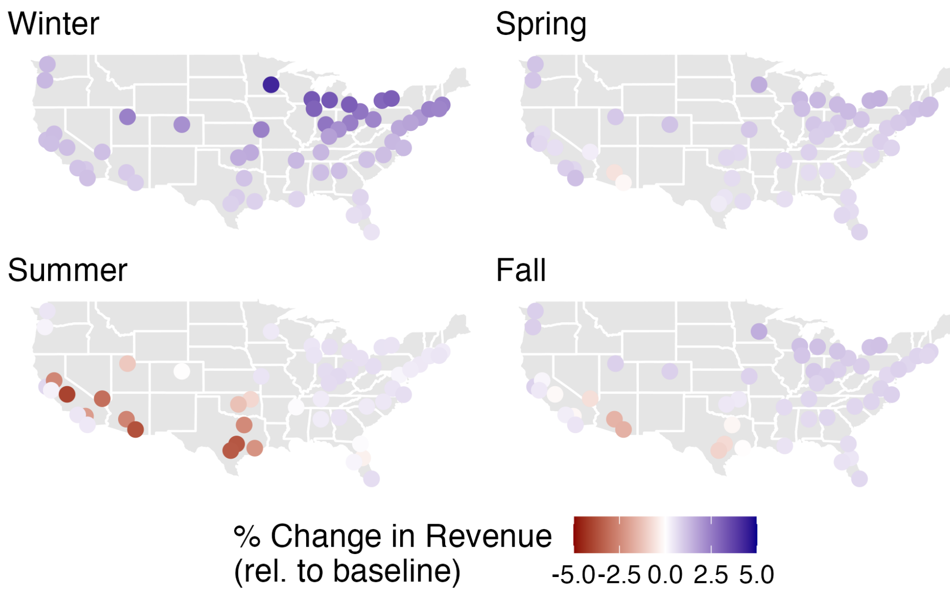
Storefronts in the Broad Southwest (West, Southwest and South NOAA climate regions) are the most vulnerable to heat increases, followed by the Southeast. Any amount of warming is damaging to the Broad Southwest, whereas all other regions see initial increases in revenue due to currently cool days moving 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.

Temperature increases have different effects across seasons. Figure 10 plots the revenue change by city using Model (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.[2] These cities in the Broad Southwest would have the most to gain from using urban green space 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 green space, the Broad Southwest is able to mitigate all losses due to temperature increases by moving to a high green space scenario (Figure 9). In the baseline green space scenario, the average storefronts' revenue would increase by 1.85 percent annually solely due to the heat mitigating service green space provides. In the most

[2]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 Model (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.

severe warming scenario, the Broad Southwest only experiences a 0.12 percent loss of revenue under the high green space scenario. This is in comparison to a 3.25 percent loss that the region would experience in this severe scenario at its baseline green space. This region has the most to gain because it already experiences extreme heat and has relatively little urban green space (Table 2).

The annual revenue changes projected using a linear and logged recovered main effect specification for Equation 7 are plotted in Appendix Figure A3. The amenity value of green space is much larger than the benefit of the cooling service, regardless of function specification. All regions experience more than a 10 percent increase in annual revenue under all climate scenarios when incorporating green space's amenity value.

5.6 Years to Cover Cost of High Green Space Scenario

This papers presents the number of years it would take the cover the cost of moving from the baseline green space scenario to a high green space scenario ($\geq$ 10 percent). I present the result for the Broad Southwest region under the baseline climate scenario.

When using the lower bound estimate of green spaces' value to storefronts, moving to the high green space scenario for the average storefront in the Southwest would increase revenue 1.85 percent annually. The median surrounding green space 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 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 is $750 (Murphy-Dunning, 2025).

Following, the cost of moving to the high green space scenario is $75 thousand dollars. The annual benefit is 18.5 thousand dollars. It would take 4.05 years for the businesses to recuperate the planting cost of the trees. For the Broad Southwest region, this length of time only becomes shorter under climate scenarios because the revenue increase over what it would be under any climate scenario increase past 2 percent.

In the baseline climate scenario, other regions do not have as much to gain in terms of revenue increases from green space mitigating the effect of extreme heat. These regions currently do not experience enough extreme hot days that need to be mitigated, and also already enjoy much higher levels of green space than the Broad South West.

5.7 Robustness and Placebo Tests

This paper tests the robustness and legitimacy of the results in multiple ways.

To test whether the main results are sensitive to how surrounding green space is measured, I re-estimate Model (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 green space are fairly robust across buffer sizes. All models show that the effect of green space on revenue begins to spike upward at 32.5 °C and peaks at 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 A7 summarize these findings, showing that the moderating effect of green space on heat-induced revenue losses is consistent across buffer specifications, although varying in precision.

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 green space (see Appendix Figure A2). This result is expected, because outdoor green space should not be complimented to storefronts entirely contained indoors.

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 but using delivery services more. Instead, the 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.

[Insert robustness to dropping covid]

[Insert robustness to dropping Phoenix]

6 Conclusion and Discussion

This paper estimates the causal effect of extreme heat and urban green space 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 green space provides a valuable buffer against these damages. A one percent increase in tree canopy cover raises storefront revenue by roughly one percent under normal conditions, reflecting a general amenity effect. During periods of extreme heat, this benefit more than doubles. When temperatures exceed 35 °C, the same one-percent increase in canopy corresponds to nearly a two-percent gain in revenue. A two-stage estimation strategy recovers the part of this effect that represents a recovered amenity value absorbed by fine brand-by-city fixed effects. Together, these findings show that green space 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 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).

The 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 green space 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 (Manning and Fenichel, 2024). By aligning private benefits with public returns, urban green space emerges as a scalable, potentially self-financing adaptation strategy.

In sum, this paper shows that extreme heat threatens storefront revenue, that urban green space provides both amenity and climate-regulating benefits, and that these benefits are strongest where the risks are highest. Green space 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

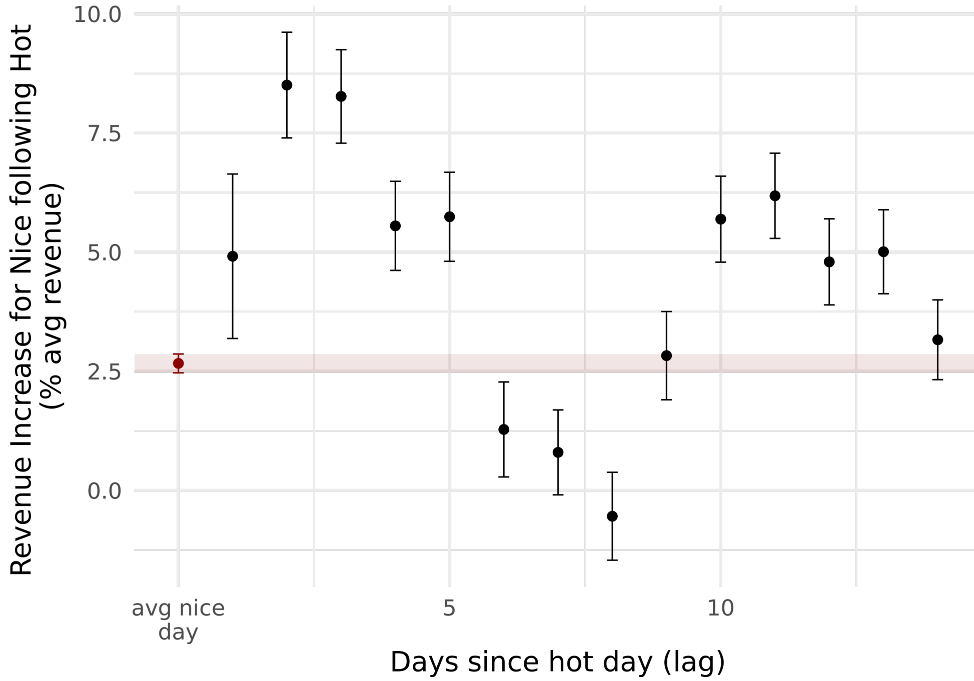
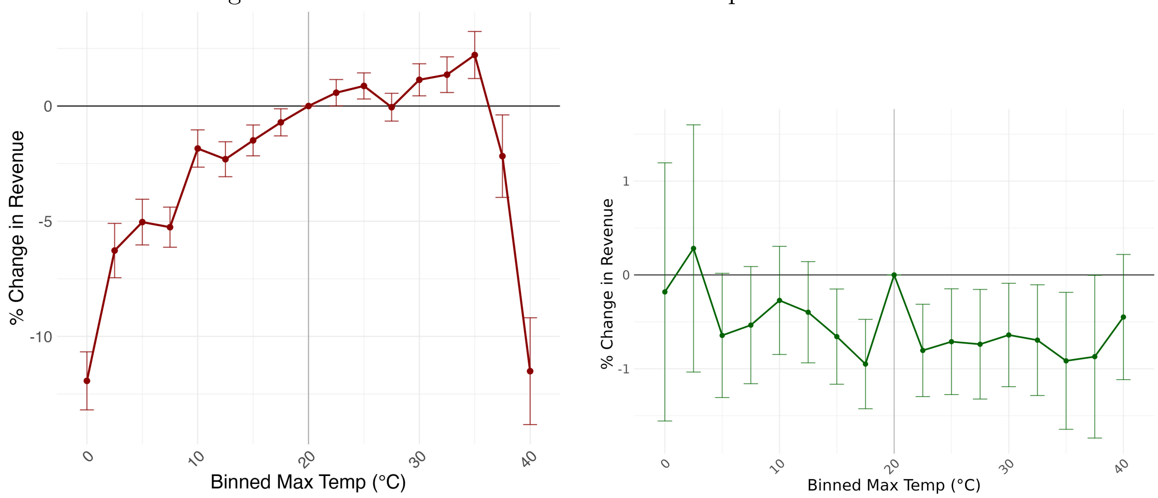


Figure A2: Placebo: No Evidence of Green Space Effect in Malls



Marginal Effect of Heat

Marginal Effect of Green Space

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

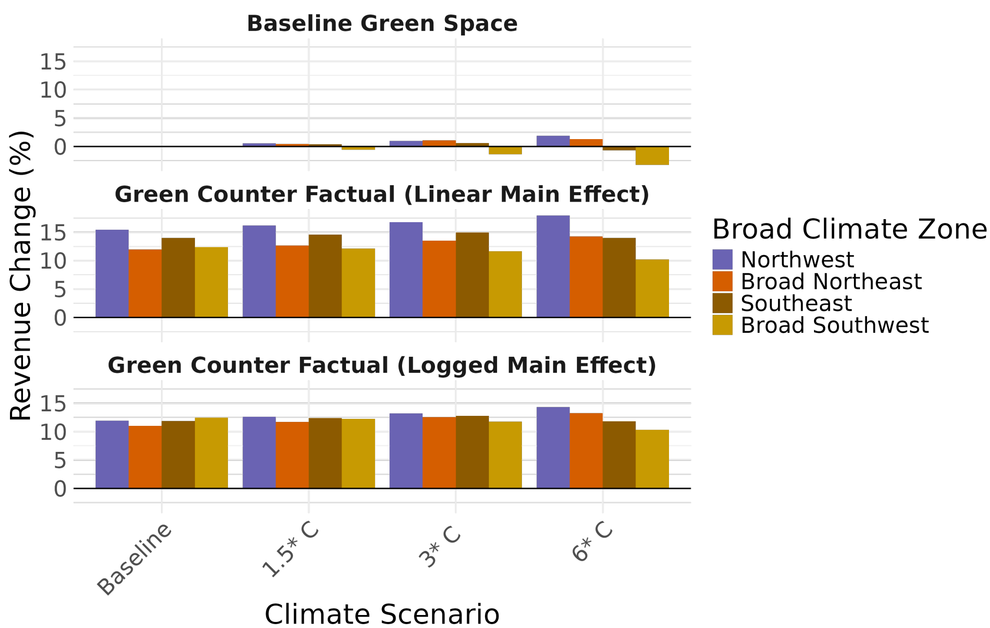


Table A1: Summary of median surrounding green space by city, and average temperature

	City	Median Green Space	Average Temp (˚C)
1	Portland, OR	14.23	18.25
2	Raleigh, NC	13.69	22.02
3	Pittsburgh, PA	12.99	18.00
4	Atlanta, GA	12.02	22.84
5	Minneapolis, MN	11.68	17.90
6	Charlotte, NC	11.34	22.41
7	Memphis, TN	11.25	22.71
8	Richmond, VA	10.50	21.12
9	Baltimore, MD	9.64	20.19
10	Jacksonville, FL	9.55	26.74
11	Tampa, FL	9.26	27.86
12	Nashville, TN	9.00	22.02
13	Milwaukee, WI	8.46	16.60
14	Virginia Beach, VA	8.35	21.17
15	Kansas City, MO	8.15	20.30
16	Rochester, NY	7.96	16.56
17	Buffalo, NY	7.23	16.25
18	Orlando, FL	7.23	28.20
19	Salt Lake City, UT	7.13	18.90
20	Cincinnati, OH	6.96	19.20
21	Seattle, WA	6.72	17.02
22	Louisville, KY	5.95	20.20
23	Miami, FL	5.93	29.07
24	Indianapolis, IN	4.82	18.29
25	Cleveland, OH	4.69	17.03
26	Detroit, MI	4.65	17.35
27	Philadelphia, PA	4.26	19.16
28	San Jose, CA	3.96	23.32
29	Columbus, OH	3.94	18.61
30	Denver, CO	3.90	19.71
31	Chicago, IL	3.23	17.34
32	Houston, TX	3.09	27.06
33	Austin, TX	3.04	26.59
34	Sacramento, CA	2.93	24.81
35	Riverside, CA	2.75	25.86
36	San Diego, CA	2.53	22.51
37	New Orleans, LA	2.43	25.69
38	Fresno, CA	2.14	25.15
39	San Antonio, TX	2.04	27.38
40	Dallas, TX	1.95	25.02
41	New York, NY	1.83	18.22
42	Boston, MA	1.53	17.27
43	Los Angeles, CA	1.28	23.87
44	Tulsa, OK	1.07	23.15
45	Oklahoma City, OK	0.63	22.97
46	Las Vegas, NV	0.58	24.68
47	Phoenix, AZ	0.51	27.22
48	San Francisco, CA	0.35	19.00
49	Tucson, AZ	0.28	27.65

Table A2: 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
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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

Figure A4: Robustness check for various radii buffer specifications for the effect of green space on revenue

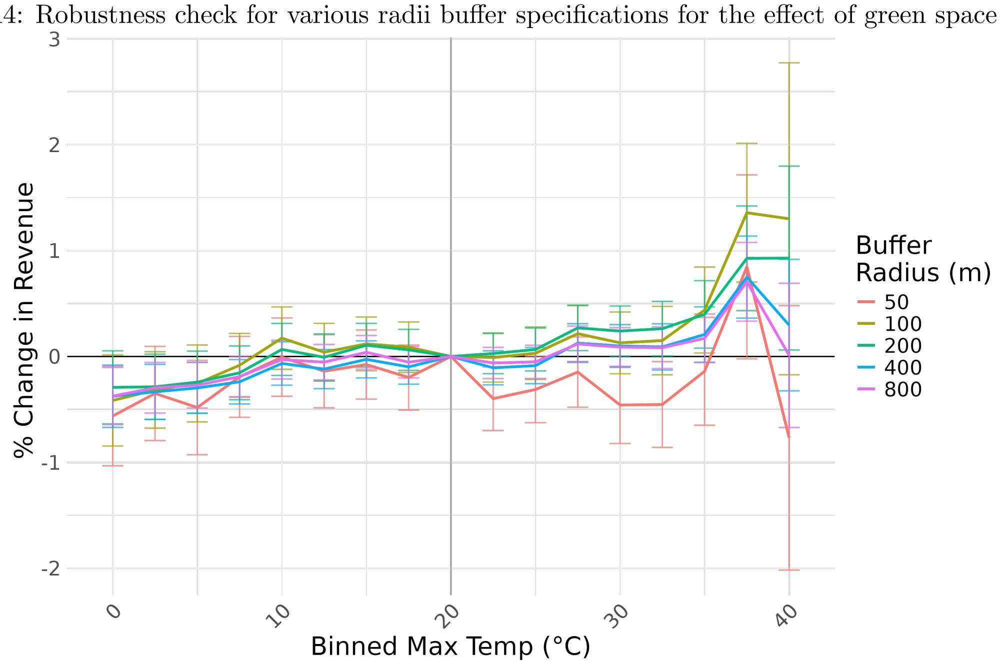

Table A3: Temporal Substitution in Response to Heat – Cumulative Effects

	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
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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
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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 A4: 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 A5: The Effect of Temperature on Revenue

	reg_g
Dependent Var.:	log_spend
Share in 25–45K	0.1645*** (0.0476)
Share in 45–60K	0.1089* (0.0533)
Share in 60–75K	-0.1930*** (0.0580)
Share in 75–100K	0.5068*** (0.0551)
Share in 100–150K	1.092*** (0.0594)
Share >150K	0.8011*** (0.0541)
Storefront Size (m2)	0.0001*** (1.74e-5)
Parking Lot	-0.1429*** (0.0369)
Bin: 0 °C	-0.1115*** (0.0155)
Bin: 2.5 °C	-0.0558*** (0.0141)
Bin: 5 °C	-0.0456*** (0.0119)
Bin: 7.5 °C	-0.0431*** (0.0098)
Bin: 10 °C	-0.0410*** (0.0092)
Bin: 12.5 °C	-0.0470*** (0.0082)
Bin: 15 °C	-0.0362*** (0.0077)
Bin: 17.5 °C	-0.0196** (0.0066)
Bin: 22.5 °C	-0.0007 (0.0066)
Bin: 25 °C	0.0034 (0.0069)
Bin: 27.5 °C	-0.0204** (0.0077)
Bin: 30 °C	-0.0107 (0.0084)
Bin: 32.5 °C	0.0037 (0.0099)
Bin: 35 °C	-0.0035 (0.0125)
Bin: 37.5 °C	-0.0906*** (0.0186)
Bin: 40 °C	-0.2096*** (0.0263)
Tree Canopy Covery	0.0002 (0.0008)
Bin: 0 °C x Tree Canopy Covery	-0.0030. (0.0016)
Bin: 2.5 °C x Tree Canopy Covery	-0.0029* (0.0014)
Bin: 5 °C x Tree Canopy Covery	-0.0025* (0.0013)
Bin: 7.5 °C x Tree Canopy Covery	-0.0018. (0.0010)
Bin: 10 °C x Tree Canopy Covery	0.0004 (0.0010)
Bin: 12.5 °C x Tree Canopy Covery	-0.0005 (0.0008)
Bin: 15 °C x Tree Canopy Covery	0.0011 (0.0007)
Bin: 17.5 °C x Tree Canopy Covery	0.0005 (0.0006)
Bin: 22.5 °C x Tree Canopy Covery	0.0005 (0.0006)
Bin: 25 °C x Tree Canopy Covery	0.0010 (0.0007)
Bin: 27.5 °C x Tree Canopy Covery	0.0028*** (0.0008)
Bin: 30 °C x Tree Canopy Covery	0.0024* (0.0009)
Bin: 32.5 °C x Tree Canopy Covery	0.0022* (0.0011)
Bin: 35 °C x Tree Canopy Covery	0.0033* (0.0014)
Bin: 37.5 °C x Tree Canopy Covery	0.0082** (0.0026)
Bin: 40 °C x Tree Canopy Covery	0.0086* (0.0037)
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	0.39571
Within R2	0.00786

Table A6: 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	4.268*** (0.0190)	4.136*** (0.0651)	4.135*** (0.0651)	4.081*** (0.0669)	4.079*** (0.0695)
Mean Tree Canopy (200 m)	-0.0039 (0.0026)	0.0096*** (0.0024)		0.0313*** (0.0066)	0.0324* (0.0142)
as.factor(naics_code)445120		0.1404. (0.0735)	0.1451* (0.0734)	0.1394. (0.0734)	0.1394. (0.0734)
Pharmacies & Drug Stores		0.5166*** (0.0727)	0.5121*** (0.0727)	0.5097*** (0.0726)	0.5096*** (0.0726)
Cosmetic & Beauty Supply Stores		0.1754 (0.2133)	0.1721 (0.2133)	0.1997 (0.2131)	0.2000 (0.2132)
Gas Stations w/ Conv. Stores		0.1499 (0.0970)	0.1744. (0.0965)	0.1761. (0.0972)	0.1760. (0.0972)
Hobby, Toy & Game Stores		0.9084*** (0.2133)	0.9058*** (0.2133)	0.9334*** (0.2131)	0.9337*** (0.2132)
All Other Gen. Merch. Stores		-0.7974*** (0.0754)	-0.7915*** (0.0752)	-0.7871*** (0.0754)	-0.7874*** (0.0755)
Full-Service Restaurants		0.4836*** (0.1114)	0.4956*** (0.1113)	0.4959*** (0.1113)	0.4968*** (0.1117)
Limited-Service Restaurants		0.1227. (0.0662)	0.1192. (0.0662)	0.1228. (0.0661)	0.1228. (0.0661)
Snack & Nonalc. Bev. Bars		-0.2016** (0.0708)	-0.2072** (0.0709)	-0.2085** (0.0707)	-0.2086** (0.0707)
Automotive Shops		1.172*** (0.1575)	1.154*** (0.1577)	1.145*** (0.1575)	1.144*** (0.1578)
Beauty Salons		0.4181** (0.1577)	0.4196** (0.1576)	0.4172** (0.1574)	0.4178** (0.1576)
log(Mean Tree Canopy)			0.0428*** (0.0106)		
Mean Canopy: Squared				-0.0013*** (0.0004)	-0.0014 (0.0016)
Mean Canopy: Cubed					4.76e-6 (5.12e-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	0.00061	0.18790	0.18804	0.19053	0.19053
Adj. R2	0.00035	0.18532	0.18547	0.18775	0.18753

Table A7: 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 A8 and plotted in Figure 1.

Table A8: 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:

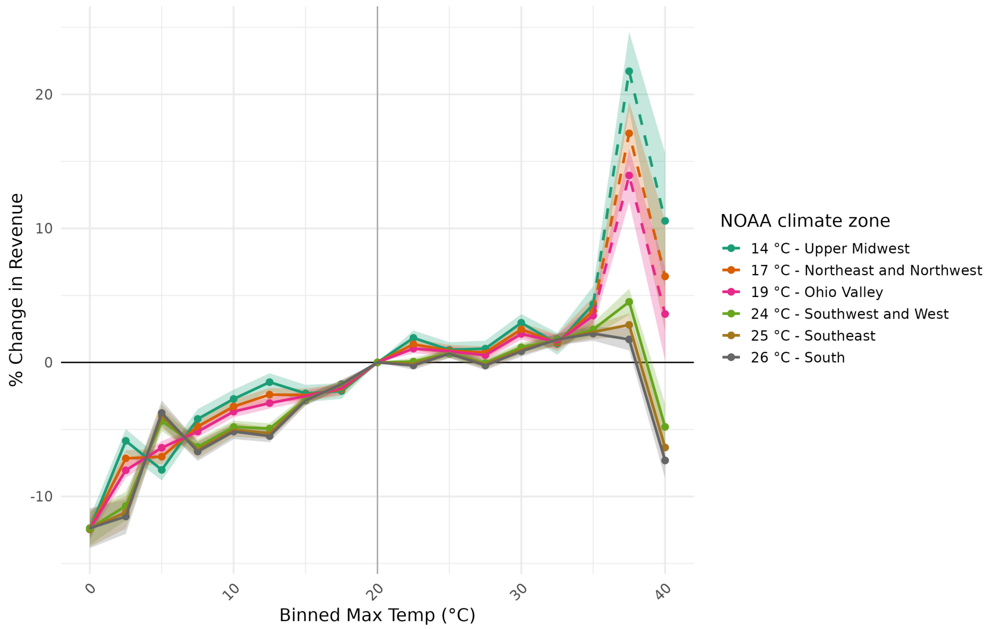
$$\ln(R_{it}) = \boldsymbol{\beta_I}\mathbf{I}_{it} + \sum_h \beta_h\,\mathbb{I}(H_{it}=h) + \sum_h \delta_h\,\mathbb{I}(H_{it}=h)\times\overline{T}_c + \alpha_i + \tau_t + \epsilon_{it}, \tag{9}$$

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 A5: 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.

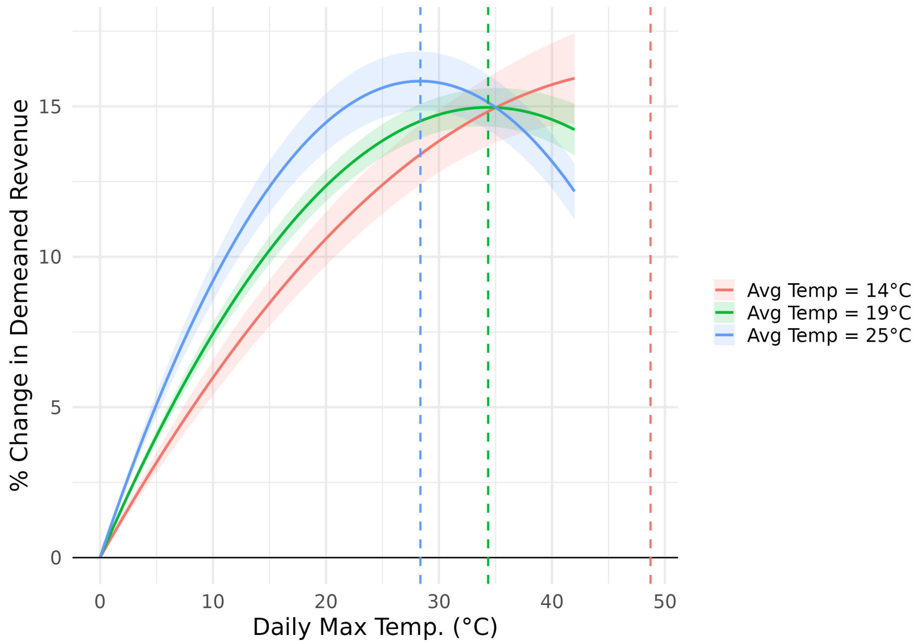
Figure A5 presents the results from the non-parametric interaction model. In warmer regions, revenue declines sharply at high temperatures, with losses exceeding 5 percent on days above 37.5,°C. In contrast, cooler regions show imprecisely estimated effects at these temperatures.

The parametric interaction model (Figure A6) 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.

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 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.

Figure A6: The Effect of Temperature in Different Regions



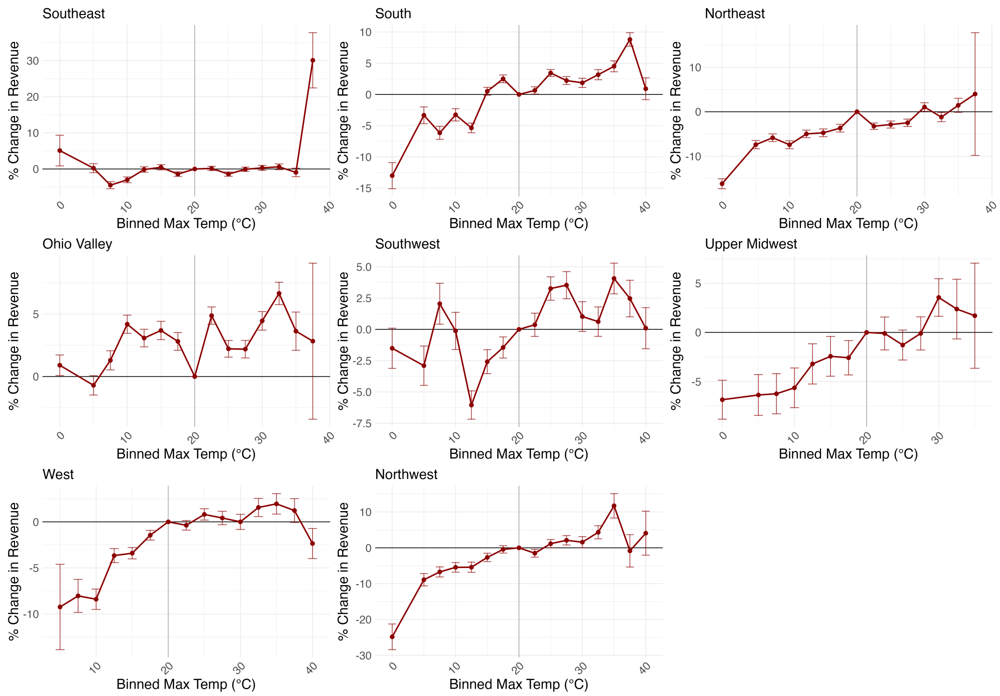
Overall, this exercise suggests that while regional adaptation may be important in global comparisons, within the United States the revenue response to extreme heat is relatively uniform across climate regions. The final section of this appendix explores this more closely.

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 2). The Northeast's behavior at high temperatures can be explained by a lack of power. Figure A7 shows the estimated effects.

Figure A7: 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 A8 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)).

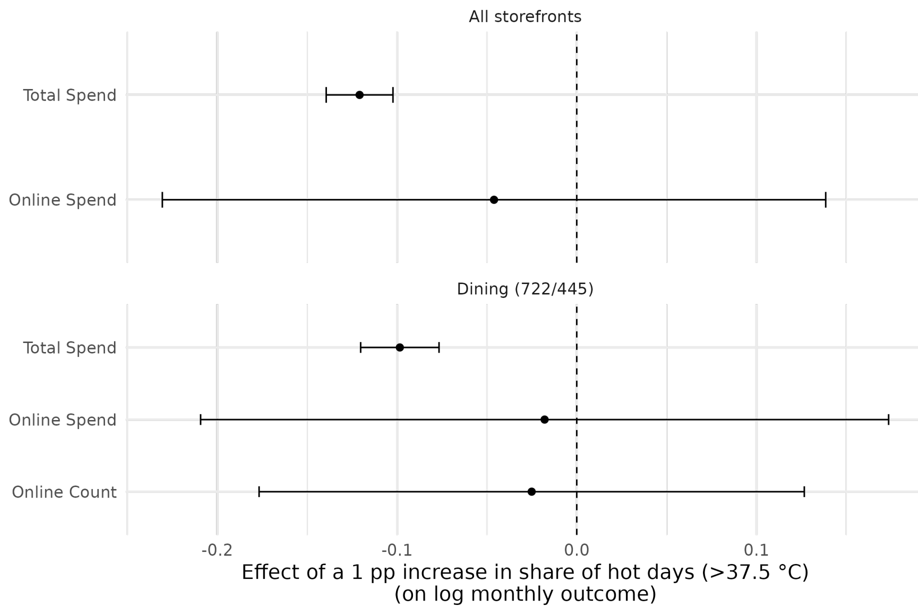


Figure A8: Effect of Hotter Months on Total Spending and Delivery Services

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