How is climate fuelling the thirst for sweetness? Exploring drivers and adaptation*

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Abstract

Amid the current syndemic of obesity and climate change, little is known about the effect of extreme temperatures on dietary behaviour. Using exogenous daily variations in weather and a nationally representative consumer panel in the U.S., we find that extreme heat increases the volume purchased of sugary drinks, with persistent impacts even after accounting for inter-temporal purchase shifts. We explore heterogeneous effects and a range of potential drivers, including changes in shopping habits, inter-channel substitutions, retailers' price adjustments, and psychological biases. Results reveal higher impacts among the most vulnerable households and no evidence of long-run adaptation by historical heat exposure. We combine our estimates with output from climate models for 2080-2099. Our projections indicate that climate change may increase sugary drink purchases.

Keywords: adaptation, climate change, extreme temperatures, retail, sugary drinks, unhealthy diets

JEL Codes: D12, Q54, I12

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1 Introduction

The United States (U.S.) is the first-most sugar-loving nation in the world. The average person consumes more than twice the World Health Organization's recommended daily sugar intake.[1,2] Two out of five American adults are obese, representing the highest prevalence among OECD countries (OECD, 2017). Elevated body weight is associated with approximately half a million excess deaths per year in the U.S. and the annual cost of obesity to the healthcare system is estimated at $173 billion (Ward et al., 2022).[3] Meanwhile, the country is increasingly facing the impacts of climate change. As in most of the world, extreme weather events, particularly extreme temperatures, are becoming more frequent and intense.[4] Previous studies have highlighted how extreme temperatures negatively impact economic productivity (Deryugina and Hsiang, 2014; Burke et al., 2015b), labour supply (Jessoe et al., 2018; Somanathan et al., 2021), education and learning (Park et al., 2020; Zhang et al., 2023), aggregate household consumption (Lee and Zheng, 2023; Lai et al., 2022), direct health outcomes (Deschênes and Greenstone, 2011; Barreca et al., 2016), physical activity (Obradovich and Fowler, 2017), as well as agricultural outcomes (Costinot et al., 2016; Burke and Emerick, 2016). However, little is known about how they affect dietary patterns.

Americans are among the highest consumers of sugary drinks globally with the average adult consuming 4.9 (8-oz, 227ml) servings per week (approximately equivalent to 65 kcal per day) (Lara-Castor et al., 2023). These drinks represent the largest source of added sugar and contribute to weight gain and chronic diseases (Ricciuto et al., 2021; Malik and Hu, 2022).

[1]Based on Euromonitor Passport data for 54 countries. Source: Washington Post, *Where people around the world eat the most sugar and fat*, 2015.

[2]The World Health Organization's daily recommended sugar intake is 10% of energy intake or approximately 50g for someone of normal weight with a daily energy intake of 2,000 kcal.

[3]Source: Centres for Diseases Control and Prevention, Overweight & Obesity, *Why It Matters* (Accessed 30 April 2024).

[4]Source: U.S. Environmental Protection Agency, *Climate Change Indicators in the United States* (Accessed 24 April 2024).

From a physiological standpoint, while they contain water, sweetened soft drinks should not be consumed to fulfil the body's increased hydration needs in hot temperatures. High sugar intake may exacerbate dehydration through increased thirst and urine production as the body tries to excrete excess sugar (Rolls et al., 1990; García-Arroyo et al., 2016).[5] Many sweetened soft drinks also lack essential electrolytes like potassium. Their overconsumption may disrupt the body's electrolyte balance and affect its ability to retain water.[6] Furthermore, sugary drinks represent an empty source of calories, providing little to no nutritional value to support the body's sustenance. Increases in energy intake not compensated by physical activity may lead to net increases in body weight. Understanding how extreme temperatures may affect beverage purchasing patterns and identifying potential drivers is essential for supporting policymaking to promote healthier diets under climate change.

This paper provides the first empirical evidence of the impact of extreme temperatures on the dietary shopping habits of Americans using detailed longitudinal grocery trip data. We match soft drink purchases from a nationally representative consumer panel with zip code-level daily meteorological information, supplemented with other administrative datasets capturing local characteristics. We investigate the causal contemporaneous effect of temperatures on purchases by exploiting exogenous weather variations through panel data regressions including a rich set of location- and time-specific as well as individual household fixed effects. Our comprehensive dataset is ideal as it allows for analysing the effect within individual households over 16 years with a daily resolution of both weather and purchasing data and enables the exploration of heterogeneity across demographic groups and locations. We test for inter-temporal purchase shifts and explore potential drivers, including changes in shopping habits, inter-channel substitutions, retail price adjustments, and psychological biases. Finally, we examine the mitigating role of long-run adaptation to climate by historical

[5] This process is referred to as osmotic diuresis. High sugar intake also stimulates the release of insulin, which may enhance the reabsorption of sodium in the kidneys, further contributing to dehydration.

[6] Most sweetened soft drinks also often contain caffeine, which in high quantity may lead to dehydration.

exposure and simulate consumption changes across various climate change scenarios.

Our analysis yields several important insights. First, we find that the purchased volume of soft drinks increases non-linearly with temperature, exhibiting statistically significant positive effects above 80° Fahrenheit (F) (≈ 27°C in the Celsius scale). Colder temperatures do not affect soft drink purchases. On average, a day with a maximum temperature above 95°F (35°C) increases the volume purchased of sugary drinks in the month by 0.34% compared to a regular day with 65-70°F (≈ 18-21°C). Monthly bottled water purchases also increase (+0.75%) following a day with a maximum temperature above 95°F. Inter-temporal substitutions do not offset these immediate effects. However, while the contemporaneous effect of extreme heat is positive on diet drink purchases, it is compensated by decreases in the following months. Results are robust to various specifications.

Second, we investigate heterogeneity and the role of potential modifiers of the effect. The relative increase in sugary drink purchases following extreme heat is similar across income group levels. Urban households drive the effect, likely due to their closer proximity to stores and higher exposure through potential heat island effects. The effect is higher for households with at least one member working in an outdoor occupation, likely due to higher exposure, and households with at least one obese adult member, likely due to higher vulnerability to heat stress.

Third, in line with Lee and Zheng (2023), we find that extreme heat days only have a minor negative impact on the likelihood of shopping trips. The positive effect of extreme heat on sugary drink volume purchased is driven by trips to convenience stores for rural households. These stores tend to be closer to household locations and display more unhealthy beverage options. Assessing heterogeneous effects by the local density of food and drink establishments, we rule out heat-induced inter-channel substitutions from the on-trade sector (e.g., bars and restaurants) to grocery stores.

Fourth, we assess whether retailers are driving the effect through price adjustments during extreme heat. Using a nationally representative retail scanner dataset, we build monthly store-level price indices across universal product codes (UPC) by beverage type and find no evidence of retail price adjustment for sugary drinks and bottled water and only limited adjustments for diet drinks (-0.009%), consistent with Gagnon and López-Salido (2020) and Lee and Zheng (2023).

Fifth, Busse et al. (2015) has pointed towards projection bias and salience as psychological channels to explain how consumers are overly influenced by their emotional state and the weather at the time of purchase. Our results do not support these mechanisms to explain the effect of extreme heat on sugary drink purchases. Nevertheless, we find some evidence of a mood effect with the increase in sugary drink purchases being higher for extreme heat days without rain. Furthermore, present bias, or more generally the lack of self-control, may participate in explaining the departure from the physiological channel predictions (i.e., predicted increase in water intake, but no increase in sugary drink intake) and the irrational inter-temporal trade-offs triggered by extreme heat.

Lastly, we explore the mitigating role of higher historical exposure to extreme heat. In line with Roth Tran (2023) and Addoum et al. (2020), we find that sugary drink purchases from households that have historically experienced more extreme heat events are not less sensitive than others to contemporaneous extreme heat shocks. However, we find evidence of a significant mitigating effect for bottled water purchases.

This paper contributes to the literature in several ways. First, it relates to recent works that have studied weather effects on purchasing decisions and retail sales (He et al., 2022; Liao, 2020; Lee and Zheng, 2023; Roth Tran, 2023; Lai et al., 2022),[7] including the strand investigating psychological channels (Busse et al., 2015; Conlin et al., 2007). Second, the literature on the impact of climate change on diets has mostly focused on agricultural production, highlighting the negative direct impact of extreme temperatures on crop yield and

[7]Until recently and the advent of granular longitudinal shopping and transaction data, the literature had been focused on the impact of weather variations on economic productivity rather than consumption (Graff Zivin and Neidell, 2014; Burke et al., 2015b; Deryugina and Hsiang, 2017), except for studies on energy consumption (Auffhammer and Mansur, 2014).

food security (Wheeler and von Braun, 2013; Costinot et al., 2016). In this paper, we show that climate change also impacts dietary behaviour from the demand side. Third, while associations have been found between hot temperatures and highly processed food purchases as well as micronutrient deficiency (López-Olmedo et al., 2021; McLaughlin et al., 2023), our study provides the first evidence of a causal effect of extreme temperatures on dietary behaviour using micro-level longitudinal shopping data. Fourth, while the health economics literature has demonstrated the direct impact of climate change on morbidity and mortality (Campbell et al., 2018; Deschênes and Greenstone, 2011; White, 2017; Liao et al., 2023), we evidence a potential negative indirect health impact through unhealthy dietary choices. Finally, we contribute to a large body of work investigating adaptation to climate, including on household spending and energy consumption (Lai et al., 2022; Auffhammer, 2022), as well as labour (Behrer and Park, 2017; Jessoe et al., 2018), agricultural (Burke and Emerick, 2016; Costinot et al., 2016), and health outcomes (Barreca et al., 2016; Carleton et al., 2022).

While the average American currently experiences 13 days with a maximum temperature over 95°F per year, this number could increase to 27-50 days by mid-century and to 45-96 days each year by the end of the century, with significant regional variations.[8] Using our temperature effect estimates and downscaled daily climate predictions under two greenhouse gas emission scenarios validated by the Intergovernmental Panel on Climate Change (IPCC), we estimate that climate change is expected to stimulate sugary drink purchases by 0.73% to 1.44% by the end of this century, with likely negative implications for public health. The effect is higher in hotter climate regions with no evidence of long-run adaptation based on historical exposure. On the other hand, we project lower changes in bottled water purchases once adaptation is accounted for. Amid the current syndemic of obesity and climate change (Swinburn et al., 2019), our findings can inform policymaking to promote healthier diets under climate change, particularly in settings grappling with an obesity epidemic.

[8]Based on various greenhouse gas emission scenarios. Source: Vox, *Here's how 95°F days could become more common in your lifetime*, 2014.

This paper is divided as follows. Section 2 details the data sources and provide summary statistics. Section 3 describes the empirical strategy. Section 4 presents results and explores potential drivers and modifiers of the effect. Section 5 investigates the mitigating role of historical exposure. Section 6 presents our estimates of the future projected impact of climate change on soft drink purchases. Section 7 discusses the results and limitations and concludes.

2 Data and variable definitions

Our analysis is based on purchase data for 2004-2019 from NielsenIQ Consumer Panel; a nationally representative panel recording all their purchases intended for personal, in-home use, using an in-home scanner or mobile app. The dataset tracks household purchase data at the UPC level for food and non-food packaged grocery items from any outlet. It also includes household zip code location and demographic information such as income, the number of individuals living in the household, their head employment status, age, and race. Our outcome variable is the monthly household purchases per adult equivalent unit,[9] measured in millilitres (ml), for the following soft drink groups: 1) regular carbonated soft drink (CSD) which contains sugar; 2) fruit juice & drink; 3) diet CSD, which contains non-caloric artificial sweeteners; and 4) bottled water (non-sweetened). As a convention, *sugary drinks* refer to regular CSD and fruit juice & drink. Implicitly, we assume that the purchased drinks are shared equally between adults and based on the adult equivalent scale for adolescents and children within all households.

[9]We use the following adult equivalent unit scale: 0.77 for children < 5 years old; 0.80 for children 6-12 years old, 0.88 for 13-18 years old; Source: Food and Agriculture Organization of the United Nations, *Human Energy Requirements*, Report of a Joint FAO/WHO/UNU Expert Consultation: Rome, 17-24 October 2001.

Our analysis is based on a sample consisting exclusively of households that have purchased at least one soft drink annually (of any of the four soft drink types included in this analysis). We exclude households that change zip codes from our analysis as the exact date of their move during the year is unknown, given that panellist characteristics are only updated annually. Zip codes containing only one household in the panel are dropped. Additionally, we clean the data by filtering out outliers. This includes dropping household-years with less than 12 purchase trips (of any item, including non-beverages) and those with soft drink purchases higher than 600 litres (158.5 gallons) per adult equivalent unit for any given month.[10] Finally, we exclude households with interrupted presence in the sample but keep households whose total length in the panel is less than 16 years (the maximum length). The final sample covers purchase data from February 2004 to November 2019,[11] and comprises 5,834,433 household-month observations from 133,312 unique households in 13,522 zip codes across the contiguous U.S.[12] Table B1 presents household demographic characteristics.

We match the purchase data with the U.S. NOAA Global Historical Climatology Network meteorological daily information. Weather stations within a maximum radius of 200 km to each household's zip code centroid geolocation are considered (Barreca et al., 2016).[13] Zip code-level daily inverse-distance weighted average of the five closest weather stations are computed for maximum temperature in Fahrenheit (F), precipitation in millimeters (mm) (including both rainfall and snow melt), snowfall in mm, and average wind speed in meters

[10]600 litres (158.5 gallons) corresponds to 20 litres (5.3 gallons) per adult equivalent unit per day over 30 days. Kidneys can only remove 0.8 to 1 litre (27 to 34 ounces) per hour, so the maximum liquid quantity human kidneys can process per day is 19 to 24 litres (5 to 6.3 gallons). Source: BBC Science focus, *Is there a maximum amount of liquid a human can drink in a day?* (Accessed 30 April 2024).

[11]January of the first year and December of the last year are dropped as purchase data are missing for some days.

[12]Including the 48 contiguous states (all U.S. states except Alaska and Hawaii) and the District of Columbia.

[13]We drop weather station-years with more than three missing or quality-flagged observations.

per second (m/s) (Liao et al., 2023).[14,15]

Given that NielsenIQ Consumer Panel does not consistently capture retailer information for each good scanned at home, we use NielsenIQ Retail Scanner dataset to construct monthly price indices at the store level from January 2006 to December 2019. The dataset provides weekly pricing and sales from over 90 participating retail chains across all U.S. markets at the UPC level covering more than half the total sales volume of U.S. grocery, convenience and drug stores. It also includes retail channel type information and location (first 3-digit zip codes). We use the latter to match the data with daily weather information from the U.S. NOAA Global Historical Climatology Network at the county level, following the same inverse-distance weighted average strategy described earlier.

Table 1 displays the monthly purchased volume for the four beverage groups. The average American household in our sample purchases 3,303 ml of bottled water, 3,081 ml of regular CSD, 2,731 ml of diet CSD, and 2,328 ml of fruit juice/drink per adult equivalent unit per month. Figure B1 illustrates the degree of seasonality in purchases with peaks in the spring and the summer months. While the volume purchased decreases in the autumn months for all beverage types, it increases for regular CSD to reach levels close to the summer months in December.

Table 2 presents descriptive weather statistics. The average daily maximum temperature among the sample zip codes for 2004-2019 is 67.6°F. Figure 1 depicts the average distribution of daily maximum temperature across household-month observations, categorized into 16 bins ranging from below 25 degrees Fahrenheit (°F) (≈ -4 degrees Celsius, °C) to above 95°F (35°C). Days with a maximum temperature above 95°F or below 25°F are rare, averaging 1.1 and 0.6 days per month, respectively. Only 61.5% and 54.9% of household-years have experienced at least one such day, respectively (Figure B2). Table B2 and Figure B3 present

[14] Figure A1 displays a histogram of the distance between zip code centroids and the fifth closest station, i.e., the furthest station included in our analysis for each zip code. The furthest weather stations remain in a close radius to zip code centroids as the median distance is 32.8km, and the 95th percentile is 51.1km.

[15] In robustness analyses, we also consider daily minimum temperature.

the distribution of daily maximum temperature among zip codes in more detail. Figure B4 highlights the strong seasonality in temperatures. The number of extreme temperature days has shifted over time, which is captured in Figure B5; it depicts the observed changes in maximum temperatures across the sample time frame by comparing the total number of days above 90°F and below 30°F in 2004 and 2019. The majority of points lie above the 45-degree line for days with a maximum temperature above 90°F, underscoring the trend of rising temperatures in the U.S. even over a relatively short period. Finally, Figure B6 displays the distribution of the monthly average number of days within bins of precipitations, snowfall, and average wind speed among the sample. On average, households only experience precipitations half of the days. Snowfall is rare, less than three days per month on average, and households experience an average wind speed of over 6 m/s (≈13.4 miles per hour) only two days per month on average.

3 Main empirical strategy

We conduct multi-way fixed effects regressions at the household level, exploiting the exogeneity of weather shocks after controlling for seasonality and location (idiosyncrasy and random variation of weather) (Dell et al., 2014) (Equation 1):

$$V_{h,z,y,m} = \alpha + \sum_i \beta_i T_{i,z,y,m} + \sum_k \sum_j \mu_{k,j} W_{k,j,z,y,m} + \theta Z_{h,y} + \sigma_{z,m} + \gamma_{y,q} + \lambda_h + \varepsilon_{h,z,y,m} \quad (1)$$

where $V_{h,z,y,m}$ represents the volume purchased per adult equivalent unit during month m of year y by household h in zip code z. $T_{i,z,y,m}$ are a series of 16 bins equal to the number of days in a zip code-month for which the daily maximum temperature falls into bin i with

$i \in \{\leq 25°\text{F}, (25, 30], (30, 35], (35, 40], (40, 45], (45, 50], (50, 55], (55, 60], (60, 65], (65, 70), [70, 75), [75, 80), [80, 85), [85, 90), [90, 95), \geq 95°\text{F}\}$.[16] As other weather conditions may affect purchasing patterns, we similarly define $W_{k,j,z,y,m}$ as three series of regressors equal to the number of days in a zip code-month belonging to bin j including precipitations with $j \in \{0\text{mm}, (0, 2.5], (2.5, 5], (5, 7.5], (7.5, 10], \geq 10\text{mm}\}$; snowfall with $j \in \{0\text{mm}, (0, 1], (1, 2], (2, 3], (3, 4], \geq 4\text{mm}\}$; and average wind speed with $j \in \{(0, 2.5], (2.5, 3], (3, 3.5], (3.5, 4.5], (4.5, 6], \geq 6\text{m/s}\}$. $Z_{h,y}$ is household income, a time-varying household characteristic that might affect purchases.[17] $\sigma_{z,m}$ represent zip code $\times$ month-of-year fixed effects absorbing the average seasonal location-specific variation in weather and soft drink purchases, including holidays, as well as unobserved location characteristics. $\gamma_{y,q}$ are year $\times$ quarter-of-year fixed effects controlling for macro level shocks. Finally, λ_h are household fixed effects absorbing unobserved time-invariant household characteristics that may affect soft drink purchases. Equation 1 allows a flexible relationship between temperature and soft drink purchases.

The purchased volume includes a significant number of zeros, even after aggregating purchases to the monthly level. Thus, we estimate the expectation of quantity purchased $V_{i,t}$ by household i at time t conditional on the predictor variables $X_{i,t}$, via Poisson pseudo-maximum likelihood regressions (Wooldridge, 2010),[18] defined as:

[16] Following the approach in Graff Zivin and Neidell (2014). In the Celsius scale, this is approximately equivalent to $\{\leq -4°\text{C}, (-4, -1], (-1, 2], (2, 4], (4, 7], (7, 10], (10, 13], (13, 16], (16, 18], (18, 21), [21, 24), [24, 27), [27, 29), [29, 32), [32, 35), \geq 35°\text{C}\}$.

[17] In 2015 U.S. dollar, adjusted using World Bank, *Consumer Price Index* (Accessed 30 April 2024). As it may be endogenous, robustness results also provide an alternative specification without controlling for income.

[18] The presence of many structural zero values can lead to biased ordinary least squares (OLS) estimates and inflated standard errors. Instead, Poisson pseudo-maximum likelihood models the conditional mean of the response variable. This approach is robust to distributional misspecification and is not restricted to count data (Wooldridge, 2010). It is also robust to overdispersion as we use cluster-robust standard errors. We specifically use the iteratively reweighted least-squares algorithm developed by Correia et al. (2019) for Poisson regression models with multiple high-dimensional fixed effects. We do not have singleton observations in our sample as we drop zip codes with only one household. However, separated observations stem from beverage type-specific regressions as the sample includes all household-years that make at least one purchase of any soft drink and some households may never consume a particular type of soft drink. Separated observations, which are dropped from the estimation sample to avoid problems of perfect fit in likelihood estimations (Correia et al., 2019), explain the differences in sample sizes across the beverage-specific regressions.

$$E[V_{i,t}|\mathbf{X_{i,t}}] = \exp(\mathbf{X_{i,t}}\beta). \tag{2}$$

The β_i coefficients can be interpreted as semi-elasticities that capture the contemporaneous effect of an additional day that falls within maximum temperature bin T_i on the volume purchased in the month relative to an average temperature day. The reference bin, 65-70°F (≈ 18-21°C) captures the annual average maximum temperature across all sample zip codes (Table 2). All regressions are weighted using NielsenIQ household projection factors, enabling the results to be representative at the national level. We use robust standard errors clustered at the zip code level to allow for correlation within zip codes over time.

4 Results

4.1 Main

Results show that the volume purchased of soft drinks rises non-linearly with temperatures. It exhibits statistical significance for maximum temperatures above 80°F and peaks above 95°F (except for diet CSD which peaks at $[90, 95)$F). Colder days have non-statistically significant effects for all soft drink types with negative effects on the purchases of diet CSD and bottled water for maximum temperatures below 40°F (Figure 2). Swapping an average day with a maximum temperature between 65-70°F for a day with a maximum temperature above 95°F increases the average purchased volume of sugary drinks in the month by 0.34% or 20.2 ml (0.38% for fruit juice/drink and 0.33% for regular CSD). These results are driven by an intensive margin effect with no effect of temperatures on the extensive margin (Table 3). Extreme heat also leads to higher purchases of bottled water with a day above 95°F increasing the total volume purchased in the month by 0.75%. Diet CSD appear less sensitive to extreme heat than their sugary equivalent with a day above 95°F increasing the total volume purchased in the month by 0.22% (Table C1).

These findings are robust to the use of daily minimum temperature to define temperature bins (Figure C1). While the fixed effects included in our main specification are key to controlling for potential confounders, their combination may capture some of the variation needed to identify the full impact of temperatures on soft drink purchases. We show the robustness of our findings to other levels of time and location fixed effects: (1) county × month-of-the-year, (2) state × month-of-the-year, and (3) household × year fixed effects (excluding time-varying household income as a control) in Table C2. Finally, an important consideration is that weather could be correlated across all zip codes during a given month. This may induce some correlation in the error term across locations within a given time period. To alleviate this concern, we show that the significance of our results is robust to two-way clustering on both zip codes and month-of-the-year (Table C3).

4.2 Inter-temporal shifts

Temperature effects could be the results of short-term inter-temporal substitutions in purchases, shifting the period when consumers buy but potentially not the total volume they buy over a longer period. We use a distributed lag model (Equation 3) and test the null hypothesis that the sum of the two-month lag coefficients is equal to the negative of the respective contemporaneous period coefficient. Similarly, we test for anticipatory effects including a one-month lead.

$$\begin{aligned} V_{h,z,y,m} = \alpha + \sum_{t=-1}^{2} \sum_{i} \beta_{i,m-t} T_{i,z,y,m-t} + \sum_{k} \sum_{j} \mu_{k,j} W_{k,j,z,y,m} \\ + \theta Z_{h,y} + \sigma_{z,m} + \gamma_{y,q} + \lambda_h + \varepsilon_{h,z,y,m} \end{aligned} \tag{3}$$

To efficiently examine the impacts of both high and low temperatures, we now transition to employing five daily maximum temperature bins: ≤ 30°F, $(30, 40]$, $(40, 80)$, $[80, 90)$, and ≥ 90°F, with 40-80°F serving as the reference bin. Figure 3 plots the estimated coefficients for Equation 3 for days with a maximum temperature below 30°F and above 90°F as cumulative effects for sugary drinks, including a one-month lead and two-month lags. The effect on volume purchased in the following months is small but positive for days above 90°F. The cumulative effect over three months is non-statistically significant for days below 30°F. Our test results rule out both harvesting and anticipatory effects for extreme heat for sugary drinks as well as all other beverage types, except diet CSD. On the contrary, we do not rule out the null hypothesis of harvesting for all beverage types for extreme cold. We only reject the null hypothesis of equality between the lead coefficient and the negative of the contemporaneous effect for extreme cold for bottled water (Table D1 and Table D2).

Figure D1 displays the cumulative effect by beverage type for days with a maximum temperature below 30°F and above 90°F. Combined with results from Section 4.1, we find that extreme cold days have a limited impact on the volume purchased. While a day with a maximum temperature below 30°F has a statistically significant negative impact on the volume purchased of bottled water, purchases increase in the following month such that the cumulative effect is negative but non-statistically significant. The positive effect of days with a maximum temperature above 90°F on the volume purchased of regular CSD and bottled water is not compensated over time and only slightly compensated for fruit juice and drink after two months. On the other hand, the positive contemporaneous effect for diet CSD is fully compensated over time such that the cumulative effect is non-statistically significant, evidencing harvesting. This result also holds for the highest consumers of diet CSD and is not driven by substitutions to regular CSD (Figure D2).

4.3 Heterogeneity and potential modifiers

We explore heterogeneity by household annual income as it may be correlated with asset ownership such as air conditioning (AC) or owning a vehicle, which may mitigate heat exposure at home and during transport to grocery stores. Results show no difference in the relative effect of temperatures on sugary drink purchases by annual household income level (Figure 4). In the U.S., the consumption of sugary drinks is higher among lower-income households (Allcott et al., 2019a). As for heterogeneous effects by income level, we find no differential effects of extreme heat on sugary drink purchases by intensity of consumption. However, these effects are expressed in relative terms compared to mild temperatures through Poisson pseudo-maximum likelihood. Therefore, higher consumers increase their absolute sugary drink purchase levels significantly more than less intensive consumers as a response to extreme heat, given their higher purchase levels under mild temperatures. For bottled water, we find that purchases from lower-intensity consumers are more sensitive to extreme heat (Figure E1). Higher-intensity bottled water consumers may be households with strong preferences for bottled water above tap water or living in areas where tap water is perceived of lower quality. Their consumption may thus be more structural and less sensitive to temperature variations.

In the U.S., poverty rates are higher in rural areas across all ethnic groups.[19] AC ownership is lower in rural areas and rural households tend to cover longer distances to shop and thus may be more exposed to outdoor temperature immediately before shopping (Romitti et al., 2022; Ver Ploeg et al., 2012). However, Figure 4 shows that the positive effect of extreme heat on sugary drink volume purchased is driven by urban households. These households are likely to have easier access to stores. We do not find differential impacts by area for bottled water as both rural and urban households react equally positively to extreme heat (in relative terms) (Figure E1).

We also investigate heterogeneity by hot, mild, and cold climate zip codes, categorized based on terciles of the average maximum temperature over the 30-year period from 1974 to 2003. Figure 4 highlights minor differences in the effect of extreme heat on sugary drink

[19] Source: U.S. Department of Agriculture, Economic Research Service, *Data show U.S. poverty rates in 2019 higher in rural areas than in urban for racial/ethnic groups*, 2021.

purchases by climate region, with the demand for households in historically colder zip codes being moderately more sensitive. This suggests that consumers in historically warmer areas may be slightly better adapted to cope with hot temperatures. Naturally, we find more uncertainty in the results for extreme cold temperatures in historically hot zip codes and vice-versa, with higher confidence intervals, due to lower exposure. We find similar results for bottled water (Figure E1).

Further, we explore factors that may moderate or exacerbate the positive effect of extreme heat on sugary drink purchases. Specifically, we evaluate the effect of at least one of the household heads being employed in an outdoor occupation,[20] at least one of the adult household members being obese, as well as households having at least one child and households using AC. Practically, we interact the modifier variable ($Mod_{h,y}$) with the set of temperature bins in our main model specification.

$$\begin{aligned} V_{h,z,y,m} = \alpha + \sum_i \beta_i T_{i,z,y,m} + \sum_i \rho_i T_{i,z,y,m} \times Mod_{h,y} + \pi Mod_{h,y} \\ + \sum_k \sum_j \mu_{k,j} W_{k,j,z,y,m} + \theta Z_{h,y} + \sigma_{z,m} + \gamma_{y,q} + \lambda_h + \varepsilon_{h,z,y,m} \end{aligned} \tag{4}$$

where $Mod_{h,y}$ represent dummies respectively equal to zero for household-years with no head employed in an outdoor occupation, with no obese adult member, with no children, and with no AC use. These dummies are equal to one for household-years with at least one head employed in an outdoor occupation, with at least one obese adult member, with at least one child, and with AC use, respectively. Adult obesity is defined based on a body mass index (BMI) above 30, following international standards. Information on household mem-

[20] This includes the following occupation categories as listed in NielsenIQ Consumer Panel: foreman, carpenter, electrician, painter, plumber, exterminator, construction or road machine operator, mechanic, repairman, non-medical technician, utility lineman or serviceman, building inspector, factory machine operator, delivery man, driver for bus/taxi/truck, factory worker, transportation worker, member of the armed forces, farmer, construction worker, shipping worker, fisherman, gardener, and lumberman.

bers' height and weight used in estimating individuals' BMI is extracted from the NielsenIQ Annual Ailments, Health, and Wellness Survey, which is self-declared and complementary to the NielsenIQ Consumer Panel.[21] For AC use, we merge the U.S. Energy Information Administration (EIA) Residential Energy Consumption Survey 2005, 2009, and 2015 with the consumer panel data based on relevant demographic variables (Table E1). Particularly, we create 432 unique cells using U.S. Census regions (Northeast, Midwest, South, West), household area (urban or rural), household size (1, 2-3, or more), annual income (below USD 40K, 40-100K, above 100K), race (white, black, other non-white), and head age (below 55 or above). We obtain a mean AC use of 81.6% over the consumer panel sample, close to the U.S. nationwide average of 82-88% over the period 2005-2020.[22] Table E2 displays the prevalence of these four potential modifiers among the sample.

Table 4 reports the results of Equation 4 for sugary drinks. Employment in an outdoor occupation is associated with a higher effect of extreme heat days on household sugary drink purchases. Specifically, a day with a maximum temperature above 90°F leads to a 0.35% increase in the volume purchased of sugary drinks in the month among households with at least one head employed in an outdoor occupation compared to 0.26% for households without a head working outdoors. Outdoor workers are more exposed to extreme heat. Reducing sugary drink consumption has been highlighted as a preventive factor for heat-related illnesses among outdoor workers (El Khayat et al., 2022).

Households with at least one obese adult member also appear to drive the results. This is in line with recent findings that obese individuals may be more sensitive to heat stress (Speakman, 2018). However, these results are only based on the period 2016-2017 for which height and weight information is available from the NielsenIQ Annual Ailments, Health, and Wellness Survey. We find no differential impacts of extreme heat on bottled water purchases

[21]Information on household members' height and weight is only available for 2016 and 2017. BMI is defined as the body mass in kilograms divided by the square of the body height in meters.

[22]U.S. Energy Information Administration, *Nearly 90% of U.S. households used air conditioning in 2020* (Accessed 30 April 2024).

by outdoor occupation or adult member obesity status (Table E3). Outdoor workers and obese individuals may respond to their higher exposure or sensitivity to extreme heat by seeking energy from sugar or responding to cravings for sugar.

The demand for sugary drinks in households with children appears less reactive to heat shocks (Table 4). Such households may be more time constrained and may exhibit more consistent grocery shopping habits.[23] If accompanied with their children during grocery shopping, parents also tend to shop faster and avoid busy areas in-store (Page et al., 2018).

Finally, AC use has been documented as one of the most effective adaptation strategies to extreme heat. Barreca et al. (2016) shows that it has been responsible for most of the decline in heat-induced mortality in the U.S. since the 1960s. Nevertheless, we do not observe any statistically significant differential effects of extreme heat on the volume purchased of sugary drinks or bottled water by AC use (Table 4 and Table E3). This may be explained by the significant prevalence of car ownership,[24] the main mode of transportation in the country, with the majority of cars featuring AC, reducing exposure to extreme heat during transport to and from stores (Lee and Zheng, 2023).

4.4 Potential drivers

4.4.1 Changes in shopping habits

Temperatures may impact shopping habits, particularly the frequency of shopping trips as households may be most exposed to outdoor temperatures when travelling to stores. We find that the relationship between temperatures and the number of shopping trips in a month displays an inverse U-shaped curve, with both extremely low and high temperatures leading to fewer trips compared with the benchmark maximum temperature range of 40-80°F. Days with maximum temperatures below 30°F and over 90°F reduce the number of shopping

[23] According to responses by 900 American parents to a survey run by YouGov in 2023. Source: YouGov, *U.S.: Measuring kids' influence on parents' purchase decisions* (Accessed 30 April 2024).
[24] According to Forbes, 91.7% of American households owned at least one vehicle in 2022. Source: Forbes, *Car Ownership Statistics 2024* (Accessed 30 April 2024).

trips in the month by 0.16% and 0.05%, respectively (Table F1). Temperatures could also influence the choice of store type. Convenience stores tend to offer less healthy options and display a higher share of processed and industrialized items such as sugary drinks (Volpe et al., 2018). However, Table F1 does not show a significant difference in the relative impact of extreme temperatures on the number of trips in the month between convenience stores and other stores.[25]

The positive effect of extreme heat on the volume purchased is also similar across store types. A day above 90°F increases the volume purchased for sugary drinks and bottled water in the month by 0.32% and 0.56% in convenience stores and by 0.27% and 0.66% in other store types, respectively (Table F2).[26] However, when investigating the differential effect of extreme heat across store types by area, we find that sugary drink purchases from urban households increase proportionally across store types while rural households' purchases only increase in convenience stores (Table F3).

In line with Lee and Zheng (2023), these findings highlight that temperatures only marginally impact the likelihood of shopping trips. Regarding the impact on volume, the heat-induced increase in soft drink purchases is only driven by trips to convenience stores for rural households. Such stores may be located closer to households.

4.4.2 Inter-channel substitution

Extreme temperatures could also influence beverage sales in the unobserved on-trade sector (e.g., bars and restaurants) such that the observed increase in off-trade (e.g., grocery store) sugary drink purchases during heat events could be the result of substitutions from the on-trade sector, with no or limited impact on overall consumption. To test for this, we estimate

[25] Convenience stores also include bodegas, discount stores, liquor stores, service stations, small grocery stores, and tobacco stores.

[26] The distribution of the average monthly volume purchased per adult equivalent unit by store type in the sample is the following: 1,768.8 ml in convenience stores and 4,043.3 ml in other stores (sugary drinks); 556.5 ml in convenience stores and 1,771.5 ml in other stores (diet CSD); and 925.2 ml in convenience and 2,378.1 ml in other stores (bottled water).

the heterogeneous impact of extreme temperatures on soft drink purchases by counties' density of food and beverage establishments - a proxy for access to the on-trade sector. Establishment density is defined as the number of establishments by 1,000 inhabitants.[27] We do not evidence substitution from the on-trade to the off-trade sector. On the contrary, the coefficient on the interaction term between daily maximum temperature and the density of food and drink establishments is negative for days with a maximum temperature above 80°F. Particularly, the positive effect of a day with a maximum temperature in the range 80-90°F on sugary drink volume purchased is 32% lower for each additional establishment per 1,000 inhabitants (Table F4). Our main estimate of the effect of hot temperatures on the volume purchased of sugary drinks may thus be an underestimation of the true effect on total consumption (from both off- and on-trade) as increased consumption is also expected in food and drink establishments.

4.4.3 Price effect

Changes in soft drink volume purchased could be driven by temperature-induced variations in prices. From a standard supply-and-demand model, if the demand curve shifts to the right (e.g., temperature-induced shock leading to higher demand) while the (upward-slopping) supply curve remains fixed, prices are expected to increase. We test this hypothesis using the NielsenIQ Retail Scanner dataset for 2006-2019. This dataset contains store information and weekly prices and sales volume for each UPC with positive sales for over 30,000 stores (the exact number varies each year) from more than 90 retail chains across all U.S. markets. Only stores and UPCs with positive sales throughout the entire sample period are included in our beverage type-specific samples. We also drop stores alone in their county. The total sample size varies by beverage type, from 12,155 stores for fruit juice & drink to 15,353 stores

[27]Data sources: U.S. Census Bureau's *County Business Patterns* and the proxy North American Industry Classification System (NAICS) code 722 'Food services and drinking places', yearly; National Institutes of Health, National Cancer Institute, *U.S. County Population Data - 1969-2022*, yearly.

for regular CSD (Table F5).[28] We run the following multi-way panel fixed effect specification at the store level, clustering standard errors at the county level (Equation 5).[29]

$$\ln F_{s,c,y,m} = \alpha + \sum_{i} \beta_i T_{i,c,y,m} + \sum_{k} \sum_{j} \mu_{k,j} W_{k,j,c,y,m} + \sigma_{c,m} + \gamma_{y,q} + \lambda_s + \varepsilon_{s,c,y,m} \quad (5)$$

$F_{s,c,y,m}$ represents the Fisher price index calculated over all UPCs for store s in county c and month m of year y.[30] $\sigma_{c,m}$, $\gamma_{y,q}$, and λ_s represent county x month-of-the-year, year x quarter-of-the-year, and store fixed effects, respectively. Figure F1 shows the evolution of Fisher price indices by soft drink type over the sample period.

Results in Table 5 indicate that temperatures have only minor effects on soft drink retail prices. The effect of a day with a maximum temperature above 95°F is null or not statistically significant for regular CSD, fruit juice and drink, and bottled water. For diet CSD, swapping an average day with a maximum temperature between 65-70°F for a day with a maximum temperature above 95°F decreases the average retail price by 0.09% over the month. On the other hand, the impact of cold days on average monthly soft drink retail prices is mixed with days with a maximum temperature below 25°F increasing prices by 0.03% to 0.06% while days with a maximum temperature in the range 25-30°F decrease prices by 0.02% to 0.14%. Results are robust to the inclusion of lags (Figure F2).

In line with Lee and Zheng (2023) and Gagnon and López-Salido (2020), we observe limited retail price adjustments to extreme temperatures, unlikely to drive purchase responses for regular CSD, fruit juice and drink, and bottled water. On the other hand, the observed extreme heat-induced retail price decrease for diet CSD (-0.09%) is only 2.4 times lower

[28] All beverage-specific samples include at least one county in every State of the contiguous U.S. and the District of Columbia.

[29] The NielsenIQ Retail Scanner dataset does not include store-level projection factors, thus we perform unweighted regressions.

[30] $F_t = \sqrt{\frac{\sum p_t q_0}{\sum p_0 q_0} \times \frac{\sum p_t q_t}{\sum p_0 q_t}}$. Using January 2006 as the base period.

than the response in household volume purchased (-0.22%; see Section 4.1). Given that the demand for such beverages is elastic in the U.S., with a price elasticity estimated to lie between -1.29 and -1.91 (Zhen et al., 2011), extreme heat-induced retail price decreases may be driving the contemporaneous response in diet CSD purchases. However, while the positive effect of extreme heat days on diet CSD purchases is compensated over time (Figure D1), the impact on prices remains persistent after two months (Figure F2).

4.4.4 Psychological biases

Psychological biases may participate in explaining consumers' sensibility to high temperatures, particularly projection bias and salience (Busse et al., 2015; Liao, 2020). Projection bias states that consumers' predictions about future utility are overvalued for every future state of the world (Loewenstein et al., 2003). These biased predictions can be influenced by the current state (e.g., weather). In practice, this is evidenced by the ex-post realisation of a mistake, for example, by re-selling the convertible car bought on a sunny day in the following months with less clement weather (Busse et al., 2015). We rule out projection bias as a psychological channel driving the effect of extreme heat on sugary drink purchases as we find no evidence of harvesting effects. Indeed, heat-induced increased sugary drink purchases are most likely consumed and not stockpiled (Section 4.2), thus requiring to refill inventories in the following periods.

Salience, on the other hand, is the idea that consumers' attention may be systematically directed toward certain attributes of a good rather than others with disproportionate utility weights (Bordalo et al., 2013). It could be that the sweetness, refreshing, or comforting aspects represent such attributes for sugary drinks, which could become more salient during extreme heat days. It is hard to disentangle salience from projection bias as both channels are expected to lead to higher sugary drink purchases as a response to extreme heat. Nevertheless, Busse et al. (2015) note that salience predicts the effect of 'surprise' changes in temperatures relative to recent weather. Thus, we explore the differential effect between extreme heat days following a sudden increase in maximum temperature of at least 6°F from the previous day and other extreme heat days. The choice of 6°F is dictated by the rare occurrence of extreme heat days following day-on-day increases in maximum temperature for higher thresholds (Figure F3). Results in Figure F4 do not support the existence of salience as a mechanism explaining the temperature-sugary drink purchase relationship as day-on-day changes in maximum temperature above 90°F do not have a statistically significant impact on the purchase of sugary drinks. However, Figure F4 shows that salience may participate in explaining the impact of extreme heat on bottled water purchases. These findings are robust to the use of a higher day-on-day change in maximum temperature threshold of 9°F (Figure F5).

The effect of extreme heat on sugary drink purchases could also be driven by mood effects. Warmer days could be associated with a general higher propensity to spend on any good. Lee and Zheng (2023) and Lai et al. (2022) rule out this hypothesis as they find that extreme heat days reduce overall aggregate household spending. It could also be that a high maximum temperature is not the only driver of the effect of extreme heat days on sugary drink purchases. The nicer weather often associated with such days could also play a role (e.g., clear blue sky, more socializing). While we control for other weather variables in our main specification, including rain, a known mood shifter, we further test if the effect of extreme heat is moderated by precipitations. We find that swapping an average temperature day with a maximum temperature above 90°F and no rain increases monthly sugary drink purchases by 0.34%, while a similar day with rainfall only by 0.26% (Figure F6). These results suggest that mood effects may play a role in explaining, at least partially, the temperature-purchase relationship for sugary drinks.

5 Accounting for historical exposure

We explore whether accounting for individuals' historical exposure to extreme heat - proxied by zip code-level historical exposure - mitigates the positive impact of heat shocks on sugary drink purchases, potentially indicating adaptation to climate change. Previous literature has investigated heterogeneous impacts by historical exposure using interactions with historical time-of-year-specific normals (averages of climatic observations over a specific period) or standard deviations (Dell et al., 2014). However, Roth Tran (2023) notes that while some locations may have the same historical normals or standard deviations at different times of the year, their capacity to deal with an extreme temperature shock at these specific times may largely differ. For example, one colder location may have the same historical normal in the middle of the summer as a warmer location in the spring, but the warmer location may have more widespread AC and thus may be less reactive to an unusually hot day in the spring than the colder location for a similar unusually hot day in the middle of the summer. Instead, Roth Tran (2023) proposes to alleviate this concern by using the historical location-specific probability of an extreme temperature day (rather than both time-of-the-year- and location-specific).

We adopt Roth Tran (2023)'s specification in Equation 6, where $Pr(T_i)_z^{hist}$ represents the historical probability of a day falling into temperature bin T_i in zip code z. This probability is derived from the past 30-year weather history (1974-2003) extracted from the U.S. NOAA Global Historical Climatology Network database.[31]

$$\begin{aligned} V_{h,z,y,m} = \alpha + \sum_i \left[\phi_{1,i} T_{i,z,y,m} + \phi_{2,i} Pr_z(T_i)^{hist} \times T_{i,z,y,m}\right] + \sum_k \sum_j \mu_{k,j} W_{k,j,z,y,m} \\ + \theta Z_{h,y} + \sigma_{z,m} + \gamma_{y,q} + \lambda_h + \varepsilon_{h,z,y,m} \end{aligned} \tag{6}$$

[31]See Table B3 for summary statistics. We do not include the terms $Pr_z(T_i)^{hist}$ on their own in this specification given that they are constant for each zip code and thus collinear with household fixed effects.

where $\phi_{2,i}$ captures the mitigating effect of past exposure. When $\phi_{1,i}$ and $\phi_{2,i}$ have opposite signs, the relative effect of one extra day belonging to temperature bin T_i on purchases decreases (in absolute value) as $Pr_z(T_i)^{hist}$ increases.

Aligned with the limited heterogeneous effects across climate regions (see Section 4.3), we find no evidence to support the hypothesis that higher historical exposure reduces the contemporaneous impact of extreme heat on sugary drink purchases. Although the coefficient on the interaction terms between historical zip code-specific probabilities and temperature bins are positive for hot temperature days, they are non-statistically significant, thus also ruling out potential habit formation behaviours (Table 6). On the other hand, higher historical exposure reduces the contemporaneous effect of extreme heat on bottled water purchases. A 10 percentage point increase in the historical zip code-specific likelihood of experiencing a day with a maximum temperature above 90°F reduces the contemporaneous impact of such a day on bottled water purchases by approximately 15% (Table 6).[32]

Overall, this suggests that while the frequency and intensity of extreme heat events are expected to increase due to climate change, increased expectation or experience of such events may reduce their impact on bottled water purchases over time, but not on sugary drink purchases.

6 Climate projections

We estimate a forecast of possible changes in sugary drink purchases due to climate change between 2080-2099 and our historical sample 2004-2019 for each county. For this, we couple our estimates of the effect of maximum temperature on sugary drink purchases with

[32]Calculated as follows: $-0.0122 \times 0.1 \div 0.0081 = -15.1\%$ based on column 5 in Table 6.

county-level daily maximum temperature and precipitation projections, which are drawn from Rasmussen et al. (2016)'s probability-weighted ensemble models. These are obtained from downscaling the 21 general circulation models from the IPCC Coupled Model Intercomparison Project phase 5 (CMIP5),[33] and constructing an additional surrogate model for each CMIP5 model mirroring their spatiotemporal probabilistic distribution including tail estimates to better represent weather extremes. We specifically use projections associated with two greenhouse gas (GHG) emission scenarios or representative concentration pathways (RCP) as adopted by the Fifth Assessment Report of the IPCC: *RCP 4.5* - an intermediate scenario with GHG emissions starting to decline by 2045 thus assuming the adoption of mitigation strategies; and *RCP 8.5* - the worst-case or business-as-usual scenario with GHG emissions continuing to rise until the end of the century. These two scenarios are useful in order to incorporate future climate uncertainty into our projected impact estimations (Burke et al., 2015a). As in Hsiang et al. (2017), we produce our simulation results under each RCP using the probability-weighted average daily maximum temperature and precipitation projections across the multi-model ensemble provided by Rasmussen et al. (2016), including both the 21 CMIP5 models and their respective surrogate models.

Figure G1 presents the average number of days per year in each maximum temperature bin across sample counties for the period 2004-2019 and by climate scenario for the period 2080-2099. Across the counties in our sample, the average number of days per year with a maximum temperature above 35°C (or 95°F) was 10.8 over the period 2004-2019 and is expected to increase to 38.6 under RCP 4.5 and 72.1 under RCP 8.5 over the period 2080-2099. The average number of days in the bin $[32, 35)$C (or $\approx [90, 95)$F) is also expected to increase under both RCP scenarios. On the other hand and as a consequence, the average

[33]Climate projections from CMIP5 models have been used extensively in the economics literature to project changes in outcomes to the end of the century (Carleton et al., 2022; Lai et al., 2022; Folini et al., 2021), often by equally weighting the ensemble of CMIP5 models (e.g., taking the median across the 21 models for each daily projection).

number of days per year in all other (colder) bins is expected to decrease.[34]

Roth Tran (2023) and Lai et al. (2022) has highlighted the importance of accounting for adaptation in projecting the impact of climate change on consumer behaviour. Given that we did not identify significant effects on the interaction terms accounting for historical exposure to temperature extremes for sugary drink purchases (Table 6), we estimate the effects of future temperatures under three different specifications: one omitting historical exposure and adaptation in line with our previous findings, one accounting for historical exposure but not for adaptation, and one considering both historical exposure and adaptation to illustrate its limited role in our context. For the latter, we follow Lai et al. (2022) by using two different 30-year baselines for past exposure, either 1974-2003 or 2050-2079. In effect, increased historical exposure is used to proxy long-run adaptation which could reflect unobserved adaptation investments or learning effects related to the intensity of past exposure (Dell et al., 2014). Formally, we estimate the following three projected county-level relative changes in average monthly purchases between the years 2080-2099 compared to our baseline results in 2004-2019:

$$\Delta\hat{V}_c^{\text{NH,NA}} = f(\Delta\bar{T}_c; \hat{\beta}) \tag{7}$$

$$\Delta\hat{V}_c^{\text{H,NA}} = g(\Delta\bar{T}_c, Pr_c(T)^{1974-2003}; \hat{\phi}) \tag{8}$$

$$\Delta\hat{V}_c^{\text{H,A}} = g(\Delta\bar{T}_c, Pr_c(T)^{2050-2079}; \hat{\phi}) \tag{9}$$

where $f(\Delta\bar{T}_c; \beta) = \sum_i \beta_i \times \Delta\bar{T_{i,c}}$ and $g(\Delta\bar{T}_c, Pr_c(T)^P; \phi) = \sum_i(\phi_{1,i} \times \Delta\bar{T}_{i,c} + \phi_{2,i} \times Pr_c(T_i)^P \times \Delta\bar{T}_{i,c})$. $\hat{\beta}_i$ are estimated using Equation 1 and $\hat{\phi}_{1,i}$ and $\hat{\phi}_{2,i}$ are estimated using Equation 6 over the years 2004-2019 and the historical probabilities from 1974-2003. Es-

[34] Rasmussen et al. (2016)'s projections are provided as the number of days per year in bins of 1°C length at the county level. Thus, we transform our main Fahrenheit maximum temperature bins into equivalent Celcius maximum temperature bins. We then estimate county-level baseline maximum temperature for the period 2004-2019 using a population-weighted average of zip code maximum temperature. Source for zip code level population data: U.S. Census Bureau, *Demographic and Housing Characteristics*, 2020.

timates are reported in Table G1. $\Delta\bar{T}_{i,c} = \bar{T}_{i,c}^{2080-2099} - \bar{T}_{i,c}^{2004-2019}$ represent the change in average number of days per month in maximum temperature bin i in county c between the periods 2004-2019 and 2080-2099. $Pr_c(T_i)^P$ represents the probability of the occurrence of a day with maximum temperature belonging to bin i in county c over the 30-year period P, defined either as 1974-2003 or 2050-2079. $\Delta\hat{V}_c^{NH,NA}$, $\Delta\hat{V}_c^{H,NA}$, and $\Delta\hat{V}_c^{H,A}$ represent the estimated average relative change in monthly volume purchased in 2080-2099 relative to 2004-2019 in county c not accounting for historical exposure or adaptation (*NH,NA*), accounting for historical exposure but not adaptation (*H,NA*), and accounting for both historical exposure and adaptation (*H,A*), respectively. These county-level estimates are then averaged at the national level and by climate region.[35] A lower $\Delta\hat{V}^{H,A}$ than $\Delta\hat{V}^{H,NA}$ would be consistent with long-run adaptation based on increased historical exposure.

Figure 5 presents the projected changes in sugary drink purchases by 2080-2099. Accounting for historical exposure or adaptation widens the size of the confidence intervals but does not materially impact the point estimates. This is in line with the results from Table 6, where the coefficients on the interactions between maximum temperature bins and their historical probability are small, non-negative, and non-statistically significant for extreme heat. Our preferred specification is thus Equation 7 which does not account for historical exposure or adaptation ($\Delta\hat{V}^{\mathrm{NH,NA}}$). At the national level, monthly average sugary drink purchases is projected to increase by 0.73% under RCP 4.5 and 1.44% under RCP 8.5. For the average household in our sample, this is equivalent to an additional 39 ml and 77 ml per adult equivalent unit per month under the two different climate scenarios, respectively. Assuming an average of 10 grams (g) of sugar per 100 ml for sugary drinks,[36] this translates to an

[35]Population-weighted average across sample counties. Source: National Institutes of Health, National Cancer Institute, *U.S. County Population Data - 1969-2022*, 2019.

[36]Based on the sugar content of the most sold brand of regular CSD, fruit juice, and fruit drink: Coca-Cola (11.4g/100ml), Tropicana Pure Premium (8.4g/100ml), and Snapple fruit punch (9.2g/100ml). Sources: Statista, *Volume share of the leading CSD brands in the U.S. 2022*; Statista, *Leading brands of refrigerated orange juice in the United States 2023*; and Zippia, *The 10 largest juice brands in the United States* (Accessed 20 April 2024). Sugar content information is obtained directly from the respective websites of the aforementioned brands.

additional 3.9 g (under RCP 4.5) and 7.7 g (under RCP 8.5) of sugar per adult equivalent unit per month for the average household, equivalent roughly to 1-2 sugar cubes. For the 90th percentile household buyer of sugary drinks with an average of 14,550 ml purchased per month per adult equivalent unit, these changes in climatic conditions represent an additional 106 ml (under RCP 4.5) and 210 ml (under RCP 8.5), equivalent to 10.6 g and 21.0 g of sugar per adult equivalent unit per month (or 2.5-5 sugar cubes), respectively. These projected changes are driven by increased purchases due to more days with a maximum temperature above 90°F outweighed by decreased purchases due to fewer days with a maximum temperature between 80°F and 90°F. Figure 5 also highlights the heterogeneity in projections by climate region, showing higher relative changes in purchases in hotter regions compared to colder ones (0.81% vs. 0.68% for RCP 4.5 and 1.54% vs. 1.35% for RCP 8.5, respectively).

Figure G2 presents the results for bottled water. Without accounting for historical exposure or adaptation, the estimated average relative change in the volume purchased of bottled water between 2004-2019 and 2080-2099 is +1.98% under RCP 4.5 and +3.86% under RCP 8.5. However, in line with results from Table 6, after accounting for adaptation through increased exposure, the positive impact of future higher temperatures is reduced to +1.67% under RCP 4.5 and +3.05% under RCP 8.5. Thus, our preferred specification for bottled water is Equation 9, accounting for both historical exposure and adaptation ($\Delta\hat{V}^{\mathrm{H,A}}$). The mitigating impact of adaptation is stronger in regions with hotter climates where the relative increase in purchases is expected to be more moderate (non-statistically significant +1.16% and +1.97% for hotter climate regions, under RCP 4.5 and RCP 8.5, respectively).

Our projections focus solely on the impact of future changes in climatic conditions, all else equal. They are robust to using the median across Rasmussen et al. (2016)'s model ensemble rather than the probability-weighted average (Figure G3). They are also robust to accounting for projected changes in precipitations (Figure G4) and to the use of a richer model including more maximum temperature bins (Table G2 and Figure G5).

7 Discussion

Extreme heat affects purchasing behaviour. While previous research has shown that it reduces aggregate household consumption (Lee and Zheng, 2023; Lai et al., 2022), our findings exhibit a distinct impact on dietary behaviour, specifically on soft drink consumption. Extreme heat causes a persistent increase in sugary drink purchases, driven by an intensive margin effect. On the other hand, the immediate positive effect of extreme heat on the purchase of diet drinks, which contain non-caloric artificial sweeteners, is offset over time when accounting for inter-temporal shifts in purchases. These patterns lead us to believe that the additional sugary drink purchases induced by extreme heat may be consumed during temperature peaks, while diet drinks may be at least partially stockpiled during heat shocks such that we observe a drop in purchases of diet drinks in the following periods. In contrast, the likely immediate consumption of sugary drinks necessitates refilling the inventory in the following periods.

We explore heterogeneous effects and potential modifiers. First, the main effect of extreme heat on sugary drink purchases is driven by urban households, which tend to be located closer to any type of store than rural households and may experience higher exposure due to heat island effects.[37] In rural areas, the positive effect on purchases is only statistically significant in convenience stores, which tend to be located closer to homes and feature a higher share of unhealthy beverage options (Volpe et al., 2018). Second, we find that the likelihood of using AC does not moderate the effect of extreme heat on sugary drink purchases despite moderating their direct negative impact on health outcomes (Barreca et al., 2016). Third, we also find that the extreme heat sensitivity of sugary drink purchases is similar between households with and without children. This result is significant given the high levels of sugary drink intake among children and childhood obesity in the U.S. (Han

[37] Across the 44 most populated U.S. cities, about 55% of the population lives in census tracts with an Urban Heat Index over 8°F — meaning that people in those census tracts feel at least 8°F more heat because of the local built environment. Source: Climate Central. *Urban heat hot spots*, 2023.

and Powell, 2013). Fourth, having an outdoor occupation exacerbates the impact of extreme heat on sugary drink purchases. Finally, we find that the demand for sugary drinks is more sensitive to extreme heat in households with at least one obese adult member. These findings suggest that the potential negative public health impact of extreme heat on diets through increased sugary drink intake may be concentrated among the most exposed and vulnerable households.

We investigate several mechanisms that could explain our results. First, we explore shopping and consumption habits and only observe a limited negative impact of extreme heat on the likelihood of a shopping trip. We also find no evidence of inter-channel substitutions from out-of-home food and drink establishments. Second, we investigate whether the supply side could influence shopping behaviours by modifying prices according to the weather. Consistent with previous studies (Lee and Zheng, 2023; Gagnon and López-Salido, 2020), we detect only minor non-statistically significant temperature-induced price adjustments by retailers, which could not explain our results. Third, we consider whether extreme heat-induced increases in sugary drink purchases could be driven by psychological mechanisms. From a physiological perspective, one would predict extreme heat to increase only water consumption to fulfil hydration needs but no changes in sugary drink intake. We investigate three potential psychological biases that could explain departures from the physiological channel: salience, projection bias, and mood swings. Significant sudden increases in temperatures have been linked to salience, which may underlie the impact of extreme heat on impulsive purchase decisions, such as those for convertible cars and AC (Busse et al., 2015; He et al., 2022). However, our results do not support such a mechanism for sugary drinks. We also rule out projection bias given that we do not observe any harvesting effect or stockpiling of sugary drinks following extreme heat shocks. Nevertheless, we find evidence of a mood effect with precipitations playing a minor moderating role in the impact of extreme heat on sugary drink purchases. Present bias is another psychological mechanism that could explain our main effect. Consumers may overweight the value they place on immediate consumption, leading to biased maximization of inter-temporal utility (Laibson, 1997; O'Donoghue and Rabin, 1999). They may poorly anticipate or internalise the potential future negative health effects associated with sugary drink intake and may respond to immediate cravings and seek short-term pleasures (Allcott et al., 2019b). Irrational inter-temporal trade-offs can be triggered by environmental cues (Ruhm, 2012). We find that the positive effect of extreme heat on sugary drink purchases is higher among households with obese adult members. Higher body weight has been found associated with present bias preferences and the lack of self-control in general (Courtemanche et al., 2015; Stoklosa et al., 2018). In summary, mood swings and present bias could represent psychological mechanisms behind our results.

There are potential caveats to our analysis. First, we are only capturing households' self-scanned purchases and assume these are distributed evenly between adults and based on the adult equivalent scale for adolescents and children within all households. However, we cannot verify if these purchases are shared with guests, nor can we observe actual individual consumption. Second, while home-scan panel data capture purchase trends reasonably well, purchases are typically under-reported (Leicester and Oldfield, 2009). Soft drinks may not make it home to be scanned if they are consumed beforehand. If the level of under-reporting remains constant between mild temperature days and extreme temperature shocks, we would be accurately estimating the relative change in purchases. However, if extreme heat drives under-reporting, our estimate would represent a lower bound of its effect on purchases.[38] While home-scan panel data remains the best data source for this type of analysis, it is important to acknowledge their limitations. Third, we cannot fully disentangle between demand and supply response effects beyond price adjustments. Retailers may use marketing campaigns and in-store product placement to encourage the consumption of specific products during temperature peaks. Fourth, we only control for a limited number of potentially

[38]To assess this risk, we perform a similar specification as Equation 1 but using the NielsenIQ Retail Scanner dataset and find consistent results for retail sales, alleviating our concerns regarding selective under-reporting in the consumer panel. Results are available from the authors upon request.

confounding environmental factors. Others, such as air pollution have been found to impact obesity (Deschenes et al., 2020). Nevertheless, evidence of the direct effect of air pollution on off-trade food purchasing behaviours is limited (Fan et al., 2022). Furthermore, it is not clear which dimensions of air pollution should be controlled for (e.g., gases, particulate matters) and certain pollutants are correlated with some weather variables, which poses the challenge of disentangling their interactions (Buckley et al., 2014). Finally, our analysis disregards the income effect of extreme heat as a driver of the main effects. We assume that short-term temperature hikes do not increase household income and thereby spending on soft drinks. On the contrary, the long-term higher occurrences of extreme heat have been found to negatively impact labour supply and household income (Neidell et al., 2021; Deryugina and Hsiang, 2014; Jessoe et al., 2018), but this is not identified in our adaptation analysis.

There is a concern that our main specification, which aggregates purchase data at the monthly level, may underestimate the impact of daily temperature extremes. We favoured a monthly analysis for two main reasons. First, unlike previous studies of the impact of extreme temperatures on aggregate household consumption (Lee and Zheng, 2023; Lai et al., 2022), we examine the purchase of specific items. Soft drinks can typically be stored and do not require the same frequency of purchase as other food items, such as fresh food, do. Thus, our monthly aggregation minimizes zero-purchase household-month observations and is more representative of purchasing patterns.[39] Second, we want to reduce the noise caused by autocorrelation in daily maximum temperature. Figure A2 shows a 95% correlation between daily maximum temperature and its one-day lag. Previous studies have aggregated data at the weekly or 10-day level to address this issue (Lee and Zheng, 2023; Lai et al., 2022). However, the autocorrelation remains high after these short periods (84% after seven

[39] On average across the sample, a household takes 108 trips to stores per year. Most of these trips do not involve purchasing soft drinks. We still observe significant censoring at zero even after aggregating the data at the monthly level. Figure A3 shows that the average number of months per year per household with at least one positive purchase is as low as four for bottled water and up to seven for fruit juice & drink. This supports the use of a Poisson pseudo-maximum likelihood regression approach on monthly data.

days, 82% after 10 days).

Our analysis cannot draw conclusions on the projected overall effect of additional sugary drink purchases on body weight. To assess its impact on the average weight of the population, one would need to consider, at a minimum, the impact of extreme temperatures on individuals' overall diets and physical activity levels. The identified average increase in Americans' caloric intake from sugary drinks could potentially be offset by a climate-induced reduction in overall intake from other sources or by an increase in physical activity. Climate change is likely to increase net physical activity levels in colder months and regions of the U.S., but the opposite is expected for summer months, especially in hotter regions (Obradovich and Fowler, 2017). We consider this limitation as an important question for future research.

Nevertheless, we take the view that the projected climate-induced increase in sugary drink purchases is likely to have a negative overall impact on diets and should be seen as a public health concern. These beverages represent empty calories with little to no nutritional value[40] and constitute the largest source of added sugar intake in Americans' diets. Increases in sugary drink intake could, at best, be neutralized if offset by a reduction in other sugary intakes rather than a reduction in calories from nutritious foods. This projected increase also goes against the recent decline in sugary drink intake and the positive effects of public health policies such as local soda taxes (Welsh et al., 2011; Ricciuto et al., 2022).

Our analysis has societal implications. Americans' poor dietary patterns are threatening both health and environmental sustainability (Willett et al., 2019; Crippa et al., 2021). Amidst climate change and the expected increase in the frequency of extreme heat events, this paper is the first to highlight their impact on dietary behaviour. Using climate model predictions under two GHG emission scenarios, we project a rise in sugary drink purchases by the end of the century of 0.73% to 1.44% compared to 2004-2019 levels. We find no

[40]Except 100% fruit juices. However, while they often contain healthful nutrients like vitamins and minerals, their consumption should also be limited as they contain just as much sugar and calories as regular CSD.

evidence of adaptation based on increased historical exposure to extreme heat. Historically hotter areas as well as more exposed and vulnerable households, such as those with members working outdoors or being obese, may see stronger increases in sugary drink purchases. Our findings contribute to informing policymaking aimed at promoting healthier diets under climate change, particularly in settings grappling with an obesity epidemic.

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Figures

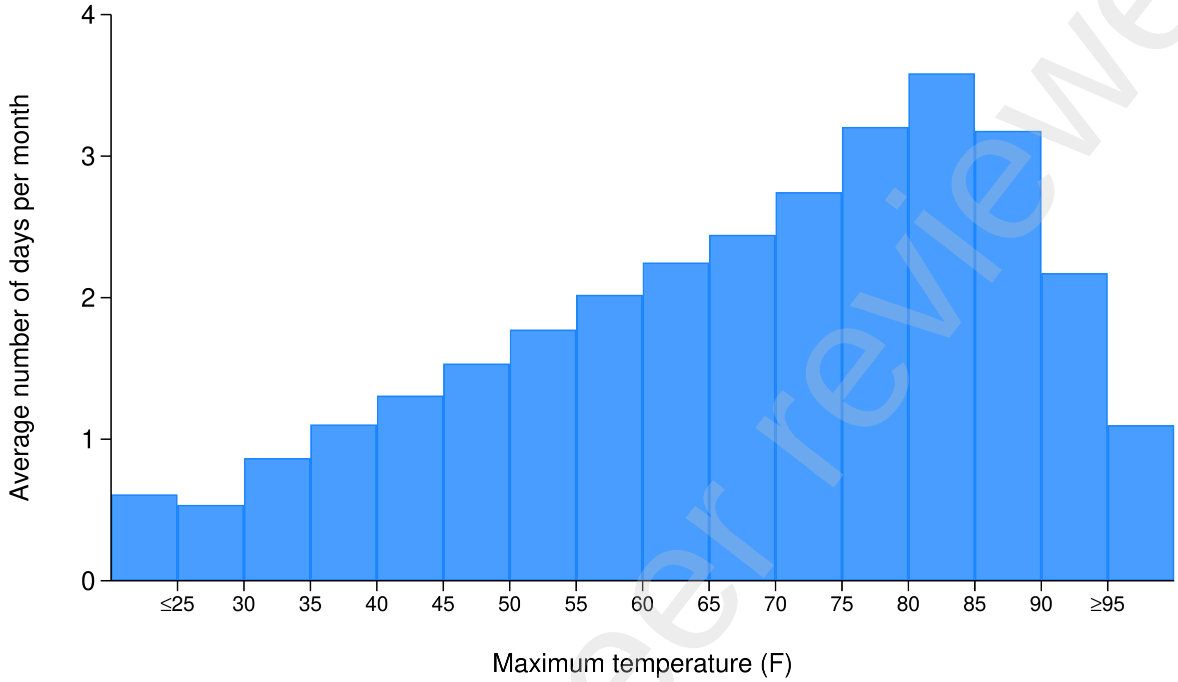

Figure 1. **Monthly distribution of daily maximum temperature, 2004-2019.** $N = 5,834,433$ household-month observations. F: Fahrenheit.
Back to Section 2.

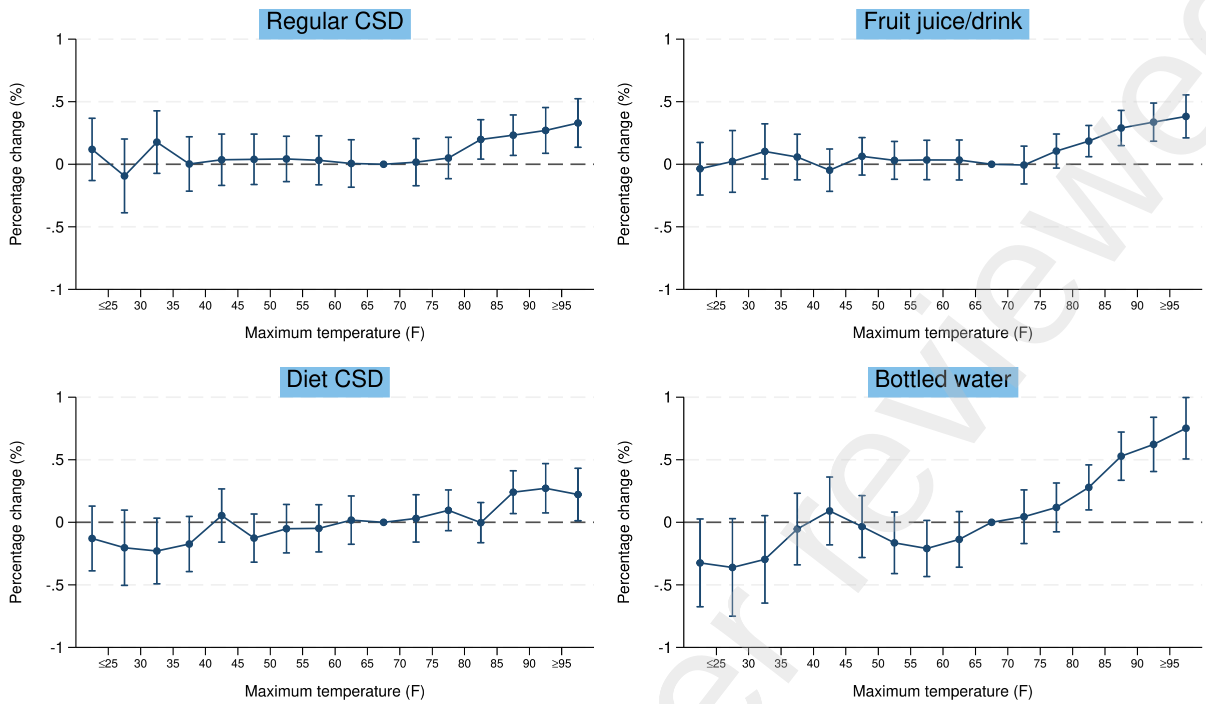

Figure 2. **The average effect of daily maximum temperature on monthly soft drink volume purchased, by soft drink type.** This figure shows results from regressing the specification in Equation 1 estimated via Poisson pseudo-maximum likelihood. Vertical segments show the 95% confidence interval. The reference maximum temperature bin is (65-70)F. Projection factors are used. Robust standard errors are clustered at the zip code level. CSD: carbonated soft drink. F: Fahrenheit. Table C1 shows the same results in table format.
Back to Section 4.1.

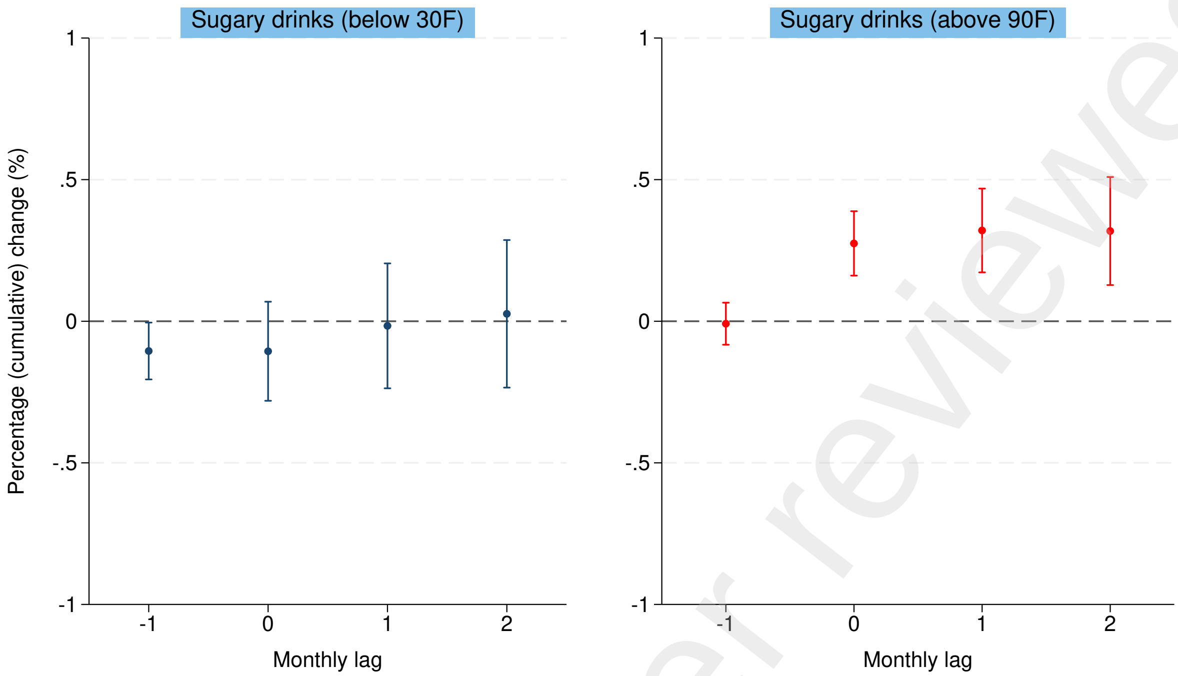

Figure 3. **The cumulative effect of daily maximum temperature below 30°F and above 90°F on monthly sugary drink volume.** This figure shows results from regressing the specification in Equation 3 for days with a maximum temperature (a) below ≤ 30°F and (b) above ≥ 90°F, via Poisson pseudo-maximum likelihood. Plot represents the cumulative effect $\sum_{t=-1}^{2} \hat{\beta}_{i,m-t}$. The reference maximum temperature bin is (40-80)F. As a matter of space, we do not present the results for the bins $(30, 40]$F and $[70, 80)$F, but these bins are included in the regression. Vertical segments show the 95% confidence interval. Projection factors are used. Robust standard errors are clustered at the zip code level. F: Fahrenheit. Back to Section 4.2.

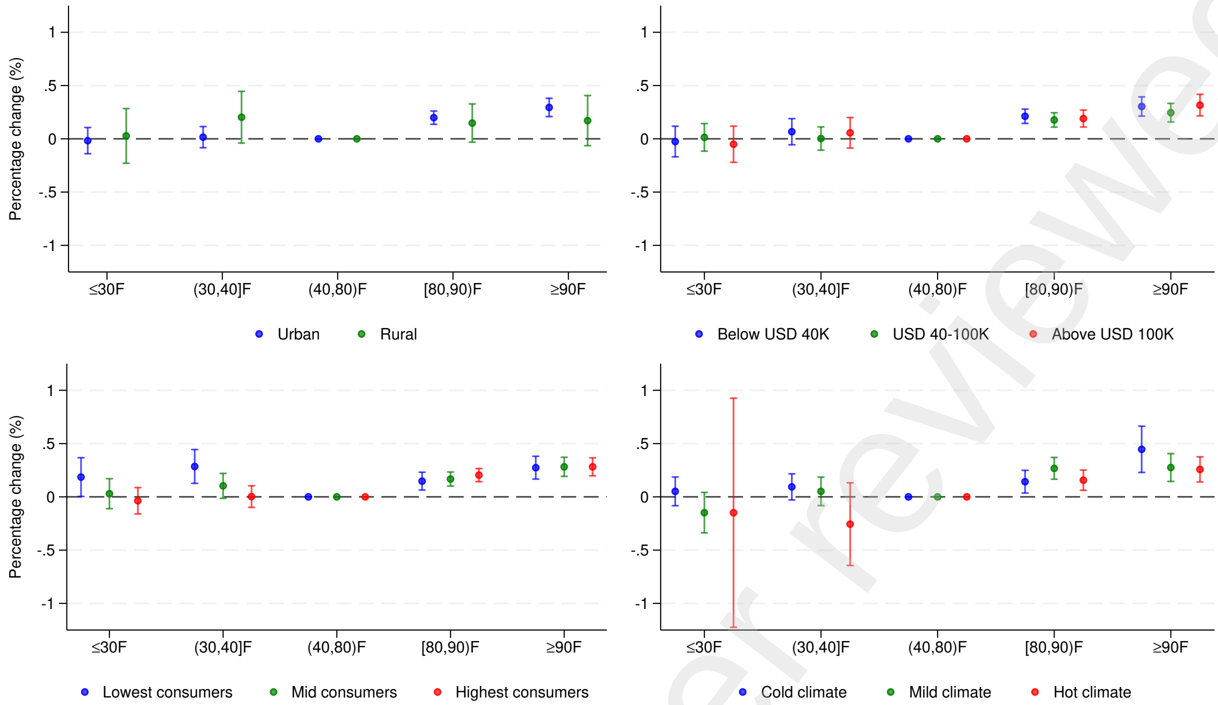

Figure 4. **The average effect of daily maximum temperature on monthly sugary drink volume purchased, by annual household income, area, intensity of consumption, and climate region.** This figure displays results from regressing the specification in Equation 1 interacting each temperature bin with two types of county areas (urban, rural; source: U.S. Census Bureau, 2010), three household annual income levels (below USD 40K, between USD 40-100K, above USD 100K), three intensity of consumption levels (based on terciles of yearly total volume per adult equivalent unit), and three climate regions (based on terciles of average zip code maximum temperature over the period 1974-2003), via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (40-80)F. Projection factors are used. Vertical segments show the 95% confidence interval. Robust standard errors are clustered at the zip code level. F: Fahrenheit. USD: U.S. dollars, base 2015.
Back to Section 4.3.

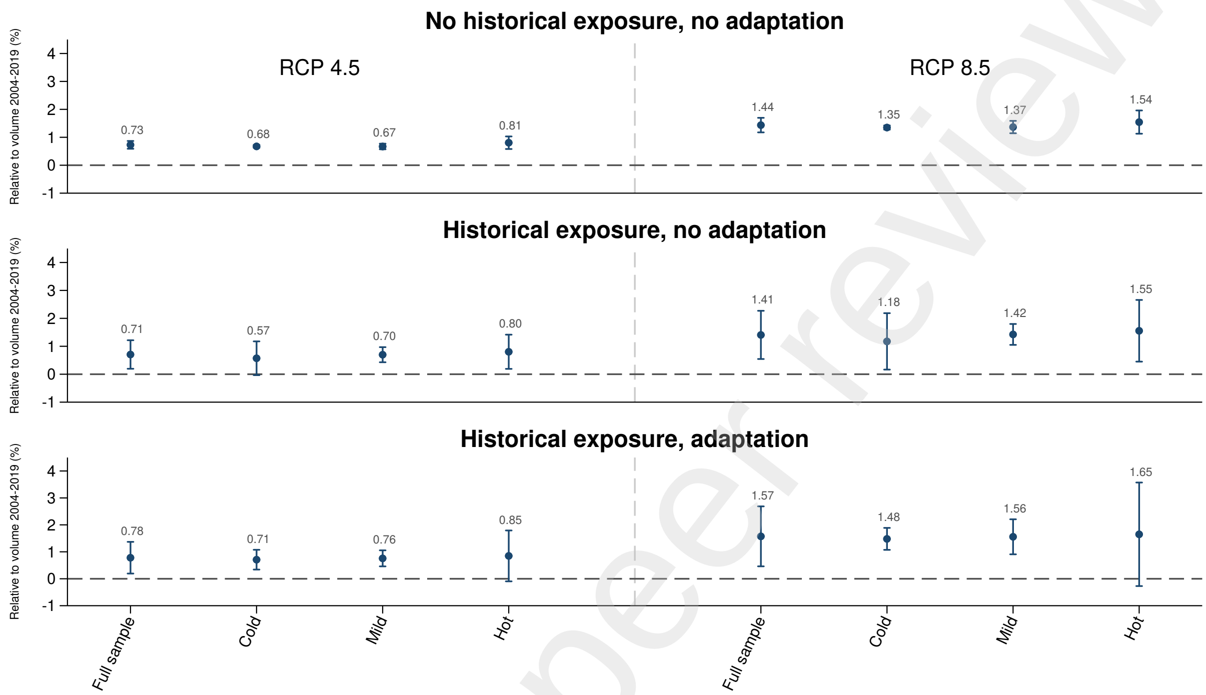

Figure 5. **Average relative change in the volume purchased of sugary drink from climate projections by climate region, with and without accounting for historical exposure and adaptation, from 2004-2019 to 2080-2099.** This figure shows the relative effect of changes in maximum temperatures on sugary drink volume purchased in 2080-2099 relative to 2004-2019 derived from Equation 7 ($\Delta\hat{V}^{NH,NA}$; no historical exposure, no adaptation), Equation 8 ($\Delta\hat{V}^{H,NA}$; historical exposure, no adaptation), and Equation 9 ($\Delta\hat{V}^{H,A}$; historical exposure, adaptation). Population-weighted average across sample counties (source: National Institutes of Health, National Cancer Institute, U.S. county population data, 2019). Results are shown for the national aggregate and for three climate regions under two greenhouse gas emission scenarios, RCP 4.5 and RCP 8.5. The hot, mild, and cold regions include sample counties within three terciles of average maximum temperature over the period 1974-2003. Maximum temperature predictions are derived from county-level probability-weighted averages across the multi-model ensemble from Rasmussen et al. (2016). Vertical segments show the 95% confidence intervals.

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Tables

	mean	sd	min	max
Regular CSD	3,081.5	27.2	0.0	481,929.8
Fruit juice/drink	2,328.0	14.5	0.0	221,564.7
Diet CSD	2,730.6	31.2	0.0	531,772.9
Bottled water	3,303.3	33.0	0.0	494,483.7

Table 1. **Monthly soft drink volume purchased per adult equivalent unit, in millilitres, 2004-2019.** $N = 5,834,433$ household-month observations. We use the following adult equivalent unit scale: 0.77 for children < 5 years old; 0.80 for children 6-12 years old, 0.88 for 13-18 years old; Source: Food and Agriculture Organization of the United Nations, Human Energy Requirements, Report of a Joint FAO/WHO/UNU Expert Consultation: Rome, 17-24 October 2001. Projection factors are used. CSD: carbonated soft drink. sd: standard deviation.
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	mean	sd	min	max
Max temperature (F)	67.6	19.5	-22.2	122.3
Min temperature (F)	47.2	18.1	-44.4	95.0
Mean temperature (F)	57.4	18.5	-30.7	106.6
Precipitations (mm)	2.9	7.5	0.0	537.9
Snowfall (mm)	1.7	12.1	0.0	798.3
Wind speed (m/s)	3.2	1.6	0.0	44.9

Table 2. **Daily weather characteristics at zip code level, 2004-2019.** $N = 45,296,720$ zip code-day observations. sd: standard deviation; F: Fahrenheit; mm: millimeters; m/s: meter per second.
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	Absolute change	Relative change	Extensive margin	Intensive margin
≤ 25F	0.8359	0.0005	-0.0002	0.0002
	(4.7384)	(0.0009)	(0.0003)	(0.0008)
$(25, 30]$F	-6.0748	-0.0007	-0.0000	-0.0007
	(5.7189)	(0.0011)	(0.0003)	(0.0009)
$(30, 35]$F	3.8953	0.0014	-0.0001	0.0013*
	(4.8415)	(0.0009)	(0.0003)	(0.0008)
$(35, 40]$F	-0.8629	0.0002	-0.0005**	-0.0001
	(4.1061)	(0.0008)	(0.0002)	(0.0007)
$(40, 45]$F	-2.4834	-0.0001	-0.0001	0.0006
	(3.9111)	(0.0007)	(0.0002)	(0.0006)
$(45, 50]$F	1.7317	0.0005	-0.0003	0.0000
	(3.6203)	(0.0007)	(0.0002)	(0.0006)
$(50, 55]$F	1.2354	0.0003	-0.0002	0.0005
	(3.3680)	(0.0007)	(0.0002)	(0.0006)
$[80, 85)$F	9.9490***	0.0018***	-0.0001	0.0017***
	(2.9953)	(0.0006)	(0.0002)	(0.0005)
$[85, 90)$F	13.9259***	0.0025***	-0.0000	0.0019***
	(3.2018)	(0.0006)	(0.0002)	(0.0005)
$[90, 95)$F	16.3390***	0.0029***	0.0001	0.0026***
	(3.6295)	(0.0007)	(0.0002)	(0.0006)
≥ 95F	20.1970***	0.0034***	0.0002	0.0026***
	(3.9804)	(0.0007)	(0.0002)	(0.0006)
N	5834298	5820876	5834298	4291365
Weather controls	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Model	OLS	PPML	OLS	Log-OLS

Table 3. **The average effect of daily maximum temperature on monthly sugary drink volume purchased per adult equivalent unit.** This table shows the results of (1) the main specification in Equation 1 using ordinary least squares (OLS) in levels as absolute change, (2) using Poisson pseudo-maximum likelihood (PPML) as relative change, (3) using a dummy for positive purchase as the dependent variable via OLS as incidence or extensive margin, and (4) using log-transformed volume conditional on purchase as the dependent variable via OLS as intensive margin. The reference maximum temperature bin is (65-70)F. As a matter of space, we do not present the results for the bins $(55, 60]$F, $(60, 65]$F, $[70, 75)$F, and $[75, 80)$F, but these bins are included in the regression. Projection factors are used. Robust standard errors are clustered at the zip code level. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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	Outdoor	Obese	Children	AC use
$\leq$ 30F	-0.0003	-0.0024	-0.0004	-0.0008
	(0.0006)	(0.0044)	(0.0006)	(0.0016)
$\leq$ 30F$\times$ Mod	0.0007	-0.0004	0.0012**	0.0007
	(0.0006)	(0.0029)	(0.0006)	(0.0016)
$[30, 40)$F	0.0003	-0.0001	0.0005	0.0017
	(0.0005)	(0.0029)	(0.0005)	(0.0012)
$[30, 40)$F$\times$ Mod	0.0003	0.0018	-0.0003	-0.0015
	(0.0006)	(0.0024)	(0.0006)	(0.0012)
$(80, 90]$F	0.0018***	0.0008	0.0022***	0.0014**
	(0.0003)	(0.0015)	(0.0003)	(0.0006)
$(80, 90]$F$\times$ Mod	0.0005	-0.0001	-0.0009***	0.0007
	(0.0003)	(0.0008)	(0.0002)	(0.0006)
$\geq$ 90F	0.0026***	0.0005	0.0031***	0.0019***
	(0.0004)	(0.0023)	(0.0004)	(0.0007)
$\geq$ 90F$\times$ Mod	0.0009***	0.0030**	-0.0010***	0.0012*
	(0.0003)	(0.0014)	(0.0003)	(0.0006)
N	5820876	448145	5820876	5820876
pseudo R^2	0.562	0.734	0.563	0.562
Weather controls	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Table 4. **Interaction effects between maximum temperature and potential modifiers of the effect on the monthly volume purchased of sugary drinks.** This table displays results from regressing the specification in Equation 4 estimated via Poisson pseudo-maximum likelihood. Mod represents outdoor (column 1), obese (column 2), children (column 3), and AC use (column 4). Outdoor equals 1 for years in which at least one household head has an outdoor occupation. Obese equals 1 for years in which at least one adult household member is obese (based on a body mass index above 30 as estimated from self declared height and weight information, only provided for 2016-2017). Children equals 1 for years in which at least one household member is a child. AC use equals 1 for years in which the household used AC. Source for height and weight information: NielsenIQ Annual Ailments, Health, and Wellness Survey. Source for AC use data: U.S. Energy Information Administration Residential Energy Consumption Survey 2005, 2009, and 2015 matched on demographics (see Table E1). The reference maximum temperature bin is (40-80)F. Projection factors are used. Robust standard errors are clustered at the zip code level. AC: air conditioning. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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	Regular CSD	Fruit juice/drink	Diet CSD	Bottled water
$\leq$ 25F	1.0003*	1.0004**	1.0003	1.0006
	(0.0002)	(0.0002)	(0.0002)	(0.0005)
$(25, 30]$F	0.9993***	0.9998	0.9986***	0.9998
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
$(30, 35]$F	1.0000	0.9998	1.0001	1.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$(35, 40]$F	1.0000	1.0003*	0.9997*	1.0003
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
$(40, 45]$F	0.9998	1.0000	0.9996**	1.0000
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$(45, 50]$F	0.9999	0.9998*	0.9999	1.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$(50, 55]$F	0.9999	0.9999	1.0002	0.9999
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$[80, 85)$F	0.9998	0.9999	0.9995***	1.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
$[85, 90)$F	0.9998	0.9999	0.9992***	0.9999
	(0.0002)	(0.0001)	(0.0002)	(0.0002)
$[90, 95)$F	1.0001	1.0001	0.9995***	1.0004*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$\geq$ 95F	0.9998	1.0001	0.9991***	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
N	2579304	2042040	2220792	2371824
adj. R^2	0.715	0.679	0.705	0.747
Weather controls	Yes	Yes	Yes	Yes
County x month of year FE	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes
Store FE	Yes	Yes	Yes	Yes

Table 5. **The average effect of daily maximum temperature on monthly retail prices, by soft drink type.** This table shows results from regressing Equation 5 via ordinary least squares. The reference maximum temperature bin is (65,70)F. As a matter of space, we do not present the results for the bins $(55, 60]$F, $(60, 65]$F, $[70, 75)$F, and $[75, 80)$F, but these bins are included in the regression. Dependent variable: ln of Fisher price index (base: January 2006). The coefficients are exponentiated and should be interpreted as change ratios. Robust standard errors are clustered at the county level. CSD: carbonated soft drink. F: Fahrenheit. FE: fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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	Sugary drinks			Bottled water		
	(1)	(2)	(3)	(4)	(5)	(6)
$\leq$ 30F	-0.0001	-0.0017	-0.0038	-0.0032***	-0.0018	-0.0028
	(0.0006)	(0.0011)	(0.0024)	(0.0012)	(0.0020)	(0.0045)
$\leq$ 30F $\times$ $Pr_z(\leq 30)^{hist}$		0.0183*			-0.0130	
		(0.0096)			(0.0191)	
$\leq$ 30F $\times$ (top half)			0.0039			-0.0003
			(0.0024)			(0.0046)
$(30, 40]$F	0.0004	-0.0006	-0.0004	-0.0007	-0.0052**	-0.0038*
	(0.0005)	(0.0013)	(0.0010)	(0.0010)	(0.0023)	(0.0020)
$(30, 40]$F $\times$ $Pr_z((30, 40])^{hist}$		0.0105			0.0398**	
		(0.0107)			(0.0194)	
$(30, 40]$F $\times$ (top half)			0.0010			0.0037*
			(0.0011)			(0.0021)
$[80, 90)$F	0.0019***	0.0014**	0.0016***	0.0038***	0.0033***	0.0038***
	(0.0003)	(0.0006)	(0.0005)	(0.0005)	(0.0010)	(0.0008)
$[80, 90)$F $\times$ $Pr_z([80, 90))^{hist}$		0.0022			0.0014	
		(0.0020)			(0.0035)	
$[80, 90)$F $\times$ (top half)			0.0006			-0.0003
			(0.0006)			(0.0010)
$\geq$ 90F	0.0028***	0.0027***	0.0027***	0.0063***	0.0081***	0.0080***
	(0.0004)	(0.0006)	(0.0008)	(0.0008)	(0.0011)	(0.0013)
$\geq$ 90F $\times$ $Pr_z(\geq 90)^{hist}$		0.0009			-0.0122**	
		(0.0033)			(0.0055)	
$\geq$ 90F $\times$ (top half)			0.0002			-0.0023
			(0.0008)			(0.0015)
N	5820876	5820876	5820876	5436272	5436272	5436272
pseudo R^2	0.562	0.562	0.562	0.568	0.568	0.568
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. **Interaction effects between maximum temperature and historical exposure on the monthly volume purchased of sugary drink and bottled water.** This table shows results from regressing Equation 1 (column 1) and Equation 6 (column 2) as well as Equation 6 but replacing $Pr_z(T_i)^{hist}$ by an indicator for whether the historical frequency of days in bin T_i is above the median historical frequency (column 3), all estimated via Poisson pseudo-maximum likelihood. The share of historical observations for which T_i days occur ($Pr_z(T_i)^{hist}$) remains fixed over time for any given zip code z for all i and is estimated based on weather data from the U.S. NOAA Global Historical Climatology Network for 1974-2003. The reference maximum temperature bin is (40-80)F. Projection factors are used. Robust standard errors are clustered at the zip code level. FE: fixed effects. F: Fahrenheit. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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Appendix

A. Data cleaning

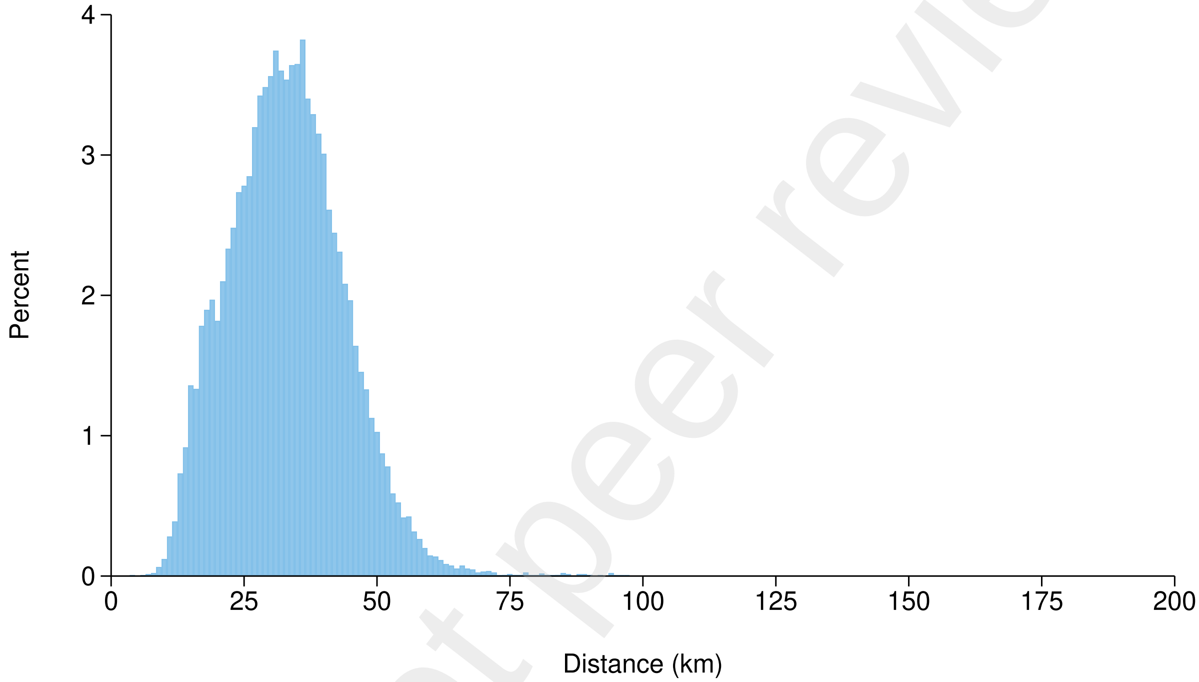

Figure A1. **Distance to the furthest (fifth) weather station accounted in inverse-distance weighted average daily maximum temperature, 2004-2019.** $N = 7,582$ weather stations. km: kilometre.
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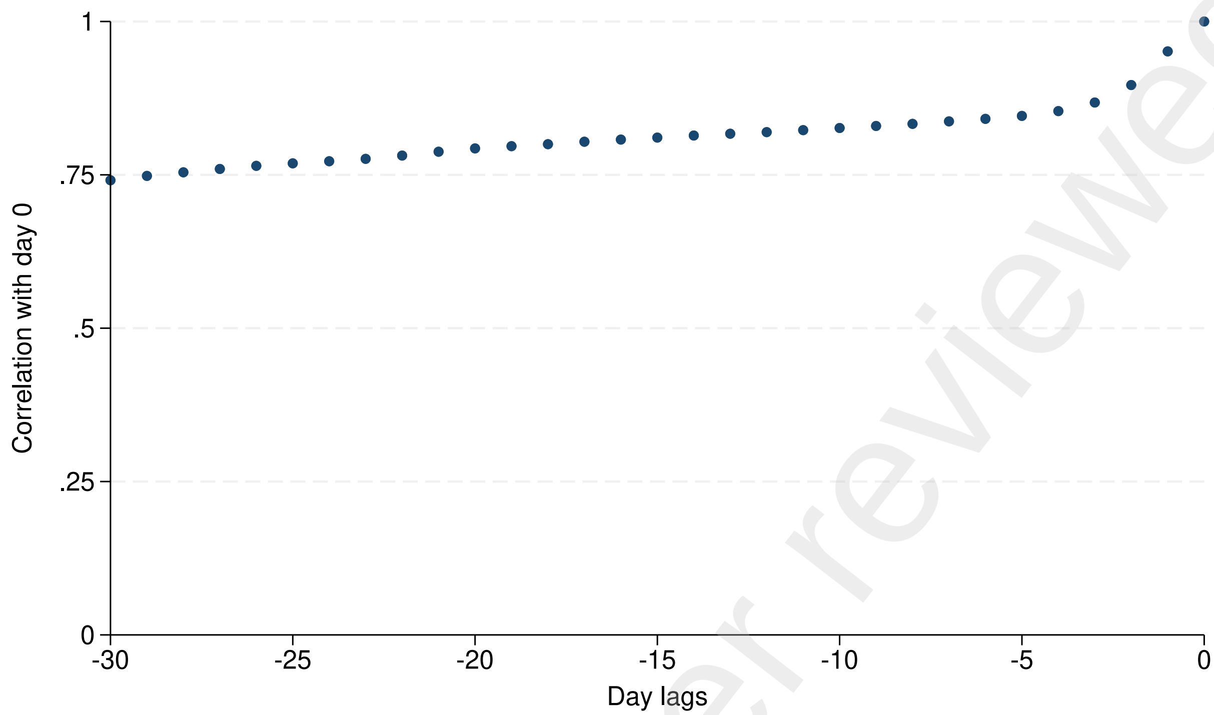

Figure A2. **Autocorrelation in daily maximum temperature, 2004-2019.** This figure shows the correlation between Day 0 and its 30 lags for maximum temperature across the sample. $N = 45,296,720$ zip code-day observations.
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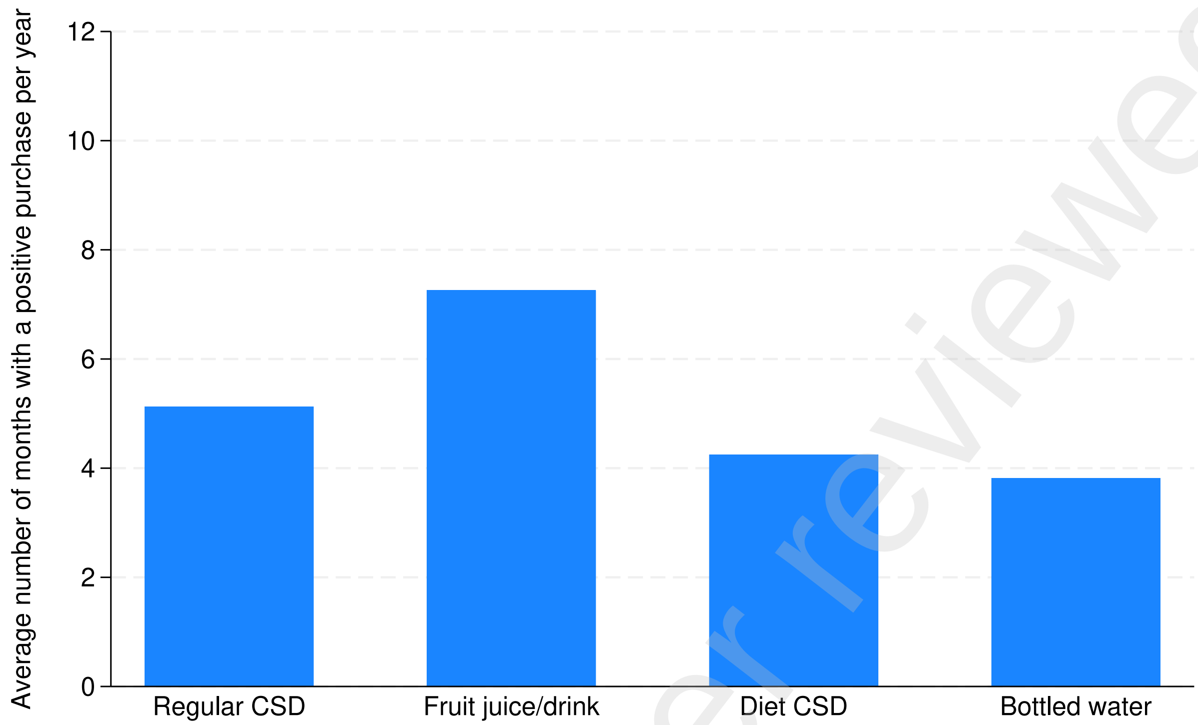

Figure A3. **Average number of months with a positive purchase per year, by soft drink type, 2004-2019.** $N = 5,834,433$ household-month observations. CSD: carbonated soft drink..
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B. Descriptive statistics

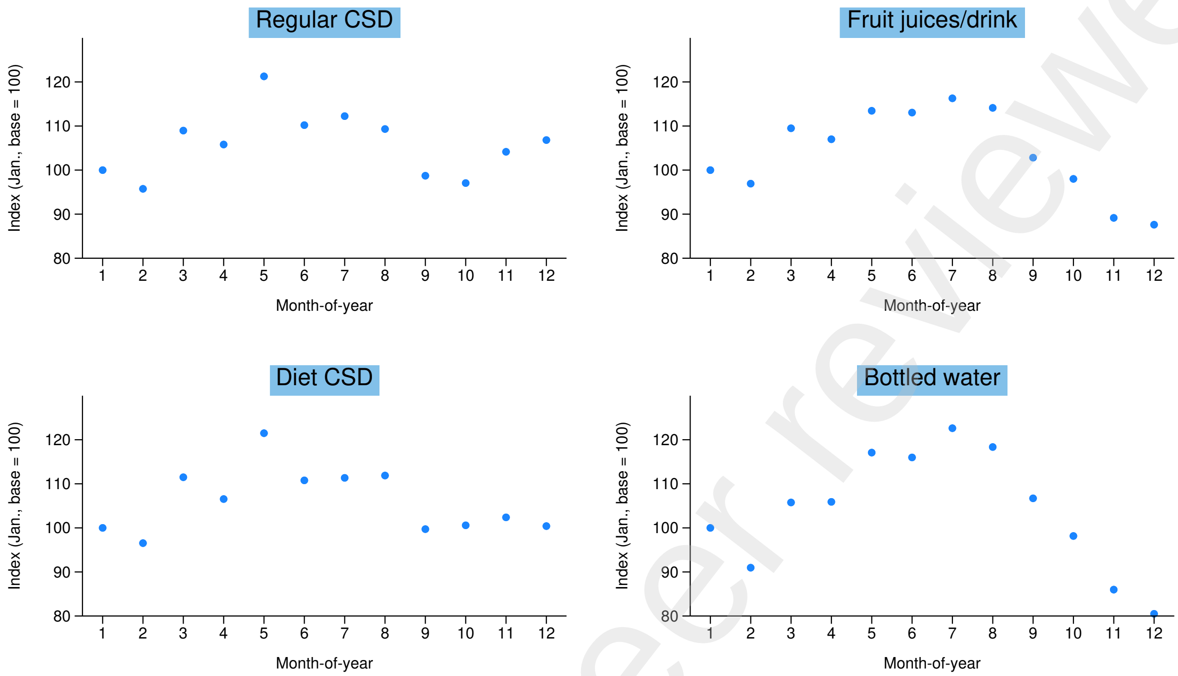

Figure B1. **Household month-of-year average purchased volume per adult equivalent unit, by soft drink type, 2004-2019.** $N = 5,834,433$ household-month observations. Base = 100 in January. CSD: carbonated soft drink.
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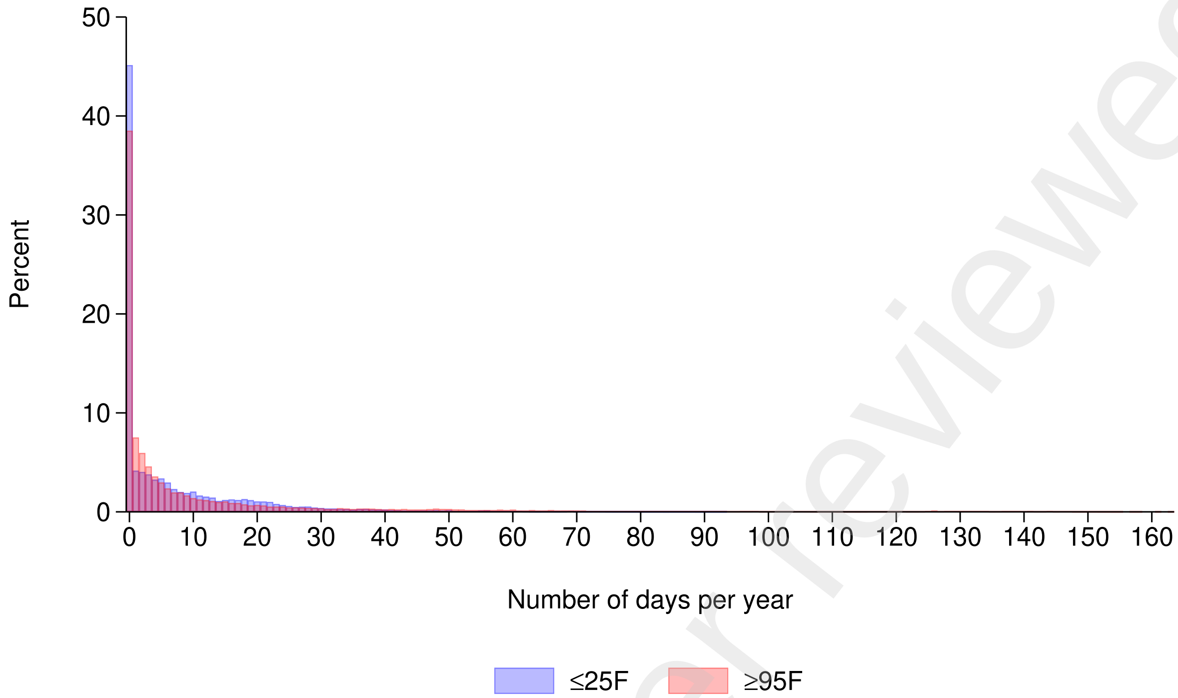

Figure B2. **Distribution of the number of days with maximum temperature above 95°F and below 25°F by household-year, 2004-2019.** $N = 490,847$ household-year observations. F: Fahrenheit.
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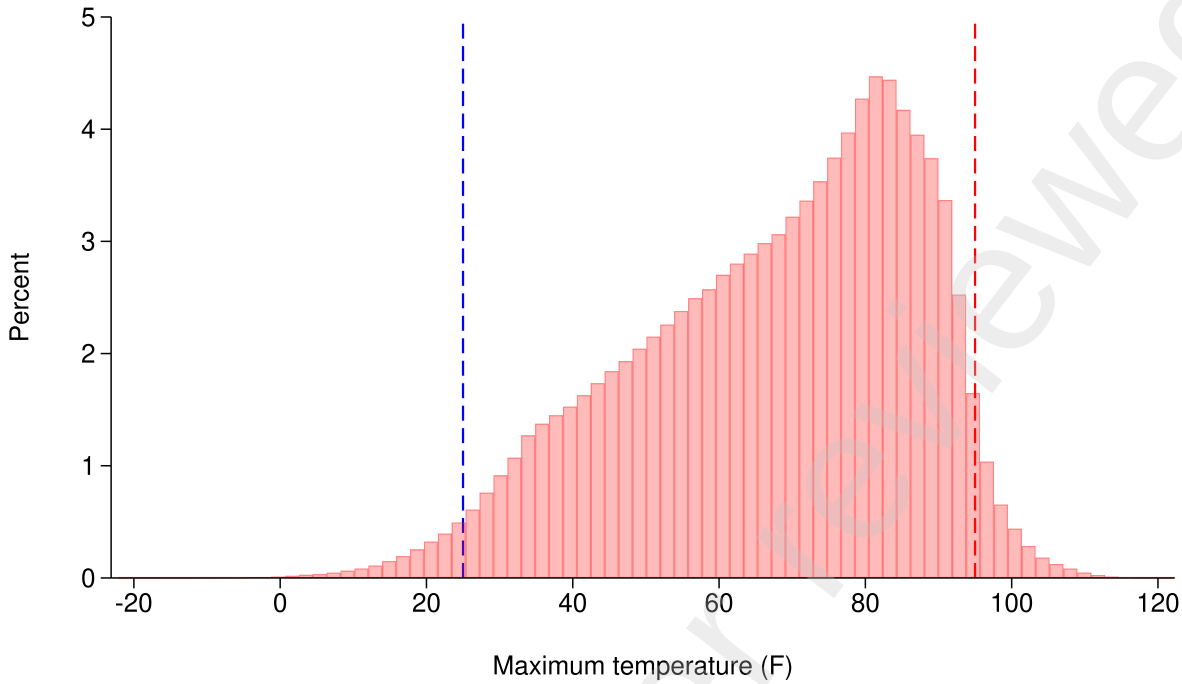

Figure B3. **Daily maximum temperature at zip code level, 2004-2019.** $N = 45,296,720$ zip code-day observations. Vertical dotted blue and red lines represent 25°F and 95°F, respectively. F: Fahrenheit.
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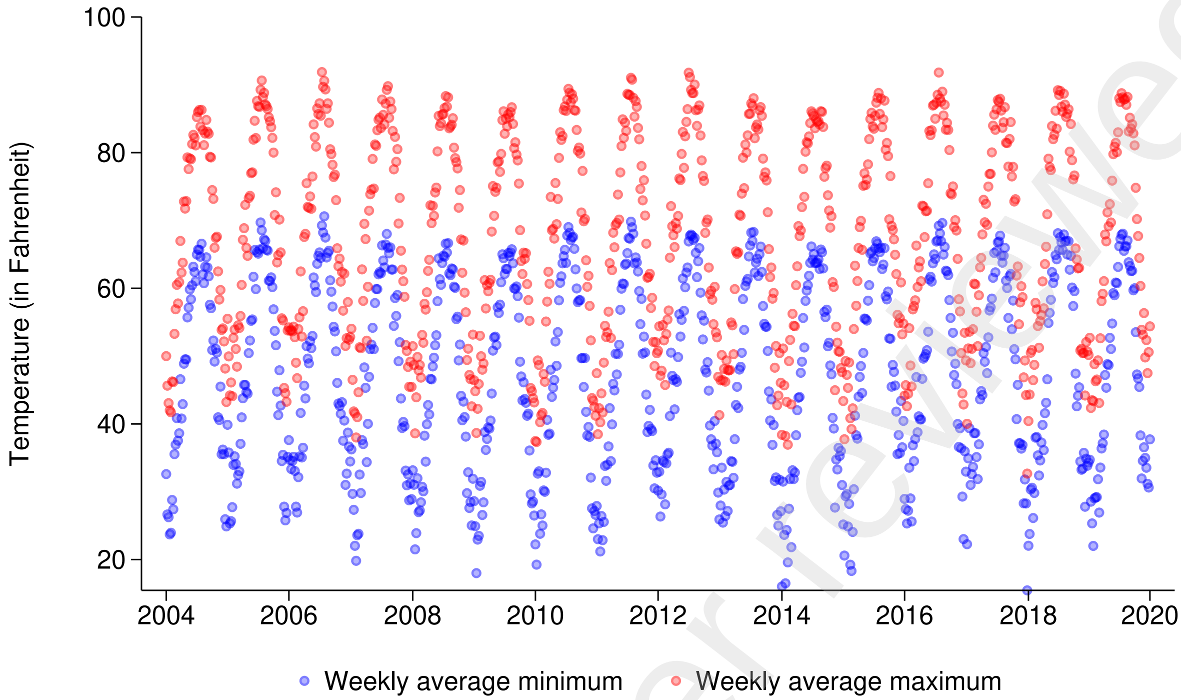

Figure B4. **Weekly average minimum and maximum temperature across all zip code-weeks, 2004-2019.** $N = 6,484,126$ zip code-week observations.
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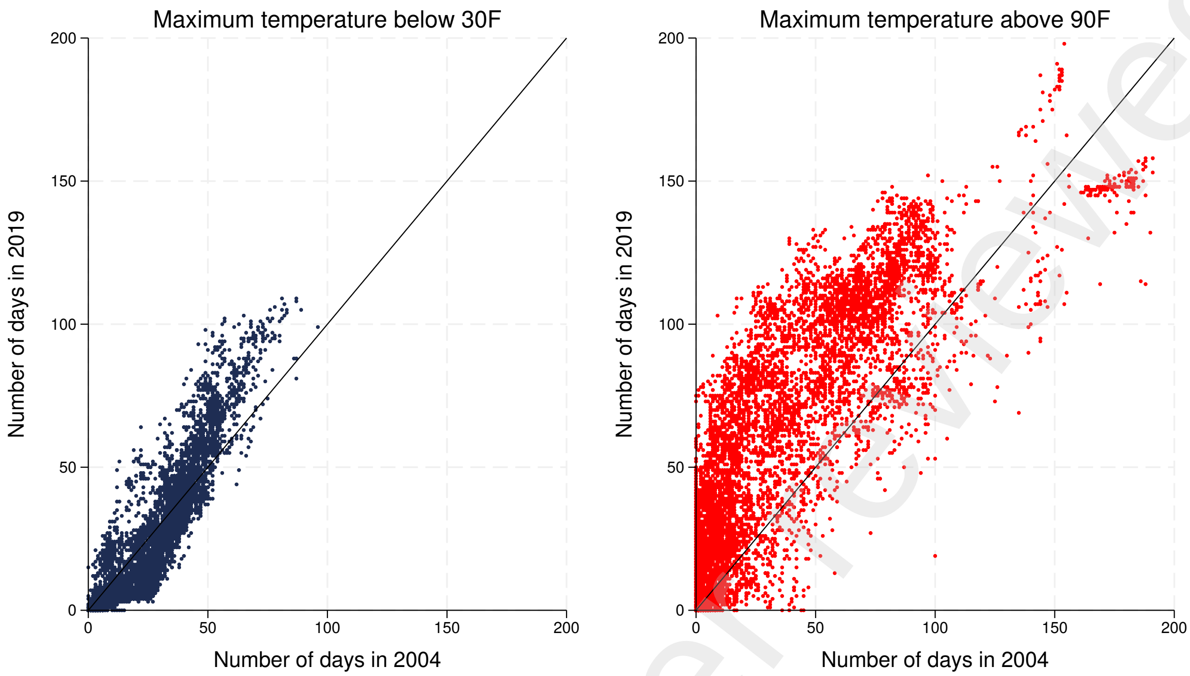

Figure B5. **Change in maximum temperature over the sample zip codes, 2004-2019.** $N = 13,522$ zip codes. F: Fahrenheit.
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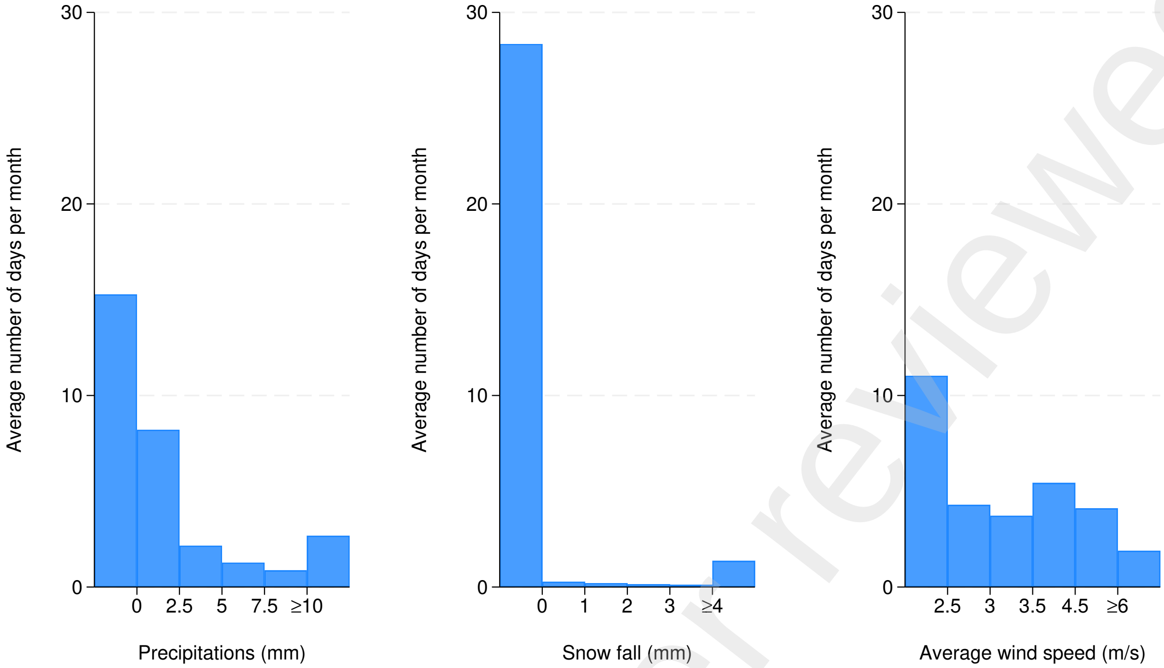

Figure B6. **Distribution of daily precipitations, snowfall, and average wind speed by household-month, 2004-2019.** $N = 5,834,433$ household-month observations. Observations below 0 mm represent no precipitations or no snowfall (there are no negative values). mm: millimeters; m/s: meters per second.

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	mean	sd
Size	2.6	0.0
Head age	51.8	0.1
Income $\geq$ USD 100K	0.226	0.002
Race: Black	0.110	0.002
Race: Asian	0.034	0.001
Race: Hispanic	0.124	0.002

Table B1. **Household characteristics, 2004-2019.** $N = 490,847$ household-year observations. HH: household, K: thousands, sd: standard deviation, USD: U.S. dollar (base 2015). Back to Section 2.

	mean	sd	min	max	N
$\leq$ 25F	18.3	6.0	-22.2	25.0	964,894
$(25, 30]$F	27.7	1.4	25.0	30.0	839,533
$(30, 35]$F	32.7	1.4	30.0	35.0	1,346,842
$(35, 40]$F	37.6	1.4	35.0	40.0	1,718,049
$(40, 45]$F	42.6	1.4	40.0	45.0	2,005,900
$(45, 50]$F	47.6	1.4	45.0	50.0	2,329,294
$(50, 55]$F	52.6	1.4	50.0	55.0	2,664,708
$(55, 60]$F	57.5	1.4	55.0	60.0	3,007,626
$(60, 65]$F	62.5	1.4	60.0	65.0	3,341,116
$(65, 70)$F	67.5	1.4	65.0	70.0	3,635,736
$[70, 75)$F	72.6	1.4	70.0	75.0	4,074,190
$[75, 80)$F	77.6	1.4	75.0	80.0	4,737,556
$[80, 85)$F	82.5	1.4	80.0	85.0	5,271,759
$[85, 90)$F	87.4	1.4	85.0	90.0	4,652,351
$[90, 95)$F	92.1	1.4	90.0	95.0	3,168,951
$\geq$ 95F	99.1	3.8	95.0	122.3	1,538,190
Total	67.6	19.5	-22.2	122.3	45,296,696

Table B2. **Daily maximum temperature across temperature bins and zip code-days, 2004-2019.** F: Fahrenheit. sd: standard deviation; N: number of observations.
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	mean	sd	min	max
≤ 25F	8.0	11.0	0.0	77.6
$(25, 30]$F	6.7	6.7	0.0	27.7
$(30, 35]$F	11.1	9.7	0.0	35.4
$(35, 40]$F	14.8	11.0	0.0	40.9
$(40, 45]$F	16.7	10.3	0.0	45.7
$(45, 50]$F	18.9	10.6	0.0	67.6
$(50, 55]$F	21.3	10.1	0.1	75.8
$(55, 60]$F	24.5	9.3	0.6	107.5
$(60, 65]$F	28.2	9.4	2.1	113.1
$(65, 70)$F	31.0	9.9	8.3	96.1
$[70, 75)$F	34.4	9.3	11.0	107.5
$[75, 80)$F	38.3	9.1	1.8	81.5
$[80, 85)$F	41.1	13.0	0.5	108.3
$[85, 90)$F	35.8	20.1	0.0	123.0
$[90, 95)$F	23.2	20.7	0.0	107.3
≥ 95F	11.3	21.4	0.0	144.7

Table B3. **Historical number of days by maximum temperature bins and zip code-year, 1974-2003.** $N = 124,018$ zip code-year observations. F: Fahrenheit. sd: standard deviation.

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C. Additional main results and robustness checks

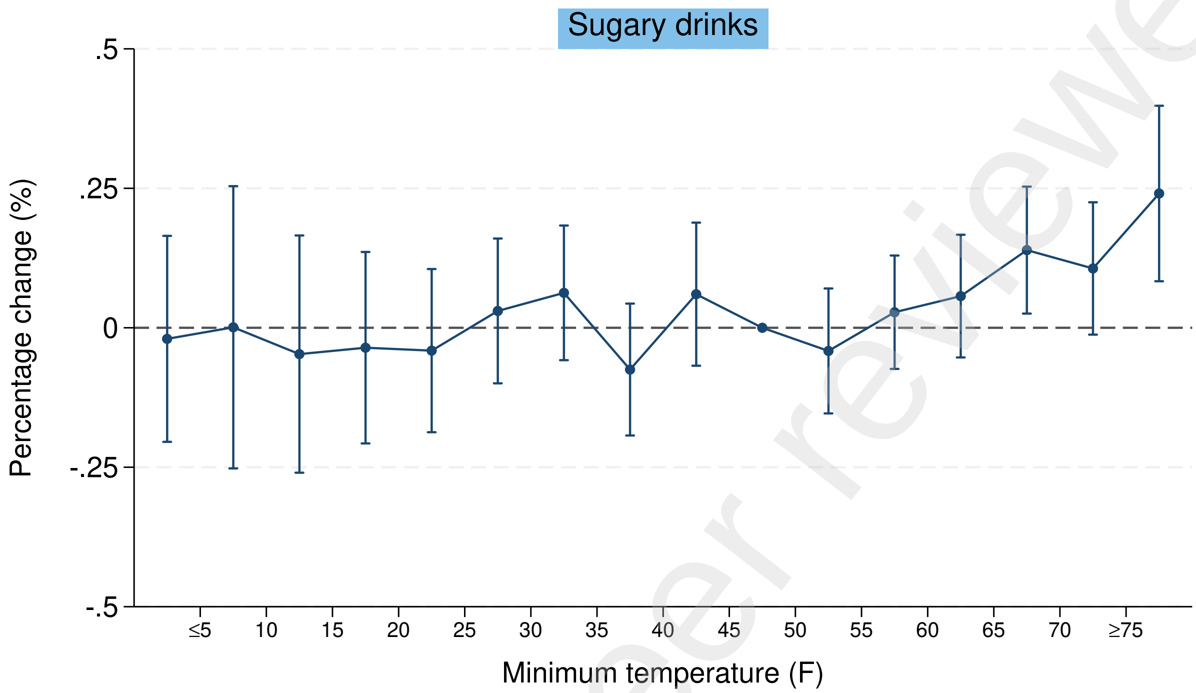

Figure C1. **The average effect of daily minimum temperature on monthly sugary drink volume purchased.** This figure shows results from regressing the specification in Equation 1 replacing maximum temperature bins by minimum temperature bins, via Poisson pseudo-maximum likelihood. Vertical segments show the 95% confidence interval. The reference minimum temperature bin is (45-50)F. Projection factors are used. Robust standard errors are clustered at the zip code level. F: Fahrenheit.
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	Regular CSD	Fruit juice/drink	Diet CSD	Bottled water
≤ 25F	0.0012	-0.0004	-0.0013	-0.0032*
	(0.0013)	(0.0011)	(0.0013)	(0.0018)
$(25, 30]$F	-0.0009	0.0002	-0.0020	-0.0036*
	(0.0015)	(0.0013)	(0.0015)	(0.0020)
$(30, 35]$F	0.0018	0.0010	-0.0023*	-0.0030*
	(0.0013)	(0.0011)	(0.0013)	(0.0018)
$(35, 40]$F	0.0000	0.0006	-0.0017	-0.0005
	(0.0011)	(0.0009)	(0.0011)	(0.0015)
$(40, 45]$F	0.0004	-0.0005	0.0005	0.0009
	(0.0010)	(0.0009)	(0.0011)	(0.0014)
$(45, 50]$F	0.0004	0.0006	-0.0013	-0.0003
	(0.0010)	(0.0008)	(0.0010)	(0.0013)
$(50, 55]$F	0.0004	0.0003	-0.0005	-0.0016
	(0.0009)	(0.0008)	(0.0010)	(0.0013)
$[80, 85)$F	0.0020**	0.0019***	-0.0000	0.0028***
	(0.0008)	(0.0006)	(0.0008)	(0.0009)
$[85, 90)$F	0.0023***	0.0029***	0.0024***	0.0053***
	(0.0008)	(0.0007)	(0.0009)	(0.0010)
$[90, 95)$F	0.0027***	0.0034***	0.0027***	0.0062***
	(0.0009)	(0.0008)	(0.0010)	(0.0011)
≥ 95F	0.0033***	0.0038***	0.0022**	0.0075***
	(0.0010)	(0.0009)	(0.0011)	(0.0013)
N	5650042	5788838	5234563	5436272
pseudo R^2	0.600	0.491	0.692	0.568
Weather controls	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Table C1. **The average effect of daily maximum temperature on monthly soft drink volume purchased, by soft drink type.** This table shows results from regressing the specification in Equation 1 via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (65-70)F. As a matter of space, we do not present the results for the bins $(55, 60]$F, $(60, 65]$F, $[70, 75)$F, and $[75, 80)$F, but these bins are included in the regression. Projection factors are used. Robust standard errors are clustered at the zip code level. CSD: carbonated soft drink. FE: fixed effects. F: Fahrenheit. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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	(1)	(2)	(3)	(4)
≤ 25F	0.0005	0.0005	-0.0003	-0.0007
	(0.0009)	(0.0009)	(0.0008)	(0.0008)
$(25, 30]$F	-0.0007	-0.0010	-0.0011	-0.0014
	(0.0011)	(0.0010)	(0.0010)	(0.0010)
$(30, 35]$F	0.0014	0.0013	0.0011	0.0000
	(0.0009)	(0.0009)	(0.0009)	(0.0008)
$(35, 40]$F	0.0002	0.0001	-0.0001	-0.0008
	(0.0008)	(0.0008)	(0.0007)	(0.0007)
$(40, 45]$F	-0.0001	-0.0003	-0.0003	0.0003
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
$(45, 50]$F	0.0005	0.0004	0.0003	-0.0006
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
$(50, 55]$F	0.0003	0.0003	0.0002	-0.0002
	(0.0007)	(0.0006)	(0.0006)	(0.0006)
$[80, 85)$F	0.0018***	0.0018***	0.0019***	0.0017***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
$[85, 90)$F	0.0025***	0.0024***	0.0025***	0.0026***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
$[90, 95)$F	0.0029***	0.0029***	0.0032***	0.0029***
	(0.0007)	(0.0006)	(0.0006)	(0.0006)
≥ 95F	0.0034***	0.0034***	0.0037***	0.0035***
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
N	5820876	5825007	5825316	5759497
pseudo R^2	0.562	0.541	0.535	0.662
Weather controls	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	No
Household FE	Yes	Yes	Yes	No
Year x quarter of year FE	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	No	No	Yes
County x month of year FE	No	Yes	No	No
State x month of year FE	No	No	Yes	No
Household x year FE	No	No	No	Yes

Table C2. **The average effect of daily maximum temperature on monthly sugary drink volume purchased, with various location and time fixed effects.** This table shows results from regressing the main specification in Equation 1 via Poisson pseudo-maximum likelihood (column 1), including county × month (column 2), state × month (column 3), and household × year fixed effects (column 4). The reference maximum temperature bin is (65-70)F. As a matter of space, we do not present the results for the bins $(55, 60]$F, $(60, 65]$F, $[70, 75)$F, and $[75, 80)$F, but these bins are included in the regression. Projection factors are used. Robust standard errors are clustered at the zip code level. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Back to Section 4.1.

	(1)	(2)
≤ 25F	0.0005	0.0005
	(0.0009)	(0.0011)
$(25, 30]$F	-0.0007	-0.0007
	(0.0011)	(0.0015)
$(30, 35]$F	0.0014	0.0014
	(0.0009)	(0.0013)
$(35, 40]$F	0.0002	0.0002
	(0.0008)	(0.0005)
$(40, 45]$F	-0.0001	-0.0001
	(0.0007)	(0.0010)
$(45, 50]$F	0.0005	0.0005
	(0.0007)	(0.0007)
$(50, 55]$F	0.0003	0.0003
	(0.0007)	(0.0009)
$[80, 85)$F	0.0018***	0.0018***
	(0.0006)	(0.0004)
$[85, 90)$F	0.0025***	0.0025***
	(0.0006)	(0.0005)
$[90, 95)$F	0.0029***	0.0029***
	(0.0007)	(0.0005)
≥ 95F	0.0034***	0.0034***
	(0.0007)	(0.0006)
N	5820876	5820876
pseudo R^2	0.562	0.562
Weather controls	Yes	Yes
Time-varying HH controls	Yes	Yes
Zip code x month of year FE	Yes	Yes
Year x quarter of year FE	Yes	Yes
Household FE	Yes	Yes

Table C3. **The average effect of daily maximum temperature on monthly sugary drink volume purchased, with two-way standard error clustering.** This table shows results from regressing the main specification in Equation 1 (i.e., clustering at zip code level) (column 1) and with two-way standard error clustering at zip code and month-of-the-year level (column 2), via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (65-70)F. As a matter of space, we do not present the results for the bins $(55, 60]$F, $(60, 65]$F, $[70, 75)$F, and $[75, 80)$F, but these bins are included in the regression. Projection factors are used. Robust standard errors are clustered at the zip code level (1) and at the zip code and month-of-year level (2). F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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D. Inter-temporal shifts

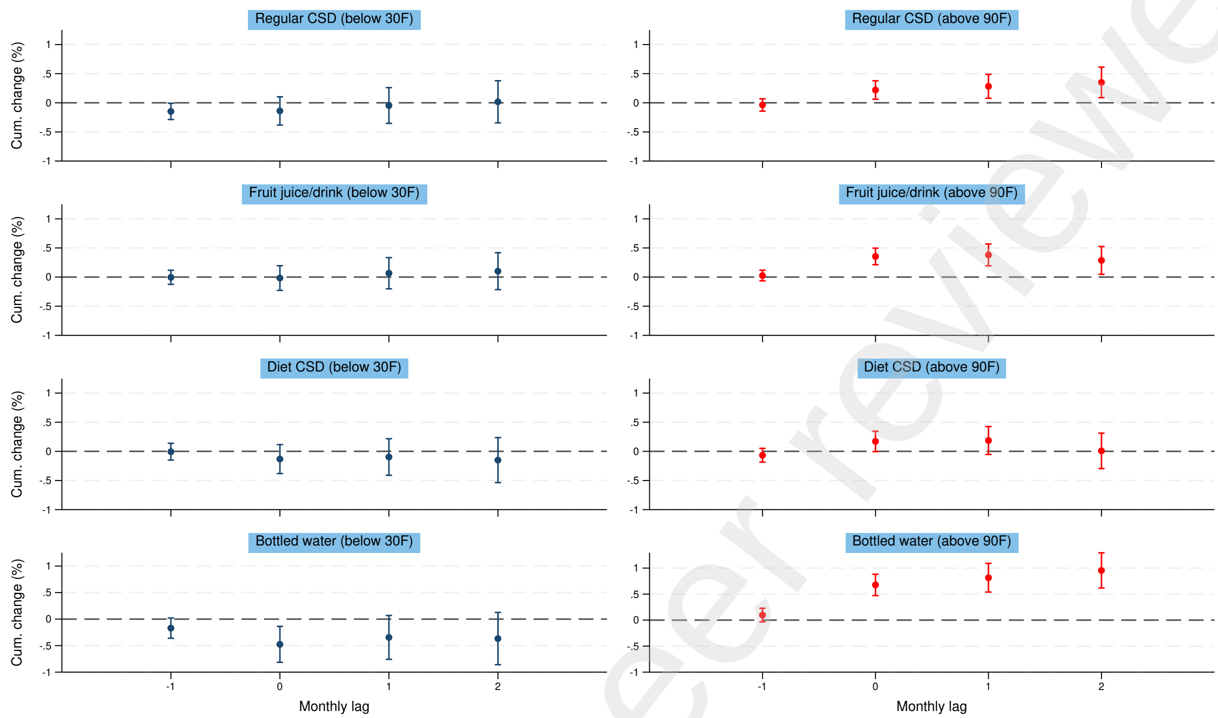

Figure D1. **The cumulative effect of daily maximum temperature below 30°F and above 90°F on monthly soft drink volume, by soft drink type.** This figure shows results from regressing the specification in Equation 3 for days with a maximum temperature (a) below $\leq$ 30°F and (b) above $\geq$ 90°F, by soft drink type, via Poisson pseudo-maximum likelihood. Plot represents the cumulative effect $\sum_{t=-1}^{2} \hat{\beta}_{i,m-t}$. The reference maximum temperature bin is (40-80)F. As a matter of space, we do not present the results for the bins $(30, 40]$F and $[70, 80)$F, but these bins are included in the regression. Vertical segments show the 95% confidence interval. Projection factors are used. Robust standard errors are clustered at the zip code level. Cum.: cumulative. F: Fahrenheit.
Back to Section 4.2 or Section 4.4.3.

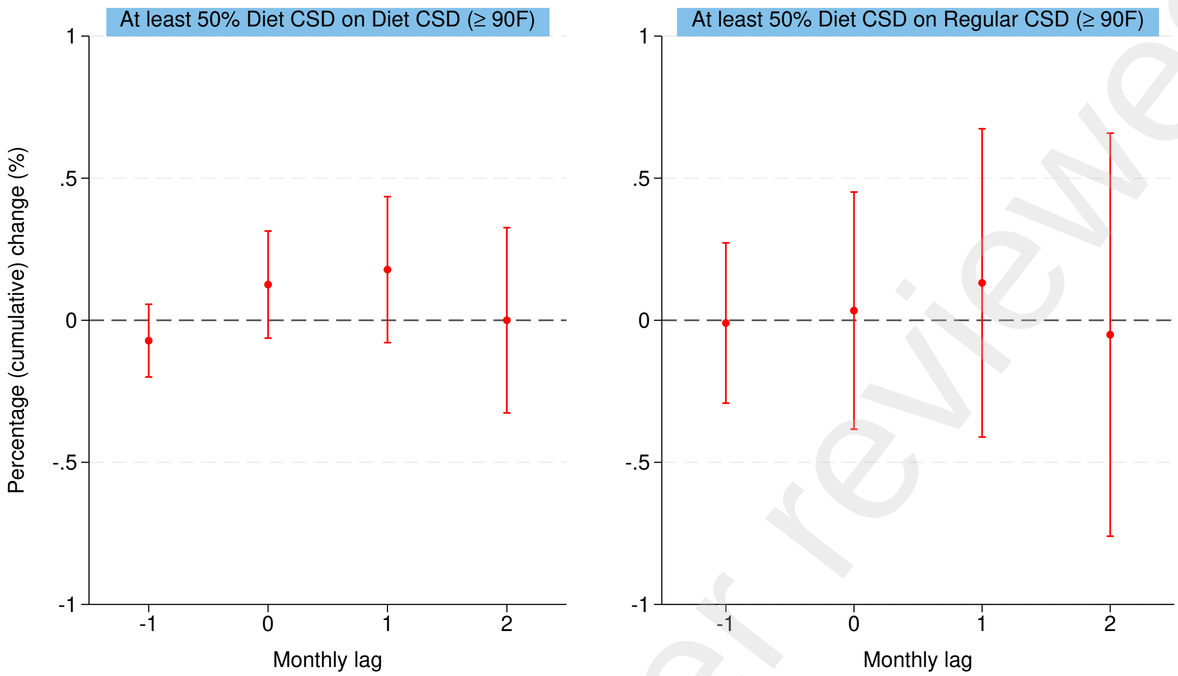

Figure D2. **The cumulative effect of daily maximum temperature above 90°F on monthly diet CSD and regular CSD volume purchased for households with diet CSD representing at least 50% of total CSD purchases.** This figure shows results from regressing the specification in Equation 3 for days with a maximum temperature above ≥ 90°F, via Poisson pseudo-maximum likelihood. Only households with a total diet CSD volume purchased representing at least 50% of total CSD purchases (regular CSD + diet CSD) over the sample period are kept. Plot represents the cumulative effect $\sum_{t=-1}^{2} \hat{\beta}_{i,m-t}$. The reference maximum temperature bin is (40-80)F. As a matter of space, we do not present the results for the bins $\leq$ 30F, $(30, 40]$F and $[70, 80)$F, but these bins are included in the regression. Vertical segments show the 95% confidence interval. Projection factors are used. Robust standard errors are clustered at the zip code level. F: Fahrenheit.
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	Sugar drinks	Regular CSD	Fruit juice/drink	Diet CSD	Bottled water
$\geq$ 90F	0.000	0.002	0.001	0.056	0.000
$\leq$ 30F	0.223	0.280	0.419	0.374	0.333

Table D1. **Harvesting tests, p-values.** This table shows p-value results from testing the null hypothesis that $\sum_{t=1}^{2} \hat{\beta}_{i,m-t} = -\hat{\beta}_{i,m}$ from Equation 3. Projection factors are used. Robust standard errors are clustered at the zip code level. CSD: carbonated soft drink.
Back to Section 4.2.

	Sugar drinks	Regular CSD	Fruit juice/drink	Diet CSD	Bottled water
$\geq$ 90F	0.000	0.007	0.000	0.055	0.000
$\leq$ 30F	0.235	0.260	0.879	0.296	0.006

Table D2. **Anticipation tests, p-values.** This table shows p-value results from testing the null hypothesis that $\hat{\beta}_{i,m+1} = -\hat{\beta}_{i,m}$ from Equation 3. Projection factors are used. Robust standard errors are clustered at the zip code level. CSD: carbonated soft drink.
Back to Section 4.2.

E. Heterogeneity and potential modifiers

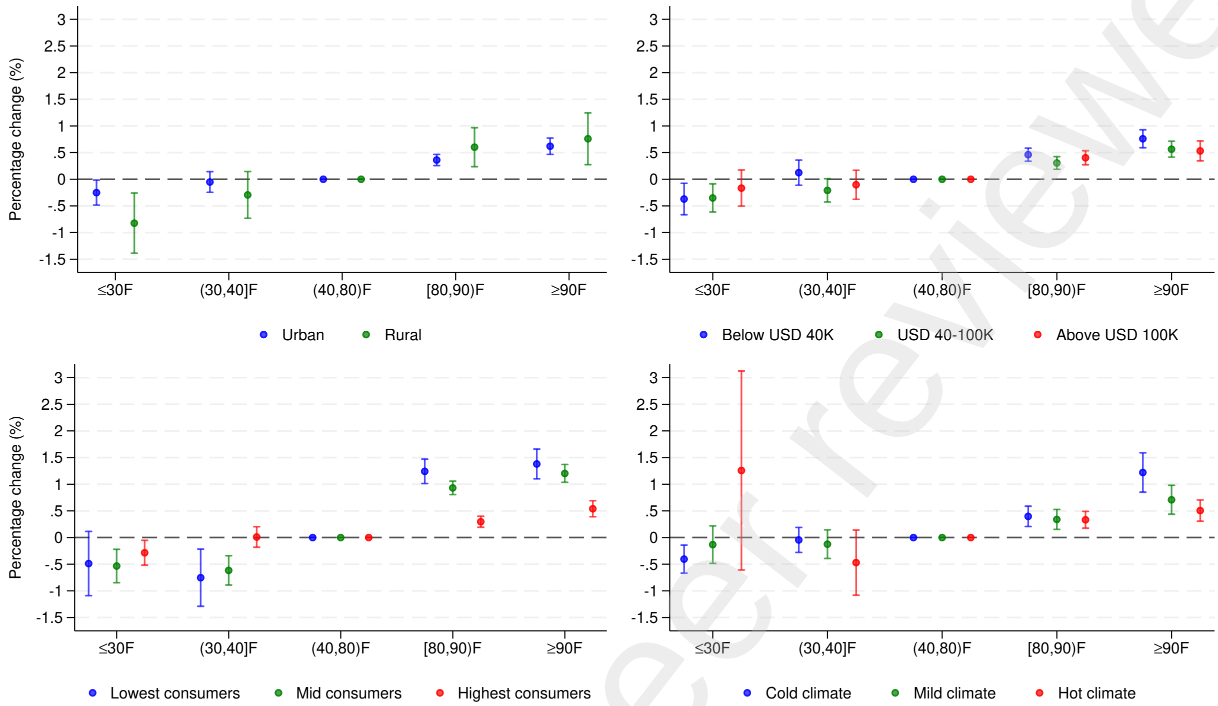

Figure E1. **The average effect of daily maximum temperature on monthly bottled water volume purchased, by annual household income, area, intensity of consumption, and climate region.** This figure displays results from regressing the specification in Equation 1 interacting each temperature bin with two types of county areas (urban, rural; source: US Census Bureau, 2010), three household annual income levels (below USD 40K, between USD 40-100K, above USD 100K), three intensity of consumption levels (based on terciles of yearly total volume per adult equivalent unit), and three climate regions (based on terciles of average zip code maximum temperature over the period 1974-2003), via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (40-80)F. Projection factors are used. Vertical segments show the 95% confidence interval. Robust standard errors are clustered at the zip code level. F: Fahrenheit. USD: U.S. dollars, base 2015.

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	Air conditioning use
Midwest	0.438**
	(0.176)
South	0.957***
	(0.151)
West	-0.639***
	(0.186)
Rural	-0.287***
	(0.088)
HH size: 2-3	0.195***
	(0.031)
HH size: ≥ 4	0.239***
	(0.063)
HH income: USD 40-100K	0.297***
	(0.057)
HH income: $\geq$ USD 100K	0.472***
	(0.089)
HH head age: ≥ 55	0.116***
	(0.022)
HH race: Black	-0.315***
	(0.075)
HH race: Other non-white	-0.228***
	(0.066)
N	22150

Table E1. **Predictors of air conditioning use.** This table displays the correlation between household demographic characteristics and air conditioning use using the U.S. Energy Information Administration Residential Energy Consumption Survey (RECS) 2005, 2009, and 2015, through a probit regression. The dependent variable is air conditioning use. RECS survey weights are used to represent the entire U.S. population. Robust standard errors are clustered at the U.S. Census division level. HH: household. USD: U.S. dollar, base 2015. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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	mean	sd	N
Outdoor employed member	0.209	0.002	5,834,433
Obese member	0.529	0.004	475,824
Children	0.351	0.002	5,834,433
AC use	0.816	0.002	5,834,433

Table E2. **Prevalence of modifiers among the sample.** Outdoor equals 1 for years in which at least one household head has an outdoor occupation. Obese equals 1 for years in which at least one adult household member is obese (based on a body mass index above 30 as estimated from self declared height and weight information, only provided for 2016-2017). Children equals 1 for years in which at least one household member is a child. AC use equals 1 for years in which the household used AC. Source for height and weight information: NielsenIQ Annual Ailments, Health, and Wellness Survey. Source for AC use data: U.S. Energy Information Administration Residential Energy Consumption Survey 2005, 2009, and 2015 matched on household demographics (see Table E1). The reference maximum temperature bin is (40-80)F. Projection factors are used. Robust standard errors are clustered at the zip code level. AC: air conditioning.
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	Outdoor	Obese	Children	AC use
$\leq$ 30F	-0.0029**	-0.0095	-0.0030**	-0.0049
	(0.0012)	(0.0076)	(0.0012)	(0.0043)
$\leq$ 30F$\times$ Mod	-0.0012	0.0030	-0.0003	0.0018
	(0.0014)	(0.0059)	(0.0012)	(0.0044)
$[30, 40)$F	-0.0007	-0.0008	-0.0000	0.0016
	(0.0010)	(0.0051)	(0.0010)	(0.0025)
$[30, 40)$F$\times$ Mod	-0.0002	-0.0016	-0.0027**	-0.0025
	(0.0011)	(0.0048)	(0.0011)	(0.0025)
$(80, 90]$F	0.0037***	0.0022	0.0039***	0.0034***
	(0.0005)	(0.0024)	(0.0005)	(0.0009)
$(80, 90]$F$\times$ Mod	0.0008	-0.0011	-0.0004	0.0005
	(0.0005)	(0.0014)	(0.0005)	(0.0009)
$\geq$ 90F	0.0063***	0.0035	0.0064***	0.0069***
	(0.0008)	(0.0033)	(0.0008)	(0.0012)
$\geq$ 90F$\times$ Mod	0.0002	0.0001	-0.0004	-0.0007
	(0.0007)	(0.0015)	(0.0005)	(0.0011)
N	5436272	348403	5436272	5436272
pseudo R^2	0.568	0.724	0.569	0.568
Weather controls	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Table E3. **Interaction effects between maximum temperature and potential modifiers of the effect on the monthly volume purchased of bottled water.** This table displays results from regressing the specification in Equation 4 estimated via Poisson pseudo-maximum likelihood. Mod represents outdoor (column 1), obese (column 2), children (column 3), and AC use (column 4). Outdoor equals 1 for years in which at least one household head has an outdoor occupation. Obese equals 1 for years in which at least one adult household member is obese (based on a body mass index above 30 as estimated from self declared height and weight information, only provided for 2016-2017). Children equals 1 for years in which at least one household member is a child. AC use equals 1 for years in which the household used AC. Source for height and weight information: NielsenIQ Annual Ailments, Health, and Wellness Survey. Source for AC use data: U.S. Energy Information Administration Residential Energy Consumption Survey 2005, 2009, and 2015 matched on demographics (see Table E1). The reference maximum temperature bin is (40-80)F. Projection factors are used. Robust standard errors are clustered at the zip code level. AC: air conditioning. FE: fixed effects. F: Fahrenheit. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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F. Potential drivers

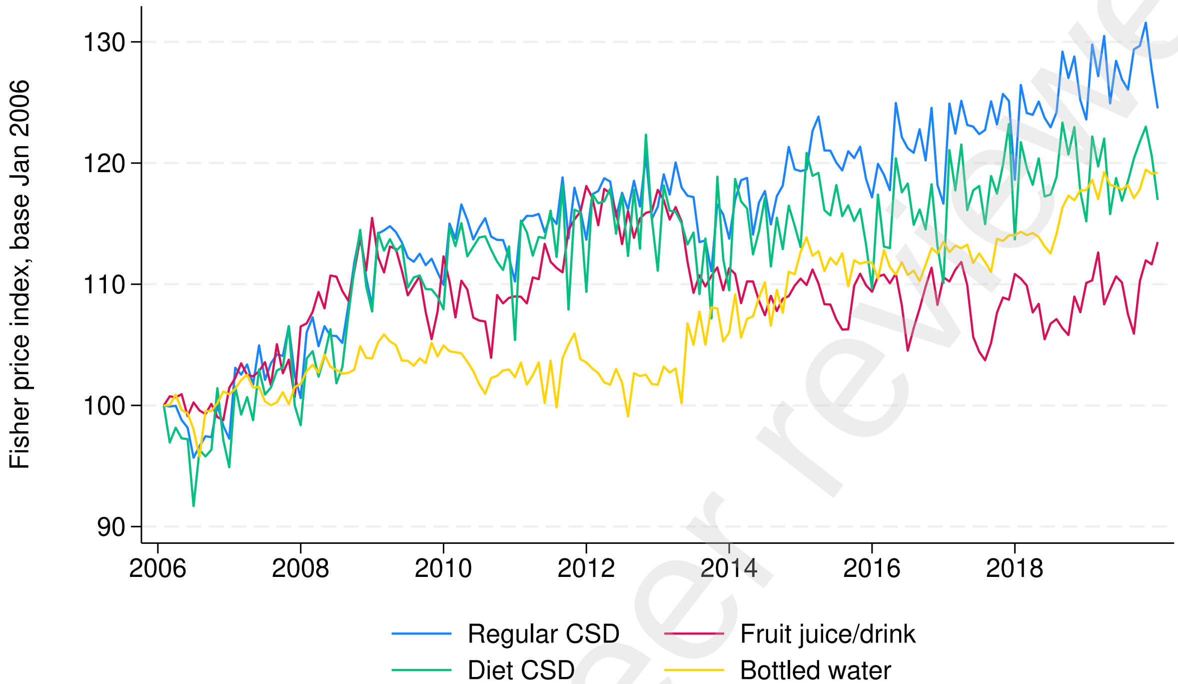

Figure F1. **Average monthly Fisher price index among sample stores, by soft drink type, 2006-2019.** Base: January 2006. CSD: carbonated soft drink. U.S. general inflation over the period 2006-2019 (source: U.S. Bureau of Labor and Statistics): 29.6%. Back to Section 4.4.3.

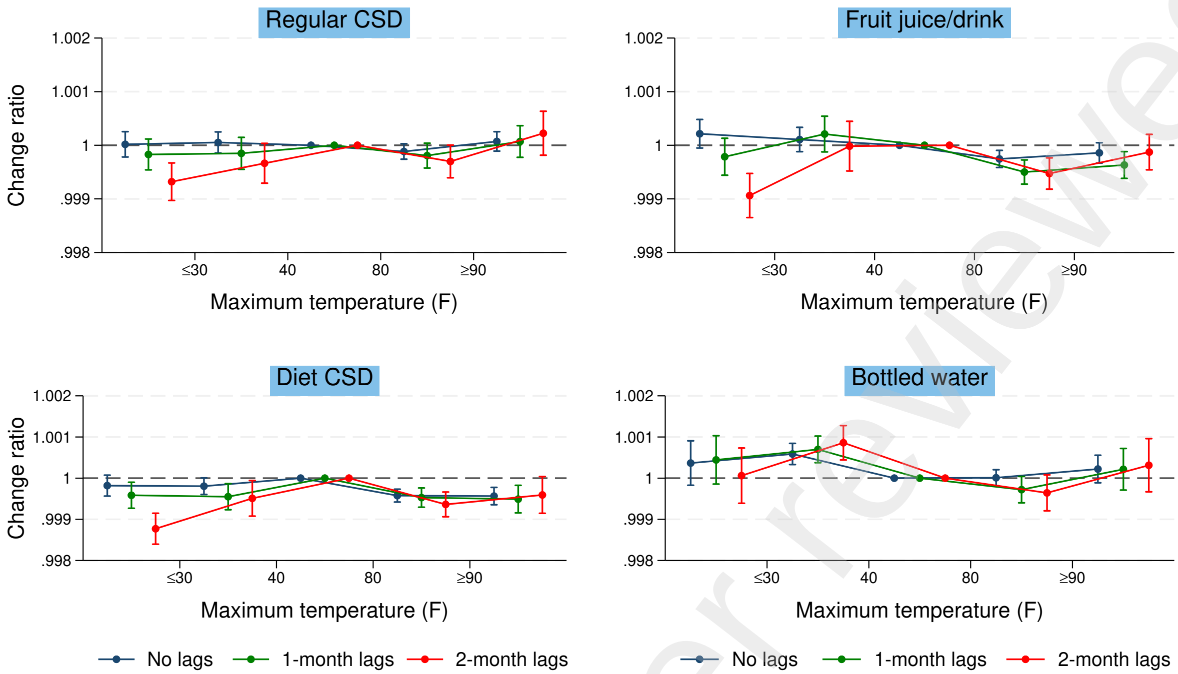

Figure F2. **The cumulative effect of daily maximum temperature on monthly retail prices, by soft drink type.** This figure shows results from regressing Equation 5, via ordinary least squares, by soft drink type. Plot represents the cumulative effect $\sum_{t=0}^{2} \hat{\beta}_{i,m-t}$. The reference maximum temperature bin is (40,80)F. Dependent variable: ln of Fisher price index (base: January 2006). The coefficients are exponentiated and should be interpreted as change ratios. Vertical segments show the 95% confidence interval. Robust standard errors are clustered at the county level. CSD: carbonated soft drink. F: Fahrenheit.
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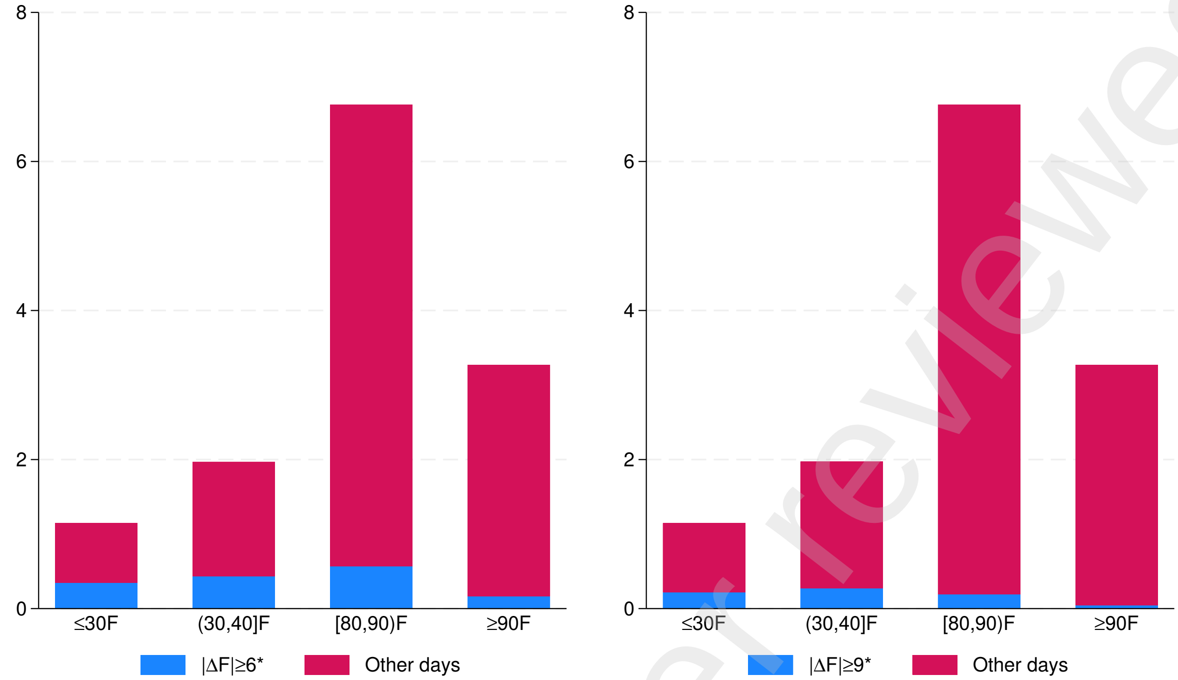

Figure F3. **Monthly distribution of day-on-day differences in maximum temperature, 2004-2019.** $N = 5,834,433$ household-month observations. Day-on-day differences for temperature bin i are defined as $\Delta F = TMAX_d - TMAX_{d-1}$ with $TMAX_d$ belonging to bin i. * Only counting positive (negative) day-on-day differences for maximum temperature above (below) the reference maximum temperature bin (40,80)F. F: Fahrenheit.
Back to Section 4.4.4.

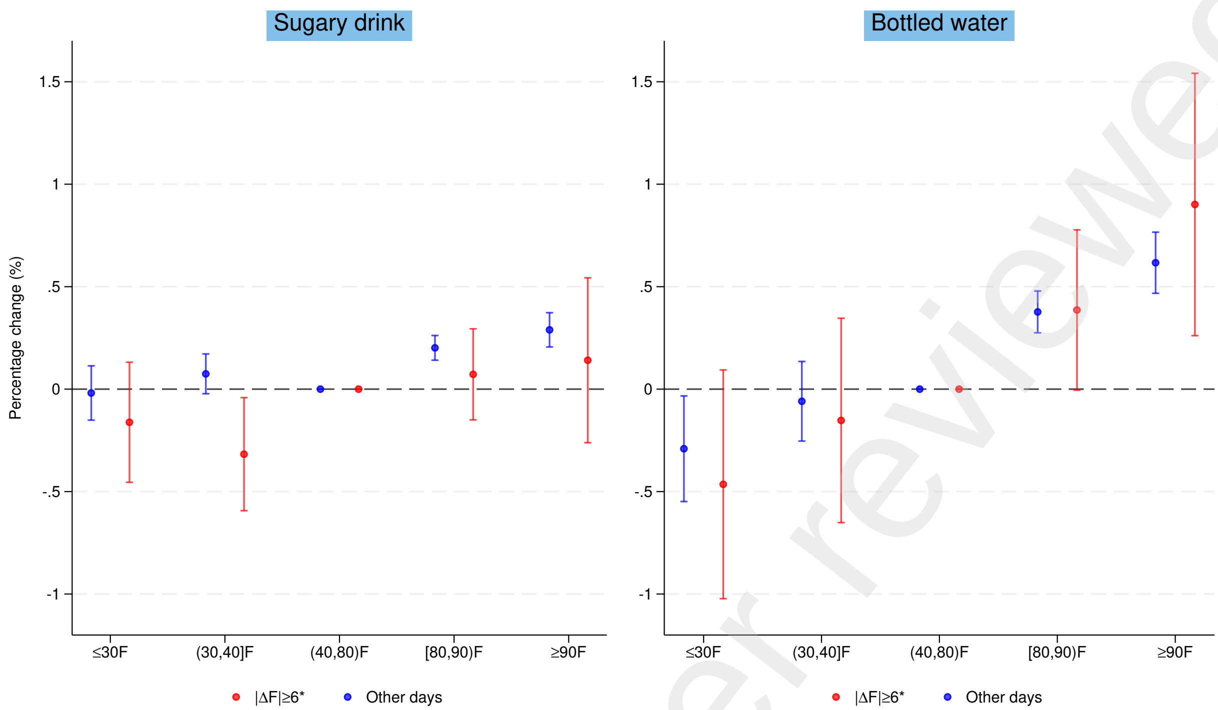

Figure F4. **The average effect of daily maximum temperature on the monthly volume purchased of sugary drink and bottled water, by day-on-day difference.** This table shows the results of the main specification in Equation 1 via Poisson pseudo-maximum likelihood, duplicating each temperature bin by its occurrence following and not following a day-on-day difference in maximum temperature (ΔF) of at least 6°F. * Only counting positive (negative) day-on-day differences for maximum temperature above (below) the reference bin. The reference maximum temperature bin is (40,80)F. Projection factors are used. Vertical segments show the 95% confidence interval. Robust standard errors are clustered at the zip code level. F: Fahrenheit.
Back to Section 4.4.4.

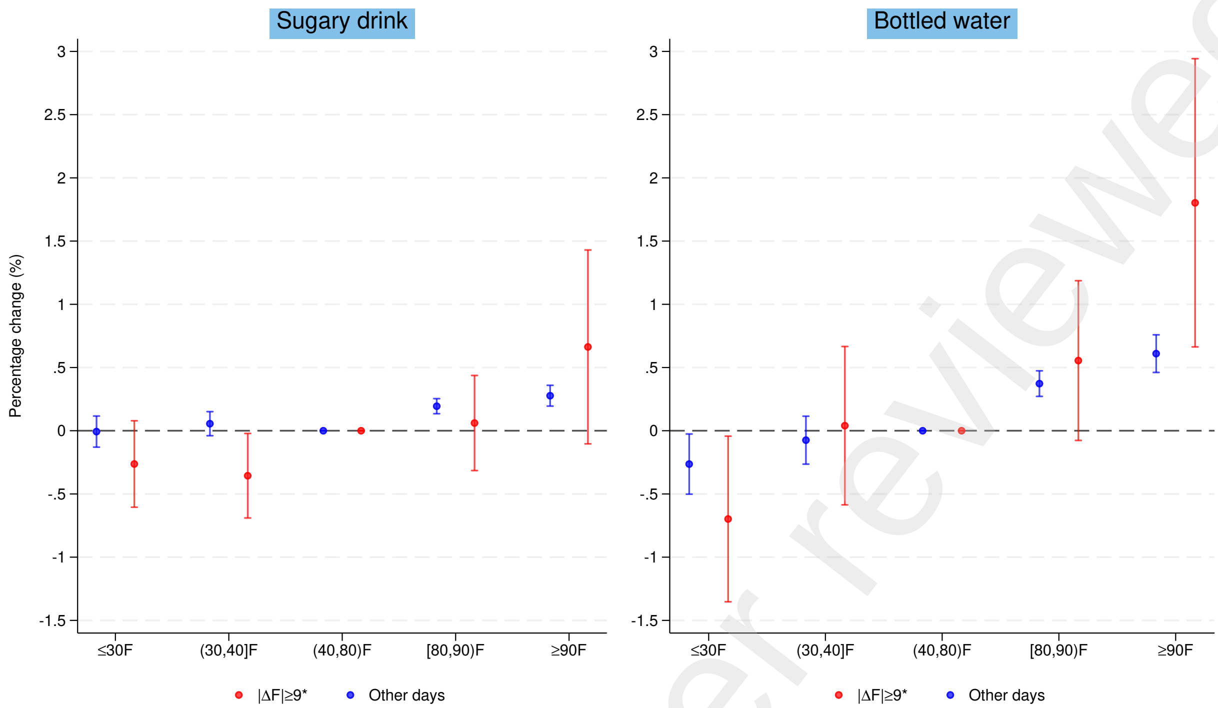

Figure F5. **Sensitivity more stringent threshold: The average effect of day-on-day differences in maximum temperature on sugary drink and bottled water volume purchased.** This table shows the results of the main specification in Equation 1 via Poisson pseudo-maximum likelihood, duplicating each temperature bin by its occurrence following and not following a day-on-day difference in maximum temperature (ΔF) of at least 9°F. * Only counting positive (negative) day-on-day differences for maximum temperature above (below) the reference bin. The reference maximum temperature bin is (40,80)F. Projection factors are used. Vertical segments show the 95% confidence interval. Robust standard errors are clustered at the zip code level. F: Fahrenheit.
Back to Section 4.4.4.

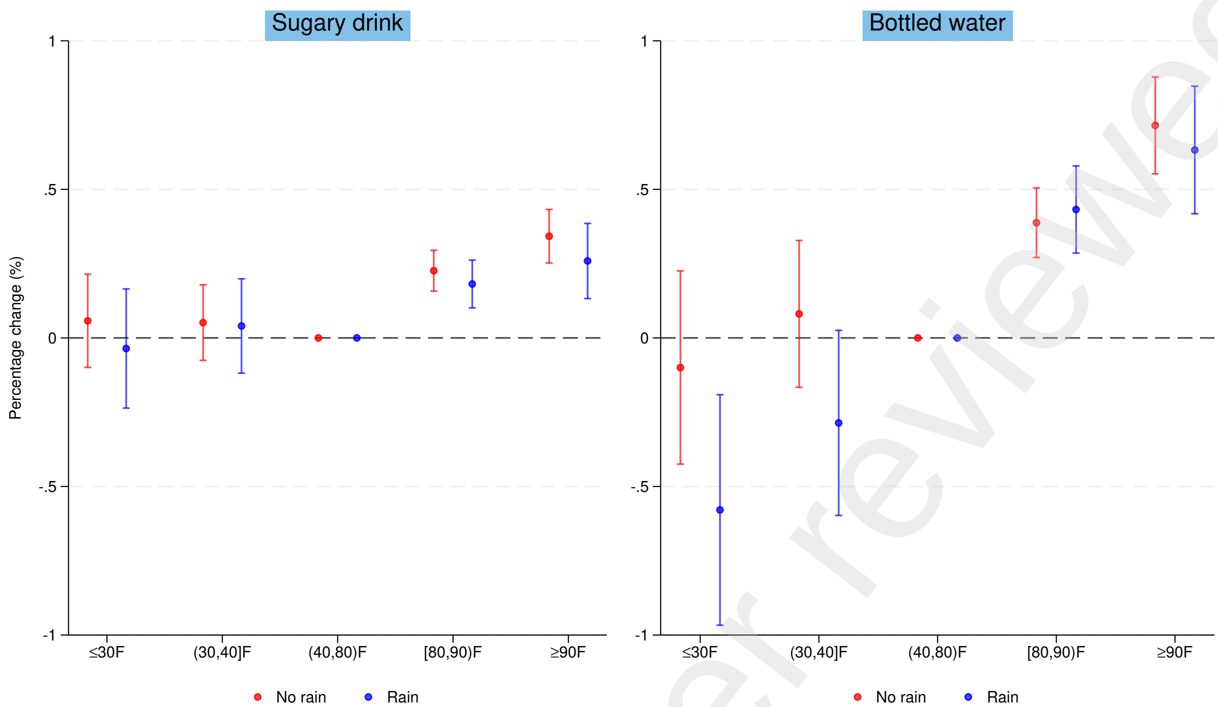

Figure F6. **The average effect of daily maximum temperature on the monthly volume purchased of sugary drink and bottled water, by precipitation.** This figure shows the results of the main specification in Equation 1 via Poisson pseudo-maximum likelihood, duplicating each temperature bin by its occurrence with and without rain (0 mm). Precipitations are omitted as controls because of collinearity. The reference maximum temperature bin is (40,80)F. Projection factors are used. Vertical segments show the 95% confidence interval. Robust standard errors are clustered at the zip code level. F: Fahrenheit. Back to Section 4.4.4.

	Any stores	Convenience stores	Other stores
≤ 30F	-0.015***	-0.007***	-0.008***
	(0.002)	(0.001)	(0.002)
$(30, 40]$F	-0.001	-0.001	0.000
	(0.002)	(0.001)	(0.001)
$[80, 90)$F	-0.004***	-0.002**	-0.002***
	(0.001)	(0.001)	(0.001)
≥ 90F	-0.005***	-0.002**	-0.003***
	(0.002)	(0.001)	(0.001)
N	5834298	5834298	5834298
adj. R^2	0.644	0.637	0.639
Weather controls	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Mean of Y (# trips)	9.12	3.44	5.68

Table F1. **The average effect of daily maximum temperature on the monthly occurrence of shopping trips, by store type.** This table shows the results of the main specification in Equation 1, via ordinary least squares, replacing the dependent variable by the monthly number of trips to each store type. The reference maximum temperature bin is (40,80)F. The dependent variable is in level and coefficents are to be interpreted as absolute change. Convenience stores also include bodegas, discount stores, liquor stores, service stations, small grocery stores, and tobacco stores. Projection factors are used. Robust standard errors are clustered at the zip code level. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Back to Section 4.4.1.

	Sugary drink Convenience	Sugary drink Other	Diet CSD Convenience	Diet CSD Other	Bottled water Convenience	Bottled water Other
$\leq$ 30F	0.0020	-0.0009	0.0030*	-0.0028***	-0.0052**	-0.0025*
	(0.0012)	(0.0007)	(0.0018)	(0.0011)	(0.0023)	(0.0014)
$(30, 40]$F	0.0030***	-0.0006	-0.0018	-0.0015*	-0.0028	0.0002
	(0.0010)	(0.0006)	(0.0015)	(0.0009)	(0.0020)	(0.0011)
$[80, 90)$F	0.0021***	0.0020***	-0.0003	0.0016***	0.0035***	0.0041***
	(0.0006)	(0.0004)	(0.0008)	(0.0006)	(0.0010)	(0.0006)
$\geq$ 90F	0.0032***	0.0027***	0.0026**	0.0017**	0.0056***	0.0066***
	(0.0008)	(0.0005)	(0.0012)	(0.0008)	(0.0014)	(0.0009)
N	5302780	5758347	4034957	4930057	4256325	5108977
pseudo R^2	0.588	0.536	0.646	0.652	0.586	0.551
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes

Table F2. **The average effect of daily maximum temperature on monthly volume purchased of soft drink, by soft drink type and store type.** This table shows the results of the main specification in Equation 1 by store type estimated via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (40,80)F. Convenience stores also include bodegas, discount stores, liquor stores, service stations, small grocery stores, and tobacco stores. Robust standard errors are clustered at the zip code level. CSD: carbonated soft drink. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Back to Section 4.4.1.

	Sugary drink Convenience	Sugary drink Other
≤ 30F	0.0022*	-0.0010
	(0.0013)	(0.0007)
≤ 30F$\times$ Rural	-0.0010	0.0006
	(0.0023)	(0.0020)
$(30, 40]$F	0.0028***	-0.0006
	(0.0010)	(0.0006)
$[30, 40)$F$\times$ Rural	0.0013	0.0010
	(0.0022)	(0.0016)
$[80, 90)$F	0.0021***	0.0021***
	(0.0006)	(0.0004)
$(80, 90]$F$\times$ Rural	0.0000	-0.0006
	(0.0014)	(0.0014)
≥ 90F	0.0031***	0.0030***
	(0.0008)	(0.0005)
≥ 90F$\times$ Rural	0.0007	-0.0032*
	(0.0017)	(0.0018)
N	5302780	5758347
pseudo R^2	0.588	0.536
Weather controls	Yes	Yes
Time-varying HH controls	Yes	Yes
Zip code x month of year FE	Yes	Yes
Year x quarter of year FE	Yes	Yes
Household FE	Yes	Yes

Table F3. **The average effect of daily maximum temperature on monthly volume purchased of sugary drinks, by store type and area.** This table shows the results of the main specification in Equation 1 by store type estimated via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (40,80)F. Convenience stores also include bodegas, discount stores, liquor stores, service stations, small grocery stores, and tobacco stores. Robust standard errors are clustered at the zip code level. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Back to Section 4.4.1.

	Sugary drink	Diet CSD	Bottled water
$\leq$ 30F	-0.0001	-0.0001	-0.0061
	(0.0021)	(0.0033)	(0.0042)
$\leq$ 30F $\times$ Est. density	0.0000	-0.0006	0.0014
	(0.0010)	(0.0015)	(0.0021)
$(30, 40]$F	0.0008	-0.0036	-0.0025
	(0.0017)	(0.0025)	(0.0037)
$(30, 40]$F $\times$ Est. density	-0.0002	0.0010	0.0009
	(0.0008)	(0.0012)	(0.0018)
$[80, 90)$F	0.0050***	0.0033	0.0100***
	(0.0012)	(0.0022)	(0.0022)
$[80, 90)$F $\times$ Est. density	-0.0016***	-0.0013	-0.0033***
	(0.0006)	(0.0011)	(0.0011)
$\geq$ 90F	0.0033**	0.0013	0.0107***
	(0.0015)	(0.0024)	(0.0026)
$\geq$ 90F $\times$ Est. density	-0.0002	0.0005	-0.0023*
	(0.0008)	(0.0012)	(0.0014)
N	5819204	5233030	5434654
pseudo R^2	0.562	0.692	0.568
Weather controls	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes

Table F4. **Interaction effects between daily maximum temperatures and the density of food and drink establishments on the monthly volume purchased of soft drink, by soft drink type.** Establishment density built using the number of North American Industry Classification System (NAICS) code 722 'Food services and drinking places' establishments divided by county-level population data, using yearly data from the U.S. Census Bureau's County Business Patterns and the National Cancer Institute (establishment per 1,000 inhabitants). The establishment density term is not included in the regression by its own given that it is constant for each county and thus collinear with household fixed effects. Regression via Poisson pseudo-maximum likelihood. The reference maximum temperature bin is (40,80)F. Projection factors are used. Robust standard errors are clustered at the zip code level. CSD: carbonated soft drink. F: Fahrenheit. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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	Regular CSD	Fruit juice/drink	Diet CSD	Bottled water
Stores	15,353	12,155	13,219	14,118
Counties	158	161	150	156
States	49	49	49	49
Observations	2,579,304	2,042,040	2,220,792	2,371,824

Table F5. **Final sample size, retail scanner dataset, 2006-2019.** Sample period January 2006 to December 2019. The 49 States correspond to the 48 States in the contiguous U.S. and the District of Columbia. CSD: carbonated soft drink.
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G. Climate projections

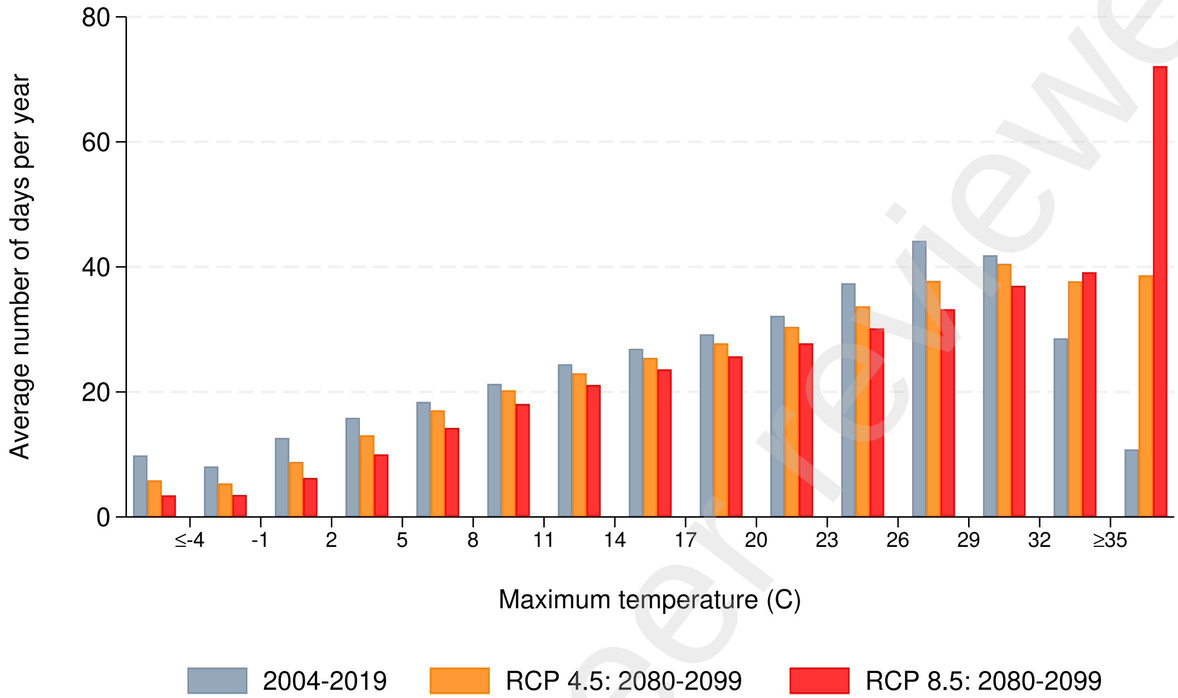

Figure G1. **Distribution of annual daily maximum temperature, for 2004-2019 and for 2080-2099 under RCP 4.5 and RCP 8.5.** $N = 2,463$ counties. The period 2004-2019 is estimated using the U.S. NOAA Global Historical Climatology Network meteorological daily information. The predicted maximum temperature data for the period 2080-2099 is estimated as a probability-weighted average across the multi-model ensemble developed by Rasmussen et al. (2016). We use two greenhouse gas emission scenarios: RCP 4.5 and RCP 8.5. RCP: Representative concentration pathways. C: Celsius.
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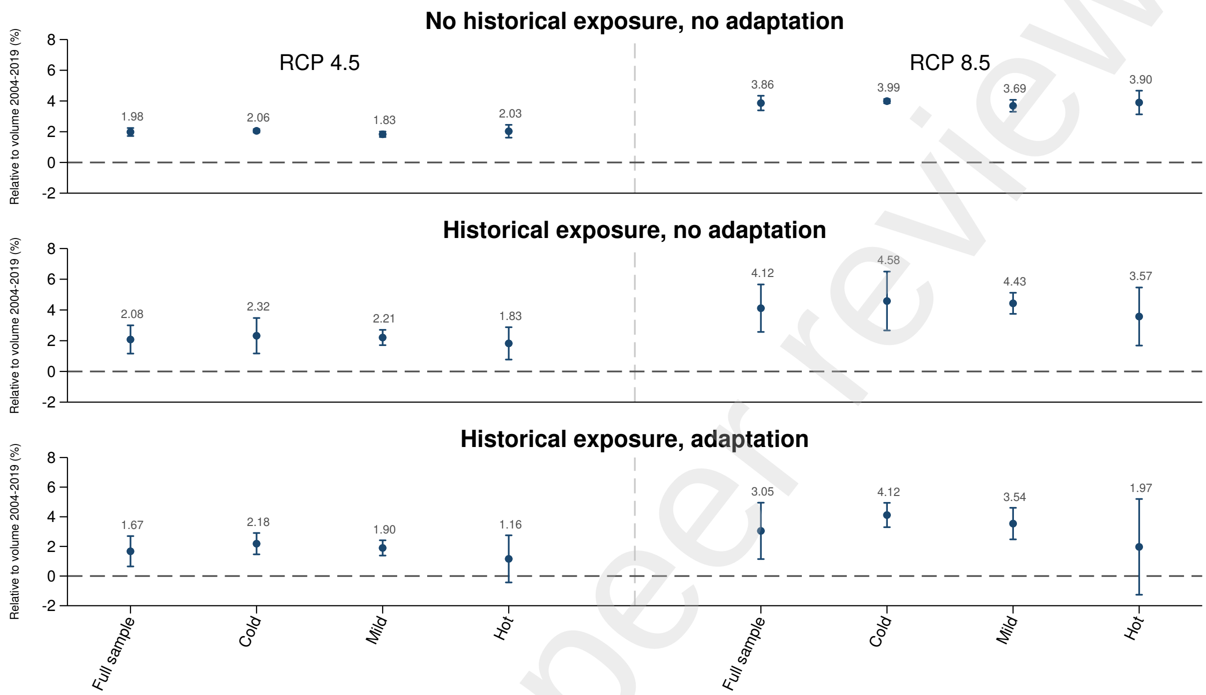

Figure G2. **Average relative change in the volume purchased of bottled water from climate projections by climate region, with and without accounting for historical exposure and adaptation, from 2004-2019 to 2080-2099.** This figure shows the relative effect of changes in maximum temperatures on bottled water volume purchased in 2080-2099 relative to 2004-2019 derived from Equation 7 ($\Delta\hat{V}^{NH,NA}$; no historical exposure, no adaptation), Equation 8 ($\Delta\hat{V}^{H,NA}$; historical exposure, no adaptation), and Equation 9 ($\Delta\hat{V}^{H,A}$; historical exposure, adaptation). Population-weighted average across sample counties (source: National Institutes of Health, National Cancer Institute, U.S. county population data, 2019). Results are shown for the national aggregate and for three climate regions under two greenhouse gas emission scenarios, RCP 4.5 and RCP 8.5. The hot, mild, and cold regions include sample counties within three terciles of average maximum temperature over the period 1974-2003. Maximum temperature predictions are derived from county-level probability-weighted averages across the multi-model ensemble from Rasmussen et al. (2016). Vertical segments show the 95% confidence intervals.
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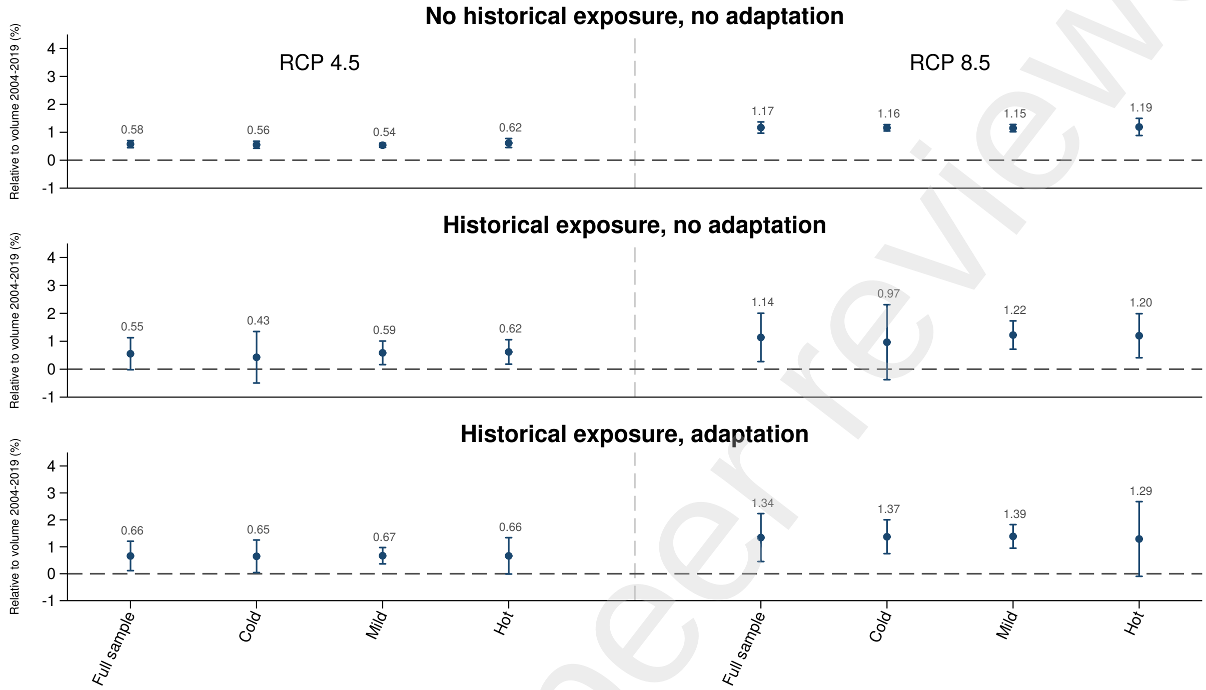

Figure G3. **Sensitivity using the median across climate multi-model ensemble: Average relative change in the volume purchased of sugary drink from climate projections by climate region, with and without accounting for historical exposure and adaptation, from 2004-2019 to 2080-2099.** This figure shows the relative effect of changes in maximum temperatures on sugary drink volume purchased in 2080-2099 relative to 2004-2019 derived from Equation 7 ($\Delta\hat{V}^{NH,NA}$; no historical exposure, no adaptation), Equation 8 ($\Delta\hat{V}^{H,NA}$; historical exposure, no adaptation), and Equation 9 ($\Delta\hat{V}^{H,A}$; historical exposure, adaptation). Population-weighted average across sample counties (source: National Institutes of Health, National Cancer Institute, U.S. county population data, 2019). Results are shown for the national aggregate and for three climate regions under two greenhouse gas emission scenarios, RCP 4.5 and RCP 8.5. The hot, mild, and cold regions include sample counties within three terciles of average maximum temperature over the period 1974-2003. This figure represents a sensitivity analysis of Figure 5 in which we use maximum temperature predictions derived from the median across the county-level multi-model ensemble from Rasmussen et al. (2016) instead of the probability-weighted average across the models ensemble. Vertical segments show the 95% confidence intervals.
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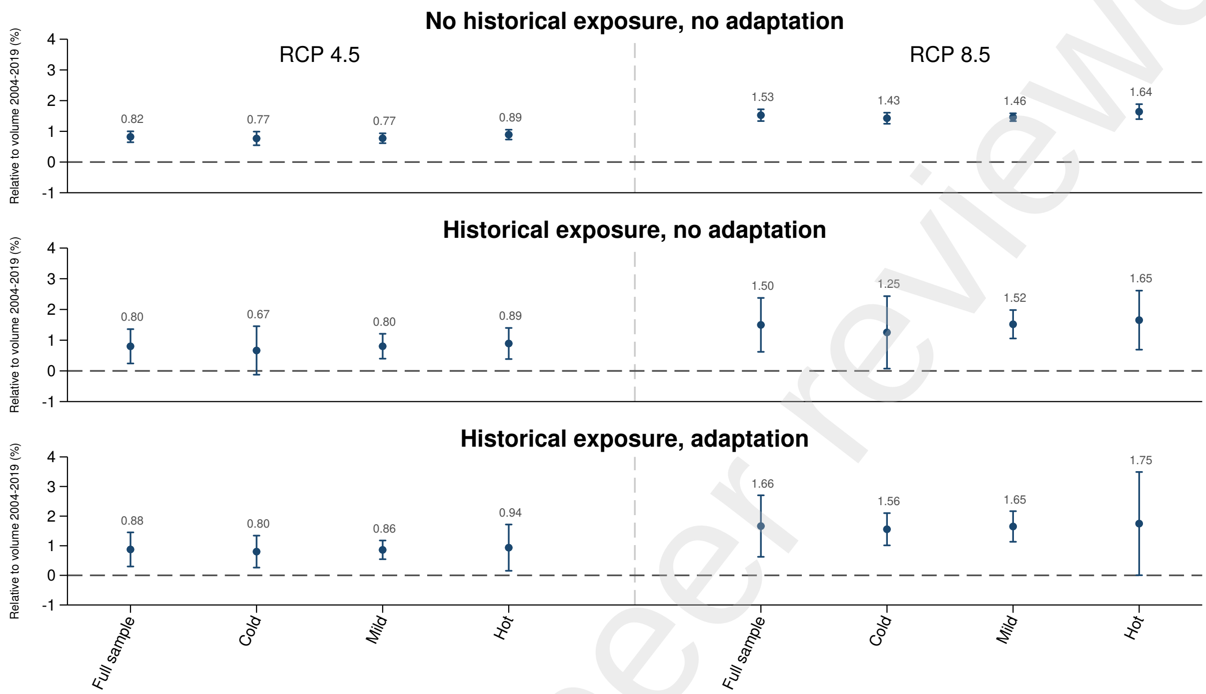

Figure G4. **Sensitivity accounting for projected precipitations: Average relative change in the volume purchased of sugary drink from climate projections by climate region, with and without accounting for historical exposure and adaptation, from 2004-2019 to 2080-2099.** This figure shows the relative effect of changes in maximum temperatures and precipitations on sugary drink volume purchased in 2080-2099 relative to 2004-2019 derived from Equation 7 ($\Delta\hat{V}^{NH,NA}$; no historical exposure, no adaptation), Equation 8 ($\Delta\hat{V}^{H,NA}$; historical exposure, no adaptation), and Equation 9 ($\Delta\hat{V}^{H,A}$; historical exposure, adaptation). Population-weighted average across sample counties (source: National Institutes of Health, National Cancer Institute, U.S. county population data, 2019). Results are shown for the national aggregate and for three climate regions under two greenhouse gas emission scenarios, RCP 4.5 and RCP 8.5. The hot, mild, and cold regions include sample counties within three terciles of average maximum temperature over the period 1974-2003. Maximum temperature predictions are derived from county-level probability-weighted averages across the multi-model ensemble from Rasmussen et al. (2016). This figure represents a sensitivity analysis of Figure 5 in which we consider changes in both maximum temperatures and precipitations instead of considering only changes in maximum temperatures. Vertical segments show the 95% confidence intervals.
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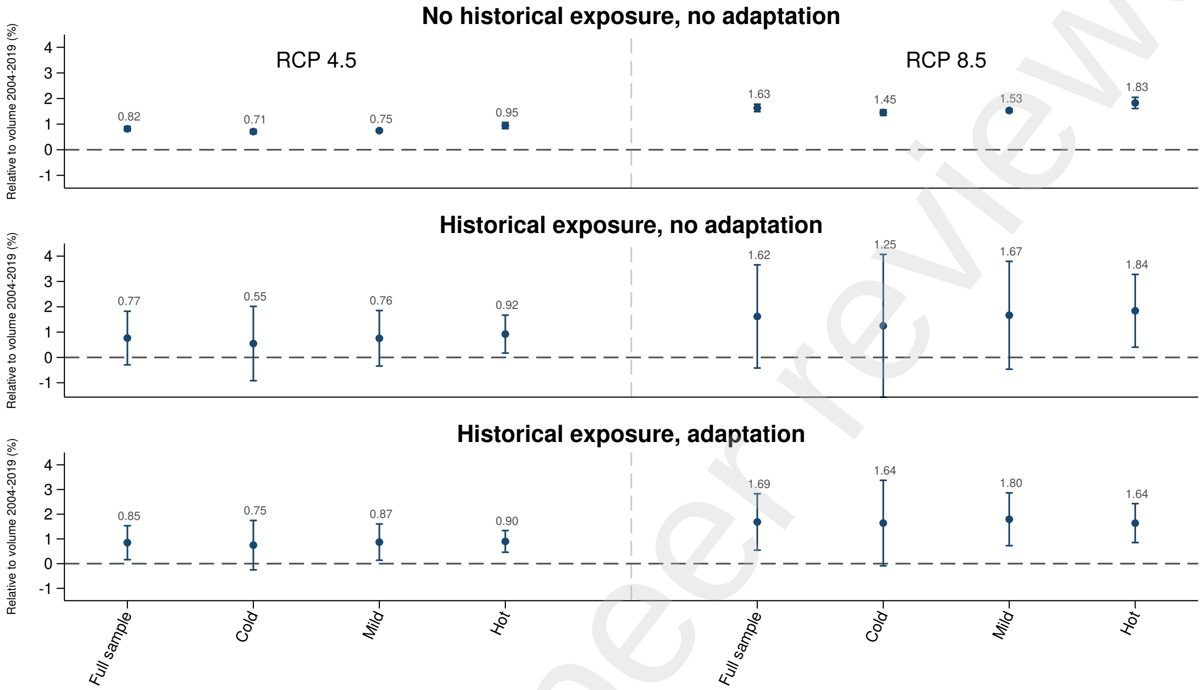

Figure G5. **Sensitivity using a richer model: Average relative change in the volume purchased of sugary drink from climate projections by climate region, with and without accounting for historical exposure and adaptation, from 2004-2019 to 2080-2099.** This figure shows the relative effect of changes in maximum temperatures on sugary drink volume purchased in 2080-2099 relative to 2004-2019 derived from Equation 7 ($\Delta\hat{V}^{NH,NA}$; no historical exposure, no adaptation), Equation 8 ($\Delta\hat{V}^{H,NA}$; historical exposure, no adaptation), and Equation 9 ($\Delta\hat{V}^{H,A}$; historical exposure, adaptation). Population-weighted average across sample counties (source: National Institutes of Health, National Cancer Institute, U.S. county population data, 2019). Results are shown for the national aggregate and for three climate regions under two greenhouse gas emission scenarios, RCP 4.5 and RCP 8.5. The hot, mild, and cold regions include sample counties within three terciles of average maximum temperature over the period 1974-2003. Maximum temperature predictions are derived from county-level probability-weighted averages across the multi-model ensemble from Rasmussen et al. (2016). This figure represents a sensitivity analysis of Figure 5 in which we use purchase response estimates from a richer and more flexible model (Table G2). Vertical segments show the 95% confidence intervals.
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	Sugary drinks		Bottled water	
	(1)	(2)	(3)	(4)
≤ -1C	-0.0001	-0.0016	-0.0030**	-0.0018
	(0.0006)	(0.0011)	(0.0012)	(0.0020)
$\leq -1\text{C} \times Pr_z(\leq -1)^{hist}$		0.0183*		-0.0095
		(0.0094)		(0.0189)
$(-1, 5]$C	0.0003	-0.0009	-0.0002	-0.0054**
	(0.0005)	(0.0012)	(0.0009)	(0.0022)
$(-1, 5]\text{C} \times Pr_z((-1, 5])^{hist}$		0.0123		0.0437***
		(0.0095)		(0.0170)
$[26, 32)$C	0.0018***	0.0013**	0.0039***	0.0038***
	(0.0003)	(0.0006)	(0.0005)	(0.0011)
$[26, 32)\text{C} \times Pr_z([26, 32))^{hist}$		0.0021		0.0000
		(0.0020)		(0.0037)
≥ 32C	0.0029***	0.0029***	0.0070***	0.0090***
	(0.0004)	(0.0006)	(0.0008)	(0.0011)
$\geq 32\text{C} \times Pr_z(\geq 32)^{hist}$		0.0004		-0.0131**
		(0.0032)		(0.0052)
N	5820876	5820876	5436272	5436272
pseudo R^2	0.562	0.562	0.568	0.568
Weather controls	Yes	Yes	Yes	Yes
Time-varying HH controls	Yes	Yes	Yes	Yes
Zip code x month of year FE	Yes	Yes	Yes	Yes
Year x quarter of year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Table G1. **Purchase response estimates for climate projections, sugary drink and bottled water.** This table shows results from regressing Equation 1 (columns 1 and 3) and Equation 6 (columns 2 and 4), via Poisson pseudo-maximum likelihood. The share of historical observations on which T_i days occur ($Pr_z(T_i)^{hist}$) remains fixed over time for any given zip code z for all i and is estimated based on weather data from the U.S. NOAA Global Historical Climatology Network for 1974-2003. The reference maximum temperature bin is (5-26)C. Projection factors are used. Robust standard errors are clustered at the zip code level. C: Celsius. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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	Sugary drinks	
	(1)	(2)
≤ -4C	0.0009	0.0001
	(0.0009)	(0.0013)
$\leq -4\text{C} \times Pr_z(\leq -4)^{hist}$		0.0181
		(0.0160)
$(-4,-1]$C	0.0001	-0.0031
	(0.0010)	(0.0024)
$(-4,-1]\text{C} \times Pr_z((-4,-1])^{hist}$		0.0916*
		(0.0551)
$(-1,2]$C	0.0018**	0.0030
	(0.0008)	(0.0021)
$(-1,2]\text{C} \times Pr_z((-1,2])^{hist}$		-0.0144
		(0.0318)
$(2,5]$C	0.0005	-0.0028
	(0.0007)	(0.0021)
$(2,5]\text{C} \times Pr_z((2,5])^{hist}$		0.0535*
		(0.0294)
$(5,8]$C	0.0004	-0.0027
	(0.0007)	(0.0023)
$(5,8]\text{C} \times Pr_z((5,8])^{hist}$		0.0465
		(0.0321)
$(8,11]$C	0.0009	0.0016
	(0.0006)	(0.0014)
$(8,11]\text{C} \times Pr_z((8,11])^{hist}$		-0.0087
		(0.0167)
$[26,29)$C	0.0019***	0.0012
	(0.0005)	(0.0010)
$[26,29)\text{C} \times Pr_z([26,29))^{hist}$		0.0056
		(0.0066)
$[29,32)$C	0.0030***	0.0025***
	(0.0006)	(0.0008)
$[29,32)\text{C} \times Pr_z([29,32))^{hist}$		0.0049
		(0.0047)
$[32,35)$C	0.0033***	0.0021**
	(0.0006)	(0.0009)
$[32,35)\text{C} \times Pr_z([32,35))^{hist}$		0.0111*
		(0.0058)
≥ 35C	0.0039***	0.0044***
	(0.0007)	(0.0008)
$\geq 35\text{C} \times Pr_z(\geq 35)^{hist}$		-0.0036
		(0.0056)
N	5820876	5820876
pseudo R^2	0.562	0.562
Weather controls	Yes	Yes
Time-varying HH controls	Yes	Yes
Zip code x month of year FE	Yes	Yes
Year x quarter of year FE	Yes	Yes
Household FE	Yes	Yes

Table G2. **Sensitivity using a richer model: Purchase response estimates for climate projections, sugary drink.** This table shows results from regressing Equation 1 (column 1) and Equation 6 (column 2), via Poisson pseudo-maximum likelihood. The share of historical observations on which T_i days occur ($Pr_z(T_i)^{hist}$) remains fixed over time for any given zip code z for all i and is estimated based on weather data from the U.S. NOAA Global Historical Climatology Network for 1974-2003. The reference maximum temperature bin is (17-20)C. As a matter of space, we do not present the results for the bins $(11,14]$C, $(14,17]$C, $[20,23)$C, and $[23,26)$C, but these bins are included in the regression. Projection factors are used. Robust standard errors are clustered at the zip code level. C: Celsius. FE: fixed effects. HH: household. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
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