Extreme Temperatures, Adaptation Capacity, and Household Retail Consumption

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Abstract

While the large cost of extreme temperatures on production is well documented, relatively little is known about its impact on consumption despite its importance for welfare. Using high-frequency micro-shopping data from U.S. households, we report three findings. First, deviating from mild temperatures negatively affects the number of store visits, but the impact on overall purchases is moderated by greater purchases per store visit, especially for extremely cold days. Second, households actively manage inventory over time, which nullifies the impact of extreme cold. However, extreme heat appears to have a persistent negative impact on consumption. Third, passenger cars substantially moderate the negative impact of extreme temperatures on consumption while rideshare services or public transit do not produce comparable moderating effects. These findings suggest that the economic cost of extreme temperatures on consumption is likely to be concentrated on disadvantaged households.

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1 Introduction

As greenhouse gases accumulate in the atmosphere, the world is getting continuously warmer: every decade since the 1960s has been warmer than the one before (NASA 2020). At the same time, recent studies have pointed out a linkage between the warming Arctic and more frequent extreme cold across the Northern Hemisphere (Cohen et al. 2021). Earlier work documented that such temperature change—mostly focusing on heat—harms productivity, human capital formation, labor supply, health conditions, and economic growth (Deschenes and Moretti 2009; Barreca et al. 2016; Burke and Emerick 2016; Burke et al. 2015b; Dell et al. 2012, 2014; Somanathan et al. 2021; Graff Zivin and Neidell 2014; Park et al. 2020). While these studies provide useful insights to understand the impact of climate change on production, relatively little is known about its impact on consumption.[1]

However, understanding the relationship between extreme temperatures and consumption is also important for at least three reasons. First, consumption is one of the key determinants of economic welfare (Deaton and Zaidi 2002; Chen and Ravallion 2010; Attanasio and Pistaferri 2016), and thus identifying the impact of temperature shocks on consumption helps to deepen our understanding of the welfare cost of climate change. Second, given the availability of effective yet costly adaptation technologies, investigating the differential impact by socioeconomic status can shed light on the distributional consequences of climate change. Third, investigating consumption responses may help enhance our understanding about the mechanism behind earlier findings on the relationship between heat and firm production (Addoum et al. 2020; Li et al. 2020).

In this paper, we provide some of the first empirical evidence on the impact of extreme temperatures on U.S. household retail consumption using micro shopping data. We link the Nielsen consumer panel to county-level temperature data and flexibly estimate the impact of temperatures on retail consumption. In doing so, we investigate both contemporaneous and cumulative effects to test whether a temperature shock has a lasting impact on consumption. Further, we explore the role of adaptation by estimating the moderating effect of different modes of transportation available for shopping trips. The analysis exploits plausibly exogenous deviations from county-specific weekly

[1] This paper aims to study the impact of climate change on consumption using weather variations, a method pioneered by Deschênes and Greenstone (2007) (for more formal discussion, see Hsiang (2016), for instance). To the best of our knowledge, relatively little work has focused on the relationship between climate change and consumption, but we do note that numerous papers as early as Steele (1951) have studied the relationship between weather variations and sales to understand either business implications or consumer biases.

temperature patterns, which allows us to estimate the causal effect of additional hot or cold days on household consumption.

Our empirical analysis produces three key results. First, we find that deviating from mild temperatures negatively affects the number of store visits, but the impact on overall purchases is moderated by higher purchases per store visit, especially for extremely cold days. Specifically, one additional day with a daily mean temperature below 10°F (above 90°F) reduces the weekly number of store visits by 0.9% (0.4%). For the total expenditure and the quantity purchased in a given week, we find that extreme heat reduces both by up to 0.5%, while extreme cold leads to a moderate *increase* in both despite fewer store visits.[2] We show that this is a direct consequence of higher expenditure (and quantity purchased) per store visit on colder days. To explore the nature of higher spending per visit, we separately estimate the impact of extreme temperatures on three different product types: perishable food, storable food, and non-food products. The results show that while expenditures on perishable or non-food items remain constant or decline as the daily mean temperature deviates from a moderate condition, expenditures on storable food products increase sharply in extreme cold.

Second, we estimate a distributed lag model to investigate the potential dynamic impact of temperature shocks. We find that the negative impact of extreme temperatures on the number of store visits is long-lasting—even four weeks after the temperature shock, the reduction in the number of store visits remains at 1–1.5%. The quantity purchased, however, has a hump shape for extreme cold, which is consistent with the consumption pattern changes in an extremely cold week discussed earlier. Specifically, households increase inventory starting as early as the week before the temperature shock and let it return to the usual level three weeks after the temperature shock. In contrast, extreme heat leads to a persistent 0.5% decline in the quantity purchased even after four weeks following the temperature shock.

The systematic difference between extreme heat and cold might be driven by two factors. First, the benefit of stockpiling behavior can be larger on colder days because unfavorable driving conditions are more likely to materialize in winter. Consistent with this, we find that rainfall has a large negative impact on store visits only for cold days. Second, home production activity is likely to be lower during summer because of more time spent away from home.

Taking the contemporaneous and dynamic effects together, extreme temperatures seem to have

[2] We proxy quantity purchased by the total number of items purchased.

a small (up to 1.5%) but statistically significant negative effect on the number of store visits. In contrast, the negative impact on total expenditure or quantity purchased (0.5%) are present on hot days only. The magnitudes we find are smaller than those from developing countries (Lai et al. 2022; Somanathan et al. 2021) but are similar to those reported in the US (Addoum et al. 2020; Roth Tran 2022), suggesting that adaptation capacity might play a crucial role in determining the impact of temperature shocks.

In the last section, we explore the role of potential modifiers for extreme temperatures in the household consumption context. Because intense exposure to extreme temperatures mostly happens during travel to and from a shop, we focus on three different modes of transportation and estimate the moderating effect of passenger car ownership, public transit accessibility, and ride share service availability, respectively. We fit a model that includes interaction terms between moderators and temperature bins to find that having passenger cars substantially alleviates the negative impact of extreme temperatures on consumption. Specifically, all else equal, having 2.09 vehicles, which is the mean expected number of vehicles for Nielsen panelists, mitigates the negative effect by nearly 50% in comparison to households without a vehicle. In contrast, Uber service availability and higher public transit density does not seem to have any moderating effect, which implies that disadvantaged people with less access to private transportation might bear substantially higher costs from extreme temperatures. It is worth pointing out that we also explore potential alternative moderators—interchannel substitution from brick and mortar shops to online shops—or confounders—price adjustment by retailers. Our results rule out those possibilities by showing that online shopping and price do not seem to respond to extreme temperatures.

This paper contributes to three different strands of literature. First, it is related to earlier work studying the impact of climate change with a focus on temperature shocks (Addoum et al. 2020; Barreca et al. 2016; Li et al. 2020; Pankratz et al. 2019; Park et al. 2020; Park et al. 2021; Burke et al. 2015a; Burke and Emerick 2016).[3] While the existing literature focuses mostly on the production side impact, there is a small but growing number of studies on household consumption (Lai et al. 2022; He et al. 2022; Roth Tran 2022). Our study complements these papers by providing micro

[3] Given that our paper studies the relationship between weather variations and consumption activities—with an aim to understand the impact of climate change, this paper is also related to the broader literature that studies the relationship between weather and sales to investigate business impacts (Steele 1951; Petty 1963; Tian et al. 2021; Buchheim and Kolaska 2017; Bloesch and Gourio 2015; Starr-McCluer 2000) or study consumer behavioral biases using weather as a trigger (Busse et al. 2015; Conlin et al. 2007; Rind 1996).

evidence on various adaptation measures leveraged by households.

Second, we contribute to the growing literature studying ways to adapt to negative environmental conditions caused by climate change. While earlier studies have shown that air conditioning, urban green space, irrigation, high-speed railways, and relocation can substantially moderate the impact of detrimental environmental conditions (Barreca et al. 2016; He et al. 2022; Han et al. 2021; Lee 2021; Boustan et al. 2012; Finger et al. 2011; Fankhauser 2017; Barwick et al. 2022), we focus on passenger cars. While it is true that passenger cars contribute significantly to carbon emissions, the findings of this paper suggest that they substantially mitigate biological stress from climate change as well (Fan et al. 2021).

Third, because adaptation capacity, namely the mode of transportation in our context, varies across households with different socioeconomic conditions, our paper also sheds light on the distributional impact of climate change. While earlier work emphasized the distributional consequences from different levels of exposure, which is a function of geographic endowments (Burke and Tanutama 2019; Hsiang and Narita 2012; Hsiang et al. 2019, 2017), we focus on *vulnerability*, which may vary even within a relatively identical climate region due to socioeconomic conditions. In that respect, our work is related to Doremus et al. (2022), Garg et al. (2020), and Park et al. (2021), which show a temperature–driven income gap in energy spending, learning, and workplace safety, respectively. Our work differs from these by studying the gap in household retail consumption.

The paper proceeds as follows. Section 2 details the data sources and provides summary statistics on household retail consumption, temperature shock moderators, and recent temperature patterns. Section 3 describes the empirical model and presents estimation results on the effect of temperature shocks on consumption while Section 4 explores potential moderators. Section 5 concludes.

2 Data

2.1 Data Description

To understand the impact of extreme temperatures on household consumption, we collect and combine four different sets of data.

Household Retail Consumption. Our study utilizes the Nielsen Consumer Panel Dataset from 2004 to 2019, which contains purchasing information from approximately 40,000 to 60,000 US households who continuously report their purchases and household characteristics to Nielsen.[4] The data is collected through hand-held scanners, which are used by panelists to scan receipts for all purchases made for personal use. The dataset tracks the Universal Product Codes (UPCs) of all consumer goods households purchased from any outlet.[5] Products are classified into 10 departments, including health and beauty aids, non-food grocery, general merchandise, and seven different food categories.[6] Note that non-packaged grocery, gasoline, and utilities are not captured by the Nielsen dataset as they do not have UPCs.[7] Nielsen Consumer Panel data also has rich demographic information on the panelists such as location (as granular as a 5-digit zip code), income, household size, and race.

Our primary analysis aggregates transaction level data at a weekly frequency, defined as Sunday to Saturday, although there is a potential concern for underestimating the impact of extreme temperatures (in comparison to the daily frequency analysis).[8] Our choice reflects our intention to reduce the noise caused by high autocorrelation of daily temperature (Lai et al. 2022). Indeed, Online Online Appendix Figure A.1 (a) shows that the correlation between daily mean temperatures of a given day and its one-day lead or lag is 0.95, and the correlation remains high at 0.84 even before/after a week.[9] In our analysis, we weight each observation by a projection factor, which makes purchases projectable to the entire US.

Weather Variables. The weather data are drawn from the PRISM Daily datasets (Product *AN81d*) released by PRISM Climate Group at Oregon State University. The PRISM daily dataset provides climate information for each 4 by 4 km grid in the contiguous US, where each cell's information is interpolated based on the PRISM station records. We use three climate elements provided in the dataset: precipitation, which covers both rainfall and snow melt; daily minimum temperature; and daily maximum temperature, from January 2004 to December 2019. For daily mean temperature, we

[4]On average a household stays in the sample for 4.7 years.

[5]Consumer Panel also documents online expenditures as well. More discussion on online shopping can be found in Section 2.2 and Section 4.2.

[6]Food departments are dry groceries, frozen foods, dairy, deli, packaged meat, fresh produce, and alcohol. The health and beauty aids department includes products such as baby care, cosmetics, cough and cold remedies, skincare, etc. Non-food grocery includes detergents, diapers, pet care, etc.

[7]For consistency across different years, we exclude magnet data, which documents non-packaged grocery purchases, from our analysis because it is available only for a small subset of years.

[8]In the Nielsen data, weeks are defined as Sunday through Saturday and we follow this definition. As discussed in Section 3, our results are robust to the choice of the week start day.

[9]In contrast, the correlation is at most a little over 0.2 for rainfall (Online Online Appendix Figure A.1 (b)), which is more suitable for a daily level analysis as conducted in Roth Tran (2022).

take the average of the minimum and maximum temperature for each day. We convert the cell-level data to county-level data by taking the weighted average of each grid that belongs to a county. For weight, we use the fraction of cell area that falls within each county.

Temperature Shock Modifiers. We collect data on potential modifiers of a temperature shock on consumption behavior. Given that the exposure to extreme weather is concentrated on the travel between the point of origin and destination, our primary focus is on three different modes of transportation that provide differential degrees of protection: passenger cars, ride sharing, and public transit. For vehicles, we use the 2001, 2009, and 2017 National Household Transportation Survey (NHTS) from the Federal Highway Administration. Each wave has over 100,000 household responses with information on household characteristics such as region, household size, income, race, and population density. Importantly, it also documents the number of vehicles at each household, which we link to the Consumer Panel Data using demographic characteristics.

For the ride share service, we leverage differential availability of the Uber rideshare service across space and time. We use Uber launch year information for the 50 largest Metropolitan Statistical Areas from Berger et al. (2018). To measure the degree of public transit accessibility, we use the number of public transit stops for each zip code at a point in time between 2016-2018, constructed by Melendez et al. (2021) based on the National Transit Map.

Retail Store Sales Information. We use the Nielsen Retail Scanner Dataset to construct the price index at the store level from 2006 to 2019. Depending on the year, the dataset contains 30,000 to 50,000 individual stores from approximately 90 retail chains in all US markets. These stores cover various retail channels ranging from convenience stores, grocery and drug stores, and liquor shops, to mass merchandisers. Each individual store reports weekly pricing and sales volume for each UPC that had any sales during a given week. For price index construction, we use 17,030 stores that were repeatedly observed every year and have positive sales every quarter of the study period.[10]

2.2 Summary Statistics

Table 2.1 presents summary statistics for key variables used in the analysis. The variables are grouped into two categories: the first ten rows are related to household consumption activities and

[10] These stores account for 45% of all unique stores as of 2006 (the first year in our sample).

Table 2.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Mean	Std.Dev.	N
Panel A: Household Weekly Consumption					
Total Expenditure ($)	0	7,826	82	99	47,921,841
Total Number of Store Visits	0	112	3.2	3.43	47,921,841
Total Quantity (N of Items) Purchased	0	1,296	17	20	47,921,841
Exp. per Store Visit ($)	0	3,678	34	36	37,024,064
Quantity Purchased per Store Visit	0.019	461	7.53	7.91	37,024,064
Exp. on Perishable Food ($)	0	1,203	4.05	8.39	47,921,841
Exp. on Storable Food ($)	0	2,935	49	61	47,921,841
Exp. on Non-food ($)	0	7,692	29	50	47,921,841
Exp. on Cold Medicine ($)	0	1,116	0.7	4.27	47,921,841
Online Exp. ($)	0	2,362	1.2	12	47,921,841
Panel B: Household Demographic Characteristics					
Income ($)	5,000	317,095	74,883	44,457	917,692
Household Size	1	9	2.55	1.3	917,692
Race: White	0	1	0.766	0.38	917,692
Density (Population per square mile for zip code)	0	148,228	3,723	6,937	916,368

the next four rows shed light on demographic characteristics of the panelists.

A few points are worth noting. First, an average panelist spends $82 each week (or $4,264 annually). We construct a balanced panel for our analysis, suggesting that $82 is an average over both zero and non-zero expenditure weeks. These figures are inflation-adjusted to 2019 dollars using the CPI. When compared to the annual expenditure of the average US household from the Bureau of Labor Statistics, $4,264 captures about 60% of the average retail expenditure (Bureau of Labor Statistics 2020).[11] Using a unique trip ID, we also document that the total number of stores visited in a given week is on average 3.2, which means that an average household visits a store roughly every other day. Similarly, using unique product codes (i.e., UPC codes) from each product, we document that the total quantity purchased (i.e., the number of items purchased) in a given week is on average 17. By dividing the total expenditure and total quantity purchased by the number of store visits, we find that the average expenditure per store visit is $34 and the average quantity purchased (i.e., average number of items purchased) is 7.5. Note that these variables are constructed using only non-zero store visit weeks because average expenditure and quantity purchased per store visit are not defined

[11] In 2019, the average household spent $4,643 on food at home, $768 on personal care products and services, and $1,891 on other miscellaneous expenditures. Expenditures not covered by the Nielsen dataset include housing ($20,679), transportation ($10,742), food away from home ($3,526), insurance, pensions and cash contributions ($9,160), education ($1,443), health insurance ($3,529), entertainment ($3,050), and apparel and services ($1,883).

when a household has zero store visits for a given week.[12]

Second, out of the $82 weekly expenditure, roughly 65% of the total is for food purchases and 35% is for non-food purchases. Within food items, perishable foods (fresh produce and deli products) are less than 10% of the total expenditure and the rest are storable items such as dry groceries, frozen foods, dairy products, and packaged meat. We also single out cold medicine from the non-food product category despite its small contribution to the consumption basket, because it is useful to test consumption responses to temperature shocks.

Third, online shopping consists of a small fraction of the entire consumption over the sample period. Based on the averages, the online expenditure consists of a little less than 2% of the total expenditure. This is consistent with the overall trend in the US: the quarterly US retail sales data from the US Census indicate that the arithmetic mean of the fraction of e-commerce out of the entire retail expenditure over 2004-2019 is 5.6% (Census Bureau 2022). Although lower than the national average, the Nielsen data (at least partially) can capture potential switches from brick-and-mortar shops to online shops.

Lastly, a few remarks are worth noting for demographic variables. For income, we convert the income category from Nielsen data into numeric values by taking the median value of each category's income range. We further adjust for inflation using the CPI. In our analysis, we classify households into three income groups based on annual income: low (below $40,000), middle (between $40,000 and $100,000), and high (above $100,000). This minimizes measurement error in the income variable that can arise from the fact that the income record in year t reflects income in year $t - 2$ (e.g., income information in the year 2012 of consumer panel reflects income in 2010).[13]

The average household size is 2.55, which is exactly the same as the average number of people per household over 2004-2019 estimated using the Current Population Survey.[14] For many panelists, household size does not vary over time—76% of them remain the same in size while in the panel. Similarly, the fraction white is 77%, which closely mirrors the overall pattern in the US, which stands

[12]Note, the minimum of the variable "Exp. per Store Visit ($)" in Table 2.1 is 0. This is possible because of discounts or coupons that makes paid price essentially zero. Also, the minimum for the variable "Quantity Purchased per Store Visit" is lower than 1 because Nielsen data may not capture the entire set of products purchased for various reasons. For instance, some items don't have a UPC code (e.g., Magnet products) and some items aren't "coded" by Nielsen (e.g., most apparel, electronics, etc.). Further, sometimes panelists might not scan all products purchased.

[13]This happens because of the way Nielsen surveys income. For example, panelists in the 2014 panel are surveyed in September of 2013 about their total annual income at the end of 2012.

[14]https://www.census.gov/data/tables/time-series/demo/families/households.html, accessed on Sep 12, 2022.

at 75.8% (US Census Bureau 2023).

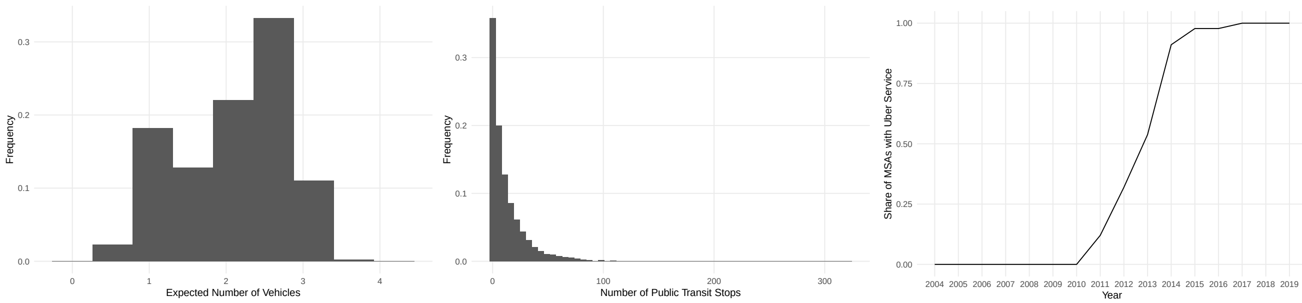
Population density, which is defined as the number of people per square mile within a zip code is on average 3,723. Given that urban areas typically have a population density of over 1,000 (Cohen et al. 2015), an average panelist in the Nielsen dataset lives in a large metropolitan city.[15]

Figures 2.1 (a)-(c) show the distribution of potential moderators for extreme temperatures. Figure (a) shows the expected number of vehicles for each Nielsen panelist. For this, we merge the National Household Transportation Survey with the Nielsen Consumer Panel data based on the demographic variables that are particularly relevant for vehicle ownership (see Online Appendix Table A.1). Specifically, we create cells using household size (1, 2-3, 4 or more), household income (Below $40,000, $40,000 - $100,000, and over $100,000), race (white, black, others), density, namely, population per square mile at the zip code level (below 1,000, 1,000-5,000, and over 5,000), four census regions (Northeast, Midwest, South, and West), and year (2001, 2009, and 2017). We calculate the average number of vehicles per household for each of 972 cells using sample weights and merge it with the Nielsen household data. The histogram suggests that the majority of households have 1-3 vehicles (mean 2.09) while 8% of households have less than 1 vehicle.

Figure 2.1 (b) illustrates the distribution of the number of transit stops per zip code during 2016-2018, which proxies the degree of access to public transit. The data come from Melendez et al. (2021), which has spatially merged the National Transit Map with ZCTA boundaries from the Census Bureau. The data is a snapshot of public transit status at a point between 2016-2018 for the areas administered by one of 270 regional transit agencies choosing to report to the National Transit Map. Because of the selection issue—that is, we do not know about the transit status for areas served by non-reporting transit agencies—we only keep observations with a positive number of transit stops, which implies that households living in areas served by non-reporting transit agencies are excluded from the transit effect analyses.[16] The plot shows that the number of stops has a large

[15] To put this in context, the population density in the City of Houston and City of Dallas are 3,661 and 3,684, respectively (Cohen et al. 2015). The median population density in our sample is lower at 1,135 and is comparable to that of Jacksonville City (1,127) and Oklahoma City (1,006).

[16] Online Appendix Table A.2 shows more details about the implication of this sample restriction. There are 23,115 unique zip codes that appear at least once (as part of the panelists' residency information) in the Nielsen homescan dataset, and only 28% of them appear in the National Transit Map (16,694 missing versus 6,421 non-missing). Perhaps not surprisingly, areas with denser transit networks seem to have chosen to report to the National Transit Map: for instance, as the second column shows, the zip code level population density is over 7 times higher for zip codes included in the National Transit Map. Further, as the third column shows, the total population for the two groups of zip codes are almost identical despite a large difference in the number of zip codes with and without the transit information, a pattern that appears in the Nielsen sample as well as the last column indicates (460,896 for non-missing zip codes and



(a) Expected Number of Vehicles (b) Number of Public Transit Stops (c) Uber Launch Year

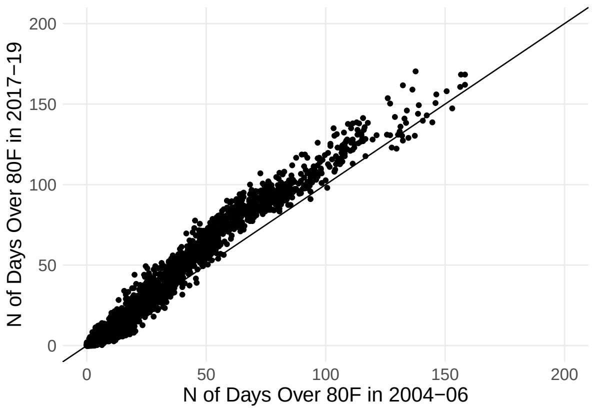
Figure 2.1: Availability of Potential Temperature Shock Moderators. Figure (a) shows the distribution of expected number of vehicles for Nielsen panelists while (b) shows the distribution of the number of public transit stops per zip code. Figure (c) illustrates the cumulative distribution of Uber launch year for the 50 largest Metropolitan Statistical Areas.

variation, with the average number of stops per zip code at 97. Figure (c) shows the share of the MSAs with Uber service for each year in the sample. The figure is produced based on the 50 largest MSAs following Berger et al. (2018). The figure shows that the most dramatic increase occurred between 2012 and 2014, and by 2015, every MSA except for Buffalo and Rochester, NY had the service. We spatially merge the panelist zip code with the MSA map and create a dummy variable for Uber availability based on the launch year.

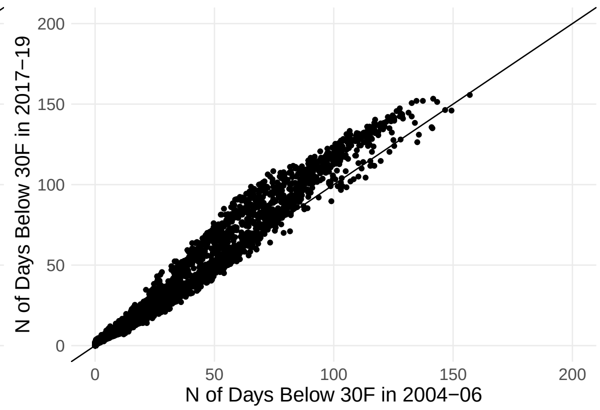
In Figures 2.2 (a)–(d), we illustrate how the temperature pattern has changed over our sample period. In panel (a) and (b), each dot represents a single county in our dataset, where the x-axis indicates the annualized number of days in 2004–06 with a mean daily temperature over 80°F or below 30°F and the y-axis illustrates the 2017–19 equivalent.[17] Two observations emerge from panels (a)-(b). First, the distribution of extreme temperatures became more polarized. Namely, places with fewer hotter (colder) days in 2004–06 had fewer hotter (colder) days in 2017–19 while places with a higher number of hotter (colder) days in 2004–06 experienced more hotter (colder) days in 2017–19. Second, the magnitude is large. For instance, for places with 50 days exposures (for both hot and cold) in 2004–06, the increase can be as large as 25–30 additional days. Plots (a)–(b) provide evidence of changing temperature patterns even for a relatively short period of time.

456,796 for missing zip codes). Note, this sample restriction is applied to the transit effect analysis only.

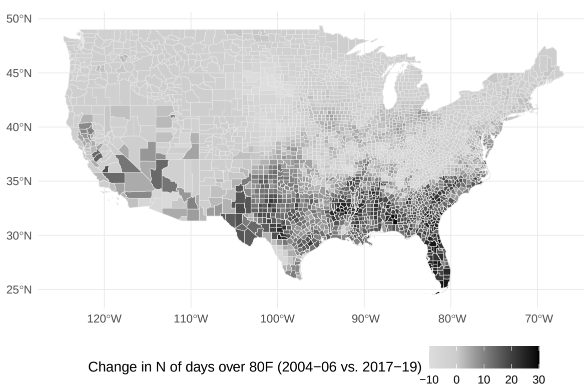
[17] Here, we use 80°F and 30°F as thresholds for extreme temperatures, which differs from the thresholds we use in subsequent empirical analyses—90°F and 10°F—to make Figures 2.2 more informative. That is, because three year averages inherently smooth out the year-to-year fluctuations in temperatures, there are substantially smaller number of counties that ever experience "extreme temperatures" under the latter thresholds. Importantly, it should not create concerns for our source of identification because we exploit year-to-year temperature variations.



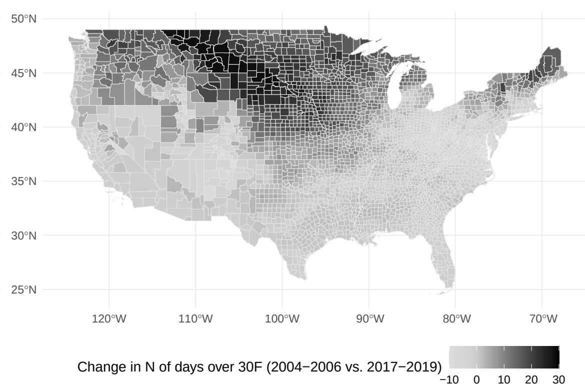
(a) Number of Days with Mean Daily Temperature over 80F in 2004-2006 and 2017-2019



(b) Number of Days with Mean Daily Temperature below 30F in 2004-2006 and 2017-2019



(c) Spatial Distribution of the Change in Number of Days with Daily Mean Temperature over 80F



(d) Spatial Distribution of the Change in Number of Days with Daily Mean Temperature below 30F

Figure 2.2: Change in Temperatures Over Time (2004-2006 vs. 2017-2019). Figures (a) and (b) show how the number of days with a mean daily temperature over 80F and below 30F has evolved between 2004-2006 and 2017-2019, respectively. Figures (c) and (d) show the corresponding spatial distribution. We use a three-year average for each county.

Panels (c)–(d) corroborate polarization of temperature distribution from panels (a)–(b). We find that over the last 15 years, a cooler part of the country (the northwest) experienced far more cold days while a warmer part of the country (the southeast) experienced far more hot days. Note, the extent of additional hot or cold days could be much larger than 30 because these the values are topped out at 30 for visibility.

3 The Impact of Temperature Shocks on Retail Consumption

3.1 Contemporaneous Effect

Our main empirical exercise is to estimate the impact of extreme temperatures on weekly household retail consumption activities. Specifically, we estimate equation (1), which exploits deviations from county-specific weekly temperature patterns.

$$Y_{icwmy} = \sum_k \beta^k T^k_{cwy} + \gamma \mathbf{X}_{cwy} + FEs + \epsilon_{icwmy} \quad (1)$$

Here Y_{icwmy} is various consumption outcomes for a household i living in county c in week w, month m at year y. Specifically, we study the total expenditure and its building blocks to investigate the margins of adjustments. To fix the idea, consider weekly household expenditure $Exp_{iw} = \sum_k p^k q^k_i$ where k represents each store, p^k is the price for store k and q^k_i is the quantity purchased from store k by household i, which in practice is measured by the number of items purchased. Our outcome variables include (in addition to Exp_{iw}) the total number of store visits $\sum_k 1_{q^k_i>0}$,[18] the total quantity purchased $\sum_k q^k_i$, the average expenditure per store visit $\frac{\sum_k p^k q^k_i}{\sum_k 1_{q^k_i>0}}$, and the average quantity purchased per store visit $\frac{\sum_k q^k_i}{\sum_k 1_{q^k_i>0}}$.[19] We also explore these outcome variables separately for three mutually exclusive but collectively exhaustive product categories $j \in$ {Perishable food, Storable food, and non-food}.

Control vector $\mathbf{X}_{cwy}$ includes precipitation and its square term for county c in week-year wy. We also include four different sets of fixed effects. Specifically, individual household fixed effects control for time-invariant unobserved household characteristics that might affect consumption activities.

[18] If a household visits the same store twice within a week, each visit is counted separately.
[19] In this section, we abstract away from potential change in p^k. We test if extreme temperatures impact price in Section 4.2.

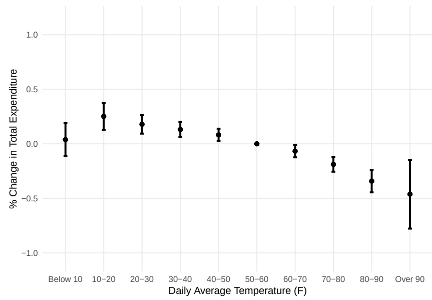
We also include county by week-of-year (e.g., week $1, 2, \cdots, 52$) fixed effects to exploit year-to-year variation in temperatures for the same county at the same time of the year. Year by month fixed effects control for macro level shocks for each year-month while income group fixed effects controls for a known demand shifter. The key independent variables are the measure of temperature T^k_{cwy}, which is the number of days in a county-week-year that the daily average temperature belongs to bin k where $k \in \{\text{Below } 10°F, 10-20°F, 20-30°F, 30-40°F, 40-50°F, 50-60°F, 60-70°F, 70-80°F, 80-90°F, \text{Over } 90°F\}$. For temperature extremes, we focus on Below $10°F$ and Over $90°F$ bins, which have similar relative frequency (Online Appendix Figure A.2).

Equation (1) allows a flexible relationship between temperature and consumption outcomes. Throughout various estimation models, we omit the $50-60°F$ temperature bin, and thus the interpretation of β^k is the impact of replacing one day (in a given week) from a moderate temperature $(50-60°F)$ to the temperature of bin k on consumption outcomes.

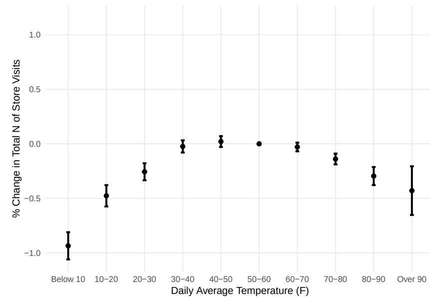
Figures 3.1 (a)-(f) show the contemporaneous impact of extreme temperatures on various consumption outcomes. While equation (1) is estimated using outcome variables in their original scale, the estimated coefficients are expressed in percentages in Figures 3.1 (a)-(f) by dividing them with the mean value of each variable.[20] In Figures (a)-(c), we find that while the number of store visits shows a clear "inverse-U shape" relationship with respect to the temperature, expenditure and the quantity purchased have a peak at the $10-20°F$ bin. Specifically, we find that while swapping a day with a daily mean temperature between 50-60$°F$ in a given week to a day with daily mean temperature below $10°F$ (over $90°F$) reduces the number of store visits by 0.9% (0.4%), both expenditure and quantity purchased are negatively affected only in hotter days—where the magnitudes in percentage are almost identical to the effect on the number of trips.

In Figures (d)-(e), we explore the impact of having one additional day of extreme temperatures in a given week on the average expenditure and average quantity purchased, where the denominator is the total number of store visits per week. We find that on colder days, households purchase roughly 1% more items per store visit (and spend roughly 0.8% more). This implies that purchasing more per visit is an important margin of adjustment that allows households to reduce their exposure to extreme cold weather without compromising their nutritional needs. In contrast, we find that the

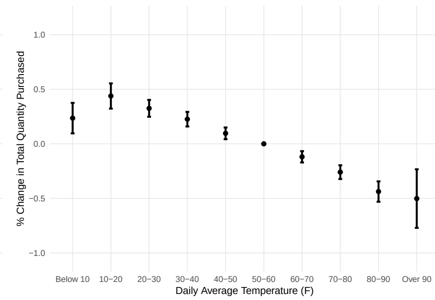
[20]Online Appendix Tables A.3 and A.4 present all the coefficients appearing in Figures 3.1 (a)-(f) in the original scale. The tables also present mean values for each outcome variables that have been used for percentage conversion.



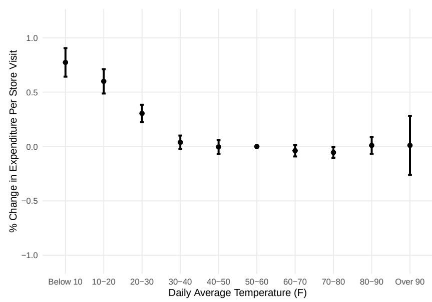
(a) Total Expenditure



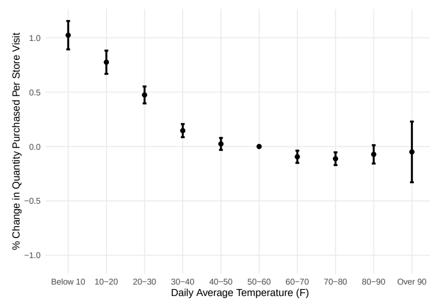
(b) Total N of Store Visits



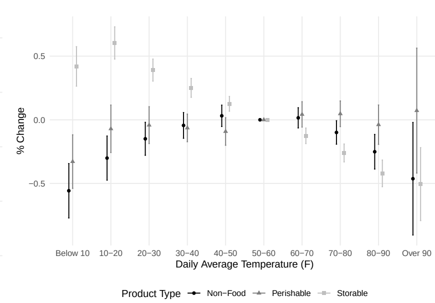
(c) Total Quantity Purchased



(d) Expenditure Per Store Visit



(e) Quantity Purchased Per Store Visit



(f) Total Expenditure by Product Type

Figure 3.1: Temperature and Household Weekly Consumption. Figures (a)-(f) show the estimated coefficients from equation (1) on various outcome variables. (a)-(e) are for all product groups and (f) is for three separate product groups (perishable food, storable food, and non-food). The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each outcome variable. Standard errors are clustered at the county level.

average expenditure and quantity purchased are stable beyond the $40-50°F$ bin, which suggests that spending per trip adjustments occur only on colder days.

To further investigate the nature of consumption pattern changes, in Figure 3.1 (f), we estimate equation (1) for expenditure on three mutually exclusive but collectively exhaustive product types: perishable food, storable food, and non-food products.[21] We find that expenditures on storable food products sharply increase with additional cold days. Interestingly, demand for perishable items seems to be highly stable across different temperature conditions, presumably due to nutritional needs and limited storability. Further, non-food items, in general, seem to be of lower priority than food items in the sense that the expenditure drops sharply as daily mean temperature deviates from the moderate condition, although one important exception is a cold medicine that is highly sensitive

[21]The highest level of classification is "department" in the Nielsen homescan data. Departments 1 to 6 are food products: dry grocery, frozen foods, dairy, deli, packaged meat, and fresh produce. Departments 0 and 7–9 are non-food items such as beauty and health, non-food grocery, alcohol, and general merchandise. We classify deli and fresh produce as perishable food; the dry groceries, frozen foods, dairy, and packaged meat as storable food; and the rest as non-food products.

to temperature (see Online Appendix Figure A.7), presumably for health reasons (Deschenes and Moretti 2009). Finally, columns (4)-(6) of Online Appendix Table A.4 suggest that the results are highly similar when we use quantity purchased as opposed to expenditure as an outcome variable.

It is also worth emphasizing that a combination of individual effects for three different product categories fully explains the overall effect. To fix the idea, take the sum of the estimated changes in expenditure (in levels) on three product types for one additional day with daily mean temperature below $10°F$ as opposed to 50-$60°F$ from columns (1)-(3) of Online Appendix Table A.4. Then, the sum ($-0.0133 + 0.2048 - 0.1606 = 0.0309$) is almost identical to the change in total expenditure (again, in levels) from Online Appendix Table A.3 (0.0310). This exercise helps identify the key driver of the overall effect as well as explore changes in the composition of the consumption basket.

We show that our results are robust to a series of alternative specifications. First, in Online Appendix Figure A.3, we present a Poisson regression version of equation (1). We find that the result is similar to our main specification not only in terms of overall patterns but also in terms of magnitude. Given this similarity, we choose to use untransformed outcome variables for our main specification because non-linear estimation is computationally burdensome. Second, Online Appendix Figure A.4 shows that the inclusion of a county-specific linear time trend, which could capture, for instance, a county-specific temperature increase over time, produces essentially identical results. Third, in Online Appendix Figure A.5, we include the household size fixed effect to control for another potential demand shifter (i.e., households with larger size tend to purchase more). The figure shows that our results are robust to the inclusion of household size FE, which is not surprising given that household size does not change for 76% of the panelists during the time that they provide data to Nielsen. Lastly, Online Appendix Figure A.6 shows that the choice of week start day does not affect our results on the contemporaneous effects.

Taken together, findings from this section indicate that households reduce trips to stores in unfavorable weather conditions, but the potential margins of adjustment can differ depending on whether the daily temperature is hot or cold. Specifically, while we observe a more-than-offsetting increase in expenditures per visit for colder days, no such patterns appear for hotter days. In the next section, we explore another margin of adjustment, intertemporal substitution, to test if households employ different adaptation strategies on hotter days.

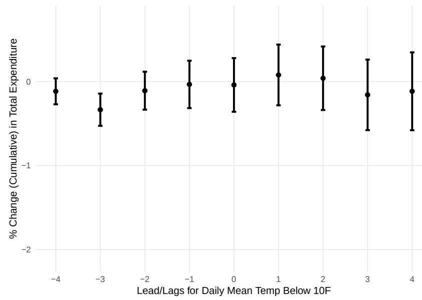
3.2 Dynamic Effect

Section 3.1 shows that households increase their expenditure per store visit during cold temperatures to meet their nutritional needs while reducing exposure to unpleasant weather. In this section, we explore another potential margin of adjustment—intertemporal substitution. Given easily accessible weather forecast information, households might change the timing of store visits to minimize their exposure to extreme temperatures. Investigating the impact of extreme temperatures over time is important from the welfare perspective as well because it allows us to determine whether households *defer* or *reduce* consumption.

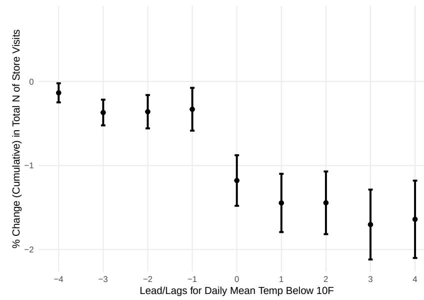
To investigate this possibility, we estimate a distributed lag model in equation (2). While a typical distributed model focuses on estimating the lagged periods, we include leads to allow potential anticipatory behavior. Here, $T^k_{cy,w-t}$ is the number of days with the daily mean temperature belonging to bin k in a county-year-lagged week (of $w-t$). Similar to equation (1), we omit the $50-60°F$ temperature bin, and thus the interpretation of β^k_{w-t} is the impact of replacing one day (in a given week) from a moderate temperature ($50-60°F$) to the temperature of bin k on consumption outcomes at lead or lag week $w-t$. Our results are presented in cumulative effect ($\sum_{t=-4}^{T}\beta^k_{w-t}$) where we calculate standard errors using the delta method.

$$Y_{icwmy} = \sum_{t=-4}^{4}\sum_{k}\beta^k_{w-t}T^k_{cy,w-t} + \gamma\mathbf{X}_{cwy} + FEs + \epsilon_{icwmy} \tag{2}$$

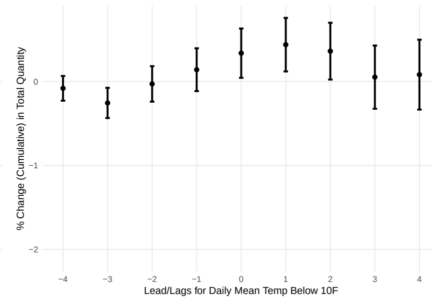
In Figures 3.2 (a)-(c), we plot the cumulative effect of extreme cold (below $10°F$) on three different outcome variables using estimated coefficients from equation (2). We start by noting that the weekly expenditure in panel (a) is strikingly stable at 0 over time, which suggests that being exposed to extremely cold weather does not make households spend more or less. However, Figures 3.2 (b)-(c) indicate that the null effect in Figure 3.2 (a) does not mean that households do not change their shopping behavior. Consistent with findings from Section 3.1, we find that the number of store visits sharply declines on the week with extremely cold weather and remains at -1.5% four weeks after the cold weather exposure, suggesting that the impact is likely to be long-lasting. Figure 3.2 (c) shows that despite fewer store visits, households maintain their needs. Specifically, households increase inventory starting as early as the week before the temperature shock and let it gradually return to the usual level until week +3. Such an anticipatory behavior in response to predicted adverse weather



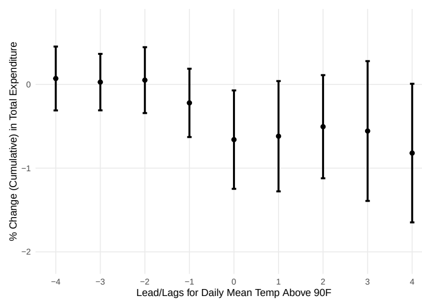
(a) Expenditure (Below 10F)



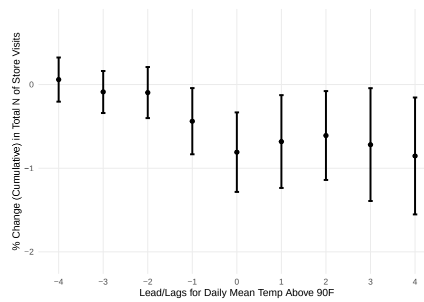
(b) N of Store Visits (Below 10F)



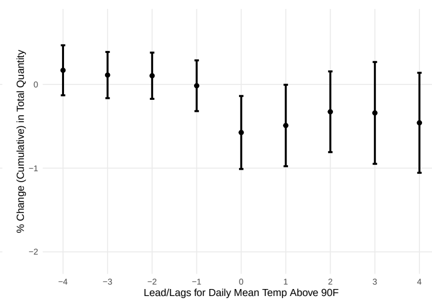
(c) Quantity Purchased (Below 10F)



(d) Expenditure (Above 90F)



(e) N of Store Visits (Above 90F)



(f) Quantity Purchased (Above 90F)

Figure 3.2: Cumulative Effect of Temperature Shock on Household Consumption. Figures (a)-(f) show the cumulative household consumption responses to temperature shocks over time, estimated using equation (2). The plot presents the cumulative effect $\sum_{t=-4}^{T} \beta_{w-t}^{k}$. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable. Figures (a)-(c) are for days with daily mean temperature below 10F and Figures (d)-(f) are for days with daily mean temperature above 90F. Standard errors for β_{w-t}^{k} are clustered at the county level. Standard errors for $\sum_{t=-4}^{T} \beta_{w-t}^{k}$ are calculated using the delta method.

conditions is consistent with earlier findings (Beatty et al. 2019). Combined with earlier results from Section 3.1, we find that households actively manage their inventory over time to maintain their nutritional needs.

In Online Appendix Figure A.8, we repeat the same exercise for three different product categories and find that the stockpiling behavior is driven by storable food item purchases. Interestingly, we also find that perishable food purchases decline over time, which might reflect a temporary substitution between storable and perishable foods. That is, while people consume the storable food they have stockpiled, they might purchase less perishable food.

Figures 3.2 (d)-(f) show the cumulative effect for extreme heat. We find that the total expenditure declines by 0.7% on the week of extreme heat (as opposed to being constant) and remains nearly 1% lower even after 4 weeks. The same is true for the number of store visits and the quantity purchased, both of which have similar magnitudes as expenditure. Interestingly, no stockpiling behavior is detected on hot days and households seem to reduce their consumption levels, although the magnitude seems relatively small at roughly 1%. When we investigate the product category specific effect, as seen in Online Appendix Figure A.8, we find that households neither stockpile storable items (figures (h) and (k)) nor change consumption levels of perishable items (figures (g) and (h)). These findings suggest that intertemporal substitution does not seem to be an adaptation strategy for hotter days.[22]

3.3 Interpreting the Estimated Effect of Extreme Temperatures on Consumption

The consumption response to very hot versus cold days can be systemically different for several reasons.[23] First, the difficulty of travel could be higher on colder days because of snow or icy roads, which makes stockpiling behavior more valuable. Indeed, earlier studies have reported that retail sales are sensitive to snowfall (Roth Tran 2022). To test this, we estimate a modified version of equation (1) where we interact a dummy variable for rain, which takes 1 if weekly precipitation exceeds 10mm, with temperature bins.[24] Online Appendix Figure A.10 shows that rainfall has a significant impact on consumption behaviors almost exclusively on colder days. For instance, when a day with moderate temperature is swapped with a day with daily mean temperature below $10°F$, the number of store visits decline by 0.7% when there is minor to no precipitation but with rainfall, the effect is twice as large at a 1.3% reduction. In contrast, for hotter days, the effect of rainfall on consumption behaviors seems small.

Second, summer provides more "defensive behavior" options that could dampen consumption responses to extreme temperatures. For instance, many households take time off from work during summer, which gives them extra ways to cope with extreme heat by spending time away from home

[22] In Online Appendix Figure A.11, we reproduce Figure 3.2 (a)-(f) using Monday as a week start day. First, note that there is no meaningful difference between results based on Sunday vs. Monday as the week start day for Over $90°F$, when both leads and lags are in the middle of the year (and thus all the weeks in the sample capture effects of full 7 days). However, there is a downward level shift for Below $10°F$ figures. This is likely to reflect the way Nielsen collects data for departing and entering panelists. For the former, their transactions will not be recorded after the last Saturday before the end of the year. For entering panelists, transactions for the last several days of the previous year starting on that last Sunday will be recorded. Thus, when we use Monday as the week start day, weeks with less than 7 days appear in December. Indeed, we find that nearly half (46%) of the "Below $10°F$" occurrences are in January. This means that the level shift is likely to be in leads, which is consistent with patterns in Online Appendix Figure A.11. Taken together, we find that our estimates are robust to the choice of the week start day. Meaningful differences emerge only on the leads of extreme cold shocks, but this relation seems to be spurious (i.e., driven by a choice of week start day by data producer).

[23] Doremus et al. (2022) suggests that extreme temperatures might have a negative impact on disposable income because of higher energy spending. This does not seem to be the primary channel in our case because they find that the increase in energy spending is more pronounced for colder days while we find no reduction in expenditure during extreme cold.

[24] 10mm is slightly lower than the median precipitation (12mm).

(Kiesnoski 2019). Similarly, summer presents richer options for tourism and dining experiences (Blue Cart 2022). Consistent with these, Figure 3.1 (f) and Online Appendix Figure A.8 collectively suggest that consumption of both storable and non-food items declines in response to extreme heat.[25]

In contrast, during winter, snowstorms that result in the closing of schools and workplaces force households to consume a larger fraction of their meals at home, thus raising the demand for food items (Gagnon and López-Salido 2020). Similarly, people might spend more time at home during extreme cold because of icy road conditions as discussed earlier or health conditions (e.g., cold or flu) as a sharp increase in cold medicine spending in colder days suggests (Online Appendix Figure A.7).[26]

Findings in Section 3 suggest that extreme temperatures (both hot and cold) reduce the number of store visits. On the other hand, the impact on total expenditure or the total quantity purchased are more nuanced: while the impact of extreme cold is muted by an increased number of purchases per store visit, extreme heat seems to cause a long-lasting reduction.

More broadly, it is worth comparing our findings to related work. For instance, Lai et al. (2022) documents an inverse-U shaped response for expenditure in a developing country context, which differs from the pattern we documented. Further, the magnitude in their paper seems much larger than ours.[27] Roth Tran (2022), in contrast, using data from the US, finds that indoor stores do not experience a reduction in sales in extreme cold while extreme heat reduces sales, which is consistent with our findings. Literature on the impact of extreme temperatures on production also reports substantial heterogeneity across countries or industries (Addoum et al. 2020; Somanathan et al. 2021; Graff Zivin and Neidell 2014). One important factor that can contextualize these findings is the difference in adaptation capacities. In the next section, we explore the role of potential modifiers for extreme temperatures in the household consumption setting.

[25] Nielsen data does not capture expenditure on food away from home. Further, while Nielsen data provides store location information at the three–digit zip code level, it is inferred from a panelist's home zip code. Thus we have limited ability to directly test these "leakage" effects both in terms of items (food at home vs. food away from home) and location (home neighborhood vs. getaway destinations).

[26] Similarly, as Online Appendix Figure A.9 (a) shows, we find that seniors refrain from non-food shopping especially during colder days in comparison to other age groups. However, in terms of cold medicine, we cannot find a difference across different age groups, which suggests that health is an important reason behind shopping trip adjustments during extreme cold.

[27] Due to specification and level of observation differences, it is somewhat difficult to directly compare, but their main result suggests that a day with extreme heat or cold reduces the 10-day cumulative expenditure by 5.9% and 3.2%, respectively.

4 Moderating Factors to a Temperature Shock

In this section, we explore factors that could moderate the negative impact of temperature shocks on consumption. In particular, given that households are most susceptible to extreme temperatures when they are traveling to shop, we evaluate the effectiveness of three different modes of transportation—passenger cars, ride share services, and public transit—that provide different levels of protection. Practically, we modify equation (1) by interacting the moderator variables with the entire set of temperature bins. The moderator variables include the number of projected vehicles, the number of public transit stops in the residing zip code, and Uber availability (an indicator variable) in the residing MSA for each panelist. This exercise not only provides an explanation for the small impact documented in Section 3, but also allows us to better understand the distributional implications of extreme temperatures due to differences in adaptation capacity across households.

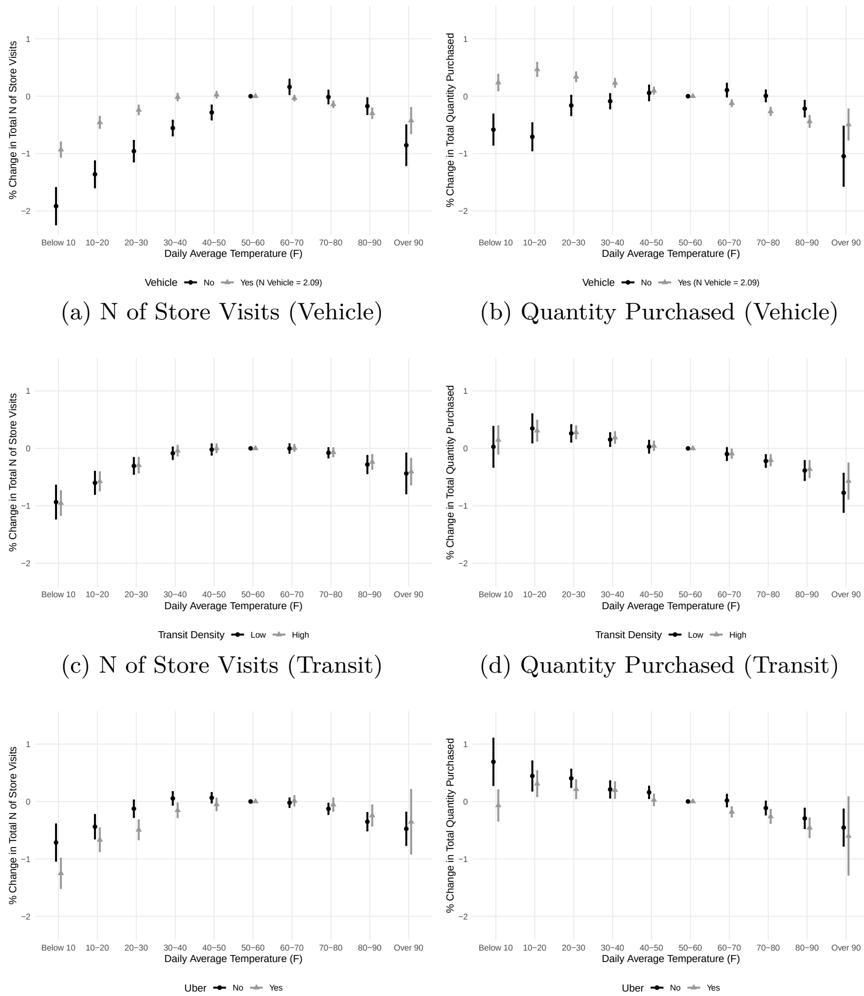
4.1 Mode of Transportation and Temperature Shock Moderation

Passenger Vehicles. The most powerful weather protection for shopping trips is likely to be provided by passenger cars. The distance from indoor spaces to the parking space is short, waiting time is essentially zero, and travel distance and time are likely to be the shortest as well. Further, modern vehicles are equipped with temperature control systems, which effectively convert travel into an indoor experience.

As detailed in Section 2.2, we merge the Nielsen Consumer Panel dataset with the National Household Transportation Survey using demographic characteristics because vehicle ownership information is not a part of the Nielsen survey questionnaire.

In Figures 4.1 (a)-(b), we compare the effect of daily mean temperatures on the total number of store visits and quantity purchased for households with (grey triangles) and without (black dots) passenger vehicles. Specifically, the black dots are the estimated coefficient for each temperature bin while the grey triangles are the sum of the estimated coefficient for each temperature bin and its interaction term with a vehicle proxy evaluated at the mean number of vehicles per panelist (2.09).[28]

[28]Note, in plotting grey triangles, we ignore the "level effect" of each modifier because we focus on understanding the moderating effect specific to each temperature bin. For instance, the coefficient for the "N Vehicles" variable in Online Appendix Table A.5 suggests that a household with the mean number of vehicles (2.09) has 0.35 (or 10%) higher store visits per week than a household without a car *independent of* the temperature level, which is ignored in plotting grey triangles.



(a) N of Store Visits (Vehicle) (b) Quantity Purchased (Vehicle)

(c) N of Store Visits (Transit) (d) Quantity Purchased (Transit)

(e) N of Store Visits (Uber) (f) Quantity Purchased (Uber)

Figure 4.1: Impact of Temperature Shock Moderators. Figures (a)-(f) show the differential impact of temperature shocks on the total expenditure and total number of store visits for three different modes of transportation. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable. Figures (a)-(b) illustrate the impact of having the mean number of vehicles (N=2.09) versus not having a vehicle. Similarly, Figures (c)-(d) illustrate the impact of having the mean number of public transit stops per zip code (N=97) versus not having a public transit stop. Figures (e)-(f) show the differential impact depending on Uber availability in the Metro area.

Standard errors for grey triangles are calculated using the delta method.

Figures (a)-(b) suggest that extreme temperatures have a large negative impact on consumption behaviors for a household without a vehicle. For instance, in Figure (a), one additional day with a daily mean temperature above $90°F$ (below $10°F$) reduces weekly number of store visits by nearly 1% (2%).[29] However, having a typical number of vehicles substantially offsets the negative impact.

[29] Online Appendix Table A.5 reports the estimated coefficients and standard errors in original scale for five different outcome variables (total expenditure, total number of store visits, total quantity purchased, expenditure per store visit,

At the mean number of vehicles (2.09), the impact of extreme heat (cold) is reduced by about 50% in comparison to the baseline (e.g., effect of an additional day with temperatures below $10°F$ is reduced to nearly 1% from the baseline of 2%). Similarly, Figure (b) shows that the impact of extreme temperatures on the quantity purchased is starkly different. In particular, while a household with an average vehicle ownership has a peak at the 10-20$°F$ bin, a household without a vehicle has a large dip (0.7% reduction) at the same temperature bin. This is plausible given that stockpiling capacity is likely to be determined by vehicle ownership.

It is important to note that the vehicle ownership variable that we interacted with the temperature bins is (1) imputed based on observable household characteristics and (2) not quasi-experimental. The first point implies that the vehicle ownership is observed with a measurement error, which creates an attenuation bias, and thus the true moderating effect is likely to be larger than what is documented in Figures (a)-(b).

The second point implies that the vehicle ownership effect we document in Figures 4.1 (a)-(b) might capture the effect of other correlated household characteristics. Given this concern, we check the robustness of our results by adding predictors of vehicle ownership as control variables. Specifically, we interact six matching variables (income, household size, race, density, NHTS survey wave, and Census region), which have been used to connect the Nielsen dataset with the NHTS data with the entire set of temperature bins and include them as fixed effects one at a time. These controls allow us to recover the impact of vehicle ownership that goes beyond income, density, etc., for a given temperature bin. Online Appendix Figure A.12 report the estimated coefficients from these six different regressions for the total number of store visits and the total quantity purchased. Note, with the exception of the model with a household size fixed effect, controlling for individual factors makes no meaningful difference.

Public transit accessibility. Figures 4.1 (c)-(d) show the moderating effect of public transit by comparing the effect of having the mean number of public transit stops within a zip code (N=97) to having zero public transit stops within a zip code on consumption outcomes. Figure (c), which depicts the impact on the number of store visits, shows that the grey triangles and black dots are essentially identical for all temperature bins, which is in striking contrast to Figure 4.1 (a). That is,

and quantity purchased per store visit).

public transit does not seem to moderate the negative impact of extreme temperatures on store visits at all. Figure (d) shows a similar pattern: while the difference in grey triangles versus black dots for the coldest and the hottest bins suggest a small moderating effect for the quantity purchased, the difference is small and statistically insignificant. Online Appendix Table A.7 reports that the impact on additional sets of outcome variables such as total expenditure, average expenditure per store visit, and average quantity purchased are similar to findings in Figures (c)-(d).

Overall, we do not find any moderating effect from having better transit accessibility, presumably because a "transit trip" inevitably involves modes other than just transit (Mohiuddin 2021). That is, to use public transit, trips to and from transit stops are essential. As these "first mile" and "last mile" trips involve exposure to extreme temperatures, households might simply choose to give up their consumption. Combined with Figures 4.1 (a)-(b), this suggests that households resorting to public transit or non-motorized transportation might have a difficult time meeting their needs in the wake of more frequent temperature shocks. Given that those are likely to be low-income households, this adds another layer of a potential distributional consequence of climate change.

Also it is worth noting that, as discussed in detail in Section 2.2, the sample for the transit analysis is limited to zip codes that appear in the National Transit Map (Melendez et al. 2021), which have a lot higher population density than zip codes not included in the map. Due to this sample restriction, we lose about half of our observations, but we believe that the remaining zip codes are a relevant sample for which to study the effect of public transit because sparsely populated areas have only limited transit coverage anyway.

Ride Share Availability. Finally, we explore whether the availability of ride share services could moderate the negative impact of extreme temperatures on consumption behaviors. Practically, we leverage the Uber service launch year information for the 50 largest Metropolitan Statistical Areas (MSAs) in the US from Berger et al. (2018). Limiting our attention to the largest 50 MSAs reduces our sample size by roughly half, but, similar to the public transit analysis, we believe that they are the right sample to explore the effect of ride share service because the service can thrive only in dense urban areas.

We interact the entire set of temperature bins with a dummy variable which takes 1 when an MSA has the Uber service. In Figure 4.1 (e), we find that the number of store visits declines to a larger extent on colder days for places with an Uber service although the magnitude is small and the difference between grey triangles and black dots are statistically insignificant. Similarly, in Figure (f), we find that the quantity purchased is slightly lower in almost all temperature bins for places with an Uber service, although the magnitude is meaningfully only for the coldest bin. Online Appendix Table A.6 also shows that the presence of an Uber service does not seem to reduce the negative impact of extreme temperatures on consumption.

These findings suggest that rideshare service availability not only fails to moderate the impact of extreme temperatures on retail consumption but also amplifies the negative impact, especially on colder days. This is surprising given that the ride share service provides a similar level of protection as passenger cars. However, these seem consistent with the ridership patterns found in prior studies. Concerning the first part—namely why the presence of a ridesharing service fails to moderate the impact of extreme temperatures, Shokoohyar et al. (2020) reports that the demand for Uber under extreme weather conditions is higher than usual on weekdays but lower on weekends. This implies that people might use Uber less frequently for non-essential activities. In the shopping context, when we take into account the cost of an Uber service, households might not switch from their status quo mode for a shopping trip (e.g., a non-motorized mode) to an Uber in response to extreme temperatures. From Table 2.1, the average expenditure amount per store visit is roughly $34, and spending extra money on ride share services would make shopping substantially more expensive. Shokoohyar et al. (2020) shows that an average fare per mile of travel is $2.25. If households travel 2 miles both ways, the transportation cost can constitute up to 26% of the shopping cost.

Concerning the second part—namely, why the presence of an Uber service exacerbates the negative impact, Gorback (2022) finds that an Uber service increases demand for restaurant services due to improved accessibility, which might explain why demand for retail consumption, in particular for groceries, decreases after an Uber launch. Consistent with this, Online Appendix Figure A.13 shows that Uber availability has a differential impact depending on product categories. In particular, we find that the demand for storable food items decreases in every temperature bin—with the largest and most statistically significant differential impact in the coldest temperature bin. In contrast, for non-food items, we cannot reject the null for the impact of Uber availability.

Before discussing potential alternative explanations, it is worth pointing out the impact of sample restrictions due to data availability. That is, results in Figure 4.1 (a)-(b) are produced from a larger sample than Figure 4.1 (c)-(d) or (e)-(f), which are restricted to the areas with public transit data or Uber availability data. To explore whether the contrast between passenger vehicle vs. Uber or public transit is a byproduct of sample restrictions, in Online Appendix Figure A.14, we reproduce Figure 4.1 (a)-(b) using the transit and Uber sample, respectively. While standard errors in general seem larger, point estimates are very similar even after the sample restrictions, which suggests that the moderating effect of passenger vehicle is not driven by sample choices.

4.2 Alternative Moderators

The discussion so far focuses on the role of transportation, but in theory there are other moderating or counterbalancing channels as well. In this section, we explore the role of interchannel substitution and price adjustments from retailers.

Interchannel Substitution While we cannot rule out the possibility that households switch to online shops when the weather is unpleasant, we believe that such an interchannel substitution plays little role in our context. First, online shopping is not a perfect substitute for brick-and-mortar shopping, especially in the earlier years of our sample period. Most online shops have several upfront fixed costs such as shipping fees, minimum purchase threshold, or membership fees, which makes online shopping expensive. Further, households have to wait for a long time to have their product be delivered. For instance, the average delivery time for Amazon, which is one of the fastest in the industry, was 8 days in 2005, 5 days in 2010, and became 2 days only in 2015 (McKinsey and Company 2020). This means that unless a temperature shock persists for an extended period, postponing shopping trips for a couple of days could be a simpler solution.

Consistent with this, we do not find that the impact of extreme temperatures on consumption activities has increased (in magnitude) over time. In Online Appendix Table A.8, we report the estimated coefficient of equation (1) for three different sample periods 2004-2008, 2009-2014, and 2015-2019 for the total number of store visits (columns (1)-(3)) and the quantity of non-food items purchased (columns (4)-(6)). Columns (1)-(3) do not seem to reject the null: while the negative impact of extreme cold (heat) on store visits became larger (smaller) over time, none of the differences are statistically significant. In columns (4)-(6), we focus on non-food items, which are more online-shopping friendly.[30] Again, the impact of extreme temperatures on non-food item purchases does not increase over time, which again rules out a meaningful interchannel substitution effect.

Second, our data show that the majority of panelists do not engage in online shopping at all, which rules out frequent interchannel substitution. Specifically, for 82% of panelists, online shopping constitutes less than 1% of their annual expenditure while only 7% of panelists spend more than 5% on online channels. This suggests that the majority of panelists almost completely rely on brick-and-mortar shops. Similarly, Wheat et al. (2021) also find that households' online shopping habits are persistent, suggesting that households are more likely to switch and stick to online shopping rather than switching between online and brick-and-mortar stores. Consistent with this, in Online Appendix Table A.9, we find that the impact of extreme temperatures on weekly online expenditure is a small negative, if anything. Similarly, Lai et al. (2022) and Roth Tran (2022) find that extreme temperatures or rainfall has little impact on online shopping.

Lastly, especially for many low-income households, online shopping might not be an accessible option. Connolly and Stavins (2015) find that cash, prepaid cards, and money orders are the most popular payment types among the lowest income groups. Also, the lowest-income consumers used cash about twice as often as the highest-income consumers. These differences in payment methods make it challenging to make purchases online.[31]

Price Change. We also explore the impact of extreme temperatures on potential price change because of its potential counterbalancing effect. For instance, retailers might engage in promotions in response to lower demand when the temperature is very high or low.

For this exercise, we construct a store-level price index using the Nielsen Retail Scanner Dataset following Leung (2021) for the 2006-2019 period. We retain 17,030 stores that were observed with positive sales throughout the entire sample period from 2007 to 2019, and thus the index is not affected by store entry or exit.

In Online Appendix Table A.10, we report the impact of temperature shock on retail prices. The dependent variable is the log of the price index. In column (1), we estimate the effect using the quarterly price index. As the data frequency is quarterly, we adjust temporal fixed effects from equation

[30] Because households typically purchase both food and non-food items in a single trip, it is hard to define the number of trips for non-food items. Thus for columns (4)-(6), we focus on the quantity purchased.

[31] However, we do note that the fraction of households substituting to the online channel in response to extreme temperatures might have increased in recent years, especially after the COVID pandemic.

(1) accordingly and include county by quarter and year by quarter fixed effects. Also, we include the store fixed effect to control for store-specific unobserved characteristics. The estimated coefficients suggest that retailers do not seem to aggressively adjust their prices in response to lower demand induced by extreme temperatures. To see this, take the coefficient from the extreme heat, which is the largest in magnitude. It suggests that being exposed to one additional day of extreme heat reduces the quarterly retail price by 0.037%. This number is over an order of magnitude smaller than the response in quantity purchased, which is a 0.5–0.8% reduction depending on the time frame (Figure 3.1 (c) and Figure 3.2 (f)). No meaningful price change in response to demand shock induced by extreme temperatures is consistent with Gagnon and López-Salido (2020), which finds no price change during snowstorms despite a demand spike.

In column (2), we repeat the same exercise using the annualized price index to further explore the nature of the price change. Again, accounting for data frequency, we use year and county fixed effects instead of year by quarter and county by quarter fixed effects. The estimated coefficients in column (2) are smaller than column (1), which suggests that the price adjustment appearing in column (1), if any, is likely to be temporary, a finding consistent with Gagnon and López-Salido (2020). When we compare the estimates in column (2) with the average annual inflation rate of 2.2% over the sample period, the magnitude is about 1% of annual price change (-0.029/2.2).[32]

In columns (3) and (4), we modify column (1) to account for recent findings that most US chains charge nearly uniform prices across stores, despite differences in local market conditions (DellaVigna and Gentzkow 2019). A practical implication is that most drug and merchandise stores, which are dominated by national chains, are much less likely to be responsive to local shocks than grocery stores, which are more likely to be located in only a few states (Leung 2021). We incorporate these findings in two different ways. In column (3), we limit our attention to grocery stores and repeat the same exercise as in column (1) following Leung (2021) and Leung and Seo (2023). Again, we find a very similar result to the previous two columns, which suggests that local temperature shocks do not meaningfully affect local prices even for grocery stores.

In column (4), we estimate the impact of temperature based on chain level exposure following

[32] The value of a dollar in 2004 is equivalent to $1.39 in 2019, which suggests an annualized inflation rate of 2.2%. The calculation is based on the CPI Inflation Calculator at https://www.bls.gov/data/inflation_calculator.htm, accessed on May 24, 2023. The CPI inflation calculator uses the Consumer Price Index for All Urban Consumers (CPI-U) U.S. city average series for all items, not seasonally adjusted.

Handbury and Moshary (2020). Given uniform pricing, national chains are not likely to change store level prices in response to local shocks. Do they change in response to a chain-level shock? To test this, we calculate chain-level exposure by taking the weighted average of county-level temperature exposure while using the revenue of each county as a weight. The estimated magnitude is similar to columns (1)-(3) and we again find a close to null effect from temperature exposure on prices. Taken together, retailers do not seem to change their prices in response to potential demand shocks from extreme temperatures. These findings are consistent with earlier work that found a small change in retail prices despite a large change in quantities sold (Gagnon and López-Salido 2020).

5 Conclusion

Climate scientists predict that extreme temperatures are likely to be more frequent in the future as climate change intensifies. While the prior literature has extensively studied the impact of heat on the production side of the economy, this paper studies how extreme temperatures affect household retail consumption. Given that retail consumption is an important component of household welfare, our findings extend our understanding of the welfare cost of climate change.

Using micro shopping data, we find a statistically significant but small (up to about 1%) reduction in the contemporaneous number of store visits due to extreme temperatures. The impact on the number of quantity consumed, however, is moderated by higher purchases per store visit, especially during extreme cold. By investigating the dynamic effect, we show that households actively manage inventory over time during extreme colds and that the cumulative impact of extreme cold on the quantity purchased is null. In contrast, extreme heat causes a small (0.5%) but persistent decline in consumption quantities. Given the large negative impact of extreme temperatures on human behavior and economic performance reported in earlier studies, the small effect we find is somewhat surprising. We explore potential explanations by estimating the impact of moderating factors. We find that passenger cars dramatically reduce the negative impact of extreme temperatures on retail consumption, but do not find a similar effect for ride share services or public transit. We rule out alternative explanations such as interchannel substitution to online shopping and price adjustment by retailers.

The findings of this paper have two implications on the welfare impact of extreme temperatures.

First, it appears that an average household in the US has effective defensive measures in place, and the welfare costs of extreme temperatures in the retail consumption context might be small. However, it is important to note that our analysis abstracted away from factors such as the economic cost of adjustments—for instance, increased time and effort devoted to planning or altering food intake patterns as a result of inventory management. If these costs are large, the welfare cost of extreme temperatures can be high even if the observed changes in purchases are relatively small. Second, the welfare costs are likely to be concentrated on disadvantaged households who do not have as much defensive measures as more affluent households. This emphasizes the role of targeted policies and interventions to mitigate the disproportionate impact on these households.

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Online Appendix for Extreme Temperatures, Adaptation Capacity, and Household Retail Consumption

A Additional Tables and Figures

Table A.1: Predictors of Vehicle Ownership

	(1)
Constant	5.515***
	(1.341)
Race:Other	0.1529***
	(0.0268)
Race:White	0.3148***
	(0.0208)
density1	-0.0406***
	(0.0028)
Household Size	0.2733***
	(0.0070)
inc1	0.0071***
	(0.0002)
Midwest	0.1937***
	(0.0325)
South	0.1378***
	(0.0337)
West	0.2376***
	(0.0316)
Year	-0.0025***
	(0.0007)
Observations	349,660

Note:
Column (1) shows the correlation between household demographic characteristics and the number of vehicles possessed using the National Household Transportation Survey of 2001, 2009, and 2017. The dependent variable is the number of vehicles. Regressions are weighted by the National Household Transportation Survey weights to represent the entire US population. Standard errors are clustered on state. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.2: Zip codes Characteristics by Transit Information Availability

Transit Info	N zip codes	Population Density	Total Population	N Panelist-Year
Missing	16,694	622	137,103,155	456,796
Not Missing	6,421	4,442	160,153,670	460,896

Note:
This table shows the characteristics of zip codes that appear at least once in the Nielsen consumer panel dataset (as panelist's residency zip code) with missing and non-missing public transit information. A zip code has missing transit information when a zip code is not covered by the National Transit Map. Population density comes from the zipcodeR package, which draws from the 2010 decennial census. For total population, we use American Community Survey when available (after 2011) and the 2010 decennial census in other cases. The last column shows the number of unique panelists by year that belong to each group (missing versus non-missing zip codes).

Table A.3: Extreme Temperatures and Household Weekly Consumption

	(1)	(2)	(3)	(4)	(5)
N of Days Below 10F	0.0310	-0.0299***	0.0410***	0.2659***	0.0771***
	(0.0633)	(0.0020)	(0.0124)	(0.0231)	(0.0050)
N of Days 10-20F	0.2054***	-0.0153***	0.0763***	0.2061***	0.0584***
	(0.0509)	(0.0016)	(0.0103)	(0.0197)	(0.0041)
N of Days 20-30F	0.1461***	-0.0082***	0.0566***	0.1047***	0.0357***
	(0.0355)	(0.0013)	(0.0069)	(0.0140)	(0.0030)
N of Days 30-40F	0.1072***	-0.0008	0.0393***	0.0134	0.0110***
	(0.0290)	(0.0009)	(0.0059)	(0.0109)	(0.0023)
N of Days 40-50F	0.0666***	0.0007	0.0167***	-0.0013	0.0018
	(0.0239)	(0.0008)	(0.0048)	(0.0110)	(0.0021)
N of Days 60-70F	-0.0552**	-0.0009	-0.0208***	-0.0131	-0.0071***
	(0.0236)	(0.0007)	(0.0046)	(0.0094)	(0.0022)
N of Days 70-80F	-0.1539***	-0.0045***	-0.0452***	-0.0189**	-0.0085***
	(0.0280)	(0.0008)	(0.0056)	(0.0091)	(0.0023)
N of Days 80-90F	-0.2794***	-0.0095***	-0.0762***	0.0036	-0.0054*
	(0.0430)	(0.0014)	(0.0083)	(0.0135)	(0.0032)
N of Days Above 90F	-0.3772***	-0.0138***	-0.0874***	0.0036	-0.0037
	(0.1315)	(0.0036)	(0.0238)	(0.0477)	(0.0107)
Precipitation	-0.0008	-0.0004***	0.0007***	0.0028***	0.0010***
	(0.0012)	(3.84e-5)	(0.0002)	(0.0005)	(0.0001)
Precipitation^2	-4.3e-5***	-1.38e-6***	-1.18e-5***	1.2e-6	-1.2e-6**
	(6.5e-6)	(1.85e-7)	(1.33e-6)	(2.42e-6)	(5.64e-7)
Dep.Var	Expenditure	N Visits	Quantity	Avg Exp	Avg Quantity
Mean. Dep.Var	81.7	3.2	17.4	34.4	7.5
Fixed-Effects:					
Year × Month FE	Yes	Yes	Yes	Yes	Yes
County × Week-of-Year FE	Yes	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Observations	47,921,631	47,921,631	47,921,631	37,023,909	37,023,909

Note:
Coefficients are estimated based on equation (1) in original scale. The mean dependent variable is averaged over the entire households over the entire sample years and is used to calculate the percentage changes as in Figure 3.1. The average expenditure in column (4) is total expenditure divided by the total number of visits only for the weeks with non-zero store visits. Similarly, the average quantity purchased in column (5) is total quantity purchased divided by the total number of visits only for weeks with non-zero store visits. Regressions are weighted by the Nielsen Consumer Panel projection factor to project the estimates for the entire US population. Standard errors are clustered on county. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.4: Extreme Temperatures and Household Weekly Consumption (by Product Type)

	(1)	(2)	(3)	(4)	(5)	(6)
N of Days Below 10F	-0.0133***	0.2048***	-0.1606***	-0.0026**	0.0673***	-0.0237***
	(0.0044)	(0.0387)	(0.0314)	(0.0011)	(0.0095)	(0.0034)
N of Days 10-20F	-0.0029	0.2949***	-0.0866***	0.0003	0.0869***	-0.0109***
	(0.0039)	(0.0316)	(0.0255)	(0.0009)	(0.0080)	(0.0027)
N of Days 20-30F	-0.0017	0.1908***	-0.0430**	0.0003	0.0632***	-0.0068***
	(0.0030)	(0.0216)	(0.0191)	(0.0006)	(0.0053)	(0.0018)
N of Days 30-40F	-0.0026	0.1225***	-0.0127	2.38e-5	0.0414***	-0.0021
	(0.0022)	(0.0185)	(0.0149)	(0.0005)	(0.0047)	(0.0014)
N of Days 40-50F	-0.0037*	0.0613***	0.0090	-0.0003	0.0169***	0.0002
	(0.0022)	(0.0145)	(0.0124)	(0.0005)	(0.0037)	(0.0013)
N of Days 60-70F	0.0017	-0.0614***	0.0045	0.0001	-0.0213***	0.0004
	(0.0021)	(0.0152)	(0.0117)	(0.0005)	(0.0037)	(0.0012)
N of Days 70-80F	0.0019	-0.1272***	-0.0286**	-0.0002	-0.0410***	-0.0040***
	(0.0021)	(0.0175)	(0.0136)	(0.0005)	(0.0043)	(0.0014)
N of Days 80-90F	-0.0016	-0.2056***	-0.0723***	-0.0009	-0.0638***	-0.0115***
	(0.0032)	(0.0261)	(0.0200)	(0.0007)	(0.0062)	(0.0022)
N of Days Above 90F	0.0029	-0.2468***	-0.1333**	-7.4e-5	-0.0670***	-0.0203***
	(0.0101)	(0.0714)	(0.0650)	(0.0023)	(0.0171)	(0.0063)
Precipitation	-0.0002	0.0018**	-0.0024***	3.35e-5	0.0010***	-0.0003***
	(0.0001)	(0.0008)	(0.0006)	(2.67e-5)	(0.0002)	(6.31e-5)
Precipitation^2	-2.74e-6***	-2.9e-5***	-1.12e-5***	-9.94e-7***	-9.01e-6***	-1.79e-6***
	(4.61e-7)	(4.42e-6)	(2.69e-6)	(1.41e-7)	(1.1e-6)	(2.96e-7)
Product	Perishable	Storable	Non-Food	Perishable	Storable	Non-Food
Outcome	Expenditure	Expenditure	Expenditure	Quantity	Quantity	Quantity
Mean. Dep.Var	28.8	4.1	48.8	3.6	1.1	12.8
Fixed-Effects:						
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Week-of-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,921,631	47,921,631	47,921,631	47,921,631	47,921,631	47,921,631

Note:
Coefficients are estimated based on equation (1) for three mutually exclusive but collectively exhaustive product types (perishable food, storable food, and non-food) for two different outcomes (total expenditure and total quantity purchased) in original scale. The mean dependent variable is averaged over the entire households over the entire sample years and is used to calculate the percentage changes as in Figure 3.1 (f). Regressions are weighted by the Nielsen Consumer Panel projection factor to project the estimates for the entire US population. Standard errors are clustered on county. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.5: The Impact of Extreme Temperatures on Consumption Behaviors by Vehicle Ownership

	(1)	(2)	(3)	(4)	(5)
N of Vehicles	7.835***	0.1709***	1.581***	2.038***	0.3981***
	(0.3209)	(0.0115)	(0.0599)	(0.1293)	(0.0269)
Precipitation	-0.0008	-0.0004***	0.0007***	0.0028***	0.0010***
	(0.0012)	(3.84e-5)	(0.0002)	(0.0005)	(0.0001)
Precipitation^2	-4.31e-5***	-1.38e-6***	-1.18e-5***	1.21e-6	-1.2e-6**
	(6.48e-6)	(1.85e-7)	(1.32e-6)	(2.42e-6)	(5.67e-7)
N of Days Below 10F	-0.5503***	-0.0613***	-0.1013***	0.2535***	0.0762***
	(0.1237)	(0.0052)	(0.0233)	(0.0472)	(0.0109)
N of Days 10-20F	-0.7118***	-0.0436***	-0.1231***	0.2028***	0.0621***
	(0.1051)	(0.0037)	(0.0209)	(0.0393)	(0.0082)
N of Days 20-30F	-0.2348***	-0.0307***	-0.0280*	0.2150***	0.0544***
	(0.0759)	(0.0029)	(0.0150)	(0.0279)	(0.0058)
N of Days 30-40F	-0.1901***	-0.0178***	-0.0152	0.1443***	0.0389***
	(0.0569)	(0.0021)	(0.0110)	(0.0217)	(0.0045)
N of Days 70-80F	0.0705*	-0.0004	0.0010	-0.0170	-0.0038
	(0.0413)	(0.0018)	(0.0085)	(0.0176)	(0.0045)
N of Days 80-90F	-0.0098	-0.0055**	-0.0377***	-0.0041	-0.0055
	(0.0607)	(0.0022)	(0.0121)	(0.0234)	(0.0054)
N of Days Above 90F	-0.6364***	-0.0273***	-0.1821***	0.0260	-0.0193*
	(0.2425)	(0.0057)	(0.0458)	(0.0589)	(0.0114)
N of Vehicles × N of Days Below 10F	0.2799***	0.0151***	0.0683***	0.0039	4.01e-5
	(0.0610)	(0.0022)	(0.0113)	(0.0221)	(0.0049)
N of Vehicles x N of Days 10-20F	0.4496***	0.0139***	0.0979***	0.0024	-0.0017
	(0.0513)	(0.0016)	(0.0102)	(0.0197)	(0.0042)
N of Vehicles x N of Days 20-30F	0.1866***	0.0110***	0.0416***	-0.0540***	-0.0091***
	(0.0354)	(0.0012)	(0.0071)	(0.0134)	(0.0028)
N of Vehicles x N of Days 30-40F	0.1446***	0.0083***	0.0266***	-0.0641***	-0.0137***
	(0.0266)	(0.0010)	(0.0051)	(0.0103)	(0.0021)
N of Vehicles x N of Days 70-80F	-0.1095***	-0.0020**	-0.0226***	-0.0010	-0.0023
	(0.0179)	(0.0008)	(0.0036)	(0.0079)	(0.0019)
N of Vehicles x N of Days 80-90F	-0.1310***	-0.0019*	-0.0186***	0.0041	0.0001
	(0.0273)	(0.0010)	(0.0052)	(0.0102)	(0.0023)
N of Vehicles x N of Days Above 90F	0.1250	0.0066***	0.0460**	-0.0104	0.0077
	(0.0868)	(0.0023)	(0.0187)	(0.0246)	(0.0057)
Dep.Var	Expenditure	N Visits	Quantity	Avg Exp	Avg Quantity
Mean. Dep.Var	81.7	3.2	17.4	34.4	7.5
Observations	47,902,322	47,902,322	47,902,322	37,010,563	37,010,563

Note:
This table shows how vehicle ownership moderates the impact of extreme temperatures in each outcome variable's original scale. The N of Vehicles variable shows the marginal effect of one unit increase in the predicted number of vehicles owned by each panelists. Though 40-50F and 60-70F bins and their interaction terms are omitted from the table for the interest of space, they are included in the regression. All standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.6: The Impact of Extreme Temperatures on Consumption Behaviors by Uber Availability

	(1)	(2)	(3)	(4)	(5)
Uber	0.0860	-0.0413**	0.2537***	0.4436*	0.1199***
	(0.5665)	(0.0195)	(0.0924)	(0.2298)	(0.0385)
Precipitation	-0.0013	-0.0004***	0.0007**	0.0034***	0.0012***
	(0.0017)	(5.92e-5)	(0.0003)	(0.0006)	(0.0001)
Precipitation^2	-4.02e-5***	-1.2e-6***	-1.16e-5***	6.62e-9	-1.91e-6***
	(6.22e-6)	(1.71e-7)	(1.14e-6)	(2.86e-6)	(4.51e-7)
N of Days Below 10F	0.4223***	-0.0230***	0.1161***	0.2849***	0.0813***
	(0.1564)	(0.0052)	(0.0346)	(0.0463)	(0.0102)
N of Days 10-20F	0.1729	-0.0141***	0.0746***	0.1721***	0.0480***
	(0.1129)	(0.0034)	(0.0218)	(0.0382)	(0.0087)
N of Days 20-30F	0.2414***	-0.0040*	0.0679***	0.0911***	0.0266***
	(0.0749)	(0.0024)	(0.0129)	(0.0232)	(0.0050)
N of Days 30-40F	0.1042	0.0017	0.0353***	-0.0060	0.0035
	(0.0633)	(0.0018)	(0.0122)	(0.0197)	(0.0043)
N of Days 70-80F	-0.1127**	-0.0041***	-0.0191**	-0.0228	-0.0031
	(0.0502)	(0.0015)	(0.0097)	(0.0171)	(0.0040)
N of Days 80-90F	-0.2727***	-0.0113***	-0.0495***	-0.0206	-0.0024
	(0.0757)	(0.0025)	(0.0145)	(0.0233)	(0.0058)
N of Days Above 90F	-0.3991**	-0.0153***	-0.0765***	-0.0531	-0.0040
	(0.1698)	(0.0046)	(0.0270)	(0.0552)	(0.0106)
Uber × N of Days Below 10F	-0.7204***	-0.0172***	-0.1276***	-0.0793	-0.0041
	(0.1951)	(0.0058)	(0.0419)	(0.0717)	(0.0163)
Uber x N of Days 10-20F	-0.1047	-0.0073*	-0.0225	0.0384	0.0195*
	(0.1499)	(0.0042)	(0.0273)	(0.0551)	(0.0114)
Uber x N of Days 20-30F	-0.2235*	-0.0118***	-0.0319*	-0.0100	0.0093
	(0.1163)	(0.0030)	(0.0189)	(0.0400)	(0.0072)
Uber x N of Days 30-40F	0.0157	-0.0067***	-0.0019	0.0308	0.0129*
	(0.0952)	(0.0025)	(0.0168)	(0.0388)	(0.0070)
Uber x N of Days 70-80F	-0.0206	0.0024	-0.0246**	-0.0055	-0.0092**
	(0.0609)	(0.0023)	(0.0114)	(0.0209)	(0.0043)
Uber x N of Days 80-90F	0.0227	0.0035	-0.0276*	0.0428	-0.0023
	(0.0907)	(0.0037)	(0.0167)	(0.0333)	(0.0074)
Uber x N of Days Above 90F	0.0080	0.0039	-0.0245	0.0863**	-0.0080
	(0.2394)	(0.0107)	(0.0595)	(0.0362)	(0.0095)
Dep.Var	Expenditure	N Visits	Quantity	Avg Exp	Avg Quantity
Mean. Dep.Var	81.6	3.2	16.8	34.3	7.3
Observations	26,138,627	26,138,627	26,138,627	20,149,527	20,149,527

Note:
This table shows how Uber availability moderates the impact of extreme temperatures. We use a version of equation (1) that interacts Uber, a dummy variable that takes 1 if a metro area has an Uber service, with a full set of temperature bins. Though 40-50F and 60-70F bins and their interaction terms are not shown for the interest of space, they are included in the regression. All standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.7: The Impact of Extreme Temperatures on Consumption Behaviors by Transit Density

	(1)	(2)	(3)	(4)	(5)
N Stops	-1.363***	-0.0268	-0.2077**	-0.2855	-0.0355
	(0.4841)	(0.0222)	(0.0973)	(0.1802)	(0.0417)
Precipitation	-0.0028	-0.0005***	0.0004	0.0028***	0.0011***
	(0.0017)	(5.25e-5)	(0.0003)	(0.0006)	(0.0001)
Precipitation^2	-3.96e-5***	-1.15e-6***	-1.07e-5***	-6.68e-7	-1.78e-6***
	(1.06e-5)	(2.16e-7)	(1.84e-6)	(2.8e-6)	(4.86e-7)
N of Days Below 10F	-0.1562	-0.0303***	0.0046	0.2357***	0.0758***
	(0.1447)	(0.0047)	(0.0293)	(0.0505)	(0.0109)
N of Days 10-20F	0.0796	-0.0195***	0.0576***	0.2053***	0.0593***
	(0.1068)	(0.0032)	(0.0207)	(0.0415)	(0.0080)
N of Days 20-30F	0.1163*	-0.0099***	0.0433***	0.0856***	0.0296***
	(0.0654)	(0.0023)	(0.0122)	(0.0257)	(0.0050)
N of Days 30-40F	0.0501	-0.0027*	0.0254***	0.0184	0.0135***
	(0.0503)	(0.0017)	(0.0094)	(0.0191)	(0.0041)
N of Days 70-80F	-0.1553***	-0.0025*	-0.0364***	-0.0294*	-0.0102**
	(0.0451)	(0.0013)	(0.0087)	(0.0168)	(0.0040)
N of Days 80-90F	-0.2839***	-0.0091***	-0.0638***	-0.0012	-0.0067
	(0.0782)	(0.0025)	(0.0140)	(0.0219)	(0.0052)
N of Days Above 90F	-0.4947***	-0.0141**	-0.1281***	-0.0379	-0.0221**
	(0.1256)	(0.0057)	(0.0281)	(0.0382)	(0.0102)
N Stops $\times$ N of Days Below 10F	0.0956	-0.0006	0.0204	0.0028	-0.0024
	(0.0777)	(0.0029)	(0.0153)	(0.0249)	(0.0062)
N Stops x N of Days 10-20F	-0.0026	0.0009	-0.0068	0.0145	0.0004
	(0.0816)	(0.0022)	(0.0146)	(0.0300)	(0.0049)
N Stops x N of Days 20-30F	0.0020	0.0004	0.0029	0.0119	0.0023
	(0.0431)	(0.0017)	(0.0078)	(0.0174)	(0.0042)
N Stops x N of Days 30-40F	0.0412	0.0015	0.0060	0.0092	-0.0017
	(0.0291)	(0.0010)	(0.0055)	(0.0106)	(0.0023)
N Stops x N of Days 70-80F	0.0182	0.0003	0.0024	-0.0003	-0.0012
	(0.0268)	(0.0009)	(0.0056)	(0.0122)	(0.0024)
N Stops x N of Days 80-90F	0.0566*	0.0015	0.0044	0.0107	-0.0002
	(0.0338)	(0.0013)	(0.0074)	(0.0148)	(0.0026)
N Stops x N of Days Above 90F	0.0931	0.0010	0.0349**	0.0076	0.0081*
	(0.1077)	(0.0059)	(0.0156)	(0.0160)	(0.0043)
Dep.Var	Expenditure	N Visits	N Items	Avg Exp	Avg N Items
Mean. Dep.Var	80.9	3.2	16.6	33.5	7.1
Observations	24,074,807	24,074,807	24,074,807	18,590,308	18,590,308

Note:
This table shows how transit density moderates the impact of extreme temperatures. We use a version of equation (1) that interacts N Stops, which is the number of transit stops at the zip code level, with a full set of temperature bins. Though 40-50F and 60-70F bins and their interaction terms are omitted from the table for the interest of space, they are included in the regression. All standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.8: The Impact of Extreme Temperatures on Consumption Behaviors by Sample Period

	(1)	(2)	(3)	(4)	(5)	(6)
N of Days Below 10F	-0.0283***	-0.0316***	-0.0389***	-0.0226***	-0.0307***	-0.0268***
	(0.0041)	(0.0041)	(0.0031)	(0.0070)	(0.0064)	(0.0045)
N of Days 10-20F	-0.0168***	-0.0166***	-0.0210***	-0.0092	-0.0146***	-0.0162***
	(0.0032)	(0.0027)	(0.0028)	(0.0058)	(0.0046)	(0.0039)
N of Days 20-30F	-0.0128***	-0.0102***	-0.0115***	-0.0152***	-0.0068**	-0.0103***
	(0.0024)	(0.0020)	(0.0021)	(0.0041)	(0.0033)	(0.0031)
N of Days 30-40F	-0.0057***	-1.85e-5	-0.0014	-0.0090***	-0.0018	0.0014
	(0.0018)	(0.0016)	(0.0017)	(0.0034)	(0.0027)	(0.0023)
N of Days 40-50F	-3.22e-5	-0.0004	0.0008	0.0009	-0.0023	-0.0008
	(0.0016)	(0.0013)	(0.0015)	(0.0030)	(0.0022)	(0.0020)
N of Days 60-70F	-0.0011	-0.0025**	0.0027**	8.97e-5	0.0010	0.0017
	(0.0014)	(0.0012)	(0.0012)	(0.0026)	(0.0022)	(0.0019)
N of Days 70-80F	-0.0019	-0.0050***	-0.0028**	-0.0008	-0.0045*	-0.0032
	(0.0016)	(0.0014)	(0.0013)	(0.0031)	(0.0025)	(0.0022)
N of Days 80-90F	-0.0091***	-0.0110***	-0.0075***	-0.0119***	-0.0146***	-0.0108***
	(0.0025)	(0.0022)	(0.0019)	(0.0044)	(0.0036)	(0.0028)
N of Days Above 90F	-0.0145**	-0.0141**	-0.0085	-0.0283*	-0.0233**	-0.0161
	(0.0074)	(0.0059)	(0.0053)	(0.0147)	(0.0100)	(0.0104)
Precipitation	-0.0005***	-0.0004***	-0.0003***	-0.0003*	-0.0002	-0.0002**
	(9.87e-5)	(0.0001)	(5.11e-5)	(0.0002)	(0.0002)	(8.36e-5)
Precipitation^2	-1.96e-6***	-1.03e-6	-1.81e-6***	-2.29e-6*	-1.53e-6	-2.06e-6***
	(6.9e-7)	(8e-7)	(2.48e-7)	(1.38e-6)	(1.22e-6)	(3.78e-7)
Period	2004-2008	2009-2014	2015-2019	2004-2008	2009-2014	2015-2019
Product	Total	Total	Non-Total	Non-food	Non-food	Non-food-Food
Outcome	N Visits	N Visits	N Visits	Quantity	Quantity	Quantity
Fixed-Effects:						
Year × Month	Yes	Yes	Yes	Yes	Yes	Yes
County × Week-of-Year	Yes	Yes	Yes	Yes	Yes	Yes
Income Group	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,570,860	19,151,352	16,199,419	12,570,860	19,151,352	16,199,419

Note:
This table illustrates how the total number of store visits (columns (1)-(3)) and the total quantity of non-food items purchased (columns (4)-(6)) with respect to extreme temperatures have changed over the sample period (2004-2008, 2009-2014, and 2015-2019). These coefficients are estimated using equation (1) and are in their original scale. All standard errors are clustered at the county level. *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A.9: The Impact of Extreme Temperatures on Online Consumption

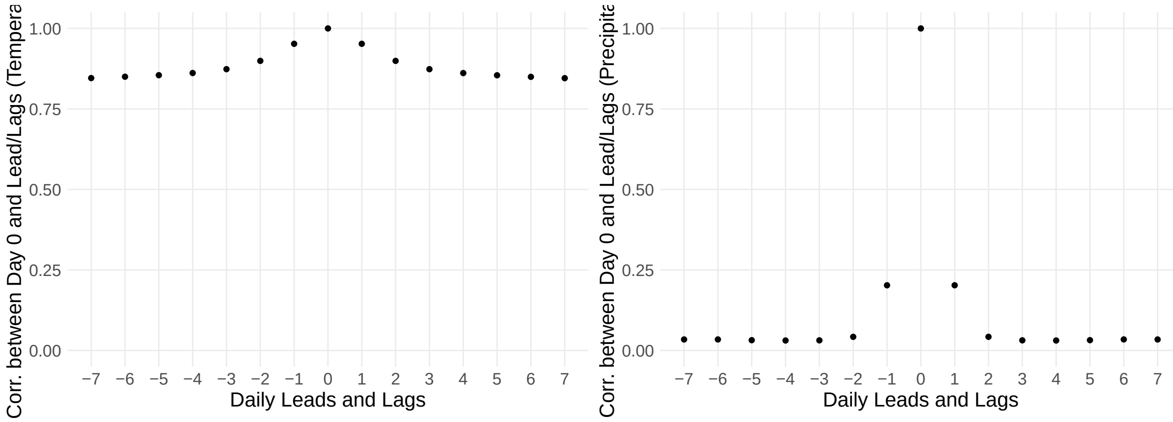
	(1)	(2)
N of Days Below 10F	-0.0111	-0.0080
	(0.0086)	(0.0068)
N of Days 10-20F	-0.0135**	-0.0083
	(0.0065)	(0.0050)
N of Days 20-30F	-0.0119**	-0.0074*
	(0.0055)	(0.0042)
N of Days 30-40F	-0.0014	-0.0018
	(0.0037)	(0.0029)
N of Days 40-50F	-0.0040	-0.0031
	(0.0036)	(0.0029)
N of Days 60-70F	-0.0051*	-0.0040
	(0.0029)	(0.0026)
N of Days 70-80F	-0.0084***	-0.0067**
	(0.0031)	(0.0027)
N of Days 80-90F	-0.0096**	-0.0075*
	(0.0049)	(0.0044)
N of Days Above 90F	-0.0084	-0.0072
	(0.0129)	(0.0112)
Precipitation	-0.0005***	-0.0003**
	(0.0002)	(0.0001)
Precipitation^2	-4.35e-7	-6.93e-7
	(5.57e-7)	(7.23e-7)
Mean. Dep.Var	1.2	
Fixed-Effects:		
Year × Month FE	Yes	Yes
County × Week-of-Year FE	Yes	Yes
Income Group FE	Yes	Yes
Household FE	Yes	Yes
Family	OLS	Poisson
Observations	47,921,631	29,347,489

Note:
This table illustrates the impact of extreme temperatures on the total expenditure on online shops using equation (1) using OLS . All standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A.10: Price Response to Temperature Shocks

	(1)	(2)	(3)	(4)
N of Days Below 10F	-0.00013**	-0.00022***	-0.00015**	-0.00112***
	(6.58e-5)	(5.85e-5)	(7.1e-5)	(0.00023)
N of Days 10-20F	0.00012***	7.24e-6	-7.9e-5	0.00051***
	(4.13e-5)	(3.99e-5)	(5.44e-5)	(0.00017)
N of Days 20-30F	-0.00016***	-0.00022***	-3.57e-5	-0.00043***
	(3.78e-5)	(3.67e-5)	(4.13e-5)	(0.00013)
N of Days 30-40F	-0.00010***	-0.00011***	-0.00014***	-0.00021***
	(3.65e-5)	(3.23e-5)	(3.09e-5)	(5.56e-5)
N of Days 40-50F	-0.00012***	-0.00014***	-0.00014***	-0.00056***
	(3.57e-5)	(3.75e-5)	(4.22e-5)	(8.18e-5)
N of Days 60-70F	-9.18e-5***	-5.39e-5*	7.14e-5**	-0.00044***
	(2.69e-5)	(3.06e-5)	(3.15e-5)	(5.87e-5)
N of Days 70-80F	-0.00012***	-0.00011***	8.72e-5*	-0.00024***
	(3.49e-5)	(3.51e-5)	(5.08e-5)	(4.49e-5)
N of Days 80-90F	-0.00032***	-0.00030***	-9.2e-5*	-0.00046***
	(3.74e-5)	(3.78e-5)	(5.4e-5)	(0.00011)
N of Days Above 90F	-0.00037***	-0.00029***	-0.00022*	-0.00017**
	(7.14e-5)	(6.34e-5)	(0.00013)	(8.37e-5)
Precipitation	-0.00104***	-0.00461***	-0.00174***	-0.00057
	(0.00019)	(0.00103)	(0.00055)	(0.00039)
Precipitation^2	6.87e-5***	0.00042***	0.00016***	-1.2e-5
	(2.08e-5)	(0.00013)	(4.15e-5)	(1.28e-5)
Sample	All	All	Grocery Stores	All
Store FE	Yes	Yes	Yes	Yes
Year × Quarter FE	Yes	No	Yes	Yes
County × Quarter FE	Yes	No	Yes	Yes
Year FE	No	Yes	No	No
County FE	No	Yes	No	No
Observations	953,680	238,420	227,528	953,680

Note:
This table presents the effect of extreme temperatures on retail price (log of price index). Columns (1) and (2) show the effect of store level temperature exposure on the quarterly and annual price index, respectively. Column (3) is for grocery stores only. Column (4) is estimated for all stores using chain level exposure by taking the weighted average of county-level temperature exposure while using the revenue of each county as weight. All standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.



(a) Temperature

(b) Precipiation

Figure A.1: Serial Correlations in Daily Temperatures and Precipitations. Figures (a) and (b) show the correlation between Day 0 and its 7 day leads and lags for temperature (Figure A) and precipitation (Figure B) at the county level for 2004–2019 in the contiguous US.

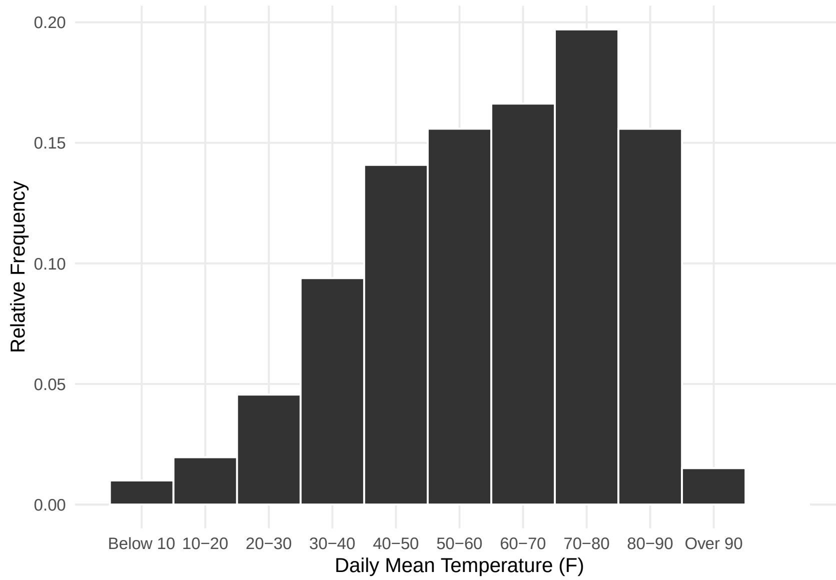
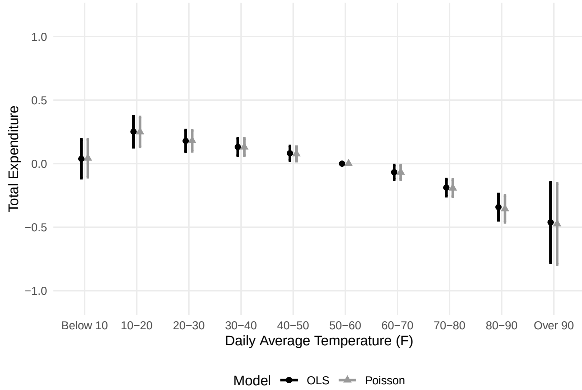
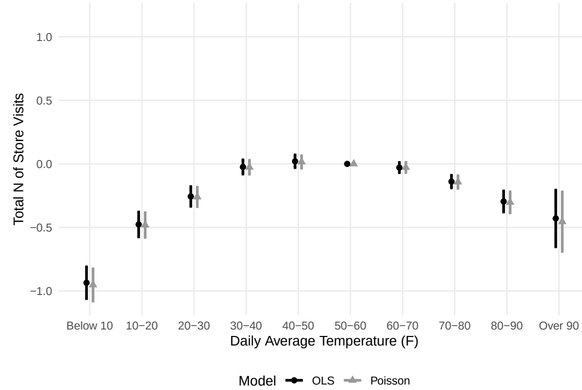


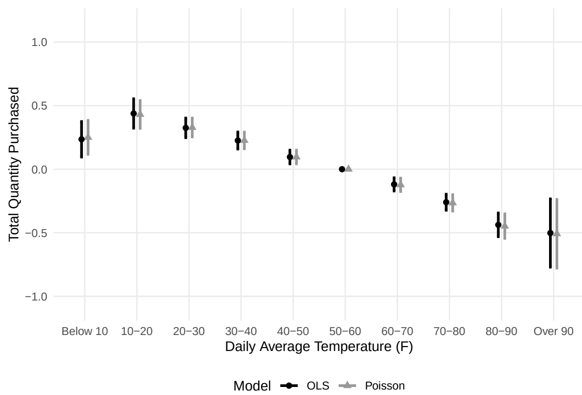
Figure A.2: Histogram of Daily Mean Temperature 2004-2019. The figure shows the distribution of daily mean temperatures across 10 temperature-day bins. Each bar represents the fraction of the number of days per year in each temperature category over 2004–2019, weighted by the number of unique panelists by county.



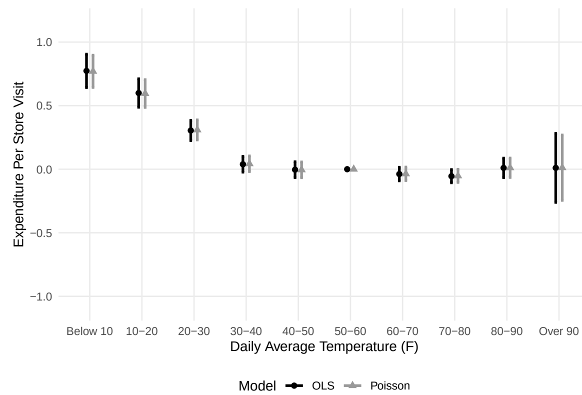
(a) Expenditure



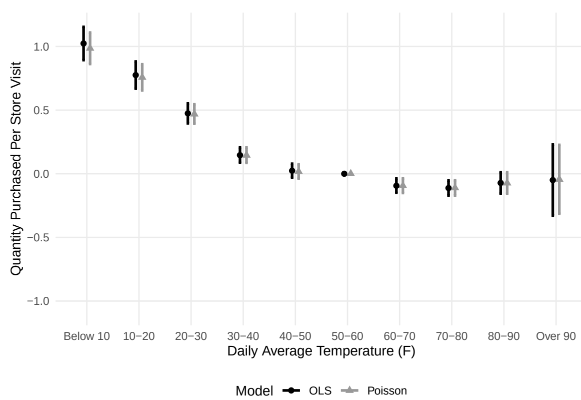
(b) N of Store Visits



(c) Quantity Purchased

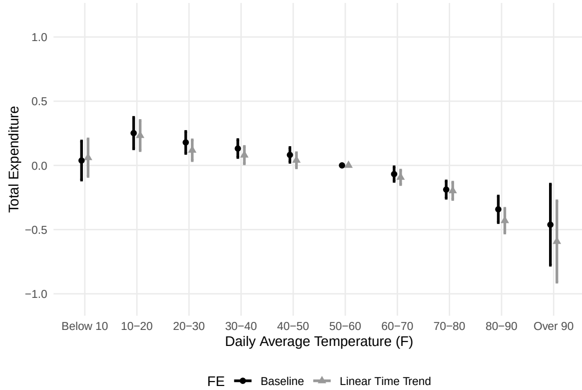


(d) Expenditure Per Store Visit

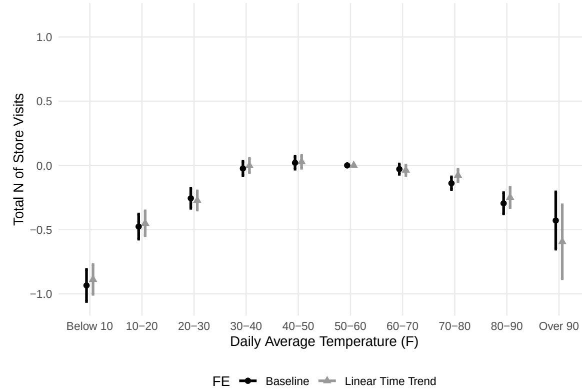


(e) Quantity Purchased Per Store Visit

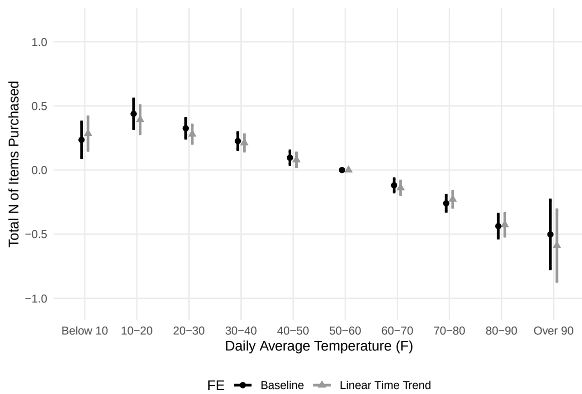
Figure A.3: Temperature and Household Consumption (OLS vs. Poisson Regression). Figure (a)-(e) show the marginal effect of temperatures on household consumption by fitting equation (1) using the OLS versus Poisson regression. The y-axis is expressed in percentages by multiplying the estimated Poisson coefficients by 100. Standard errors are clustered on county.



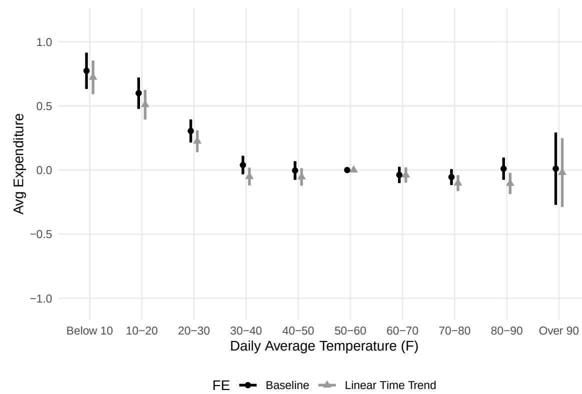
(a) Expenditure



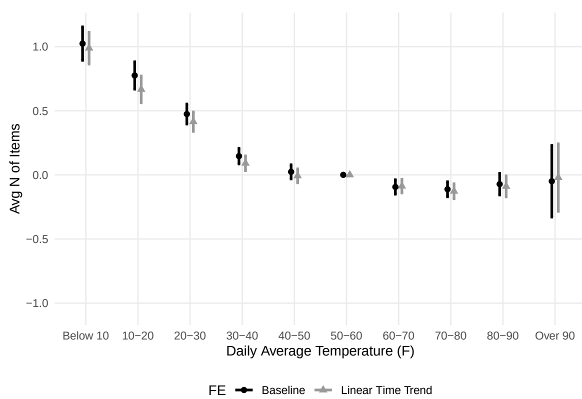
(b) N of Store Visits



(c) Quantity Purchased

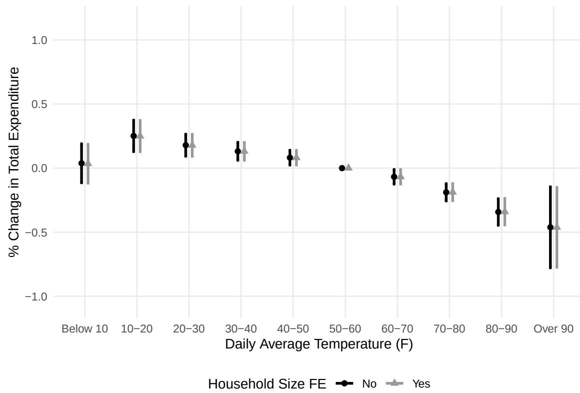


(d) Expenditure Per Store Visit

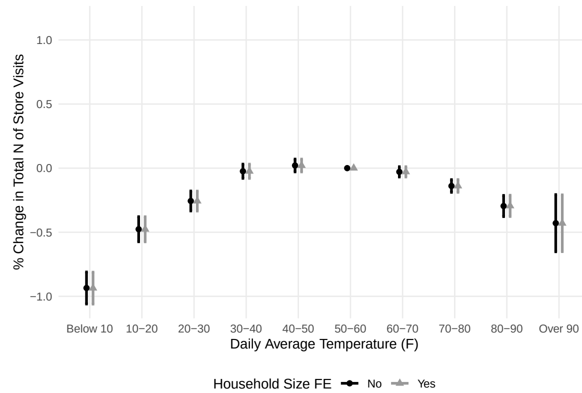


(e) Quantity Purchased Per Store Visit

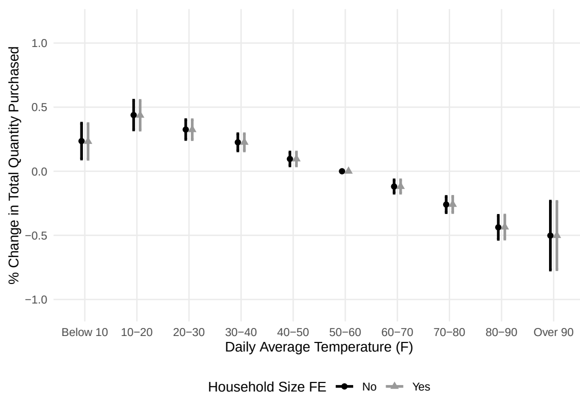
Figure A.4: Temperature and Household Consumption (Preferred Specification vs. With Linear Time Trend). Figure (a)-(e) show the marginal effect of temperatures on household consumption by fitting equation (1) using the preferred model versus a regression model with linear time trend. Standard errors are clustered on county.



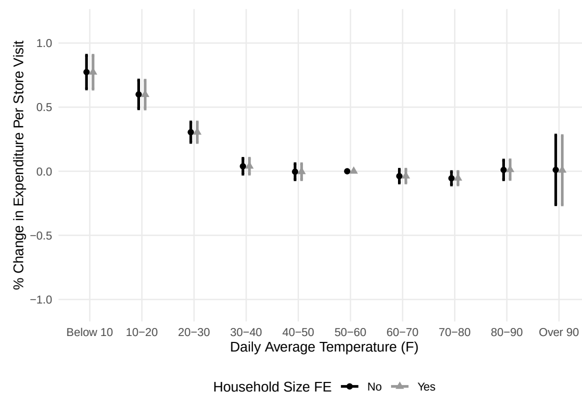
(a) Expenditure



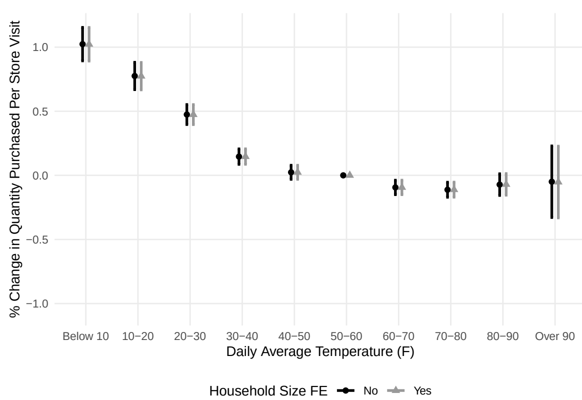
(b) N of Store Visits



(c) Quantity Purchased

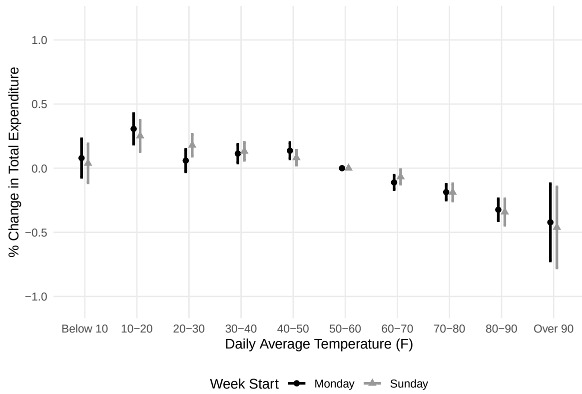


(d) Avg Expenditure

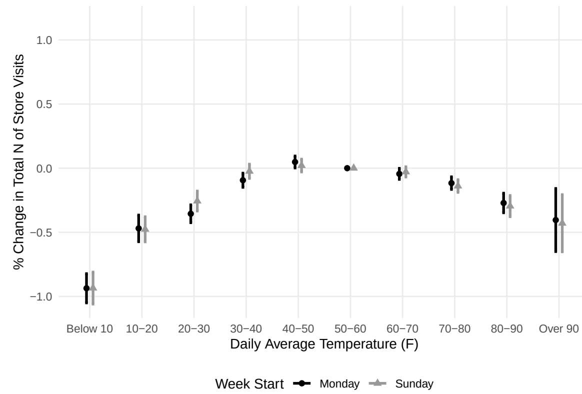


(e) Avg Quantity Purchased

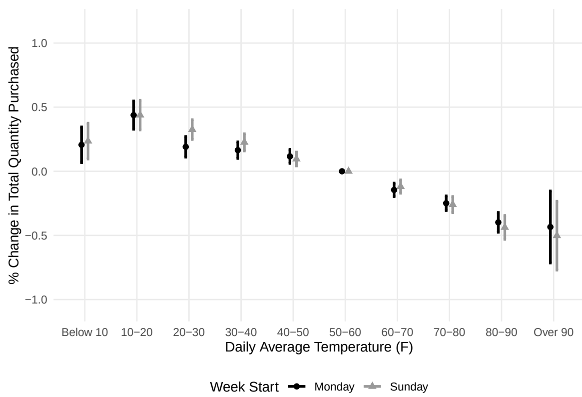
Figure A.5: Temperature and Household Consumption (With and Without Household Size Fixed Effects). Figures (a)-(e) show the marginal effect of temperatures on household consumption using equation (1) with and without the household fixed effects. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable. Standard errors are clustered on county.



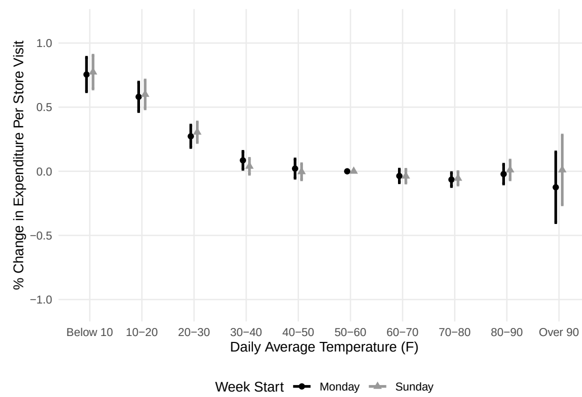
(a) Expenditure



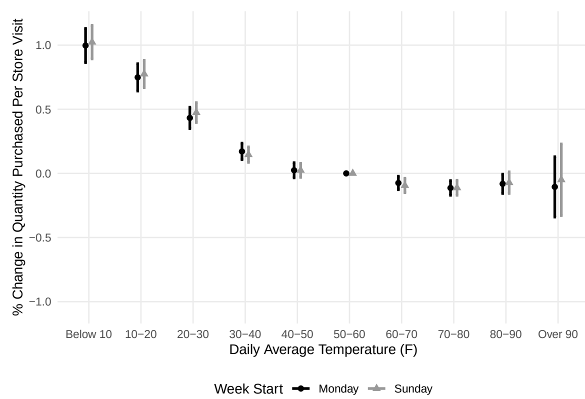
(b) N of Store Visits



(c) Quantity Purchased

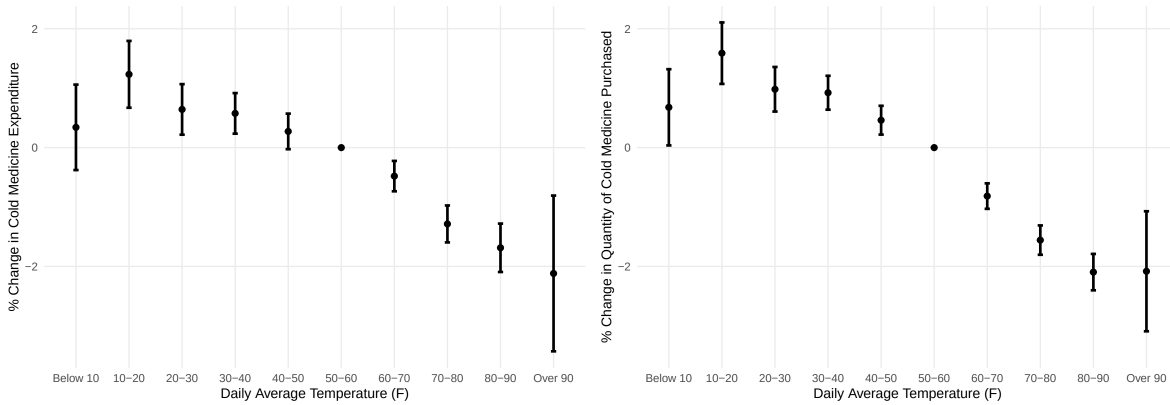


(d) Avg Expenditure



(e) Avg Quantity Purchased

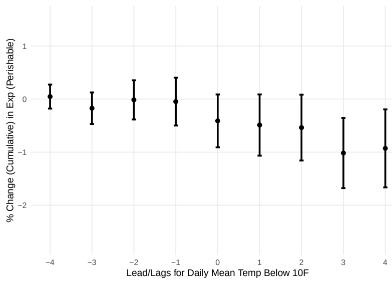
Figure A.6: Temperature and Household Consumption (Week Start: Sunday vs. Monday). Figures (a)-(e) show the marginal effect of temperatures on household consumption using equation (1) where a week is defined as Sunday through Saturday (main results) vs. alternatively defined as Monday through Sunday. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable. Standard errors are clustered on county.



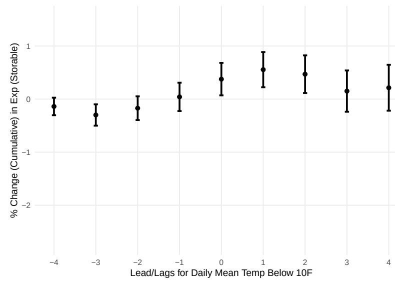
(a) Expenditure

(b) Quantity Purchased

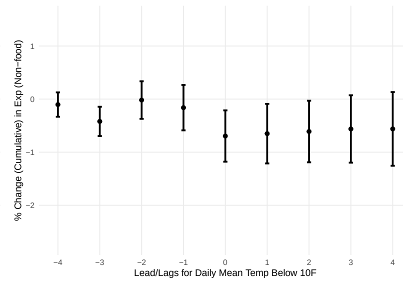
Figure A.7: Temperature and Cold Medicine Purchases. Figures (a)-(b) show the marginal effect of temperatures on household cold medicine consumption using a version of equation (1) that has cold medicine specific outcome variables. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable. Standard errors are clustered on county.



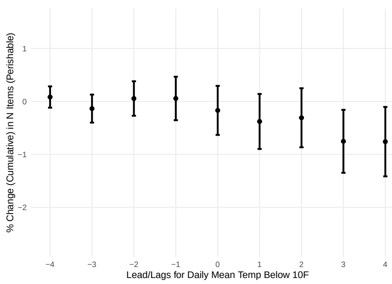
(a) 10F; Expenditure (Perishable)



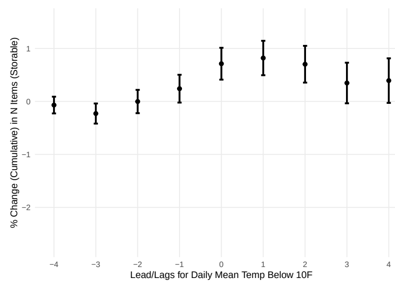
(b) 10F; Expenditure (Storable)



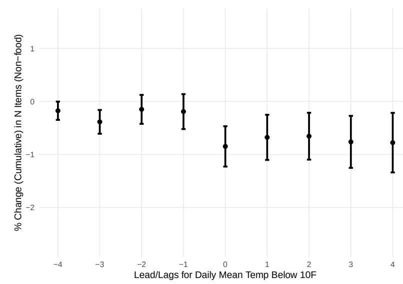
(c) 10F; Expenditure (Non-food)



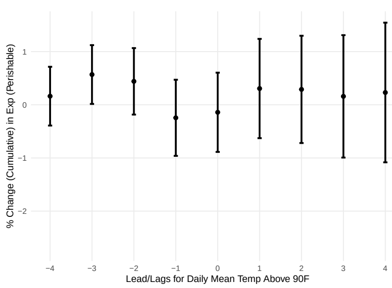
(d) 10F; Quantity (Perishable)



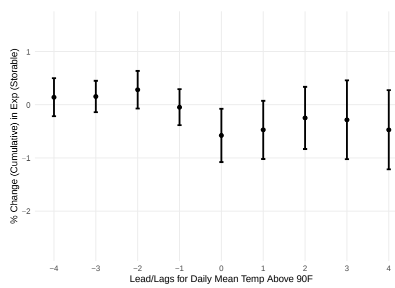
(e) 10F; Quantity (Storable)



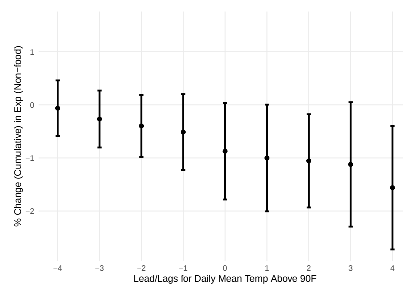
(f) 10F; N of Items (Non-food)



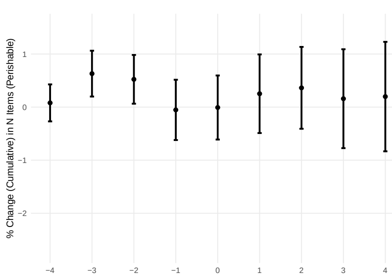
(g) 90F; Expenditure (Perishable)



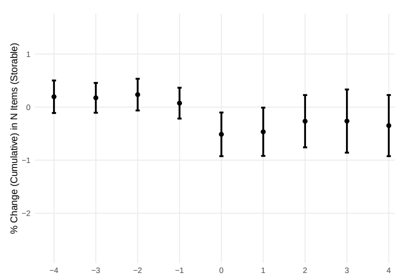
(h) 90F; Expenditure (Storable)



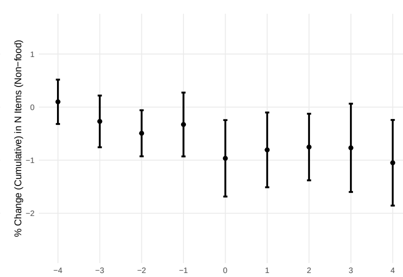
(i) 90F; Expenditure (Non-food)



(j) 90F; N of Items (Perishable)

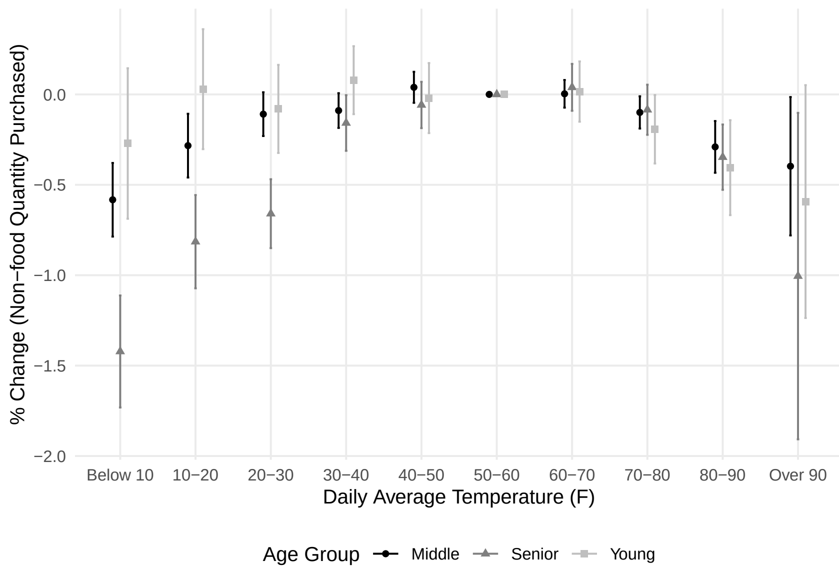


(k) 90F; Quantity (Storable)

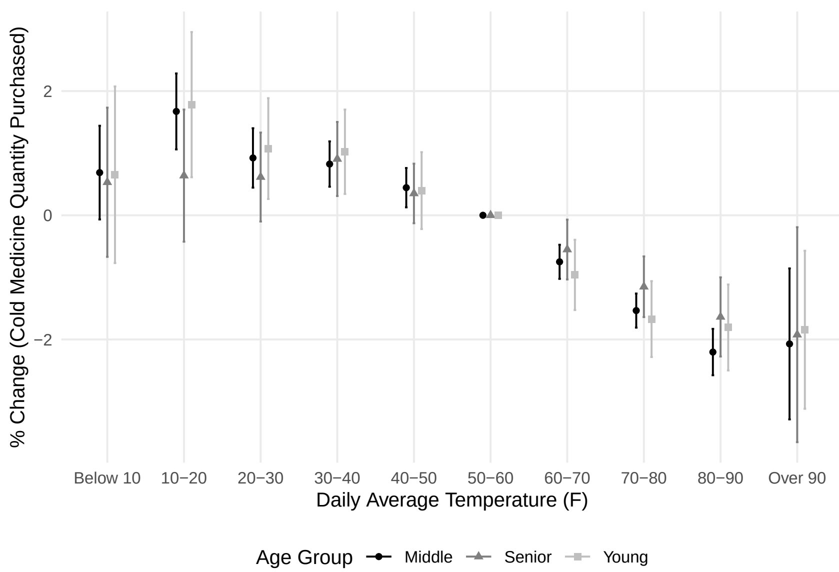


(l) 90F; Quantity (Non-food)

Figure A.8: Dynamic Impact of Temperature on Household Consumption by Product Categories. Figures (a)-(f) show the cumulative household consumption responses to temperature shocks over time, estimated using equation (2), for three different product categories. The plot presents the cumulative effect $\sum_{t=-4}^{T} \beta_{w-t}^{k}$. The y-axis represents percentages, calculated by dividing the estimated coefficient by the mean value of each variable. Figures (a)-(f) are for days with daily mean temperature below 10F and Figures (g)-(l) are for days with daily mean temperature above 90F. Standard errors are clustered at the county level. For standard errors of cumulative effects, we use the delta method.

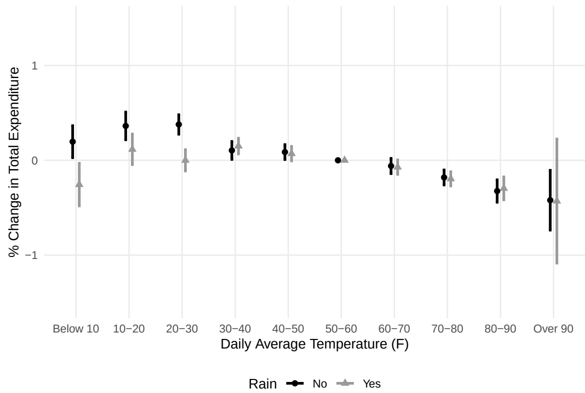


(a) Non-food Quantity Purchased

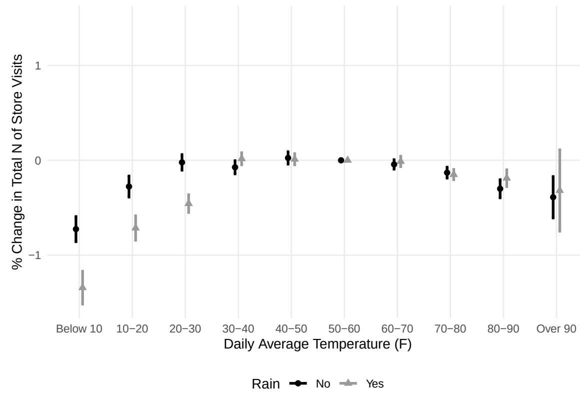


(b) Cold Medicine Quantity Purchased

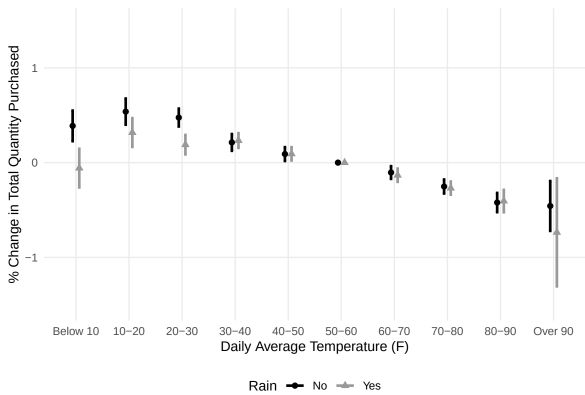
Figure A.9: Temperature and Non-food and Cold Medicine Purchases for Different Age Groups. Figures (a)-(b) show the marginal effect of temperatures on household non-food and cold medicine consumption for three different age groups using a version of equation (1). Age thresholds are 65 and above (for seniors), 40–65 (for middle-aged), and below 40 (for young people). The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable. Standard errors are clustered on county.



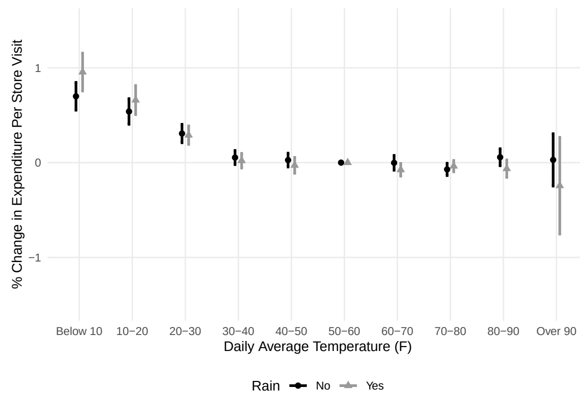
(a) Expenditure



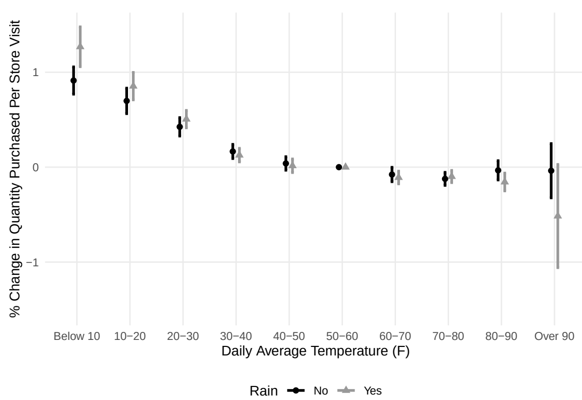
(b) N of Store Visits



(c) Quantity Purchased

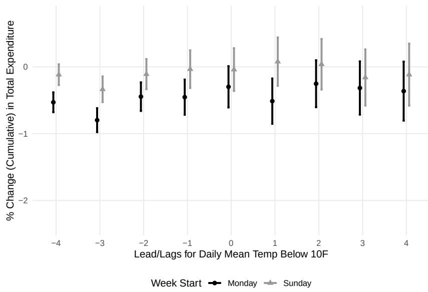


(d) Expenditure Per Store Visit

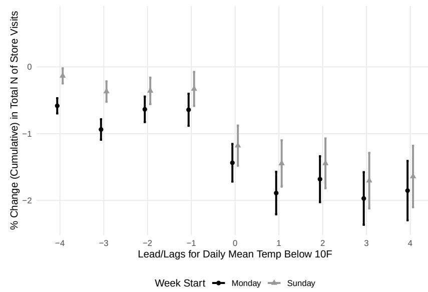


(e) Quantity Purchased Per Store Visit

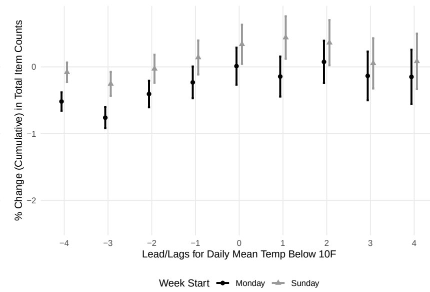
Figure A.10: Temperature and Household Consumption by Precipitation. Figures (a)-(e) show how household consumption activities respond to different temperature levels by precipitation status. Coefficients are estimated by interacting each temperature bin in equation (1) with a dummy variable that takes 1 when weekly precipitation exceeds 10mm. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable.



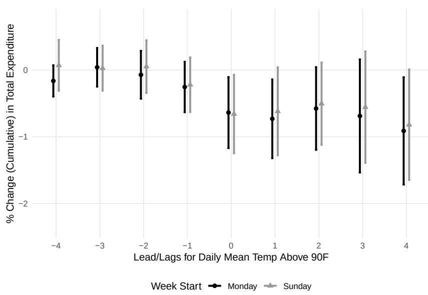
(a) Expenditure (Below 10F)



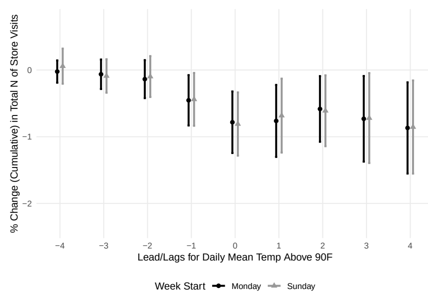
(b) N of Store Visits (Below 10F)



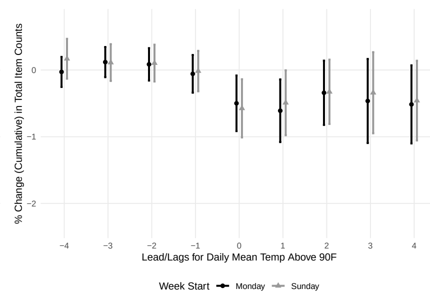
(c) Quantity Purchased (Below 10F)



(d) Expenditure (Above 90F)

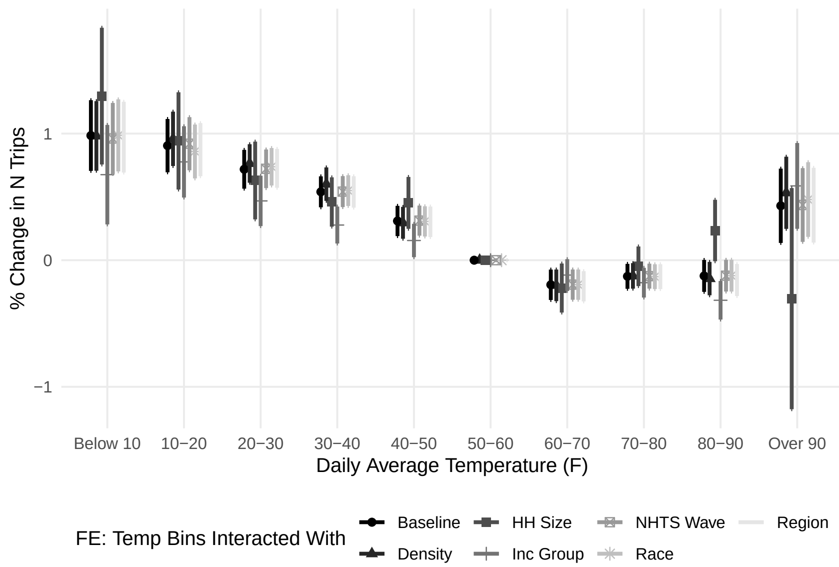


(e) N of Store Visits (Above 90F)

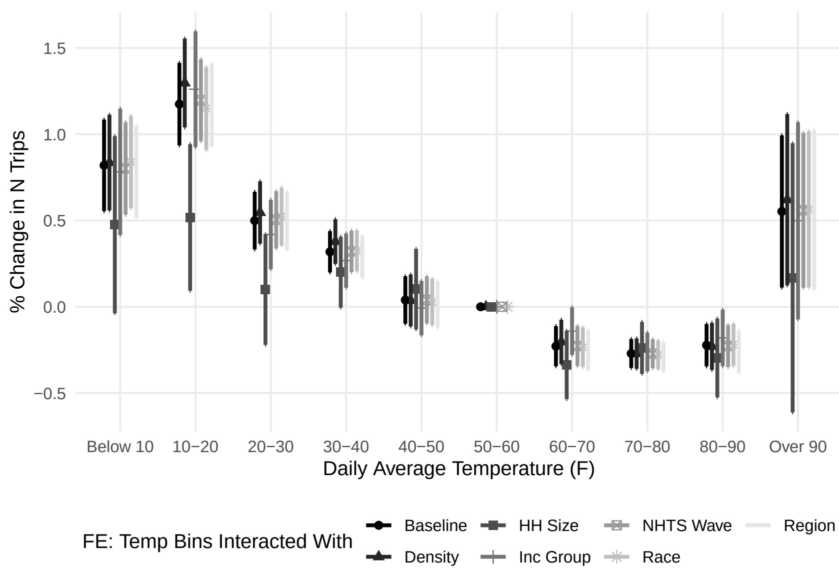


(f) Quantity Purchased (Above 90F)

Figure A.11: Dynamic Impact of Temperature on Household Consumption by Week Start Day (Sunday: benchmark, Monday: alternative). Figures (a)-(f) show the cumulative household consumption responses to temperature shocks over time, estimated using equation (2), for two different week start days (Sunday vs. Monday). The plot presents the cumulative effect $\sum_{t=-4}^{T} \beta_{w-t}^{k}$. The y-axis represents percentages, calculated by dividing the estimated coefficient by the mean value of each variable.

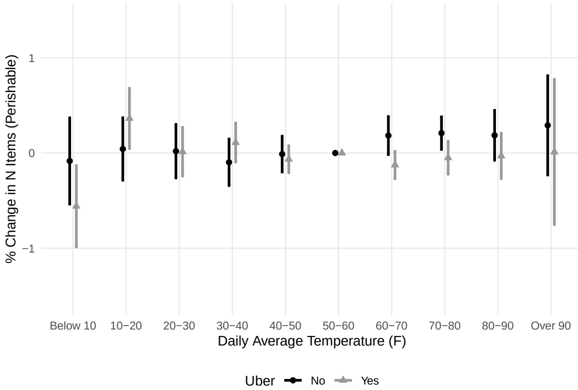


(a) Number of Store Visits

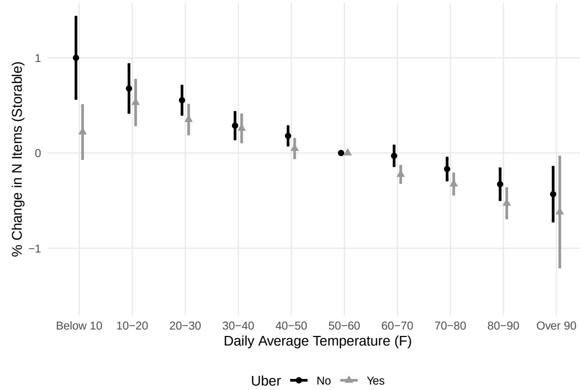


(b) Quantity Purchased

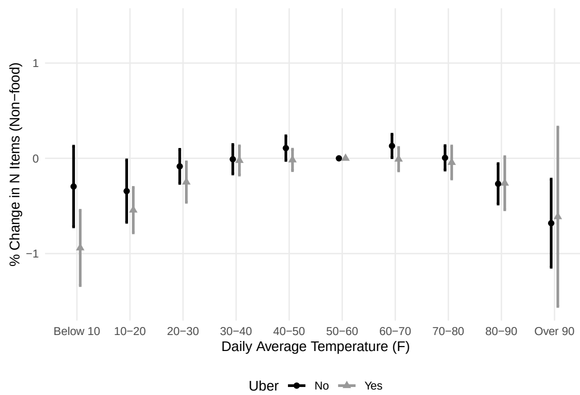
Figure A.12: Moderating Effect of Passenger Vehicles (Alternative Specifications). In these figures, we interact six matching variables (income, household size, race, density, NHTS survey wave, and Census region), which have been used to connect the Nielsen dataset with the NHTS data with the entire set of temperature bins and include them as fixed effects one at a time. We plot the estimated coefficients from six alternative specifications along with our baseline coefficients from Table A.5. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable.



(a) Perishable Food

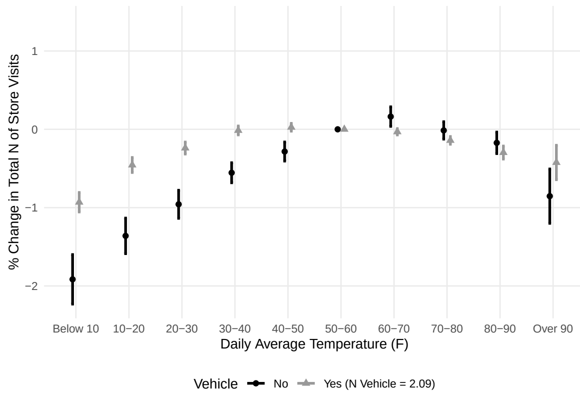


(b) Storable Food

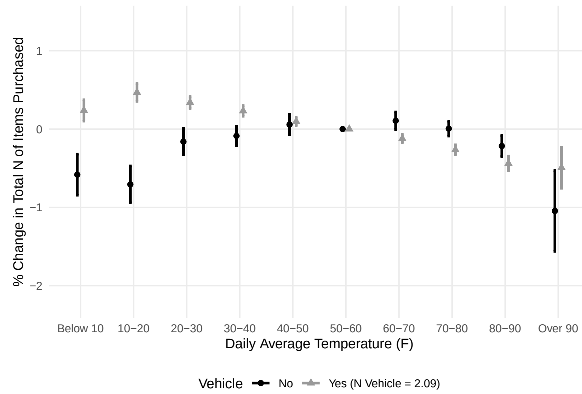


(c) Non-Food

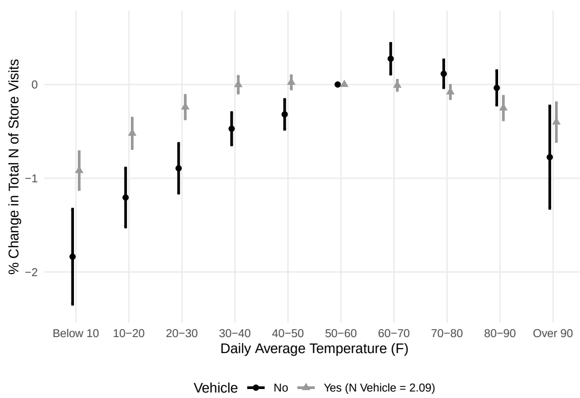
Figure A.13: Uber Availability and the Total Quantity Purchased by Product Category. Figures shows the marginal effect of Uber availability on the total quantity purchased for different temperature bins for (a) perishable food, (b) storable food, and (c) non-food products. The y-axis is expressed in percentages by dividing the estimated coefficient by the mean value of each variable.



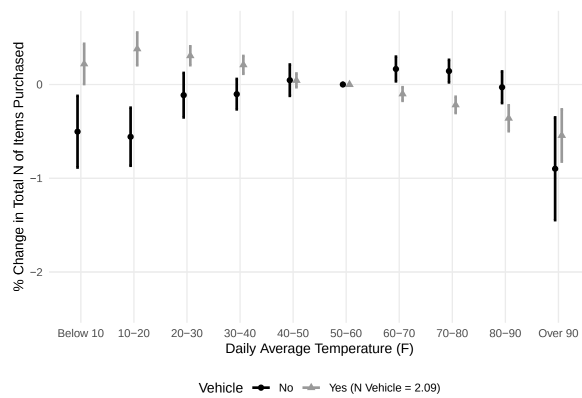
(a) N of Store Visits (Entire Sample)



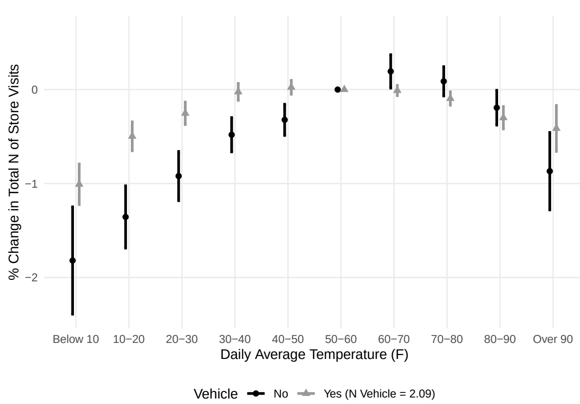
(b) Quantity Purchased (Entire Sample)



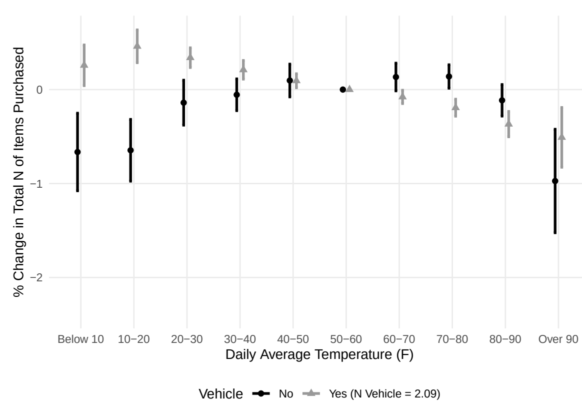
(c) N of Store Visits (Transit Sample)



(d) Quantity Purchased (Transit Sample)



(e) N of Store Visits (Uber Sample)



(f) Quantity Purchased (Uber Sample)

Figure A.14: Moderating Factors to a Temperature Shock (with Sample Restriction). Panels (a)-(b) reproduce Figure 4.1 (a)-(b) as benchmark. Panels (c)-(d) reproduce Panels (a)-(b) with the same sample as Figure 4.1 (c)-(d). Panels (e)-(f) reproduce Panels (a)-(b) with the same sample as Figure 4.1 (e)-(f).

```
R version 4.1.2 (2021-11-01)
Platform: x86_64-apple-darwin17.0 (64-bit)
Running under: macOS Big Sur 10.16

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.1/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.1/Resources/lib/libRlapack.dylib

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages:
[1] parallel  stats     graphics  grDevices utils     datasets  methods
[8] base

other attached packages:
 [1] corrr_0.4.3          knitcitations_1.0.12 prism_0.2.0
 [4] exactextractr_0.6.1  fixest_0.11.1        kableExtra_1.3.4
 [7] fst_0.9.4            rlist_0.4.6.2        car_3.1-1
[10] carData_3.0-4        sf_1.0-2             readxl_1.4.2
[13] broom_1.0.4          bit64_4.0.5          bit_4.0.4
[16] lubridate_1.9.2      forcats_1.0.0        stringr_1.5.0
[19] dplyr_1.1.0          purrr_1.0.1          readr_2.1.4
[22] tidyr_1.3.0          tibble_3.2.0         ggplot2_3.4.1
[25] tidyverse_2.0.0      data.table_1.14.0    here_1.0.1
[28] knitr_1.42

loaded via a namespace (and not attached):
 [1] nlme_3.1-153        webshot_0.5.2       httr_1.4.5
 [4] rprojroot_2.0.2     dreamerr_1.2.3      numDeriv_2016.8-1.1
 [7] tools_4.1.2         backports_1.2.1     utf8_1.2.2
[10] R6_2.5.1            KernSmooth_2.23-20  DBI_1.1.1
[13] colorspace_2.0-2    raster_3.4-13       withr_2.5.0
[16] sp_1.4-5            tidyselect_1.2.0    compiler_4.1.2
[19] textshaping_0.3.6   cli_3.6.0           rvest_1.0.3
[22] xml2_1.3.3          sandwich_3.0-1      labeling_0.4.2
[25] bookdown_0.33       scales_1.2.1        classInt_0.4-3
[28] proxy_0.4-26        systemfonts_1.0.4   digest_0.6.27
[31] rmarkdown_2.20      svglite_2.0.0       pkgconfig_2.0.3
[34] htmltools_0.5.4     fastmap_1.1.0       rlang_1.0.6
[37] rstudioapi_0.14     generics_0.1.0      farver_2.1.0
[40] zoo_1.8-9           jsonlite_1.8.4      magrittr_2.0.3
[43] Formula_1.2-4       s2_1.0.6            Rcpp_1.0.7
[46] munsell_0.5.0       fansi_0.5.0         abind_1.4-5
[49] RefManageR_1.3.0    lifecycle_1.0.3     stringi_1.7.4
[52] yaml_2.2.1          plyr_1.8.6          grid_4.1.2
[55] lattice_0.20-45     hms_1.1.2           pillar_1.8.1
[58] codetools_0.2-18    wk_0.5.0            glue_1.6.2
```

```
[61] evaluate_0.20      vctrs_0.5.2        tzdb_0.1.2
[64] cellranger_1.1.0   gtable_0.3.0       xfun_0.37
[67] e1071_1.7-8        ragg_1.2.5         class_7.3-19
[70] viridisLite_0.4.0  units_0.7-2        timechange_0.2.0
[73] ellipsis_0.3.2
```