Extreme Temperature, Adaptation Capacity, and Household Retail Consumption

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Abstract

While the large cost of extreme temperature on production is well documented, little is known about its impact on consumption, a prevailing measure of welfare. Using high-frequency micro shopping data from U.S. households, we report that deviating from mild temperature negatively affects weekly retail consumption activities. The decrease from extreme heat seems mostly driven by intertemporal substitution, but the negative impact following extreme cold is enduring—although the magnitude is economically small. We find that passenger cars substantially moderate the negative impact of extreme temperature on retail consumption—as large as 70% in comparison to the baseline of zero vehicles—while rideshare services or public transit do not produce a similar moderating effect.

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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 works have documented that such temperature change—mostly focusing on the heat—harms productivity, human capital formation, labor supply, health conditions, and economic growth (Deschenes and Moretti 2009, Dell et al. 2012, 2014, Zivin and Neidell 2014, Burke et al. 2015b, Barreca et al. 2016, Burke and Emerick 2016, Park et al. 2020, Somanathan et al. 2021). While these studies provide useful insights to understand the impact of extreme temperature on production, relatively little is known about its impact on consumption.[1]

However, understanding the relationship between extreme temperature and consumption is also important for at least two reasons. First, consumption reflects the current economic welfare (Deaton and Zaidi 2002, Chen and Ravallion 2010, Attanasio and Pistaferri 2016), and thus identifying the impact of temperature shock on consumption helps to deepen our understanding of the welfare cost of climate change. Second, investigating consumption responses could help validate earlier findings on the relationship between heat and firm outcomes (Addoum et al. 2020, Li et al. 2020).

In this paper, we provide one of the first empirical evidence on the impact of extreme temperature on U.S. household retail consumption using micro shopping data. We link the Nielsen consumer panel to county-level temperature data and non-parametrically estimate the impact of temperature on retail consumption. In doing so, we investigate both contemporaneous and dynamic 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 monthly averages and year-by-month-specific overall trends in temperature and consumption activities, 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 an inverse-U shape between household contemporaneous spending and temperature. The negative impact on contemporaneous con-

[1] Lai et al. (2022) is an important exception. This paper studies the impact of extreme temperature on consumption using high-frequency data in China.

sumption is the most pronounced with extreme heat: one additional day in a week with a daily mean temperature over 90°F reduces weekly spending by 1%. We also find a similar pattern between temperature and the frequency of shopping, which suggests that the reduction in spending is due to less frequent trips during an unpleasant (or even risky) time. Further, we report the heterogeneous impact of temperature shock across product types and climate regions, which further suggests that household actively adjust their contemporaneous shopping behavior. Specifically, we find a larger (in magnitude) effect for non-food grocery or beauty and health products, which are less essential and deferrable than fresh produce, under extreme temperatures. Further, responses to extreme heat from cooler areas such as Northeast and West are much larger than from hotter areas presumably because cooler areas are less accustomed to such shocks. Overall, we find that extreme temperature has a small but statistically significant negative impact on consumption for an average household.

Second, we estimate a distributed lag model to investigate the potential dynamic impact of a temperature shock. We find that the negative effect of hot days on contemporaneous consumption mostly reflects temporal displacement. Namely, the dip in spending during a week with hot days is compensated by higher spending in the following two weeks, and the cumulative effect of hot days is essentially null at -0.1% (95% CI: -0.013 to 0.011). However, the cumulative effect of extreme cold is larger than its contemporaneous effect at -1.1% (95% CI: -0.013 to -0.009), although the absolute magnitude is still small. One potential explanation for the asymmetry is the differential health impact of hot and cold days as documented in Deschenes and Moretti (2009). That is, the increase in mortality following extreme heat is driven by temporal displacement, while the increase in mortality following extreme cold is enduring because some respiratory conditions take time to fully develop and spread. Consistent with this hypothesis, we find that the pattern of intertemporal substitution differs across age groups. We find that the negative impact of extreme cold is larger and longer for the older group. Similarly, the magnitude of compensated consumption following extreme heat is much smaller for the older group. Taken together, the impact of temperature on household consumption seems to differ by extreme cold versus hot, but the magnitude of the cumulative impact is economically small if not null. This mirrors the findings of Addoum et al. (2020), which finds the null effect of extreme temperature on US firm sales.

Third, we investigate potential explanations for the small or null effects on household spending. Because intense exposure to extreme temperature 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, ride share service availability, and public transit accessibility, respectively. We fit a model that includes interaction terms between moderators and temperature bins to find that having passenger cars attenuates the negative impact of extreme temperatures on contemporaneous consumption. Specifically, all else equal, having 2.12 vehicles, which is the average number of expected vehicles for Nielsen panelists, mitigates the negative effect by as large as 70% in comparison to a household without a vehicle. In addition, by estimating a dynamic model, we also report that passenger cars allow smoother consumption over time. In contrast, Uber service availability and higher public transit density do not seem to have any moderating effect, which implies that disadvantaged people with less access to private transportation might bear substantially higher costs due to extreme weather conditions. It is worth pointing out that we also explore potential alternative explanations such as interchannel substitution to online or price adjustment by retailers for the small or null effects. We rule out those possibilities by showing that online shopping and price do not seem to respond to extreme temperatures.

This paper contributes to two different strands of literature. First, it is related to earlier works studying the impact of temperature change (Burke et al. 2015a, Barreca et al. 2016, Burke and Emerick 2016, Pankratz and Schiller 2019, Addoum et al. 2020, Li et al. 2020, Park et al. 2020, Park et al. 2021). This paper departs from the existing literature by turning attention to household consumption, which has been largely neglected despite its economic importance.

Second, we contribute to the growing literature studying the 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 (Finger et al. 2011, Boustan et al. 2012, Barreca et al. 2016, Fankhauser 2017, Han et al. 2021, Lee 2021, Barwick et al. 2022), we focus on adaptation capacity of 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).

Our work is most closely related to recent work by Lai et al. (2022). While both papers study the impact of extreme temperature on consumption, we believe that the findings of this paper complement Lai et al. (2022) for two reasons. First, the empirical setting of Lai et al. (2022) is China, where consumer characteristics and retail environment could be very different from the US. For instance, a larger effect size (in magnitude) identified in Lai et al. (2022) could reflect the difference in the baseline level of defensive measures. Second, we explore factors that could moderate the impact of extreme temperature.

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 shock on consumption while Section 4 explores the potential moderators. Section 5 concludes.

2 Data

2.1 Data Description

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

Household Retail Consumption. Our main outcome variables come from the Nielsen Consumer Panel Dataset from 2004 to 2019. It consists of about 40,000 to 60,000 US households who continually report their purchases—intended for personal usage—and household characteristics to Nielsen. Panelists record their shopping information by scanning receipts using hand-held scanners. The dataset keeps track of Universal Product Codes (UPCs) of all consumer goods households purchase from any outlet.[2] Products are classified into 10 departments, which include health and beauty aids, non-food grocery, general merchandise, and seven different food categories.[3] An important implication of the UPC-based data construction is that consumption of products without UPCs—products without a bar code such as non-packaged grocery, gasoline ,or utilities—are not captured by the Nielsen dataset.[4] In our analysis, we weight each observation by a projection factor, which makes purchases projectable to the entire US. Finally, Nielsen Consumer Panel data also has rich demo-

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

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

[4] 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.

graphic information of the panelists such as location (as granular as a 5-digit zip code), income, household size, and race.

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 2002 to December 2019. For the daily mean temperature, we 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 the temperature shock on consumption behavior. Given that the exposure to extreme weather is concentrated on the travel between the origin and destination, our primary focus is on three different modes of transportation that provide differential degree of protection from the exposure: passenger cars, ride share, and public transit. For vehicles, we use 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 the household characteristics such as region, household size, income, race, and population density of residing census tract. Importantly, it also documents the number of vehicles for each household, which we link to the Consumer Panel Data using demographic characteristics. For the ride share service, we leverage a differential availability of Uber service across space and time. We use Uber launch year information for the 50 largest Metropolitan Statistical Areas from Berger et al. (2018). Finally, to measure the degree of public transit accessibility, we use the number of public transit stops for each zip code at a point of time between 2016-2018, which is 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 a convenience store, 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 over the study period.[5]

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 three rows are related to household consumption activities, and the next three rows shed light on the household demographic characteristics.

A few points are worth noting. First, an average household spends \$82 each week (or \$4,264 each year). These figures are inflation-adjusted to 2019 dollars using the CPI. When compared to the annual spending of the average US household from the Bureau of Labor Statistics, \$4,264 captures about 60% of the retail spending (Bureau of Labor Statistics 2020).[6] The frequency of shopping is defined based on the number of check-out receipts. For instance, if a panelist purchased 10 items from a single store, then the shopping frequency is 1. However, if the same 10 items have been purchased from two different stores (even within the same day), then the shopping frequency is 2. The summary statistics show that an average household made one purchase roughly every other day.

Second, online shopping consists of a small fraction of the entire consumption over the sample period. By comparing across means, online spending consists of a little less than 2% of entire spending. This is consistent with the overall trend in the US: the quarterly US retail sales data from Census indicate that the arithmetic mean of the fraction of e-commerce out of the entire retail spending over 2004-2019 is 5.6% (Census Bureau 2022). Although slightly lower than the national average, the Nielsen data (at least partially) can capture potential switches from physical shops to online shops.

Third, 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 the annual income: low (below \$40,000), middle (between \$40,000 and \$100,000), and high (above \$100,000). This minimizes

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

[6] In 2019, the average household spent \$4,643 on food at home, \$768 on personal care products and services, and \$1,891 on another miscellaneous spending. Spending not covered by 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).

Table 2.1: Summary Statistics for Key Variables

Variables	Min.	Max.	Mean	Std.Dev.
Panel A: Household Consumption Outcomes				
Total Spending (Weekly)	0	7,825	81.68	98.98
Frequency of Shopping (Weekly)	0	112	3.2	3.43
Total Online Spending (Weekly)	0	2,362	1.2	12.24
Panel B: Household Demographic Characteristics				
Income	5,215	360,998	81,007	48,779
Household Size	1	9	2.55	1.3
Population Density	1	148,228	3,723	6,937

measurement error in 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).[7]

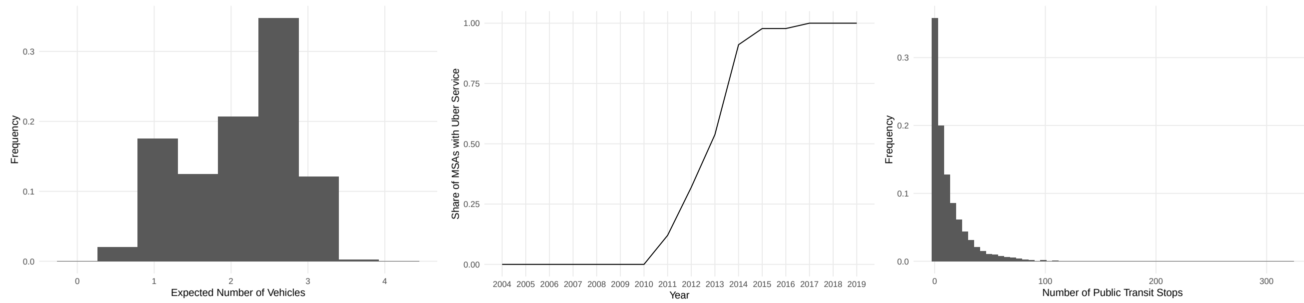
Lastly, the average household size is 2.55, which is exactly the same as the average number of people per household over 2004-2019 estimated using the Current Population Survey.[8] Population density, which is defined as the number of people per square mile within a zip code is on average 3,723. Given that urban areas typically have a population density of over 1,000, an average household in the Nielsen dataset is likely to live in a large metropolitan city (Cohen et al. 2015).[9]

Panels (a)-(c) in Figure 2.1 show the distribution of potential extreme temperature moderators. As extreme temperature exposure is concentrated on travel to and from a shop, we focus on different transportation modes. Panel (a) shows the expected number of vehicles for each Nielsen household. 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 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 (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

[7]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.

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

[9]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).



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

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

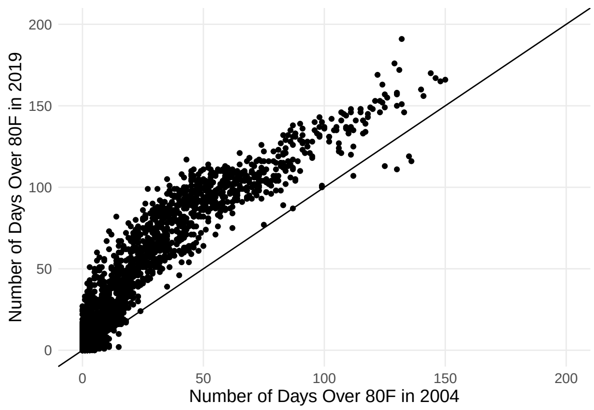
Nielsen households. The histogram suggests that the majority of the households have 1-3 vehicles (mean 2.12).

Panel (b) 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 happened 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 start year.

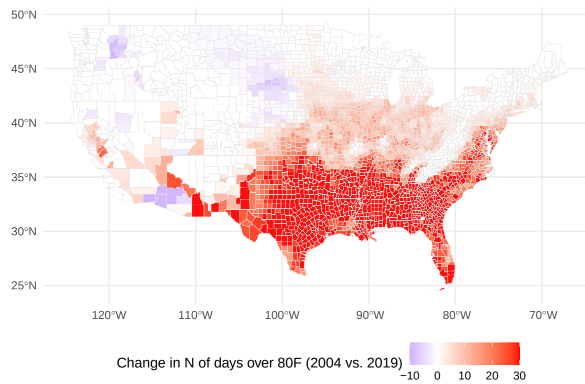
Panel (c) illustrates the distribution of the number of transit stops per zip code during 2016-2018, which proxies the degree of access to public transit. The data comes from Melendez et al. (2021), which has spatially merged the National Transit Map with ZCTA boundaries from the Census Bureau. The data captures the status of public transit between 2016-2018 for the areas administered by one of 270 regional transit agencies choosing to report to the National Transit Map. Admittedly, there might have been a temporal change in the number of public transit stops over time, but we believe that the 2016-2018 period still captures substantial variation across space. Because of the selection issue—that is, we do not know about the transit status for areas served by non-participating transit agencies, we only keep observations with a positive number of transit stops. The plot shows that the number of stops has a large variation, with an average number of stops at 97.[10]

In Figure 2.2, we illustrate how the temperature pattern has changed over our sample period. In

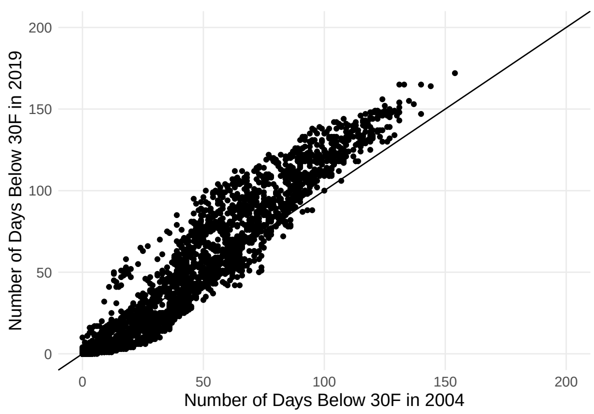
[10]The number of stops per capita and per square mile also exhibit a large variation.



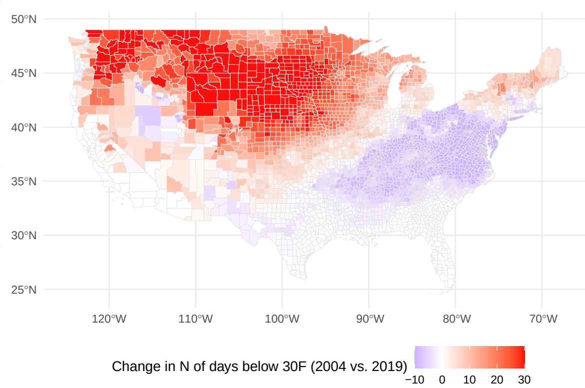
(a) Number of Days with Mean Daily Temperature over 80F° in 2004 and 2019



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



(c) Number of Days with Mean Daily Temperature below 30F° in 2004 and 2019



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

Figure 2.2: Change in Temperature Over Time. Panels (a) and (b) show how the number of days with mean daily temperature over 80F° has evolved between 2004 and 2019. Panel (a) illustrates the number of days with mean daily temperature over 80F° in 2004 and 2019 for each county. Panel (b) shows the corresponding spatial distribution. Panels (c) and (d) show how the number of days with mean daily temperature below 30F° has evolved between 2004 and 2019. Panel (c) illustrates the number of days with mean daily temperature below 30F° in 2004 and 2019 for each county. Panel (d) shows the corresponding spatial distribution. See the text for additional details.

panel (a), each dot represents a single county in our dataset, where the x-axis indicates the number of days in 2004 with a mean daily temperature over 80°F and the y-axis illustrates the 2019 equivalent. There are two points worth attention from this figure. First, almost all the dots are above the 45 degrees line, indicating that overall it became much hotter over the 15 years. Second, the magnitude is large, especially for relatively cooler places—many of them have experienced more than twice as many hot days as they used to experience over the 15 years. Plot (a) provides evidence of rising temperature even for a relatively short period of time. This coincides with findings that each of 2000-2009 and 2010-2019 has broken the record for the warmest decade since 1850 (IPCC 2021).

In panel (b), we plot the temperature change between 2004 and 2019 for each county to illustrate the spatial distribution. The map shows that the number of days with a daily mean temperature over 80°F has increased substantially in many parts of the contiguous US. While hotter places such as the East and West Central South region have experienced the most dramatic change—as depicted by dark red, which indicates gaining more than 30 additional days of hot days, relatively cooler places such as the Midwest or Mid Atlantic region have also gained more than 10 of such hot days over the past 15 years. Note, as we topped out at 30 and bottomed out at -10 for visibility, the extent of additional hot days in some places could be much larger than 30.

In panels (c)-(d), we repeat the same exercise for the number of days with a mean daily temperature below 30°F. The pattern in panel (c) is slightly different from that of the panel (a). While we find a near-universal increase in hotter days in panel (a), the distribution of colder days got more polarized. Namely, places with fewer colder days in 2004 had fewer colder days in 2019 while places with a higher number of colder days in 2004 experienced more cold days in 2019. Panel (d) shows this pattern more clearly. We find that a large fraction of the northwestern part of the contiguous US has gained a significantly larger number of colder days between 2004 and 2019. Combining panels (b) and (d) together, we know that over the last 15 years, the temperature has become more polarized: a cooler part of the country (the northwest part) experienced a lot more cold days while a warmer part of the country (the southeast part) experienced a lot more hot days. In appendix Figure A.1, we repeat the same plot using 2004-2006 versus 2017-2019 as opposed to the two end years of our sample. Although somewhat muted, the patterns in plots (a) through (d) persist, suggesting that the distribution of temperature has become more extreme over our sample period.

3 The Impact of Temperature Shock on Retail Consumption

3.1 Contemporaneous Effect

Our main empirical exercise is estimating the impact of extreme temperature on household weekly retail consumption. Specifically, we estimate equation (1), which exploits deviations from both county-specific monthly average and year-by-month average of temperature and consumption activities.

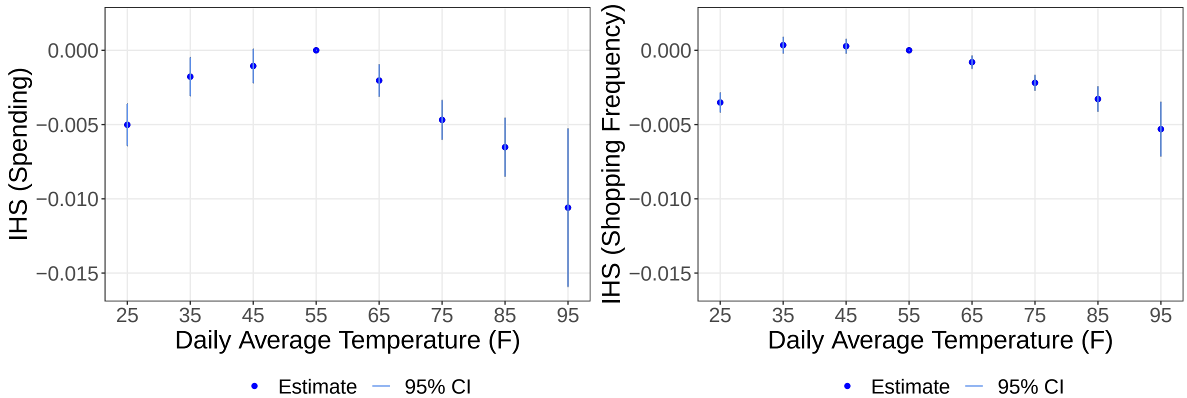
$$sin^{-1}(Y_{icwmy}) = \sum_k \beta^k T^k_{cwy} + \gamma \mathbf{X}_{cwy} + FEs + \epsilon_{icwmy} \tag{1}$$

Here Y_{icwmy} is an outcome variable such as weekly spending or weekly shopping frequency for a household i living in county c in a week w, month m at year y. We use inverse hyperbolic sine transformation because weekly data contains zero values for outcome variables.[11] 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 household characteristics, which allows us to leverage plausibly random deviations from average temperature exposure for each household. We also include county by month and income group by month fixed effects to control for county-specific and income group-specific seasonality. In addition, we include year-month fixed effects to control for economy-wide shocks. 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 $k \in \{\text{Below } 30°F, 30-40°F, 40-50°F, 50-60°F, 60-70°F, 70-80°F, 80-90°F, \text{Over } 90°F\}$.

Non-parametric regression in 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 temperature of bin k on consumption outcomes.

Figure 3.1 (a) plots the estimated coefficient from equation (1) where the outcome variable is inverse hyperbolic sine transformed weekly overall retail spending. We find a clear "inverse-U shape" relationship between spending and temperature. Namely, as the weather deviates from a moderate

[11] For instance, weekly spending is zero for 22% of the observations.



(a) Temperature and Weekly Expenditure

(b) Temperature and Weekly Numnber of Trips

Figure 3.1: Temperature and Household Consumption. Panel (a)-(b) show how household consumption activities respond to different temperature levels. The outcome variables are inverse hyperbolic sine transformed weekly expenditure (panel (a)) and weekly frequency of shopping (panel (b)), respectively. See the text for additional details.

condition (a daily mean temperature between 50-60$°F$), household spending increasingly declines. In panel (b), we find a similar but smaller response for the frequency of shopping, which coincides with the reduction in household spending.

In Appendix Table A.2, we present the result in Figure 3.1 more formally. Column (1) shows that swapping a day with a daily mean temperature between 50-60$°F$ to a day with a daily mean temperature over 90$°F$ (80-90$°F$) in a week reduces household spending by 1.1% (0.65%). To put this in context, we multiply this with the weekly average spending ($82) from Table 2.1 and find that an average household reduces spending by $0.9 ($0.53). In column (2), we repeat the same exercise for the weekly shopping frequency to find that an additional day of extreme temperature reduces shopping frequency by 0.5% or roughly 0.02 shopping per week. The effect size is comparable to Lai et al. (2022), which studied the impact of extreme heat on consumption in China.[12]

In Appendix Table A.3, we include county-specific linear time trends to account for potential temperature change over time. The estimated coefficients coincide with our preferred specification although the effect size for extremely hot days seems to be slightly larger (the hottest day bin in column (1)).

Table 3.1 presents additional evidence that households adjust consumption in response to temper-

[12]They find that the cumulative consumption impact of the past ten days' extreme hot temperature on consumption is 5.9%. When we compare our results to a specification that uses the number of days in temperature bins, the effect size in Lai et al. (2022) is similar (Extended Data Figure 4 (d)) to ours.

Table 3.1: Heterogeneous Household Weekly Spending Response to Temperature Shocks

	(1)	(2)	(3)	(4)
Panel A: Differential Effect by Product Type				
N of Days Below 30F	-0.0039***	-0.0038***	0.0007**	0.0018***
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
N of Days 30-40F	-0.0008*	-0.0020***	0.0006**	0.0017***
	(0.0004)	(0.0005)	(0.0003)	(0.0003)
N of Days 80-90F	-0.0052***	-0.0026***	-0.0010***	0.0021***
	(0.0006)	(0.0008)	(0.0004)	(0.0003)
N of Days Above 90F	-0.0097***	-0.0064***	-0.0001	0.0028***
	(0.0022)	(0.0019)	(0.0011)	(0.0010)
Product Category	Beauty & Health	Non-Food Grocery	Fresh Produce	Alcohol
Observations	47,880,120	47,880,120	47,880,120	47,880,120
Panel B: Differential Effect by Climate Region				
N of Days Below 30F	-0.0093***	-0.0120	-0.0050*	-0.0094***
	(0.0015)	(0.0095)	(0.0028)	(0.0025)
N of Days 30-40F	-0.0040***	-0.0054	-0.0047**	-0.0059***
	(0.0014)	(0.0037)	(0.0020)	(0.0016)
N of Days 80-90F	-0.0188***	-0.0026	-0.0035	-5.4e-5
	(0.0026)	(0.0027)	(0.0024)	(0.0019)
N of Days Above 90F	-0.0489	-0.0185***	-0.0064	0.0087
	(0.0359)	(0.0050)	(0.0045)	(0.0354)
Sample	Northeast	West	South	Southeast
Observations	9,300,653	4,539,734	6,069,885	8,895,946

Note:
This table presents the effect of temperature on weekly household spending for different product type and regional groups. We only report coefficients for hotter or colder temperature for the interst of space, but precipitation and its square term, and other temparature bins, except for the omitted category (50-60F), are included (for the entire set of coefficients, see appendix Table A.4 for panel A and appendix Table A.5 for panel B). All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

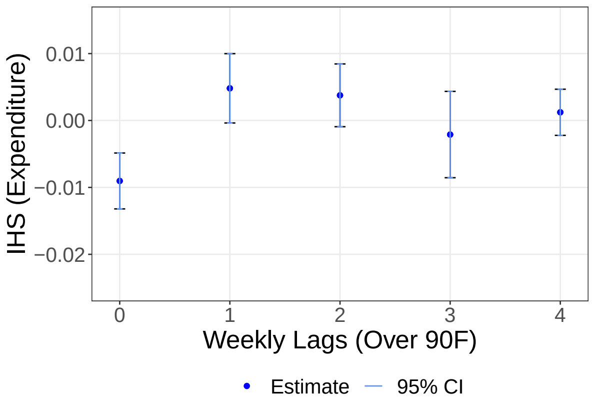
ature shocks. In panel A, we estimate the impact of temperature on different product categories. In columns (1) and (2), we present results from "beauty and health" and "non-food grocery" departments, which are more durable and thus more likely to be deferrable than food items. In columns (3) and (4), we present results from the "fresh produce" and "alcohol" department, which are the essential staple for many households and potential heat relievers.[13] If households respond to temperature shocks, we expect to find stronger responses from the first two columns. Indeed, we find much larger point estimates. For instance, one additional day of a daily mean temperature over $90°F$ reduces health and beauty department spending by 1% but has a null (positive) effect on fresh produce (alcohol). When we compare (1) and (2), the magnitude is smaller for non-food grocery presumably because households still visit grocery stores for food shopping, which makes it easier to purchase non-food grocery items as well.

In panel B, we split the sample by the NOAA climate region and estimate equation (1). The estimated coefficients show that the impact of temperature shock is substantially different across different regions. Areas with higher baseline climate (South and Southeast in columns (3) and (4)) are much more robust to the extreme than areas with cooler baseline climate (Northeast and West in columns (1) and (2)) presumably because hotter areas are better prepared for extreme heat. These patterns have been reported in earlier studies, and emphasize the role of adaptation in determining the cost of extreme temperatures (Barreca et al. 2016, Lai et al. 2022).

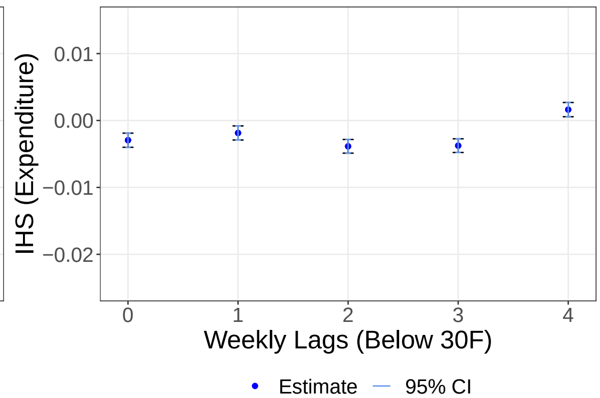
3.2 Dynamic Effect

The results in Section 3.1 do not consider the potential dynamic effect between the extreme temperature and consumption activities. That is, the negative (albeit small) impact of temperature on consumption could simply reflect households' decision to *defer* rather than *reduce* consumption. If such intertemporal substitution is prevalent, extreme temperatures might not have a lasting impact on consumption. To investigate this possibility, we estimate a distributed lag model as equation (2). Here, $T^k_{cy,w-t}$ is the number of days in a county-year-lagged week (of $w - t$) that the daily average temperature belongs to bin k. Given the number of parameters, we estimate a more parsimonious model where $k \in \{\text{Below } 30°F, 80-90°F, \text{Over } 90°F\}$. Thus the reference temperature bin is $30-80°F$.

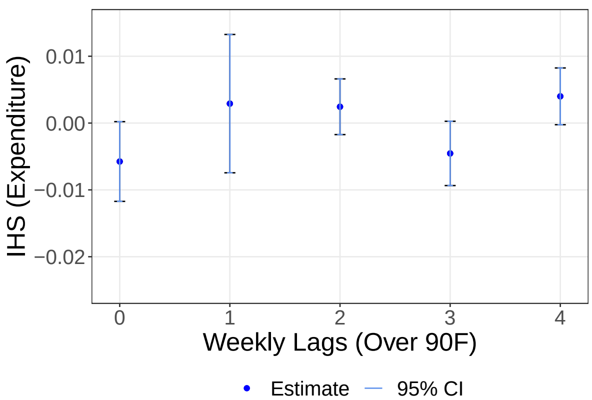
[13] Each of the four categories represents 11% (beauty and health), 13% (non-food grocery), 3% (fresh produce), and 4% (alcohol) of total spending in the sample.



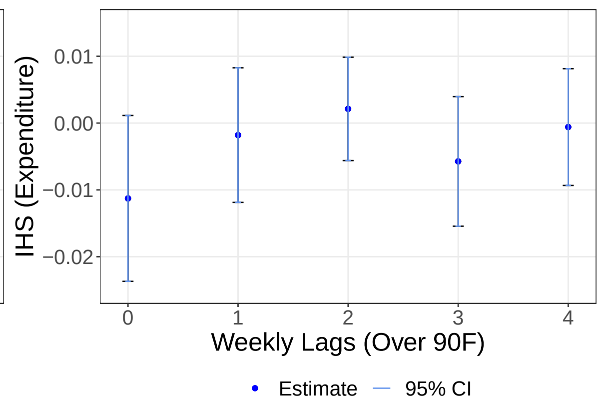
(a) Heat and Spending Over Time



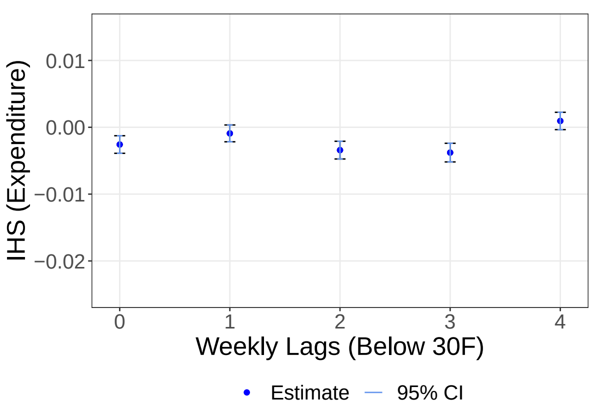
(b) Cold and Spending Over Time



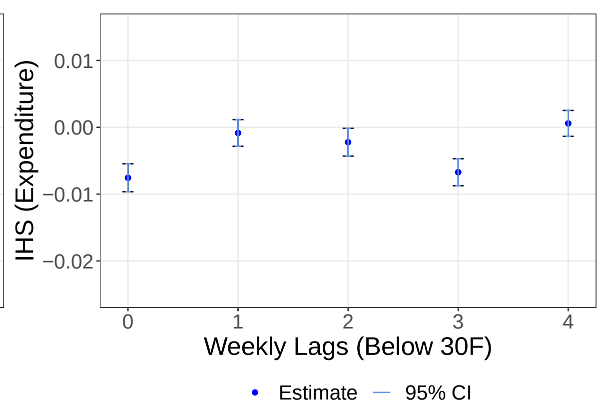
(c) Heat and Spending Over Time ($40 < \text{Age} < 65$)



(d) Heat and Spending Over Time ($\text{Age} \geq 65$)



(e) Cold and Spending Over Time ($40 < \text{Age} < 65$)



(f) Cold and Spending Over Time ($\text{Age} \geq 65$)

Figure 3.2: Temperature Shock and Household Consumption Over Time. Panel (a)-(f) show how household expenditure responds to temperature shocks over time. The outcome variables are inverse hyperbolic sine transformed weekly spending. Panel (a)-(b) illustrate the extreme temperature impact on consumption for the entire population while (c)-(d) and (e)-(f) show the impact of heat and cold for different age groups, respectively. See the text for additional details.

Importantly, the cumulative effect of temperature on consumption is obtained by $\sum_{t=0}^{4} \beta_{w-t}^{k}$, which sums up the contemporaneous and lagged effects for a given temperature bin k.

$$sin^{-1}(Y_{icwmy}) = \sum_{t=0}^{4} \sum_{k} \beta_{w-t}^{k} T_{cy,w-t}^{k} + \gamma \mathbf{X}_{cwy} + FEs + \epsilon_{icwmy} \tag{2}$$

In Figure 3.2 panel (a), we plot the estimated coefficients from equation (2) for the hottest days bin where the outcome variable is spending amount. Consistent with the earlier section, we find that one additional hot day per week reduces contemporaneous weekly spending by about 1%. However, the negative effect is almost fully compensated by higher than usual spending in the following two weeks. When we sum over the estimated coefficients, the effect size is indistinguishable from zero ($\sum_{t=0}^{4} \beta_{w-t}^{\text{Over } 90^\circ F} = -0.0013$, 95% CI: -0.013 to 0.011).[14]

In panel (b), we plot the same graphs for cold days. Interestingly, we find that the negative impact of cold days is persistent. In the case of the spending amount, exposure to the extreme cold reduces contemporaneous spending by roughly 0.3%, but compensating consumption increase happens only after a prolonged lag (in lag 4). Rather, the figure suggests that the extreme cold that happened three weeks ago still negatively affects this week's consumption. When we sum over the estimated coefficients, the cumulative impact of cold temperature shock on spending is -1.1% ($\sum_{t=0}^{4} \beta_{w-t}^{\text{Below } 30^\circ F} = -0.011$, 95% CI: -0.013 to -0.009). Why is there an asymmetry between extreme hot and cold? One potential explanation could be the differential health impact of cold versus hot days. For instance, Deschenes and Moretti (2009) shows that the mortality impact of heat is mostly "harvesting", namely temporal displacement, while the impact of cold is "delayed", which means that the contemporaneous effect underestimates the impact of the temporal shock on health. This could happen because some respiratory conditions take time to fully develop and spread (Deschenes and Moretti 2009).

Consistent with the differential health impact of hot and cold extreme temperatures, we find a heterogeneous lagged impact of extreme temperatures depending on age groups (above 65 and between 40-65). In panels (c)-(d), we plot the spending response over time for younger and older households. In comparison to the younger group, older populations scale back the contemporaneous spending

[14] Standard error is calculated using the delta method.

with a larger magnitude (at least in terms of point estimates), and we do not find as strong compensating spending response in the following weeks. The difference between the age group is even more pronounced in extreme cold. Comparing the contemporaneous effect in panels (e) and (f) suggests that the impact of extreme cold is larger for the older group, and the difference between the two groups is statistically significant. Further, the negative impact of temperature on spending is more persistent for the older group. In Appendix Figure A.2, we produce the same set of plots as Figure 3.2 for the number of shopping trips. Overall, the impact on the trip mirrors the impact on consumption, although the magnitudes are somewhat smaller.

Taken together, findings in this section suggest that the impact of temperature on household consumption differs by cold versus hot weather, but the magnitude of the cumulative impact is economically small if not null. As such, the welfare cost of extreme temperature in our context is likely to be very small.[15] This is somewhat surprising given that (1) offline shopping requires travel, which might increase the exposure to extreme temperatures, and (2) extreme temperature puts significant stress on the human body (Deschenes and Moretti 2009, Deschênes and Greenstone 2011). Why do households still engage in consumption activities from offline stores? How do they manage to do so?

4 Moderating Factors to the 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 for shopping, we evaluate the effectiveness of three different modes of transportation—passenger cars, ride share services, and public transit—that provide a different levels of protection.[16] Practically, we modify equation (1) and fully interact the moderator variable with the three temperature bin variables, namely Below $30°F, 80 - 90°F$, and Over $90°F$ to keep the model tractable.

Table 4.1: Household Consumption Response to Extreme Temperature by Mode of Transportation

	(1)	(2)	(3)
N of Days Below 30F	-0.0099***	-0.0041***	-0.0062***
	(0.0014)	(0.0011)	(0.0011)
N of Days 80-90F	-0.0052***	-0.0038***	-0.0023*
	(0.0015)	(0.0012)	(0.0013)
N of Days Above 90F	-0.0211***	-0.0074***	-0.0070
	(0.0049)	(0.0023)	(0.0044)
N of Vehicles × N of Days Below 30F	0.0030***		
	(0.0006)		
N of Vehicles x N of Days 80-90F	0.0013**		
	(0.0006)		
N of Vehicles x N of Days Above 90F	0.0071***		
	(0.0025)		
Uber × N of Days Below 30F		-0.0007	
		(0.0015)	
Uber x N of Days 80-90F		0.0020	
		(0.0016)	
Uber x N of Days Above 90F		-0.0003	
		(0.0069)	
N Stops × N of Days Below 30F			0.0009
			(0.0007)
N Stops x N of Days 80-90F			0.0002
			(0.0007)
N Stops x N of Days Above 90F			0.0003
			(0.0035)
Observations	47,899,607	26,138,627	24,074,807

Note:
This table illustrates how different mode of transportation affects the impact of extreme temperature exposure on household weekly consumption activities. For the interest of space, only temperature bins and interaction terms are presented in the main text, but the entire set of coefficents can be found in Appendix Table A.6. All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

4.1 Mode of Transportation and Temperature Shock Moderation

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

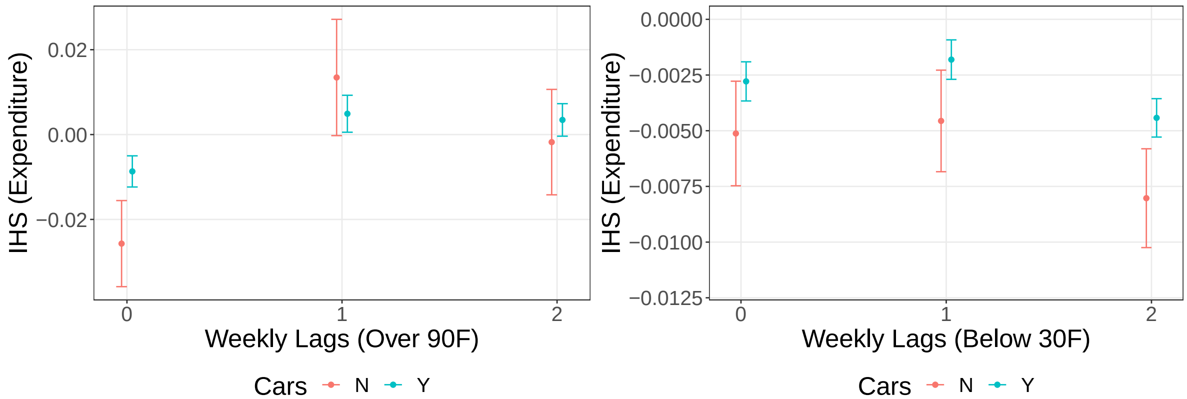
As detailed in Section 2.2, we merge the Nielsen Consumer Panel dataset with the National Household Transportation Survey using demographic characteristics because vehicle ownership information is not a part of the Nielsen survey questionnaire.

Table 4.1 column (1) shows how vehicle ownership moderates the impact of extreme temperature on contemporaneous household consumption activities. The estimated coefficients suggest that extreme temperature has a large impact on a household without a vehicle. For instance, one additional day per week with a daily mean temperature over $90°F$ (below $30°F$) reduces weekly spending by over 2% (1%). However, having a vehicle offsets the negative impact substantially. At the mean number of vehicles (2.12), the impact of extreme heat (cold) reduces by 70% (64%) in comparison to the baseline. Importantly, these coefficients are estimated after controlling for income (i.e., income group by month fixed effect), so having a vehicle provides protection that goes beyond and above the effect of income. In Appendix Table A.7 column (1), we find a similar pattern for the number of shopping trips as well. Further, in Appendix Table A.8, we use different sets of fixed effects such as county-specific linear or quadratic time trends instead of county-by-year fixed effects. These alternative models allow for location-specific temperature trend changes, and we find that the results in Table 4.1 column (1) are robust to specification choices.

In Figure 4.1, we plot the expected consumption activities for two different types of households, namely those with and without a car. To pin down the effect for a household with a car, we use the average expected number of vehicles (2.12) for the Nielsen panelists. Although not all of the estimated coefficients between the two groups are statistically significantly different, the plot suggests

[15] The welfare cost of intertemporal substitution could be large when the subjective discount rate is very high. However, recent "reasonable" estimates range from 10-35% per year (Andersen et al. 2008, Andreoni and Sprenger 2012), and even if we take 35%, deferring consumption by a week is likely to cause less than 1% loss in utility.

[16] Another reason that transportation options are important for a shopping trip is the fact that households oftentimes purchase an amount that is difficult to carry without a car. In our dataset, an average spending is $34, which does not vary too much by density. Households living in a high density neighborhood still spend $30 per trip on average.



(a) Extreme Heat

(b) Extreme Cold

Figure 4.1: Vehicle Ownership and Household Consumption Responses to Extreme Temperature Over Time. Panel (a) and (b) show how the household spending responds to extreme temperature over time depending on the vehicle ownership. I used the average number of vehicles (2.12) to calculate the projected response from a household with vehicle. The errorbars represent the 90% confidence interval. See the text for additional details.

that spending is likely to be much smoother for a household with a vehicle. For extreme heat, the extent of intertemporal substitution is much smaller for a household with a vehicle. For extreme cold, the consumption level is much closer to the average level (namely 0) throughout weeks 0 to 2, which implies that the cumulative shock is much smaller for a household with a vehicle.[17]

Ride Share Availability. Next, we explore whether the availability of ride share services could moderate the negative impact of extreme temperatures on consumption. We use the year of Uber availability as a proxy for ride share service availability for the 50 largest MSAs in the US following Berger et al. (2018). Limiting our attention to the largest 50 MSAs reduces our sample size by roughly half, but 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.

Similar to our exercise with the number of private vehicles, we interact the three temperature bins with a dummy variable which takes 1 when an MSA has Uber service. Table 4.1 column (2) reports the estimated coefficients. In contrast to the findings in column (1), we find a sharp null effect for Uber, especially for the two extreme temperature bins. In the case of the number of trips, we find similar null effects for hot days although there is an additional negative impact due to Uber's introduction for cold days. Taken together, Uber does not seem to effectively mitigate the negative

[17]To remove the level effect, we did not add the coefficient for the Number of Vehicles variable when calculating the projected consumption for a household with a vehicle.

impact of temperature shocks on household consumption.

The finding could be somewhat unexpected given that the ride share service provides a similar level of protection as passenger cars. However, this could be consistent with the rider patterns found in prior studies. For instance, Shokoohyar et al. (2020) reports that the demand for Uber under extreme weather conditions is higher than usual for weekdays but lower for weekends. This implies that people might use Uber less frequently for non-essential or deferrable activities. Further, when we take into account the cost of Uber service, households might not switch from their status quo mode of the shopping trip (presumably a non-motorized mode) to Uber in response to extreme temperatures. From Table 2.1, an average spending amount per transaction is roughly $25, 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 is as large as 36% of the shopping cost.

Public transit accessilibity. Lastly, we consider public transit as a potential shock moderator. Table 4.1 column (3) estimates the moderating effect of having 100 additional public transit stops within a zip code. 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 defer their consumption. This suggests that households resorting to public transit or non-motorized transportation might have a difficult time meeting their basic 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.

4.2 Alternative Explanations

The discussion on potential moderators so far has focused on protection during a shopping trip, but there might be other important channels as well. In this section, we explore whether interchannel substitution or price change could explain the null impact of temperature shock on consumption.

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 effect cannot be the primary explanation for the null effect. First, online shopping is not a perfect substitute for offline 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 had to wait for a quite long time for their product to 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. If households choose to substitute to the online shopping in the face of extreme temperatures, we expect to see a larger reduction in the shopping frequency over time. In Appendix Table A.9, we report that the estimated coefficient of equation (1) for three different sample periods 2004-2008, 2009-2014, and 2015-2019. Although the availability and popularity of online shopping have significantly increased over time, we do not find much difference across different sample periods, which suggests that switching to the online channel in response to temperature shock is not likely to be common.

Second, our data show that the majority of households do not engage in online shopping at all, which rules out the frequent interchannel substitution. Specifically, for 82% of households, online constitutes less than 1% of their annual spending while only 7% of households spend more than 5% on online channels. This suggests that the majority of households almost completely rely on brick-and-mortar shops.[18] Indeed, in column (3) of Appendix Table A.2, we find that the impact of the hottest temperature bin on weekly online spending is null (if anything, -0.06%). Similarly, Lai et al. (2022) finds that temperature 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 type portfolios among the lowest income groups. Also, lowest-income consumers used cash about twice as often as highest-income consumers. These differences in payment methods make it challenging to make purchases online in the first place.

Price Change. We test if price change can explain the null effect on weekly spending. For instance,

[18] Limited interchannel substitution is consistent with findings from Roth Tran (2019). 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 different online and offline.

retailers might engage in promotions to compensate for 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 keep 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 and exit.

In Appendix Table A.10, we report the impact of temperature shock on retail prices. The dependent variable is the inverse hyperbolic sine transformed price index, and thus the estimated coefficients can be interpreted as a percentage change in price in response to temperature shocks. In column (1), we estimate the effect using the quarterly price index. As the data frequency is quarterly, we adjust county by month and year by month fixed effects from equation (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 show that temperature shock is almost orthogonal to the quarterly retail price. For instance, the coefficient of the hottest day bin suggests that an additional day in a quarter with a daily mean temperature over 90°F reduces the retail price by 0.03%, which we interpret as a sharp zero. The effect size is an order of magnitude smaller for the colder days.

In column (2), we repeat the same exercise using the annualized price index because price could be sticky, and temperature-driven price adjustment might not be captured in the quarterly price index (Nakamura and Steinsson 2008, 2013). Again, accounting for the 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 even smaller than in column (1), suggesting that price adjustment frequency is not the reason behind the null effect found in column (1).

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 operationalize this fact in two different ways. In column (3), we limit our attention to grocery stores and repeat the same exercise as column (1) following Leung (2021) and Leung and Seo (2019). Again, we find a very similar result to the previous two columns, which suggests that local temperature shocks do not affect local prices even for grocery stores.

In column (4), we estimate the impact of temperature based on the chain level exposure following 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 weight. The estimated magnitude is similar to columns (1)-(3) and we again find a sharp null effect of temperature exposure on prices. Taken together, retailers do not seem to change their prices in response to potential demand shock from extreme temperatures.

5 Conclusion

Climate scientists predict that extreme temperature conditions are likely to become more frequent in the future as climate change intensifies. While prior literature has 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 households welfare, our estimates extends our understanding about the welfare cost of climate change.

Using micro shopping data, we find a statistically significant negative effect of extreme temperatures on contemporaneous consumption. By investigating dynamic effect, we show that households actively adjust the timing of shopping to reduce exposure to extreme temperature. Interestingly, our findings suggest that the impact of extreme heat is mostly temporal displacement (i.e., cumulative effect is null) while extreme cold has a lasting negative impact, which is still economically small at 1.1%. Given the large negative impact on human behavior and economic performance reported in earlier studies, the null effect is somewhat surprising. We explore potential explanations by estimating the moderating factors. We find that passenger cars dramatically reduce the negative impact of extreme temperature on household spending, 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 and price adjustment by retailers. These findings suggest that the welfare cost of extreme temperature in the context of retail shopping—albeit small—could be concentrated on disadvantaged households who mainly rely on public transit.

References

10 Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea. 2020. Temperature Shocks and Establishment Sales. The Review of Financial Studies 33:1331–1366.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström. 2008. Eliciting Risk and Time Preferences. Econometrica 76:583–618.

Andreoni, J., and C. Sprenger. 2012. Estimating Time Preferences from Convex Budgets. American Economic Review 102:3333–3356.

Attanasio, O. P., and L. Pistaferri. 2016. Consumption Inequality. Journal of Economic Perspectives 30:3–28.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro. 2016. Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. Journal of Political Economy 124:105–159.

Barwick, P. J., D. Donaldson, S. Li, Y. Lin, and D. Rao. 2022. Improved Transportation Networks Facilitate Adaptation to Pollution and Temperature Extremes. NBER Working Paper w30462.

Berger, T., C. Chen, and C. B. Frey. 2018. Drivers of disruption? Estimating the Uber effect. European Economic Review 110:197–210.

Boustan, L. P., M. E. Kahn, and P. W. Rhode. 2012. Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century. American Economic Review 102:238–244.

Bureau of Labor Statistics. 2020, September. CONSUMER EXPENDITURES - 2019.

Burke, M., and K. Emerick. 2016. Adaptation to Climate Change: Evidence from US Agriculture. American Economic Journal: Economic Policy 8:106–140.

Burke, M., S. M. Hsiang, and E. Miguel. 2015a. Climate and Conflict. Annual Review of Economics 7:577–617.

Burke, M., S. M. Hsiang, and E. Miguel. 2015b. Global non-linear effect of temperature on economic production. Nature 527:235–239.

Census Bureau. 2022. Quarterly E-Commerce Report (Time Series).

Chen, S., and M. Ravallion. 2010. THE DEVELOPING WORLD IS POORER THAN WE THOUGHT, BUT NO LESS SUCCESSFUL IN THE FIGHT AGAINST POVERTY. QUARTERLY JOURNAL OF ECONOMICS 125:1577–1625.

Cohen, D. T., G. W. Hatchard, and S. G. Wilson. 2015. Population Trends in Incorporated Places: 2000 to 2013. US Census Bureau.

Cohen, J., L. Agel, M. Barlow, C. I. Garfinkel, and I. White. 2021. Linking Arctic variability and change with extreme winter weather in the United States. Science 373:1116–1121.

Connolly, S., and J. Stavins. 2015. Payment Instrument Adoption and Use in the United States, 2009–2013, by Consumers' Demographic Characteristics. Page 51. Research {Data} {Reports}, Federal Reserve Bank of Boston.

Deaton, A., and S. Zaidi. 2002. Guidelines for Constructing Consumption Aggregates For Welfare Analysis. World Bank Publications 135.

Dell, M., B. F. Jones, and B. A. Olken. 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. American Economic Journal: Macroeconomics 4:66–95.

Dell, M., B. F. Jones, and B. A. Olken. 2014. What Do We Learn from the Weather? The New Climate-Economy Literature. Journal of Economic Literature 52:740–798.

DellaVigna, S., and M. Gentzkow. 2019. Uniform Pricing in U.S. Retail Chains*. The Quarterly Journal of Economics 134:2011–2084.

Deschenes, O., and E. Moretti. 2009. EXTREME WEATHER EVENTS, MORTALITY, AND MIGRATION. THE REVIEW OF ECONOMICS AND STATISTICS 91:659–681.

Deschênes, O., and M. Greenstone. 2011. Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. American Economic Journal: Applied Economics 3:152–185.

Fan, Y., J. Palacios, M. Arcaya, R. Luo, and S. Zheng. 2021. Health perception and commuting choice: A survey experiment measuring behavioral trade-offs between physical activity benefits and pollution exposure risks. Environmental Research Letters 16:054026.

Fankhauser, S. 2017. Adaptation to Climate Change. Annual Review of Resource Economics 9:209–30.

Finger, R., W. Hediger, and S. Schmid. 2011. Irrigation as adaptation strategy to climate change—a biophysical and economic appraisal for Swiss maize production. Climatic Change 105:509–528.

Han, L., S. Heblich, C. Timmins, and Y. Zylberberg. 2021. Cool Cities: The Value of Urban Trees:41.

Handbury, J., and S. Moshary. 2020. School Food Policy Affects Everyone: Retail Responses to the National School Lunch Program:40.

IPCC. 2021. AR6 Climate Change 2021: The Physical Science Basis.

Lai, W., S. Li, Y. Liu, and P. J. Barwick. 2022. Adaptation mitigates the negative effect of temperature shocks on household consumption. Nature Human Behaviour 6:837–846.

Lee, S. 2021. Adapting to Natural Disasters through Better Information: Evidence from the Home Seller Disclosure Requirement. MIT Center for Real Estate Research Paper.

Leung, J. H. 2021. Minimum Wage and Real Wage Inequality: Evidence from Pass-Through to Retail Prices. Review of Economics and Statistics 103:754–769.

Leung, J. H., and H. K. Seo. 2019. How Do Government Transfer Payments Affect Retail Prices and Welfare? Evidence from SNAP:83.

Li, F. W., Y. Lin, Z. Jin, and Z. Zhang. 2020. Do Firms Adapt to Climate Change? Evidence from Establishment-Level Data. SSRN Electronic Journal.

McKinsey and Company. 2020, January. Future of Retail Operations: Winning in a Digital Era.

Melendez, R., M. Li, A. Khan, I. Gomez-Lopez, P. Clarke, and M. Chenoweth. 2021. National Neighborhood Data Archive (NaNDA): Public Transit Stops by ZIP Code Tabulation Area, United States, 2016-2018.

Mohiuddin, H. 2021. Planning for the First and Last Mile: A Review of Practices at Selected Transit Agencies in the United States. Sustainability 13:2222.

Nakamura, E., and J. Steinsson. 2008. Five Facts about Prices: A Reevaluation of Menu Cost Models. Quarterly Journal of Economics 123:1415–1464.

Nakamura, E., and J. Steinsson. 2013. Price Rigidity: Microeconomic Evidence and Macroeconomic Implications. Annual Review of Economics 5:133–163.

NASA. 2020, January. NASA, NOAA Analyses Reveal 2019 Second Warmest Year on Record. Text.

Pankratz, N. M. C., and C. Schiller. 2019. Climate Change and Adaptation in Global Supply-Chain Networks. SSRN Electronic Journal.

Park, J., N. M. C. Pankratz, and A. Behrer. 2021. Temperature, Workplace Safety, and Labor Market Inequality. SSRN Electronic Journal.

Park, R. J., J. Goodman, M. Hurwitz, and J. Smith. 2020. Heat and Learning. American Economic Journal: Economic Policy 12:306–339.

Roth Tran, B. 2019. Sellin' in the Rain: Adaptation to Weather and Climate in the Retail Sector. Finance and Economics Discussion Series 2019:1–34.

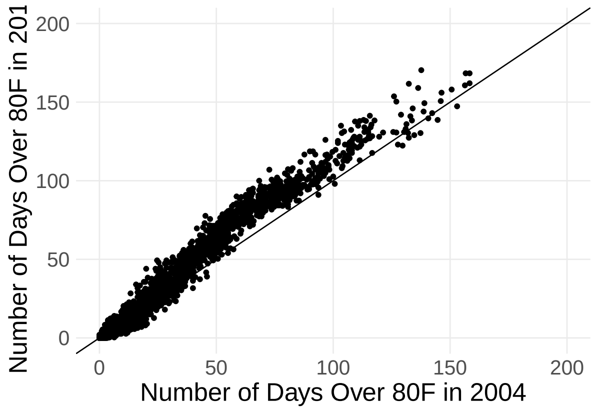
Shokoohyar, S., A. Sobhani, and A. Sobhani. 2020. Impacts of trip characteristics and weather condition on ride-sourcing network: Evidence from Uber and Lyft. Research in Transportation Economics 80:100820.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari. 2021. The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. Journal of Political Economy 129:1797–1827.

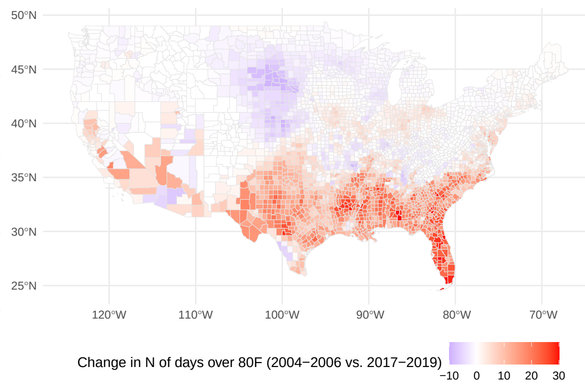
Wheat, C., J. Duguid, L. Relihan, and B. Kim. 2021. The COVID Shock to Online Retail: The Persistence of New Online Shopping Habits and Implications for the Future of Cities. SSRN Electronic Journal.

Zivin, J. G., and M. Neidell. 2014. Temperature and the Allocation of Time: Implications for Climate Change. Journal of Labor Economics 32:1–26.

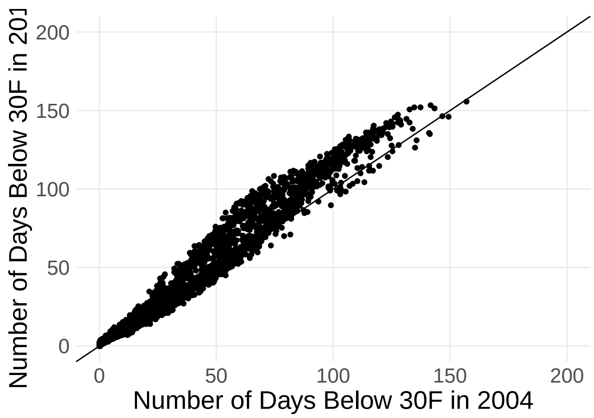
A Additional Tables and Figures



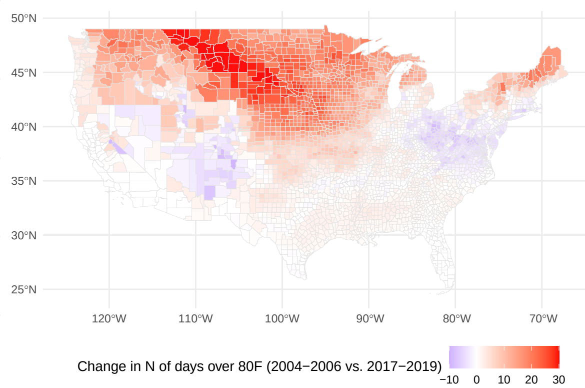
(a) Number of Days with Mean Daily Temperature over 80F in 2004-2006 and 2017-2019



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



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



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

Figure A.1: Change in Temperature Over Time (2004-2006 vs. 2017-2019). Panels (a) and (b) show how the number of days with mean daily temperature over 80F has evolved between 2004-2006 and 2017-2019. We use three-year average for each county. Panel (a) illustrates the number of days with mean daily temperature over 80F in 2004-2006 and 2017-2019 for a given county. Panel (b) shows the corresponding spatial distribution. Panels (c) and (d) show how the number of days with mean daily temperature below 30F has evolved between 2004-2006 and 2017-2019. We use three-year average for each county. Panel (c) illustrates the number of days with mean daily temperature below 30F in 2004-2006 and 2017-2019 for a given county. Panel (d) shows the corresponding spatial distribution. See the text for additional details.

Table A.1: Predictors of Vehicle Ownership

	(1)
(Intercept)	5.519***
	(1.341)
Race:Other	0.1529***
	(0.0268)
Race:White	0.3148***
	(0.0208)
Pop. Per Square Mile	-0.0406***
	(0.0028)
Household Size	0.2733***
	(0.0070)
Househld Income (in $1,000)	0.0070***
	(0.0002)
Midwest	0.1937***
	(0.0325)
South	0.1378***
	(0.0337)
West	0.2376***
	(0.0316)
Year	-0.0025***
	(0.0007)
S.E.: Clustered	by: hhst..
Observations	349,660

Note:
Column (1) shows the correlation between household demographic characteristics and the number of vehicles. The dependent variable is number of vehicles. Regressions are weighted by the National Houseohld Transportation Survey to represent the entire US population. Standard errors are clustered on state.

Table A.2: Household Weekly Response to Temperature Shocks

	(1)	(2)	(3)
N of Days Below 30F	-0.0050***	-0.0035***	-0.0005**
	(0.0007)	(0.0003)	(0.0002)
N of Days 30-40F	-0.0018***	0.0003	0.0003**
	(0.0007)	(0.0003)	(0.0002)
N of Days 40-50F	-0.0011*	0.0003	1.81e-5
	(0.0006)	(0.0002)	(0.0002)
N of Days 60-70F	-0.0020***	-0.0008***	-0.0003**
	(0.0005)	(0.0002)	(0.0001)
N of Days 70-80F	-0.0047***	-0.0022***	-0.0004***
	(0.0007)	(0.0003)	(0.0001)
N of Days 80-90F	-0.0065***	-0.0033***	-0.0003
	(0.0010)	(0.0004)	(0.0002)
N of Days Above 90F	-0.0106***	-0.0053***	-0.0006
	(0.0027)	(0.0009)	(0.0005)
Precipitation	-6.94e-5**	-8.4e-5***	-1.2e-5
	(3.18e-5)	(1.19e-5)	(7.93e-6)
Precipitation^2	-1.57e-6***	-6.62e-7***	-3.64e-8
	(1.76e-7)	(6.46e-8)	(4.18e-8)
Dep.Var	IHS (Spending)	IHS (N Trips)	IHS (Online)
Observations	47,921,631	47,921,631	47,921,631

Note:
The dependent variable in columns (1) to (3) are inverse hyperbolic sine transformed weekly total expenditure (in dollar), the total number of weekly shopping, and weekly total expenditure from online shops, respectively. Regressions are weighted by the Nielsen Consumer Panel projection factor to project the estimates to the entire US population. All regressions include a baseline set of covariates including omitted temperature bins. Standard errors are clustered on county.

Table A.3: Household Weekly Response to Temperature Shocks (With Time Trend)

	(1)	(2)	(3)
N of Days Below 30F	-0.0046***	-0.0035***	0.0044***
	(0.0007)	(0.0003)	(0.0003)
N of Days 30-40F	-0.0011*	0.0007**	-0.0007***
	(0.0007)	(0.0003)	(0.0003)
N of Days 40-50F	-0.0017***	0.0002	-0.0006**
	(0.0006)	(0.0002)	(0.0002)
N of Days 60-70F	-0.0007	-0.0005**	-0.0007***
	(0.0006)	(0.0002)	(0.0002)
N of Days 70-80F	-0.0006	-0.0008***	-0.0009***
	(0.0007)	(0.0003)	(0.0002)
N of Days 80-90F	-0.0047***	-0.0024***	-0.0008**
	(0.0010)	(0.0004)	(0.0003)
N of Days Above 90F	-0.0179***	-0.0079***	0.0018
	(0.0055)	(0.0018)	(0.0013)
Precipitation	-2.04e-5	-6.1e-5***	3.05e-5***
	(3.3e-5)	(1.24e-5)	(1.18e-5)
Precipitation^2	-1.71e-6***	-7.29e-7***	2.49e-7***
	(2.2e-7)	(8.93e-8)	(6.03e-8)
Dep.Var	IHS (Spending)	IHS (N Trips)	IHS (Online)
Observations	47,921,631	47,921,631	37,023,909

Note:
The dependent variable in columns (1) to (3) are inverse hyperbolic sine transformed weekly total expenditure (in dollar), the total number of weekly shopping, and weekly total expenditure from online shops, respectively. Regressions are weighted by the Nielsen Consumer Panel projection factor to project the estimates to the entire US population. All regressions include a baseline set of covariates including omitted temperature bins. Standard errors are clustered on county.

Table A.4: Household Weekly Spending Response to Temperature Shocks (By Product Type)

	(1)	(2)	(3)	(4)
N of Days Below 30F	-0.0039***	-0.0038***	0.0007**	0.0018***
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
N of Days 30-40F	-0.0008*	-0.0020***	0.0006**	0.0017***
	(0.0004)	(0.0005)	(0.0003)	(0.0003)
N of Days 40-50F	-0.0001	-0.0008**	0.0001	0.0005*
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
N of Days 60-70F	-0.0017***	0.0003	-0.0001	0.0008***
	(0.0004)	(0.0004)	(0.0003)	(0.0002)
N of Days 70-80F	-0.0029***	-0.0010**	-0.0008***	0.0017***
	(0.0004)	(0.0005)	(0.0003)	(0.0002)
N of Days 80-90F	-0.0052***	-0.0026***	-0.0010***	0.0021***
	(0.0006)	(0.0008)	(0.0004)	(0.0003)
N of Days Above 90F	-0.0097***	-0.0064***	-0.0001	0.0028***
	(0.0022)	(0.0019)	(0.0011)	(0.0010)
Precipitation	-18.42***	-8.786***	0.9856	-6.797***
	(2.586)	(2.701)	(2.149)	(1.689)
Precipitation^2	-10,432.7***	-11,949.3***	-9,376.0***	169.8
	(1,635.0)	(1,855.3)	(1,330.3)	(935.1)
Product Category	Beauty & Health	Non-Food Grocery	Fresh Produce	Alcohol
Observations	47,880,120	47,880,120	47,880,120	47,880,120

Note:
This table presents the effect of temperature on weekly household spending for four different product departments for the entire set of coefficients. For an abbreviated version, see panel A in Table 3.1). All standard errors are clustered at the county level. See text for additional details. *** p < 0.01, ** p < 0.05, and * p < 0.1

Table A.5: Household Weekly Spending Response to Temperature Shocks (By Region)

	(1)	(2)	(3)	(4)
N of Days Below 30F	-0.0093***	-0.0120	-0.0050*	-0.0094***
	(0.0015)	(0.0095)	(0.0028)	(0.0025)
N of Days 30-40F	-0.0040***	-0.0054	-0.0047**	-0.0059***
	(0.0014)	(0.0037)	(0.0020)	(0.0016)
N of Days 40-50F	-0.0032**	-0.0024*	-0.0031	0.0003
	(0.0014)	(0.0014)	(0.0019)	(0.0016)
N of Days 60-70F	-0.0065***	-0.0021*	-0.0009	0.0024*
	(0.0011)	(0.0011)	(0.0020)	(0.0013)
N of Days 70-80F	-0.0101***	-0.0030	-0.0025	0.0005
	(0.0013)	(0.0020)	(0.0018)	(0.0014)
N of Days 80-90F	-0.0188***	-0.0026	-0.0035	-5.4e-5
	(0.0026)	(0.0027)	(0.0024)	(0.0019)
N of Days Above 90F	-0.0489	-0.0185***	-0.0064	0.0087
	(0.0359)	(0.0050)	(0.0045)	(0.0354)
Precipitation	-0.0002**	0.0002	1.1e-5	4.79e-5
	(8.82e-5)	(0.0002)	(6.43e-5)	(7.54e-5)
Precipitation^2	-4.49e-7	-6.29e-6***	-1.68e-6***	-3.2e-6***
	(5.79e-7)	(1.84e-6)	(2.07e-7)	(5.68e-7)
Sample	Northeast	West	South	Southeast
Observations	9,300,653	4,539,734	6,069,885	8,895,946

Note:
This table presents the effect of temperature on weekly household spending for four different climate regions for the entire set of coefficients. For an abbreviated version, see panel B in Table 3.1). All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

Table A.6: Household Consumption Response to Extreme Temperature by Mode of Transportation

	(1)	(2)	(3)
N of Vehicles	0.1561***		
	(0.0062)		
Precipitation	-6.36e-5**	-3.65e-5	-7.75e-5**
	(3.19e-5)	(4.09e-5)	(3.89e-5)
Precipitation^2	-1.59e-6***	-1.59e-6***	-1.47e-6***
	(1.79e-7)	(1.51e-7)	(2.1e-7)
Uber		-0.0074	
		(0.0088)	
N Stops			-0.0184
			(0.0119)
N of Days Below 30F	-0.0099***	-0.0041***	-0.0062***
	(0.0014)	(0.0011)	(0.0011)
N of Days 80-90F	-0.0052***	-0.0038***	-0.0023*
	(0.0015)	(0.0012)	(0.0013)
N of Days Above 90F	-0.0211***	-0.0074***	-0.0070
	(0.0049)	(0.0023)	(0.0044)
N of Vehicles × N of Days Below 30F	0.0030***		
	(0.0006)		
N of Vehicles x N of Days 80-90F	0.0013**		
	(0.0006)		
N of Vehicles x N of Days Above 90F	0.0071***		
	(0.0025)		
Uber × N of Days Below 30F		-0.0007	
		(0.0015)	
Uber x N of Days 80-90F		0.0020	
		(0.0016)	
Uber x N of Days Above 90F		-0.0003	
		(0.0069)	
N Stops × N of Days Below 30F			0.0009
.			(0.0007)
N Stops x N of Days 80-90F			0.0002
.			(0.0007)
N Stops x N of Days Above 90F			0.0003
.			(0.0035)
Observations	47,899,607	26,138,627	24,074,807

Note:
This table illustrates how different mode of transportation affects the impact of extreme temperature exposure on household weekly spending. For an abbreviated version, see Table 4.1. All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

Table A.7: Household Consumption Trips to Extreme Temperature by Mode of Transportation

	(1)	(2)	(3)
N of Vehicles	0.0560***		
	(0.0028)		
Precipitation	-7.97e-5***	-7.58e-5***	-9e-5***
	(1.2e-5)	(1.61e-5)	(1.56e-5)
Precipitation^2	-6.8e-7***	-6.58e-7***	-6.26e-7***
	(6.7e-8)	(6.12e-8)	(8.41e-8)
Uber		-0.0129***	
		(0.0042)	
N Stops			-0.0078
			(0.0059)
N of Days Below 30F	-0.0094***	-0.0031***	-0.0047***
	(0.0006)	(0.0005)	(0.0005)
N of Days 80-90F	-0.0024***	-0.0019***	-0.0016**
	(0.0006)	(0.0005)	(0.0006)
N of Days Above 90F	-0.0106***	-0.0035***	-0.0035*
	(0.0019)	(0.0010)	(0.0018)
N of Vehicles × N of Days Below 30F	0.0027***		
	(0.0003)		
N of Vehicles x N of Days 80-90F	0.0005*		
	(0.0003)		
N of Vehicles x N of Days Above 90F	0.0035***		
	(0.0009)		
Uber × N of Days Below 30F		-0.0021***	
		(0.0007)	
Uber x N of Days 80-90F		0.0007	
		(0.0007)	
Uber x N of Days Above 90F		-0.0002	
		(0.0029)	
N Stops × N of Days Below 30F			0.0003
.			(0.0003)
N Stops x N of Days 80-90F			0.0001
.			(0.0003)
N Stops x N of Days Above 90F			-0.0002
.			(0.0014)
Observations	47,899,607	26,138,627	24,074,807

Note:
This table illustrates how different mode of transportation affects the impact of extreme temperature exposure on household weekly shopping trips. All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

Table A.8: Household Consumption Response to Extreme Temperature by Vehicle Ownership (Alternative Specification)

	(1)	(2)	(3)	(4)
N of Vehicles	0.1512***	0.0543***	0.1453***	0.0522***
	(0.0065)	(0.0029)	(0.0060)	(0.0027)
Precipitation	-2.36e-5	-5.93e-5***	-0.0001***	-0.0001***
	(3.3e-5)	(1.26e-5)	(3.17e-5)	(1.18e-5)
Precipitation^2	-1.7e-6***	-7.38e-7***	-1.46e-6***	-6.37e-7***
	(2.2e-7)	(9.21e-8)	(1.81e-7)	(7.08e-8)
N of Days Below 30F	-0.0097***	-0.0094***	-0.0084***	-0.0088***
	(0.0014)	(0.0006)	(0.0014)	(0.0006)
N of Days 80-90F	-0.0070***	-0.0030***	-0.0073***	-0.0031***
	(0.0014)	(0.0006)	(0.0014)	(0.0006)
N of Days Above 90F	-0.0358***	-0.0161***	-0.0280***	-0.0130***
	(0.0053)	(0.0023)	(0.0043)	(0.0017)
N of Vehicles × N of Days Below 30F	0.0030***	0.0027***	0.0029***	0.0026***
	(0.0006)	(0.0003)	(0.0006)	(0.0003)
N of Vehicles x N of Days 80-90F	0.0014**	0.0006**	0.0015**	0.0007***
	(0.0006)	(0.0003)	(0.0006)	(0.0002)
N of Vehicles x N of Days Above 90F	0.0089***	0.0043***	0.0078***	0.0039***
	(0.0022)	(0.0008)	(0.0024)	(0.0008)
Dep.Var	IHS (Amount)	IHS (Trips)	IHS (Amount)	IHS (Trips)
Trend	Linear	Linear	Quadratic	Quadratic
Observations	47,899,607	47,899,607	47,899,607	47,899,607

Note:
This table illustrates how vehicle ownership affects the impact of extreme temperature exposure on household weekly consumption activities. Regression models in this table include county-specific linear trends (columns (1) and (2)) or county-specific linear and quadratic trends (columns (3) and (4)). All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

Table A.9: Change in Frequency of Shopping Trips to Extreme Temperature by Sample Period

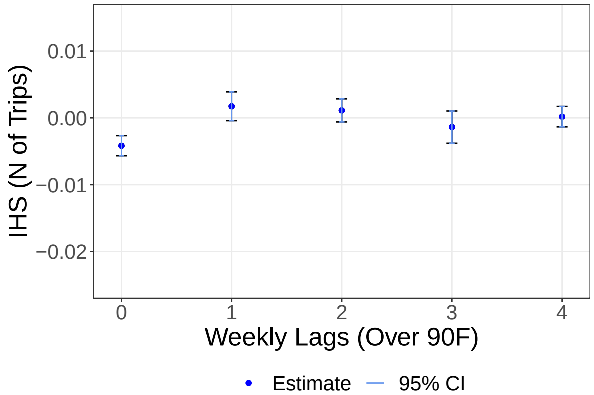
	(1)	(2)	(3)
N of Days Below 30F	-0.0003	-0.0055***	-0.0043***
	(0.0006)	(0.0005)	(0.0006)
N of Days 30-40F	0.0016***	-0.0003	0.0004
	(0.0005)	(0.0005)	(0.0005)
N of Days 40-50F	0.0015***	-0.0003	0.0001
	(0.0005)	(0.0004)	(0.0005)
N of Days 60-70F	-0.0008**	-0.0009***	-0.0004
	(0.0004)	(0.0004)	(0.0004)
N of Days 70-80F	-0.0020***	-0.0019***	-0.0023***
	(0.0004)	(0.0004)	(0.0004)
N of Days 80-90F	-0.0028***	-0.0035***	-0.0036***
	(0.0007)	(0.0006)	(0.0005)
N of Days Above 90F	-0.0056***	-0.0044***	-0.0052***
	(0.0016)	(0.0014)	(0.0013)
Precipitation	-5.25e-5*	-0.0001***	-6.78e-5***
	(2.96e-5)	(3.13e-5)	(1.59e-5)
Precipitation^2	-1.03e-6***	-2.35e-7	-7.46e-7***
	(2.41e-7)	(2.8e-7)	(8.41e-8)
Period	2004-2008	2009-2014	2015-2019
Observations	12,570,860	19,151,352	16,199,419

Note:
This table illustrates how the frequency of shopping trip with respect to the extreme temperature has changed over sample period. All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

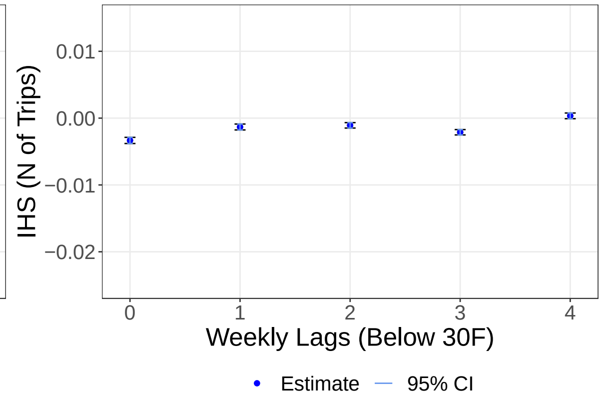
Table A.10: Price Response to Temperature Shocks

	(1)	(2)	(3)	(4)
N of Days Below 30F	-4.41e-5**	-0.0001***	-3.83e-5	-3.73e-6
	(2.18e-5)	(1.96e-5)	(3.01e-5)	(1.22e-5)
N of Days 30-40F	-8.59e-5***	-8.92e-5***	-9.1e-5***	-0.0001***
	(2.5e-5)	(2.27e-5)	(2.17e-5)	(3.2e-5)
N of Days 40-50F	-7.78e-5***	-9.05e-5***	-0.0001***	-0.0002***
	(2.48e-5)	(2.62e-5)	(3.27e-5)	(3.55e-5)
N of Days 60-70F	-6.16e-5***	-3.48e-5*	4.69e-5**	-0.0002***
	(1.77e-5)	(2.05e-5)	(2.29e-5)	(5.38e-5)
N of Days 70-80F	-7.33e-5***	-6.85e-5***	6.48e-5	-0.0001***
	(2.36e-5)	(2.35e-5)	(4.24e-5)	(3.79e-5)
N of Days 80-90F	-0.0002***	-0.0002***	-7.28e-5*	-0.0003***
	(2.45e-5)	(2.47e-5)	(4.02e-5)	(8.64e-5)
N of Days Above 90F	-0.0003***	-0.0002***	-0.0002	-5.69e-5
	(5.1e-5)	(4.47e-5)	(0.0001)	(7.41e-5)
Precipitation	-0.0007***	-0.0032***	-0.0014***	-0.0003
	(0.0001)	(0.0007)	(0.0004)	(0.0003)
Precipitation^2	4.67e-5***	0.0003***	0.0001***	-1.09e-5
	(1.5e-5)	(9.55e-5)	(3.14e-5)	(8.65e-6)
Store FE	Yes	Yes	Yes	Yes
Year $\times$ Quarter FE	Yes	No	Yes	Yes
County $\times$ Quarter FE	Yes	No	Yes	Yes
Year FE	No	Yes	No	No
Observations	953,680	238,420	227,528	953,680
Sample	All	All	Grocery Stores	All

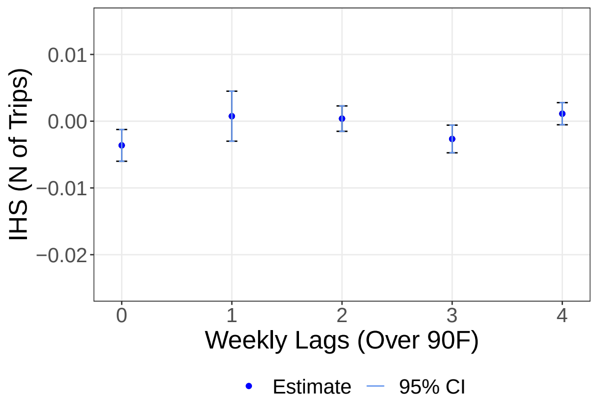
Note:
This table presents the entire set of coefficients on the effect of temperature on retail price. For an abbreviated version, see Table **??**). All standard errors are clustered at the county level. See text for additional details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$



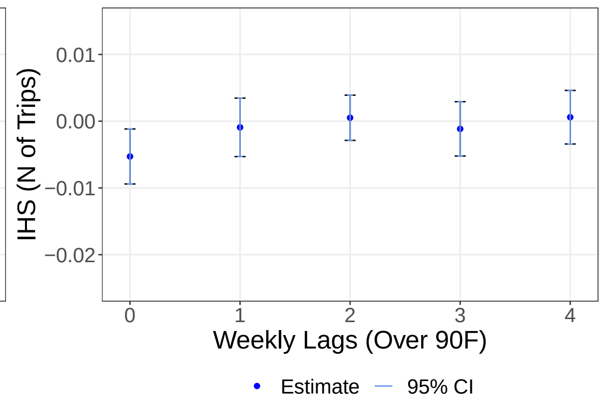
(a) Extreme Heat and N of Trips Over Time



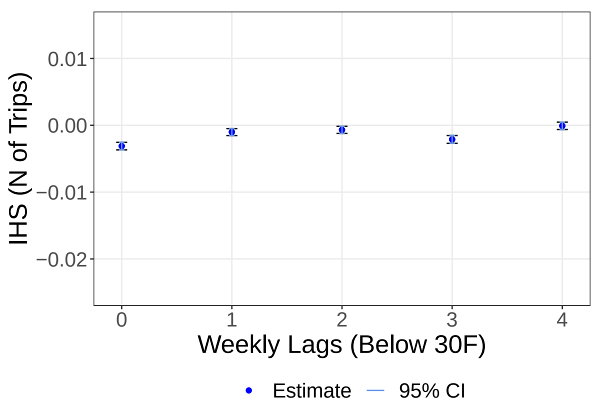
(b) Extreme Cold and N of Trips Over Time



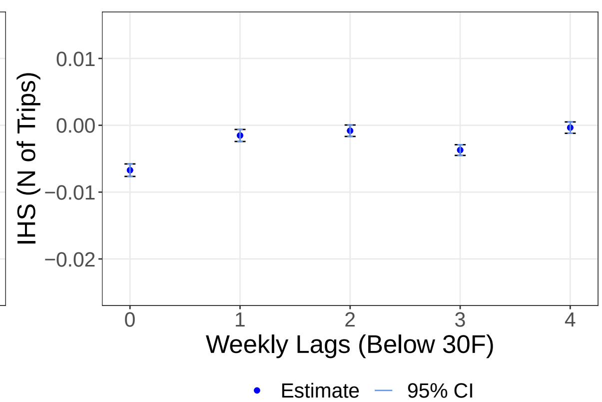
(c) Extreme Heat and N of Trips Over Time ($40 <$ Age < 65)



(d) Extreme Heat and N of Trips Over Time (Age $\geq$ 65)



(e) Extreme Cold and N of Trips Over Time ($40 <$ Age < 65)



(f) Extreme Cold and N of Trips Over Time (Age $\geq$ 65)

Figure A.2: Temperature Shock and Household Consumption Trips Over Time. Panel (a)-(f) show how household consumption trips respond to temperature shocks over time. The outcome variables are inverse hyperbolic sine transformed weekly frequency of shopping. Panel (a)-(b) illustrate the extreme temperature impact on consumption for the entire population while (c)-(d) and (e)-(f) show the impact of heat and cold for different age groups, respectively. See the text for additional details.