SCHOOL OF
ECONOMICS AND
MANAGEMENT

Spending Time, Spending Resources: The Temperature Effect on Consumption Behavior

Kushal Thapaliya

Department of Economics

Lund University School of Economics and Management

Supervisor: Adrian Nieto Castro, Ph.D.

Course: Master Thesis in Economics, 15 ECTS

Submission date: May 27, 2025

Contents

List of Figures

List of Tables

List of Abbreviations

Abstract

I investigate how temperature variations influence time allocation for the consumption of various goods and services, focusing on essential and non-essential consumption. Using data from the American Time Use Survey (ATUS) and National Oceanic and Atmospheric Administration (NOAA)'s weather records, I employ fixed-effects regression models to estimate the nonlinear impact of maximum temperature on the purchase of essential consumption, such as consumption goods and groceries, as well as non-essential consumption, such as attending sports tournaments and eating outside the home. I generally observe a U-shaped relationship between temperature and the time spent purchasing essential consumption, indicating increasing consumption with more extreme hot and cold temperatures. In contrast, a general inverted U-shaped pattern appears for most non-essential consumptions. Furthermore, the heterogeneity analysis reveals that temperature affects time allocation among people differently, by their family income, and by having a child in the household, especially for non-essential consumption. Mechanism analysis for the primary findings indicates that the pattern in time spent on essential consumption is influenced by changes in time spent at grocery stores, malls, and time spent at home, along with temperature. Similarly, the pattern of time spent on non-essential consumption is shaped by how time is spent outdoors, at the gym, and in restaurants.

Keywords: Temperature Shocks, Essential Consumption, Non-essential Consumption, Time Allocation.

Acknowledgments

I am deeply thankful to my supervisor, Adrian Nieto Castro, without whose mentorship this work wouldn't have taken this shape. I am also grateful to Lund University for giving me this opportunity. Finally, I want to thank my wife, Kritika, and my brother, Safal, for constant support and encouragement.

Chapter 1

Introduction

In recent years, we have frequently recorded the highest summer temperatures and disrupted seasonal patterns, impacting our lives in various ways. Likewise, we have adjusted our consumption behavior in response, yet limited research has been conducted on the effect of extreme temperatures on consumption. This is concerning given that consumption underpins a household's welfare (Attanasio and Pistaferri, 2016) and plays a massive role in overall macroeconomics (Muellbauer and Lattimore, 1999). Although a recent study has documented these effects on retail consumption using total expenditure and store visits (Lee and Zheng, 2025), this study thoroughly analyzes these impacts on various consumer goods and services, as well as the underlying mechanisms involved, with a focus on the time spent consuming these goods, an area that has received little investigation.

In this study, I examine the impact of maximum temperature on the time spent on essential and non-essential consumption. I define essential consumption as activities that individuals should engage in regardless of temperature, as they enhance their chances of survival. In contrast, non-essential consumption refers to activities that are unnecessary for survival. I consider grocery shopping, purchasing personal care services such as hygiene-related services, and household services as essential. While I take attending sports events, attending arts-related events, doing sports, and eating out as non-essential activities. I take these variables for the analysis because these activities should involve some monetary transaction to buy these goods and services. I then analyze the non-linear effect of temperature on various types of consumption, using data from the American Time Use Survey (ATUS)(Flood et al., 2023). In doing so, I combine time use data from the American Time Use Survey (ATUS) with National Oceanic and Atmospheric Administration (NOAA)'s (M. J. Menne et al., 2012; M. Menne et al., 2012) station-wise data on daily weather conditions from all weather stations in the US. I analyze the non-linear relationship using multiple 3°C temperature intervals as the main regressor, with the 17-20°C range serving as the benchmark interval. I conduct regression analysis with fixed effects for county, holiday, year-month, and day of the week, clustering at the county level and controlling for demographic characteristics. The results reveal a U-shaped pattern of time spent on essential goods, with peak consumption during extreme temperatures. In contrast, most non-essential consumptions show an inverted U-shaped pattern, with the lowest consumption during extreme temperatures, except for sports, which increases as temperatures rise above the benchmark interval.

I also assess the robustness of the primary results by modifying the baseline model with various fixed-effects structures, different control variables, and alternative standard errors for the clusters. The primary findings remain consistent despite variations in the model, underscoring their validity and reliability.

Additionally, I observe heterogeneity in the purchasing of non-essential goods and services among respondents living in households with children and those in high-income households, indicating the differential impact of temperature on demographic subgroups.

Furthermore, I examine the mechanism underlying my findings. The pattern I note for the time estimates dedicated to essential and non-essential activities mirrors the time estimates people allocate to different locations, addressing the "where" aspect of the causal question regarding the main findings. These results highlight a location-specific mediating effect of temperature on both essential and non-essential consumption. I detect a U-shaped trend in essential consumption driven by time spent at grocery stores, malls, and at home, while the inverted U-shaped trend in non-essential consumption is influenced by changing time allocations for outdoor activities, dining at restaurants, and exercising at home and in the gym.

1.1 Literature Review

Evidence indicates several consequences of extreme temperatures on society, ranging from deteriorating health and increased mortality (Deschenes, 2014) to rising conflict (Burke, Hsiang, and Miguel, 2015a). These effects can have cascading impacts on economies and household consumption behavior. In this context, it is clear that studying the impact of changing temperatures is essential.

Previous research has shown that temperature and climate change adversely affect health and well-being, which can influence consumption. Deschênes and Greenstone (2011) and Song et al. (2017) predict an increasing risk of temperature on health and mortality, respectively. Other studies have found similar risks associated with climate change (Barreca, Clay, Deschênes, et al., 2015; Barreca, Clay, Deschenes, et al., 2016; Burgess et al., 2017; Heutel, Miller, and Molitor, 2021). Beyond mortality, rising temperatures also have implications for fertility and reproductive health (Barreca, Deschenes, and Guldi, 2018). Barreca and Schaller (2020) suggest that higher temperatures can even affect the gestation period. In addition to health, Burke, González, et al. (2018) finds higher rates of suicide associated with elevated temperatures in the US and Mexico. Park et al. (2020) and Zivin et al. (2020) have identified adverse effects of temperature on learning and cognitive performance. The wide-ranging impacts of rising temperatures and climate change can mediate the effect of temperature on consumption, leading to broader micro and macroeconomic disequilibrium.

Unsurprisingly, Burke and Emerick (2016) implies substantial losses on US agricultural productivity due to rising temperature. Burgess et al. (2017) links it to productivity loss and increased poverty in rural India. While Jain, O'Sullivan, and Taraz (2020) demonstrates that higher temperatures reduce agricultural output and cause a short-term drop in economic growth in poorer Indian states. Thus, the loss of productivity in agriculture can spill over to income loss and consumption cuts for the vulnerable households, increasing existing inequality in income and consumption. Dell, Jones, and Olken (2012) finds broad adverse impacts of higher temperatures on poorer countries, leading to income loss and lower output across different sectors.Burke, Hsiang, and Miguel (2015b) projects global income loss and increased inequality due to high temperatures. A wide range of economic research supports this pattern. Burke and Tanutama (2019) corroborates these findings by studying the long-run consequences of prolonged heat exposure on income. Further research also highlights the unequal behavioral adaptations to consumption.

Bhattacharya et al. (2003) finds unequal adaptation between rich and poor, with poorer households in the US spending less on food. Campagnolo and De Cian (2022) finds a differentiated impact on energy demand by income level in households in Italy. Similarly, Doremus, Jacqz, and Johnston (2022) reports comparable findings in the US, while Shi et al. (2024) identifies similar effects in energy consumption from their analysis of data in China. Extreme temperatures increase income inequality and exacerbate energy poverty (Wu, Hu, and Zhang, 2025). These findings suggest that rising temperatures can impact consumer demand and consumption patterns.

Considering this, it is crucial to examine research on how climate affects consumption. Busse et al. (2015) investigates the influence of weather on car sales and identifies a psychological impact on durable goods like four-wheelers due to weather conditions. Conversely, Addoum, Ng, and Ortiz-Bobea (2020) finds no relationship between temperature and sales or production, even in industries sensitive to heat. Roth Tran (2020) highlights the negative effects of adverse weather on sales, noting that it can lead to significant and often permanent fluctuations in retail sales, with minimal intertemporal and venue substitution. Martínez-de-Albéniz and Belkaid (2021) illustrates that rainfall has a notable impact on foot traffic, increasing visits to mall stores while reducing them for street stores. Similarly, He et al. (2022) observes an increased likelihood of purchasing energy-efficient air conditioners as temperatures deviate from normal. Finally, Lee and Zheng (2025) shows a negative impact of extreme cold on store visits, mitigated by increased purchases during, with a prolonged adverse effect during hotter temperatures for purchasing retail goods.

Although this paper explores time spent on various activities, it falls within the spectrum of literature related to consumer purchase, such as Lee and Zheng (2025), and studies related to Connolly (2008), and Graff Zivin and Neidell (2014) that deal with the impact of temperature on time related to labor. Given the broad consequences of extreme temperature on various facets of life, a closer, micro-level investigation of the economic consequences of extreme temperature is warranted. This paper explicitly seeks to explore the impact of extreme temperatures on consumer behavior by examining the effect on time spent on essential and non-essential goods. In this sense, it is unique in that, while past literature has focused on the impact of temperature on other forms of consumption, it explicitly examines the time consumers spend on a broader set of consumption. In this sense, this is the first study to do so.

1.2 Data

1.2.1 Data Description

To assess the impact of temperature on consumption behavior, I use two datasets: one from the American Time Use Survey (ATUS) (Flood et al., 2023) and another from the National Oceanic and Atmospheric Administration (NOAA) (M. J. Menne et al., 2012; M. Menne et al., 2012). The ATUS, a national-level survey conducted by the Bureau of Labor Statistics (BLS) with sponsorship from the US Census Bureau, provides information on the time individuals spend on various activities during the diary day, 24 hours preceding the survey. These individuals are randomly selected, are at least fifteen years old, and have completed their final interview for the Current Population Survey (CPS)(U.S. Bureau of Labor Statistics, 2023). The data contains variables indicating various activities, including time spent in minutes on several purchasing activities, time spent in minutes on different leisure activities, time spent in minutes on rest and sleep, and so on, during the diary day. The ATUS is remarkably rich in data as it not only gives information about time spent on these activities, but also contains information regarding the total duration in minutes, starting and ending time, and where these various activities took place.

For this analysis, I use a sample from 2011 to 2023 accessed through IPUMS, part of the Institute for Social Research and Data Innovation at the University of Minnesota, which facilitates access to integrated population and sample data worldwide. Specifically, I extract variables related to activities categorized as essential and non-essential consumption.

For this research, I consider those consumptions as essential if they are critical for survival. Thus, I have taken variables indicating time spent in minutes on grocery purchases, time spent on personal care purchases such as trimming hair and doing nails, and time spent on purchasing household services as time spent on essential consumption. Similarly, I take consumption as non-essential if it is not crucial for survival. I take time spent in minutes on attending arts-related events such as concerts, visiting museums, etc., attending sporting events, doing sports, and eating out at restaurants and other places such as a food kiosk, as time spent on non-essential consumption activities. Additionally, I take location-specific variables indicating the total time in minutes spent in different places for mechanism analysis. My final dataset also includes individual and family-specific variables, such as age, gender, race, and family income, among others, from the same data source.

Similarly, I use data from NOAA for weather-related information. The NOAA dataset provides daily temperature and precipitation data from over 8,000 weather stations across the United States. For my analysis, I utilize NOAA 's GHCN-Daily dataset, which includes daily weather and climate data from more than 100,000 weather stations worldwide. It covers temperature variables, such as minimum, maximum, average, humidity, precipitation, and more, resulting in over ten million daily observations per station. I aggregate this station-level data into county-level data and merge it with the ATUS dataset using county ID and diary date identifiers to create a comprehensive county-specific panel for analysis. Since CPS suppresses data for some counties with smaller populations to maintain respondent anonymity, I only use observations where the respondent's county is identifiable. This results in a finalized dataset with 57,848 observations, which provides sufficient variation to explore the impact of temperature on various consumption-specific variables in the analysis.

Finally, I create dummy variables indicating 3° Celsius maximum temperature bins to explore the non-linear relationship between maximum temperature and time spent on various consumption activities. Meanwhile, I take the milder temperature bin of 17°-20°C as the benchmark variable for the analysis.

1.2.2 Summary Statistics

Table 1.1 presents the descriptive statistics for the variables used in the analysis. The variables have been categorized based on whether they fall above or below the benchmark temperature interval (17°-20°). Notably, the demographic characteristics in the distribution appear almost identical in both categories, indicating a balanced sample across cold and hot temperatures. The number of females above and below the benchmark bin is similar, with 55.3% in the below benchmark group and 55.1% in the above benchmark temperature group. Similarly, households with children are distributed accordingly, as the proportion of children in the below-benchmark temperature is 0.391, similar to the above-benchmark's 0.388. The proportion of natives and whites in both groups is also identical. Furthermore, the age of the respondents, the average family income, the household size, and the number of children in the household are also similar across the below-benchmark and above-benchmark temperatures, suggesting an identical distribution across hot and cold temperatures.

Further, the mean time spent on grocery purchases is similar in the below-benchmark temperature (7.943 minutes) and the above-benchmark temperature (7.295 minutes). The mean for personal care services is higher for the above-benchmark temperature (1.175 minutes) than for the below-benchmark (0.987 minutes), indicating slightly more time spent on personal care in warmer conditions. Further, the time spent on personal care is less than the total time spent on groceries. Similarly, time spent on household services shows a similar pattern.

Moreover, time spent in non-essential consumption activities indicates more notable differences, especially for time spent attending arts events and doing sports. Time spent attending arts events is higher for the above-benchmark temperature (6.323 minutes) than for the below-benchmark temperature (4.902 minutes). Also, the time spent on doing sports is higher for the above-benchmark temperature (20.774 minutes) compared to the below-benchmark temperature (15.212 minutes). In addition, time spent on attending sports events and eating outside is higher for temperatures above the benchmark, indicating a potential behavioral shift.

Also, for variables used for mechanism analysis, the time spent eating at a restaurant is higher for above-benchmark temperatures. Similarly, time spent outdoors and doing sports outdoors is higher for the above-benchmark temperature bin, indicating more time spent on these activities in warmer temperatures. However, all other variables, such as time spent at home, time spent alone, and so on, show that time spent is higher for temperatures below the benchmark temperature bin. The differences in time spent across temperature bins for these variables can indicate the mediating effect of temperature on the time spent on various types of consumption, helping make the relationship with temperature more straightforward.

Table 1.1: Descriptive Statistics

Variables	**All**		**Below Benchmark**		**Above Benchmark**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Demographic Variables						
Female	0.552	0.497	0.553	0.497	0.551	0.497
Child	0.389	0.488	0.391	0.488	0.388	0.487
Native	0.389	0.488	0.391	0.488	0.388	0.487
Age	49.699	18.0778	49.646	18.026	49.774	18.120
White	0.775	0.417	0.783	0.412	0.771	0.420
Family Income	11.331	4.044	11.533	3.992	11.223	4.056
Household Size	2.663	1.514	2.646	1.508	2.670	1.517
Number of Children	0.724	1.083	0.731	1.091	0.721	1.081
Essential Consumption						
Grocery Purchases	7.513	22.175	7.943	22.998	7.295	21.821
Personal Care Services	1.101	11.191	0.987	10.515	1.175	11.689
Household Services	0.908	10.431	0.862	11.107	0.921	9.988
Non-Essential Consumption						
Arts and Entertainment	5.786	36.694	4.902	32.057	6.323	39.449
Attending Sporting Events	1.632	19.942	1.373	16.406	1.790	21.786
Eating Outside Home	23.578	42.992	22.684	41.612	23.945	43.470
Participating in Sports	18.775	53.341	15.212	46.510	20.774	56.561
Mechanism Variable						
Eating at Restaurant	12.312	33.912	11.891	33.673	12.460	33.769
Home	496.971	274.075	506.356	272.842	491.638	274.538
Alone	376.372	291.194	381.942	291.023	374.222	291.606
Indoors	767.993	158.253	775.585	153.420	763.793	160.968
Outdoors	13.896	51.512	10.848	44.478	15.605	55.198
Grocery Stores	7.581	22.490	8.101	23.712	7.308	21.899
Other Stores	15.237	44.580	15.742	46.158	15.053	43.786
Gym	3.357	19.385	3.559	20.296	3.263	18.878
Outdoor Sports	16.944	54.106	13.612	47.062	18.786	57.312
Number of Observations	**57826**		**18660**		**34577**	

Note: Demographic variables represent the respondents' demographic characteristics. "Female", "Child", and "Native" indicate dummy variables for being a female, dummy for being a child, and dummy for being a US native citizen, respectively. Family income is represented in thousands. Essential consumption denotes the total minutes spent in activities related to essential consumption. For example, "Grocery" is the minutes spent on grocery purchases. Similarly, non-essential consumption includes the total minutes spent on non-essential consumption. The mechanism variable represents the minutes spent relating to that particular variable. For example, "Home" represents time spent at home, "Alone" represents time spent alone, and so on. Its mean value and standard deviation represent each variable. "Below (Above) Benchmark" represents observations below (above) the benchmark maximum temperature interval (17-20) °Celsius defined for the analysis.

Chapter 2

Analysis and Interpretation

2.1 The Impact of Temperature on Time Spent on Consumption

For this analysis, I allow maximum temperature to have a nonlinear effect on time spent on consumption activities. Specifically, I exploit the potential nonlinear relationship between the outcome variables, and maximum temperature, as suggested in the literature[1]. The following regression model represents the overall analysis:

$$y_i = f(T_{\max_{c(i),t(i)}}) + X_i'\beta_1 + Z_{c(i),t(i)}\beta_2 + g(t(i)) + \alpha_{c(i)} + \epsilon_i \tag{2.1}$$

In this equation, y_i denotes this paper's primary outcome variable of interest, indicating total time in minutes spent by person i on various consumption activities on a given day. The measured activities include time spent consuming essential and non-essential goods, which typically require some form of market exchange. The activities indicating essential goods consumption include purchasing groceries, household services, and personal care services. Similarly, activities indicating non-essential goods consumption include attending events, attending sports, doing sports, and eating out.

The term $f(T_{\max_{c(i),t(i)}})$ represents a non-linear function of the daily maximum temperature for person i on day t at county c. I have used maximum temperature instead of average temperature for analysis because most of the consumption activities I analyze here are done during the day, compared to times during the night when the temperature is minimum and people are possibly resting. It is the same approach taken by Graff Zivin and Neidell (2014). In model 2.1, X_i denotes a vector of demographic control variables like age, sex, race, citizenship status, and family income. β_1 captures their associated

[1]Using average temperature instead of maximum temperature did not alter the overall pattern. The robustness checks provide the corresponding results, and relevant figures are included in appendix A.4

coefficients. I have used these control variables to account for their relationship with the respective variables denoting various types of consumption. Similarly, I have used $Z_{c(i),t(i)}$ as the control variable for precipitation, accounting for the confounding relationship between maximum temperature and time spent on consumption activities, for individual i at county c on the diary day t. For this analysis, I have used the dummy variable indicating rain. β_2 captures the coefficient for it.

The term $g(t(i))$ indicates various dummy variables for year-month fixed effects, accounting for the seasonality and annual time trends, such as broader macroeconomic trends. It also includes holiday fixed effects with dummies indicating if the diary date is a public holiday, accounting for its impact on consumption activities. Further, it contains dummies for different days of the week, accounting for day of the week fixed effects on people's consumption patterns. $\alpha_{c(i)}$ indicates county fixed effect accounting for the time invariant county-specific characteristics affecting consumption and maximum temperature. Finally, ϵ_i denotes the idiosyncratic error term for person i. The specifications in model 2.1 help explore the external variation of temperature on the time spent on various consumption activities. Thus, the exogenous variation in temperature is a sufficient identification condition for the analysis.

The primary variable of interest, $T_{\max_{c(i),t(i)}}$, represents various temperature bins at $3^{\circ}C$ intervals, ranging from 2°C to 38°C. Temperatures below 2°C are grouped into a single "extremely cold" bin, while those above 38°C are grouped into a single "extremely hot" bin. The 17°-20°C interval is omitted and serves as the benchmark category, helping interpret the effect of maximum on various consumption. Here, if a given temperature falls within a particular bin, I assign a value of 1, while all other bins, including the benchmark, take a value of 0. This dummy variable approach enables the model to capture the non-linear effects of maximum temperature on the outcome variables, consistent with the existing literature, such as Graff Zivin and Neidell (2014) and Lee and Zheng (2025). Finally, I use the standard error at the county level, accounting for the arbitrary correlation between individual observations at the county level.

2.1.1 Result

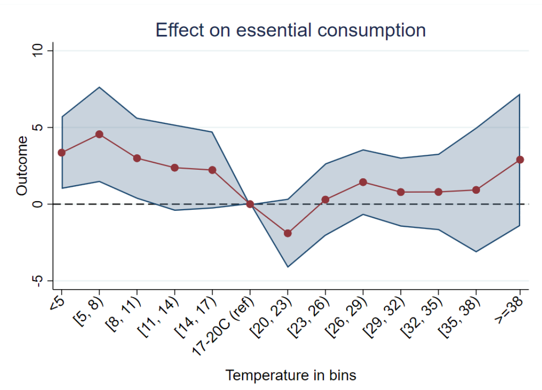
After running the regression based on the model specified above, I find a general U-shaped pattern in the time spent on the consumption of overall essential goods which is the sum of time spent on purchase of groceries, household services, and personal care purchase, as shown in Figure 2.1a. We can see that during extremely cold temperatures below 5 °C, people spend 3.357 minutes more on the overall consumption of essential goods, while they spend 2.899 minutes more during extreme hot temperatures compared to the benchmark interval. This estimate for cold temperature is significant at the conventional level of 5%. Similarly, the estimates for mild cold temperatures are also significant, and show a decreasing trend along with temperatures below the benchmark interval. Although the estimates for the hot temperature are not statistically significant, the relationship indicates a gradual increase in time spent on the consumption of essential goods above the benchmark interval. Similarly, I find the same pattern in purchasing groceries, with 1.243 minutes more spent in consumption during very cold days and 0.600 minutes more on very hot days. Household services shown in 2.1c, and personal care services shown in Figure 2.1d exhibit a similar pattern. Although personal care purchases are generally lower during most of the colder days, it is still higher in the very cold days compared to the lowest consumption in the mildly cold days. The overall pattern, with peak purchases occurring at the extreme ends of the temperature distribution, may reflect stockpiling or precautionary behavior in anticipation of prolonged exposure to harsh weather conditions. A pattern implies an adaptive response by individuals to minimize future exposure to extreme temperatures.

Similarly, I find a general inverted U-shaped pattern in the time spent on the consumption of most non-essential goods, as shown in Figure 2.2, except time spent on doing sports activities[2]. Figure 2.2a shows an increasing effect on time spent on consuming all non-essential goods. At the same time, the marginal increase in value for the estimates decreases significantly after 29°C, and the estimates' values plunge after the temperature gets to 35°C. The estimates for the time spent on overall non-essential goods are about -10, indicating a decrease in time spent on non-essential consumption holding other variables constant compared to the benchmark temperature bin for extremely cold days. Similarly, this estimate is significant at the conventional level and increases gradually until 29°°C. Then it falls to reach 1.329 During extremely hot days. While this estimate is still higher compared to the benchmark interval, it is lower compared to the peak consumption, which happens at 35°C.

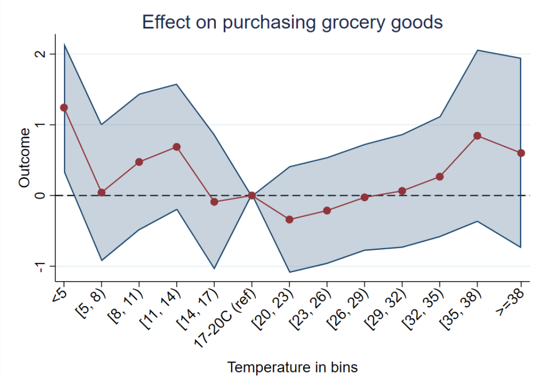
Similarly, the estimates for time spent on individual non-essential consumptions show a similar pattern. The time spent on attending arts reduces by -1.690 minutes for extreme cold and almost a similar less minutes for extreme hot days, holding other variables constant. The pattern I observe for such consumption is inverted U-shaped, showing peaking consumption happening at milder temperatures while consuming the least during extreme temperatures, as shown in Figure 2.2b. I observe a similar trend for time spent on attending sports events as shown in 2.2c. However, we see an overall increasing trend in doing sports with temperature, with the least consumption happening at extremely cold temperatures compared to benchmark temperatures[3]. It is due to an increase in the pattern of this consumption that temperature has an increasing effect on the time

[2]This finding remains robust even after controlling for college enrollment status, under the assumption that collage students participate in sports as part of their already-subscribed tuition or facility fees, see Appendix A.3.

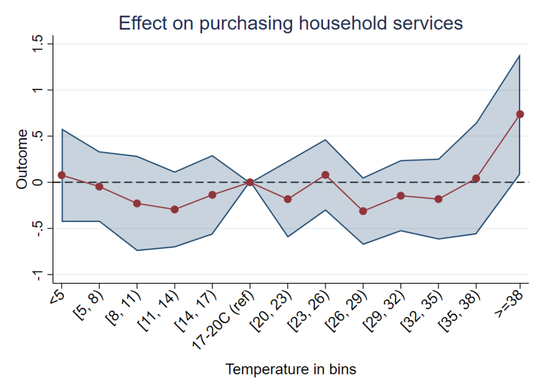
[3]When doing a mechanism analysis, I find a similar pattern in doing sports at home and gym.



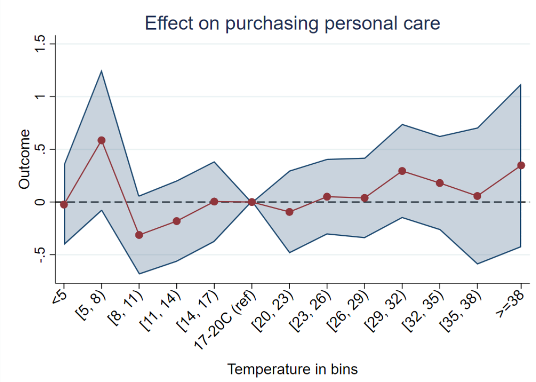
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



(c) Panel C: Effect on Household Services Purchase



(d) Panel D: Effect on Personal Care Purchase

Figure 2.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

spent on overall non-essential consumption. Finally, I observe an overall inverted U-shaped pattern for time spent on eating out of one's house[4], as we can see in Figure 2.2e, with -2.433 minutes decrease in consumption at extreme cold temperatures compared to the benchmark interval with significant effect at the conventional level. This effect increases gradually until it reaches 17°C, after which the effect gets flattened with a modest increase until 38°C, with this effect plunging to negative values on extremely hot days above 38°C. Although I didn't find a significant effect of temperature on consumption for all temperature intervals, these findings indicate the pattern of how people behave in

[4]Further analysis shows that this effect is due to the impact of the time people spend in restaurants.

response to changes in temperature by shifting the way they consume various goods and services.

Moreover, the U-shaped patterns of time spent on consumption of essential goods and services, when contrasted with the inverted U-shaped patterns observed for non-essential consumption, displays an opposite trend, indicating behavioral adaptation[5] As temperatures deviate from the benchmark bin, I also observe some fluctuations in the pattern. For instance, while individuals may generally prefer to purchase personal care services on colder days, they might reduce such purchases on extremely cold days, possibly due to a substitution effect in how time is allocated for such consumption at that temperature.

2.1.2 Robustness

In this section, I perform robustness checks by applying different model specifications to confirm the reliability of the results. These checks include exploring various regression models with distinct fixed-effects structures, different control variables, and alternative standard errors for clusters. The main findings remain stable despite the modifications in the model.

First, I check the robustness of my findings by omitting all variables that indicate demographic characteristics[6]. This approach helps explore whether fixed effects in the primary model can explain omitted variable bias. I observe a similar non-linear relationship to that of the baseline model.

Next, I run a similar regression to the baseline model with an additional control variable indicating the respondent's enrollment status in school or college[7]. This extra control ensures that the model accounts for the effect of enrollment status on time spent on various consumptions. The results also indicate the robustness of the non-linear relationship.

Then, I run another model, replacing the main regressor with average temperature instead of maximum temperature to check if the effect in the primary regression is due to the model construct because of the use of maximum temperature in the principal regression. Despite a change in magnitude, I see no effect of such a change on the pattern of a nonlinear relationship between temperature and various consumptions[8].

Next, I group the standard errors at the state level rather than the county level. This adjustment addresses broader correlations of unobserved variables not captured by county-level clustering in the main regression[9]. Additionally, I incorporate a season fixed effect

[5] I have tried to rationalize this finding using substitution effect between time spent on essential and non-essential consumption (See Appendix A.9).

[6] See Appendix A.2

[7] See Appendix A.4

[8] See Appendix A.4

[9] See Appendix A.5

in the same model to account for unobserved confounders specific to each season. Nevertheless, these modifications did not alter the pattern of the nonlinear relationship, even though there was a change in magnitude[10]. These checks demonstrate the insensitivity of my primary analysis to changes in specifications, proving its validity.

The non-linear relationship I find in the primary analysis is also robust to the addition of minimum temperature as a control[11]. Finally, by employing dummy variables to indicate whether the respondent engaged in the specified consumption activity on the designated diary day, I address the nonlinear relationship through a logistic model, incorporating the same controls and fixed effects as the primary model. Despite this modification, the pattern of the nonlinear relationship remains consistent[12].

2.2 Heterogeneous Impact

In this section, I examine how temperature impact varies across demographic groups, drawing on literature that highlights unequal behavioral responses to extreme weather. To model this, I incorporate interaction terms between maximum temperature intervals and respondent demographic characteristics in Equation 2.1. I initially focus on the overall time spent on essential and non-essential consumption, as these categories demonstrate the most significant effects across temperature bins in the primary findings and broadly capture aggregated consumption patterns.

I first explore heterogeneity by income level, given that wealthier individuals may adapt better to climate change. Respondents are categorized into income quartiles, with the bottom quartile labeled as poor and the top as rich. My analysis reveals notable heterogeneity in non-essential consumption by income, as illustrated in Figure 2.3. Wealthy individuals increase non-essential consumption as temperatures rise until very hot conditions, unlike poorer individuals. This may stem from greater resources, enabling participation in sports events or arts in heat-protected venues, or event organizers targeting wealthier audiences with higher prices on milder hot days.

Next, I investigate heterogeneity based on the presence of children under eighteen, as households with children may exhibit distinct consumption patterns in response to temperature. Figure 2.4 shows that individuals in families with children spend more time on non-essential consumption on mildly hot days above the benchmark, though this declines in hotter conditions. This likely reflects parents engaging in entertainment for their children, such as visiting amusement parks or attending movies and sports events with adolescents.

[10] See Appendix A.6
[11] Appendix A.7
[12] Appendix A.8

I do not observe significant differences in the effects of temperature on essential consumption based on income or child status. Additionally, I examine variations across other demographic groups, including gender, as men and women might have different consumption strategies due to their biological reactions to extreme temperatures; age, since older and younger individuals could exhibit different preferences; citizenship status (native vs. immigrant), as natives might possess more resources to manage extreme temperatures; and race (white vs. black), as socioeconomic disparities linked to race may shape consumption behaviors. While the magnitudes of effects show some variations, these analyses indicate no major heterogeneity (see Appendix A.10). This analysis provides guidance for future research and policy formulation by demonstrating how temperature changes distinctly affect behavior across various population segments, emphasizing the necessity of considering heterogeneity in such studies.

2.3 Mechanism Analysis

In this section, I analyze the potential mechanisms behind the observed nonlinear relationship in consumption across temperature bins to enhance understanding of the primary findings. Specifically, I estimate the time spent in minutes by individuals at different locations,using model 2.1, because these estimates can highlight the mediating effect of change in consumption behavior due to temperature. For instance, the plunge in time spent on consuming non-essential goods during extremely cold days can be explained by the reduced time people spend at stadiums and concerts. Similarly, the change in pattern in essential consumption can be driven by a change in the pattern of time people spend in malls and grocery shops. Thus, this analysis helps explore the mediating effects of other variables on essential and non-essential consumptions due to temperature.

First, I examined whether patterns in location-based time allocation could explain the change in estimates for essential goods consumption. Three key findings emerged. First, a U-shaped pattern appears in time spent at grocery stores, mirroring trends for time spent at malls, other stores, and one's home (Figure 2.5). The estimates on essential consumption closely align with time spent at malls and stores, suggesting a plausible channel for the effect of temperature on essential consumption. While grocery purchases show a similar trend to time spent at grocery stores, slight discrepancies imply these purchases may occur physically and online.

Second, the estimates for time spent at home align with the estimates for time allocated to purchasing household services (e.g., cleaning, meal preparation). This aligns with expectations, as such services typically occur at home. However, time spent at home during extreme winters is disproportionately higher. Further, estimates for time spent at home are higher than time spent on purchasing household services, indicating that time spent at home is not entirely dedicated to time for such consumption, indicating the mediating effect of being at home on such consumption.

Finally, I explore where personal care services (e.g., haircuts, nail appointments) are purchased. I adopt a different approach since the American Time Use Survey (ATUS) location variable lacks specific categories for these services. The U-shaped trend for personal care services initially appeared similar to time spent at malls and stores, but direct alignment was unclear. To resolve this, I separately analyze the time spent purchasing these services at plausible locations (others' homes, malls, and outdoor areas). Individually, none explained the trend. However, aggregating time across these locations (others' house, malls, other location as given in the 'where' variable, and outdoor) (Figure 2.5d) yielded a pattern nearly identical to the nonlinear relationship between personal care services and maximum temperature.

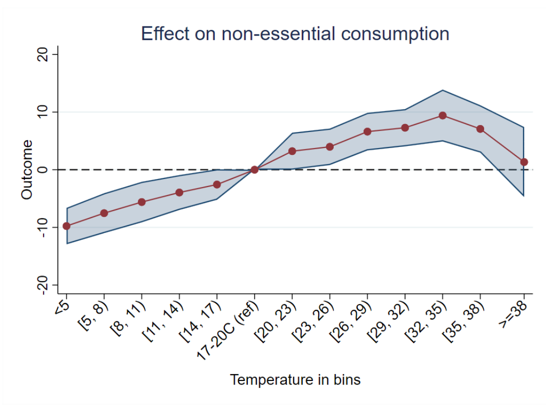
Similarly, I investigate potential mechanisms linking trends in non-essential consumption to time spent at various locations. First, an inverted U-shaped pattern emerges for time spent outside one's home, resembling trends in consumption of most non-essential goods and services, attending arts and similar events, sports events, and eating out. While these patterns do not align precisely, they broadly mirror time spent outdoors[13], suggesting these activities often occur outdoors. I also find an inverted U-shaped pattern for time spent at restaurants and eating out. However, they are not exactly similar; their pattern indicates the mediating effect of time spent in a restaurant on time spent eating out, with the least time spent on consumption during extreme temperatures and the most consumption during milder temperatures. The overall inverted U-shape implies reduced non-essential consumption during extreme temperatures, possibly because outdoor events (e.g., concerts, sports tournaments) are associated with milder weather, leading to less time outdoors in extreme conditions. Alternatively, extreme temperatures may reduce the availability of outdoor events. However, the exact causal pathway remains unclear and warrants further study. In summary, reduced non-essential consumption, such as recreational events and dining out, likely stems from less outdoor time during temperature extremes.

Additionally, I analyzed where people spend time exercising, given the rising trend in doing sports with temperature. A plausible hypothesis is increased indoor sports activity. To test this, I estimated time spent exercising at homes or yards and gyms (Figures 2.6c and 2.6b). As shown in the figure, the upward trend in sports participation is driven by increased time spent exercising at home.

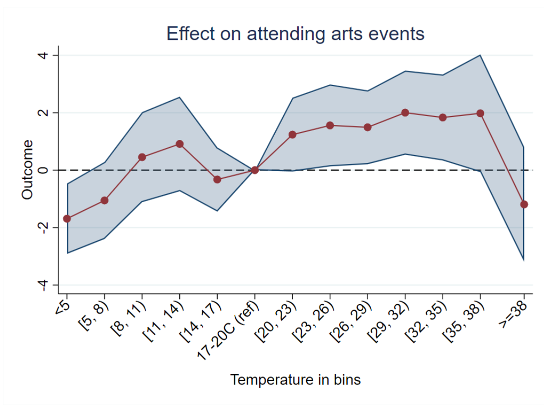
Finally, while this analysis explores potential mechanisms behind trends in essential and non-essential consumption, exploring if there is any mediating effect reflected in the non-

[13] Time spent outdoors away from home more closely matches time spent at restaurants/eating out (see Appendix A.1).

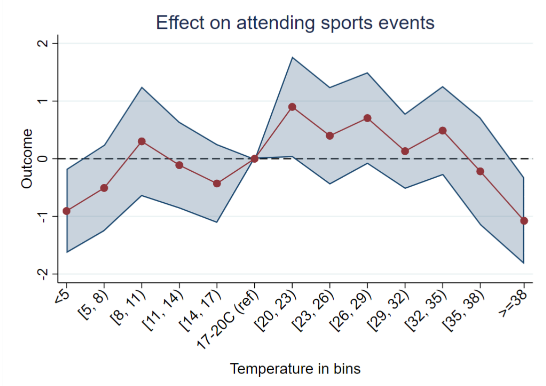
linear relationship of temperature on time spent at various locations, it primarily addresses the where dimension of the broader why question. The why, beyond temperature itself, requires further investigation. Nevertheless, this approach clarifies patterns in time allocation across consumption categories.



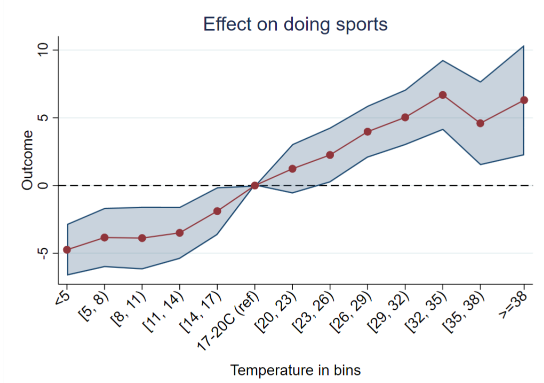
(a) Panel A: Effect on Non-Essential Goods Purchase



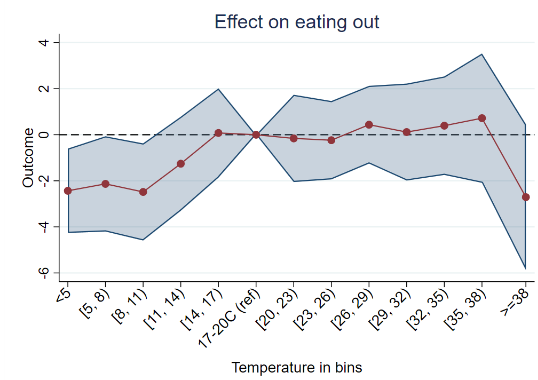
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events

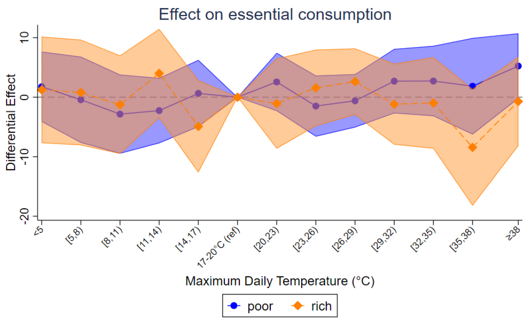


(d) Panel D:Effect on Doing Sports

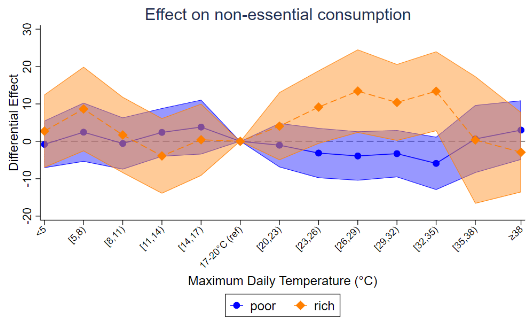


(e) Panel E: Effect on Eating Outside

Figure 2.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating out, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

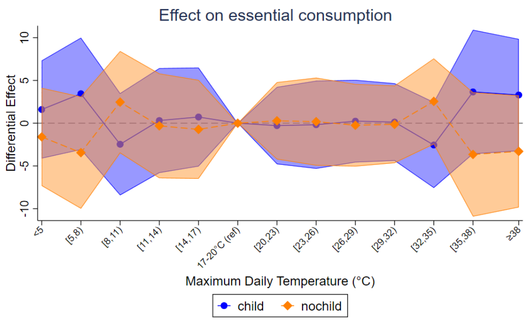


(a) Panel A: Effect on Essential Consumption by Income Level

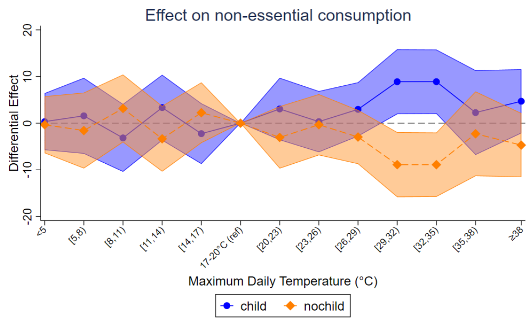


(b) Panel B: Effect on Non-essential Consumption by Income Level

Figure 2.3: Heterogeneous Effects of Temperature by Income Level. Panels A–B show interaction effects between temperature bins and variables denoting high-income and low-income households on time spent in essential and non-essential consumption, respectively. Shaded bands are 95% confidence intervals (clustered by county). Regressions control for age, sex, citizenship status, family income, race, rainfall, and fixed effects for county, holiday, year–month, and day.

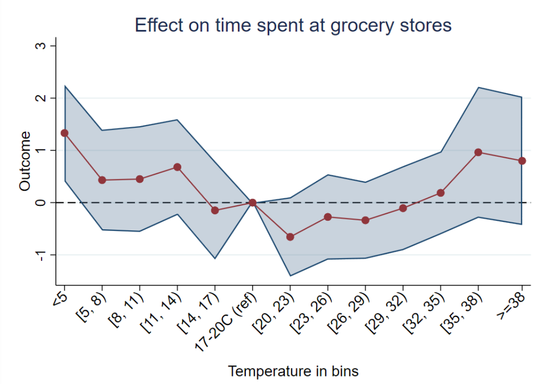


(a) Panel A: Effect on Essential Consumption by Child Presence

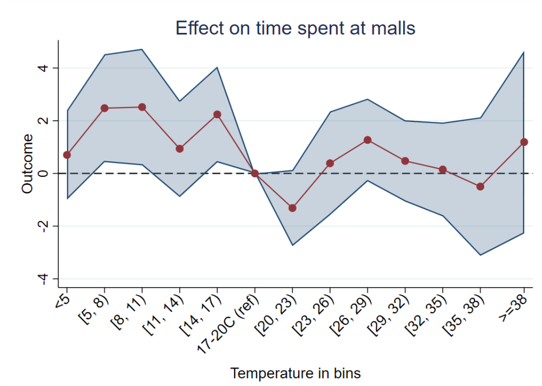


(b) Panel B: Effect on Non-essential Consumption by Child Presence

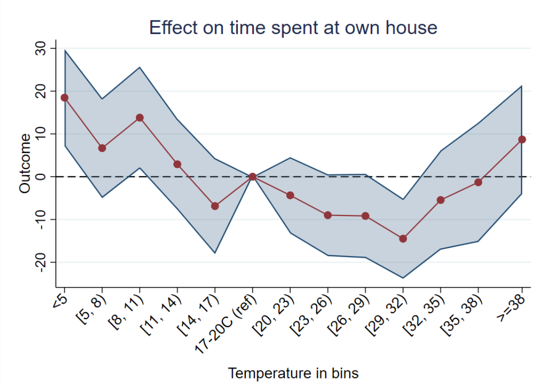
Figure 2.4: Heterogeneous Effects of Temperature by Presence of Children. Panels A–B show interaction effects between temperature bins and the variables denoting the presence of children under 18 in the household on time spent in essential and non-essential consumption, respectively. Shaded bands are 95% Regressions control for age, sex, status of citizenship, family income, race, rainfall, and fixed effects for county, holiday, year–month, and day.



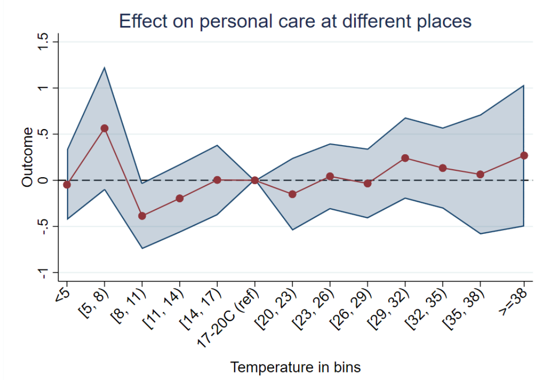
(a) Panel A:Time spent at grocery stores



(b) Panel B:Time spent at malls and other stores

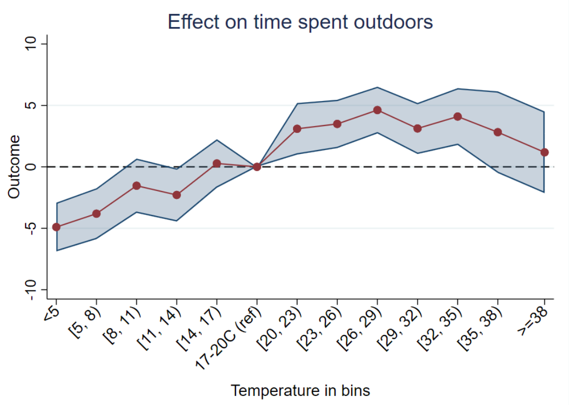


(c) Panel C:Time spent at home

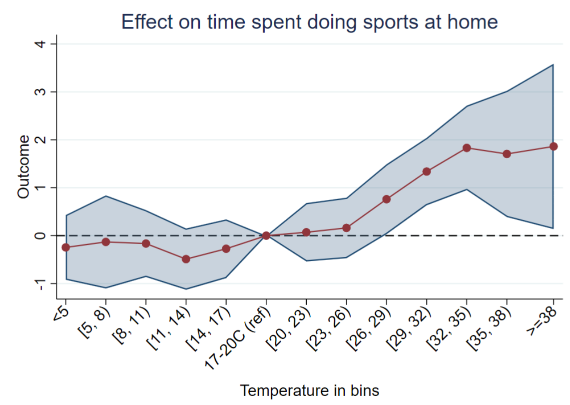


(d) Panel D:Time spent at others' houses, malls, and outdoors

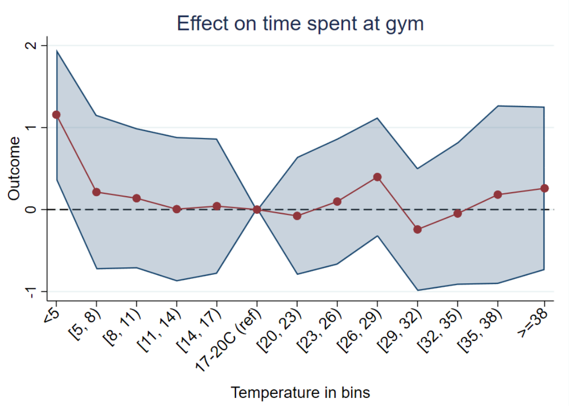
Figure 2.5: Mechanism Analysis for Essential Goods. Panels A–D display how temperature bins affect time allocation to four essential-goods locations: grocery stores, malls/other stores, home, and non-house residential places. Shaded bands are 95% confidence intervals clustered by county. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, a dummy for being a student, and fixed effects for county, holiday, year–month, and day.



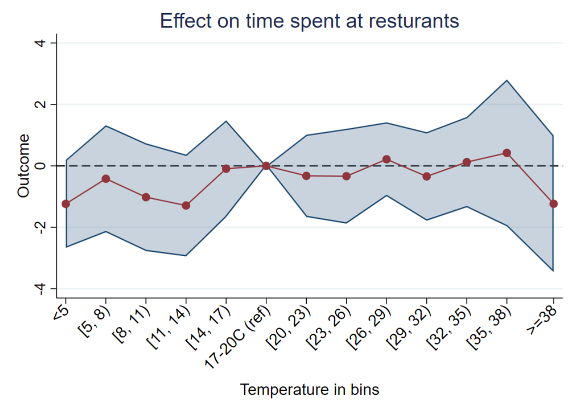
(a) Panel A: Time spent outdoors



(b) Panel B: Time spent doing sports at home



(c) Panel C: Time spent doing sports at the gym



(d) Panel D: Time spent at restaurants

Figure 2.6: Mechanism Analysis for Non-Essential Goods. Panels A–D illustrate temperature-driven changes in time spent outdoors, at-home sports, gym activities, and at restaurants. Shaded regions denote 95% confidence intervals with county-clustered standard errors. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, a dummy for being a student, and fixed effects for county, holiday, year–month, and day.

Chapter 3

Conclusion

This study explores the pattern in people's consumption behavior due to extreme temperatures. It analyzes the impact of temperature on the time people spend on various consumptions, where people actively participate in market activities. Furthermore, I divided these consumptions into essential and non-essential categories. I define essential as something that people should do regardless of the temperature—activities that enhance one's chances of survival—and non-essential as something that is not necessary for survival. For this study, I merge the data on time spent on various activities in the United States by individuals from the American Time Use Survey (ATUS) with National Oceanic and Atmospheric Administration (NOAA)'s Global Historical Climatology Network - Daily (GHCN-Daily) climate data from all the weather stations in the United States.

I analyze the non-linear relationship between maximum temperature and time spent on various consumption-related variables. I use multiple 3°C temperature intervals as the main regressor, with 17°-20°C as a benchmark interval. I run the regression using various county, holiday, year-month, and day-of-the-week fixed effects, clustering at the county level, and accounting for different demographic characteristics as control variables. The results show a U-shaped pattern for essential goods and services, indicating peak consumption during extreme temperatures. In contrast, I observe an inverted U-shaped pattern for non-essential goods and services in general, except for doing sports, which shows an increasing pattern with temperature. This indicates the potential substitution effect between essential and non-essential consumption[1]. Also, these findings are robust to several regression specifications. In addition, I observe heterogeneity in purchasing non-essential goods and services for respondents living in households with children and for people living in high-income households, indicating the differential effect of temperature on demographic subgroups.

[1] I have also analyze with this idea; see Appendix A.9

Moreover, I also analyze the potential mechanism for my findings. I find that the pattern observed for the estimates of time spent on essential and non-essential activities resembles the pattern for the estimates of time people spend in various locations. These findings underscore a location-specific mediating effect of temperature on essential and non-essential consumptions. I find a U-shaped pattern in essential consumption being driven by the time spent at grocery stores, malls, and home, while the inverted U-shaped pattern in non-essential consumption is driven by changing patterns in time spent outdoors, time spent at restaurants, and time spent doing sports at home and in the gym.

These findings have several important implications for policymakers. First, the U-shaped pattern of essential consumption implies a stockpiling behavior during extreme temperatures. Although it could be a good protective strategy to shield oneself from prolonged exposure to extreme temperatures, it can strain the supply chain during those times, risking shortages of essential goods. Further, the inverted U-shaped pattern for the non-essential goods, reducing time spent on non-essential consumption with temperature, is a concern because it threatens the sustainability of weather-dependent sectors. Thus, it requires action to mitigate the impact of extreme temperatures on such industries. For example, the restaurant industry is particularly vulnerable to such effects. Therefore, the government should encourage the construction of climate-resilient infrastructures to mitigate the impact of temperature on those sectors. Similarly, as mechanism analysis suggests, sporting venues and indoor art halls can minimize the effect on the sporting and performing arts industries. Also, the pattern in time spent on doing sports, demands for subsidized gym memberships or public recreation center access during extreme seasons. Moreover, the heterogeneous effect by income level indicates the need to subsidize poorer households to reduce the adverse impact during extreme heat.

Further, this finding has several macroeconomic implications as well. The U-shaped pattern for time spent on essential consumptions and the inverted U-shaped pattern of time spent on non-essential consumptions indicate that households cut discretionary spending during temperature extremes and reallocate resources to essential consumption, probably due to future expectations of bad weather and strained budgets. Policymakers should pay attention to not letting this temperature-induced gloominess ripple through the economy. Policymakers can help manage expectations by forecasting a climate-induced shift in consumption patterns and stimulating the economy if needed during extreme climate events. This will help reduce investment uncertainty in the climate-vulnerable sectors associated with non-essential goods, and ease inflationary pressure due to strained household budgets.

In summary, this research adds to the existing literature by assessing how extreme temperatures influence the time allocated to different consumption activities. It highlights unresolved issues regarding the relationship between temperature and time spent on various consumptions, providing potential mechanisms for the influence of extreme temperatures. This study can serve as a basis for developing equitable climate resilience, understanding household consumption behavior, and expanding economic systems.

References

Addoum, Jawad M, David T Ng, and Ariel Ortiz-Bobea (2020). "Temperature shocks and establishment sales". In: *The Review of Financial Studies* 33.3, pp. 1331–1366.

Attanasio, Orazio P and Luigi Pistaferri (2016). "Consumption inequality". In: *Journal of Economic Perspectives* 30.2, pp. 3–28.

Barreca, Alan, Karen Clay, Olivier Deschenes, et al. (2016). "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century". In: *Journal of Political Economy* 124.1, pp. 105–159.

Barreca, Alan, Karen Clay, Olivier Deschênes, et al. (May 2015). "Convergence in Adaptation to Climate Change: Evidence from High Temperatures and Mortality, 1900-2004". In: *American Economic Review* 105.5, pp. 247–51. DOI: 10.1257/aer.p20151028. URL: https://www.aeaweb.org/articles?id=10.1257/aer.p20151028.

Barreca, Alan, Olivier Deschenes, and Melanie Guldi (2018). "Maybe next month? Temperature shocks and dynamic adjustments in birth rates". In: *Demography* 55.4, pp. 1269–1293.

Barreca, Alan and Jessamyn Schaller (2020). "The impact of high ambient temperatures on delivery timing and gestational lengths". In: *Nature Climate Change* 10.1, pp. 77–82.

Bhattacharya, Jayanta et al. (2003). "Heat or eat? Cold-weather shocks and nutrition in poor American families". In: *American journal of public health* 93.7, pp. 1149–1154.

Burgess, Robin et al. (2017). "Weather, climate change and death in India". In: *University of Chicago*, pp. 577–617.

Burke, Marshall and Kyle Emerick (2016). "Adaptation to climate change: Evidence from US agriculture". In: *American Economic Journal: Economic Policy* 8.3, pp. 106–140.

Burke, Marshall, Felipe González, et al. (2018). "Higher temperatures increase suicide rates in the United States and Mexico". In: *Nature climate change* 8.8, pp. 723–729.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015a). "Climate and conflict". In: *Annu. Rev. Econ.* 7.1, pp. 577–617.

— (2015b). "Global non-linear effect of temperature on economic production". In: *Nature* 527.7577, pp. 235–239.

Burke, Marshall and Vincent Tanutama (2019). *Climatic constraints on aggregate economic output*. Tech. rep. National Bureau of Economic Research.

Busse, Meghan R et al. (2015). "The psychological effect of weather on car purchases". In: *The Quarterly Journal of Economics* 130.1, pp. 371–414.

Campagnolo, Lorenza and Enrica De Cian (2022). "Distributional consequences of climate change impacts on residential energy demand across Italian households". In: *Energy Economics* 110, pp. 106020.

Connolly, Marie (2008). "Here comes the rain again: Weather and the intertemporal substitution of leisure". In: *Journal of Labor Economics* 26.1, pp. 73–100.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2012). "Temperature shocks and economic growth: Evidence from the last half century". In: *American Economic Journal: Macroeconomics* 4.3, pp. 66–95.

Deschenes, Olivier (2014). "Temperature, human health, and adaptation: A review of the empirical literature". In: *Energy Economics* 46, pp. 606–619.

Deschênes, Olivier and Michael Greenstone (2011). "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US". In: *American Economic Journal: Applied Economics* 3.4, pp. 152–185.

Doremus, Jacqueline M, Irene Jacqz, and Sarah Johnston (2022). "Sweating the energy bill: Extreme weather, poor households, and the energy spending gap". In: *Journal of Environmental Economics and Management* 112, pp. 102609.

Flood, Sarah M. et al. (2023). *American Time Use Survey Data Extract Builder: Version 3.2*. College Park, MD and Minneapolis, MN: University of Maryland and IPUMS. DOI: 10.18128/D060.V3.2.

Graff Zivin, Joshua and Matthew Neidell (2014). "Temperature and the allocation of time: Implications for climate change". In: *Journal of Labor Economics* 32.1, pp. 1–26.

He, Pan et al. (2022). "The weather affects air conditioner purchases to fill the energy efficiency gap". In: *nature communications* 13.1, pp. 5772.

Heutel, Garth, Nolan H Miller, and David Molitor (2021). "Adaptation and the mortality effects of temperature across US climate regions". In: *Review of Economics and Statistics* 103.4, pp. 740–753.

Jain, Anuska, Roisin O'Sullivan, and Vis Taraz (2020). "Temperature and economic activity: Evidence from India". In: *Journal of Environmental Economics and Policy* 9.4, pp. 430–446.

Lee, Seunghoon and Siqi Zheng (2025). "Extreme temperatures, adaptation capacity, and household retail consumption". In: *Journal of the Association of Environmental and Resource Economists* 12.2, pp. 427–457.

Martínez-de-Albéniz, Victor and Abdel Belkaid (2021). "Here comes the sun: Fashion goods retailing under weather fluctuations". In: *European Journal of Operational Research* 294.3, pp. 820–830.

Menne, M. J. et al. (2012). "An Overview of the Global Historical Climatology Network-Daily Database". In: *Journal of Atmospheric and Oceanic Technology* 29, pp. 897–910. DOI: 10.1175/JTECH-D-11-00103.1.

Menne, M.J. et al. (2012). *Global Historical Climatology Network - Daily (GHCN-Daily), Version 3.32*. http://doi.org/10.7289/V5D21VHZ. NOAA National Climatic Data Center. Accessed April 2025.

Muellbauer, John and Ralph Lattimore (1999). "The consumption function: a theoretical and empirical overview". In: *Handbook of Applied Econometrics Volume 1: Macroeconomics*, pp. 187–267.

Park, R. Jisung et al. (May 2020). "Heat and Learning". In: *American Economic Journal: Economic Policy* 12.2, pp. 306–39. DOI: 10.1257/pol.20180612. URL: https://www.aeaweb.org/articles?id=10.1257/pol.20180612.

Roth Tran, Brigitte (2020). "Sellin'in the Rain: Adaptation to Weather and Climate in the Retail Sector". In: *Available at SSRN 3337110*.

Shi, Han et al. (2024). "The unequal impacts of extremely high temperatures on households' adaptive behaviors: Empirical evidence from fine-grained electricity consumption data". In: *Energy Policy* 190, pp. 114170.

Song, Xuping et al. (2017). "Impact of ambient temperature on morbidity and mortality: an overview of reviews". In: *Science of the Total Environment* 586, pp. 241–254.

U.S. Bureau of Labor Statistics (2023). *American Time Use Survey User's Guide: Understanding the ATUS 2003 to 2022*. https://www.bls.gov/tus/atususersguide.pdf. Accessed April 2025.

Wu, Shu, Fangfang Hu, and Zhijian Zhang (2025). "Climate change and energy poverty: Evidence from China". In: *World Development* 186, pp. 106826.

Zivin, Joshua Graff et al. (2020). "Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China". In: *Journal of Environmental Economics and Management* 104, pp. 102365.

Appendix A

A.1 Time spent in Non-Household Locations

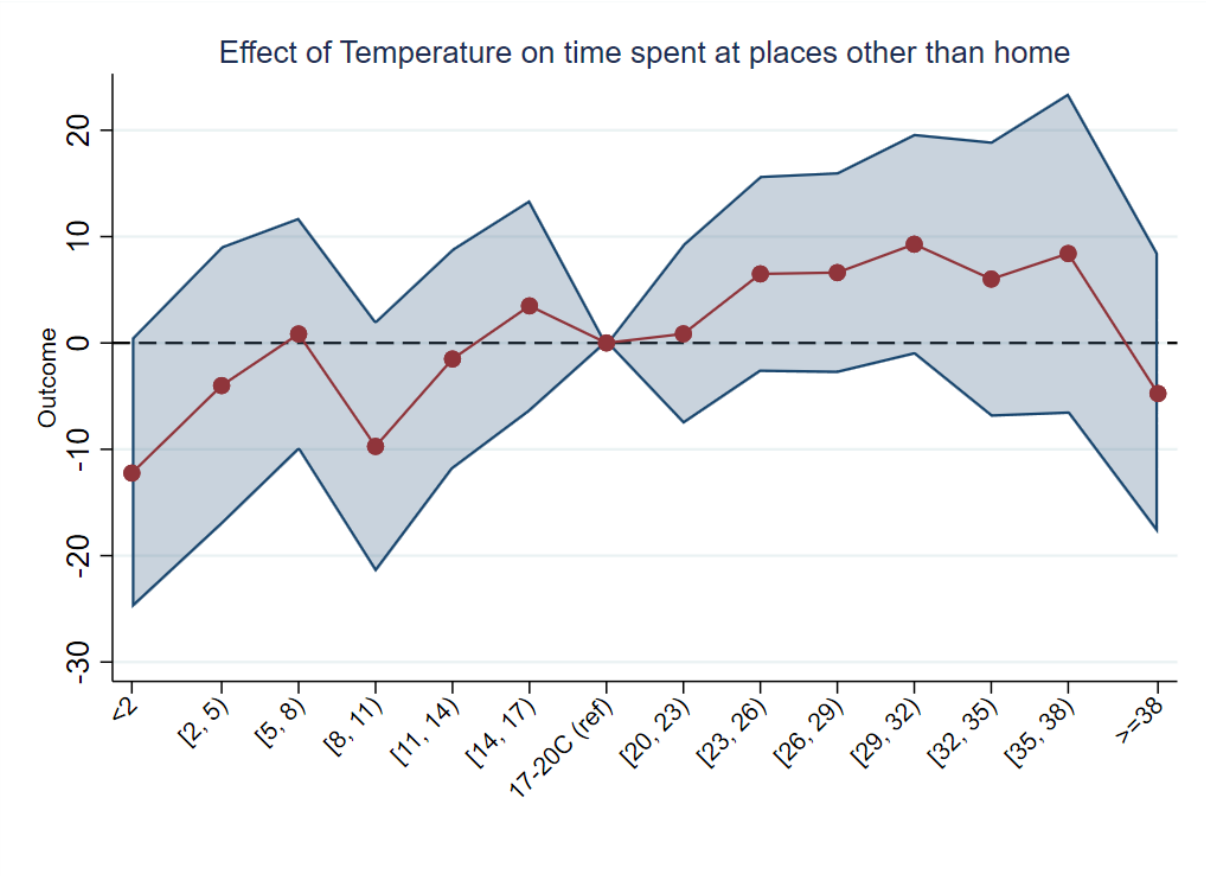
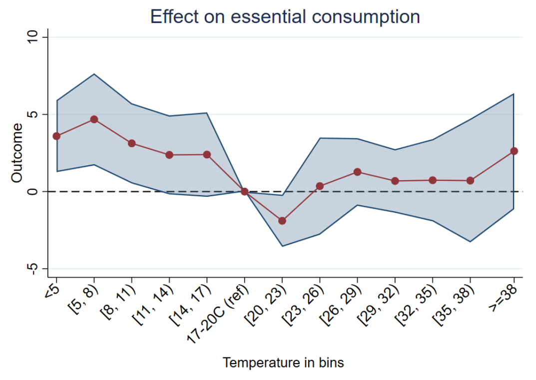


Figure A.1.1: Time Spent Out of One's House

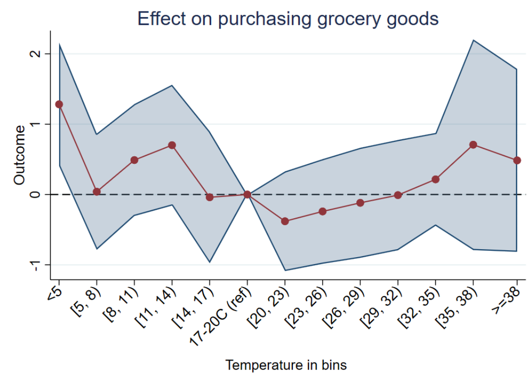
Figure A.1.2: Estimates for Time Spent Out of One's House The figure displays the effects of temperature on time spent out of one's house. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for fixed effects for county, holiday, year–month, and day.

A.2 Robustness without demographic controls

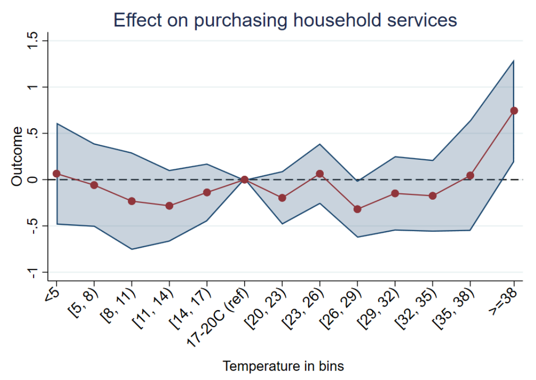
Essential Consumption: Robustness Without Demographic Controls



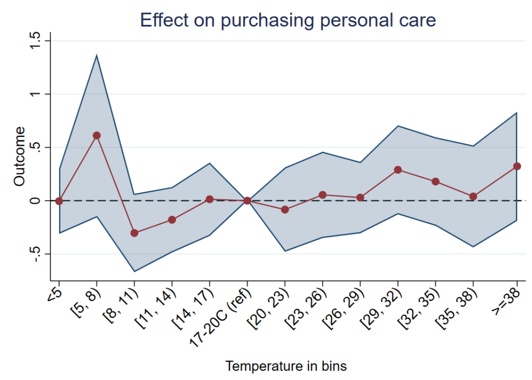
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



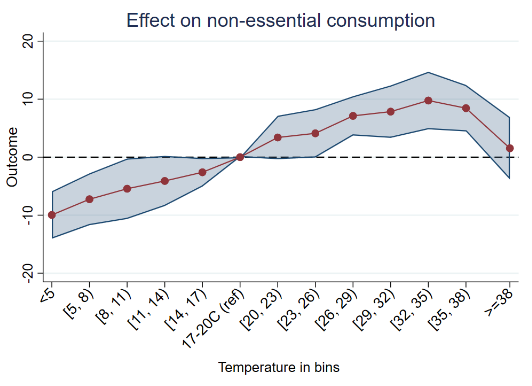
(c) Panel C: Effect on Household Services Purchase



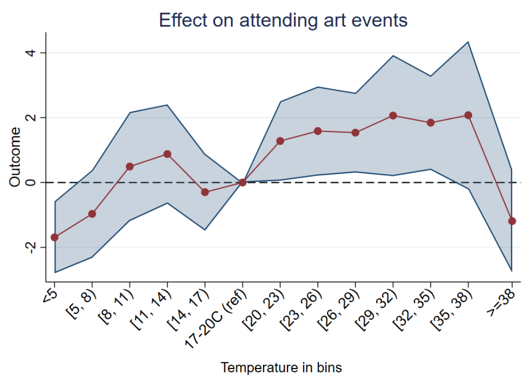
(d) Panel D: Effect on Personal Care Purchase

Figure A.2.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for fixed effects for county, holiday, year–month, and day.

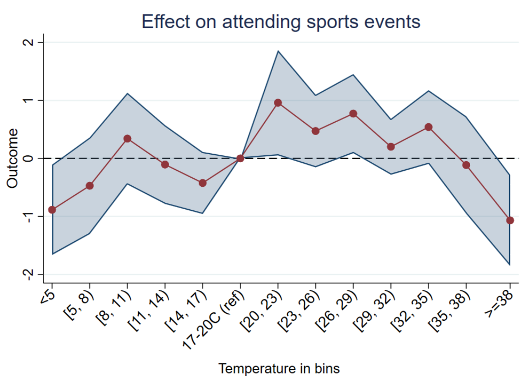
Non-Essential Consumption: Robustness Without Demographic Controls



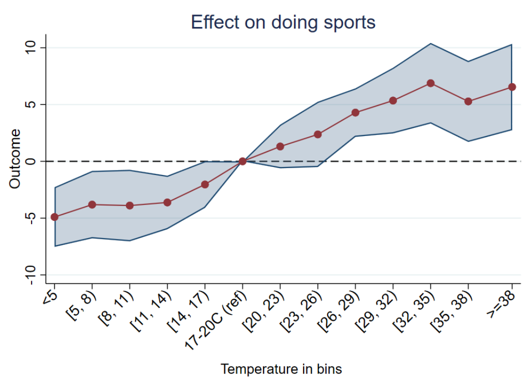
(a) Panel A: Effect on Non-Essential Goods Purchase



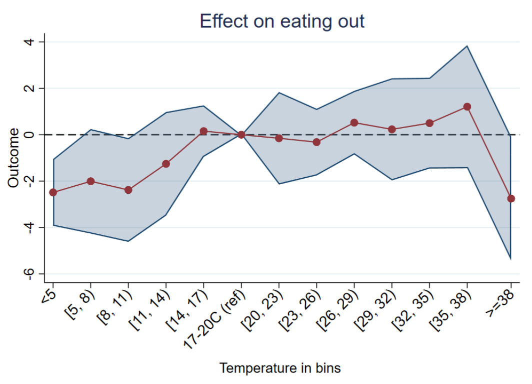
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports

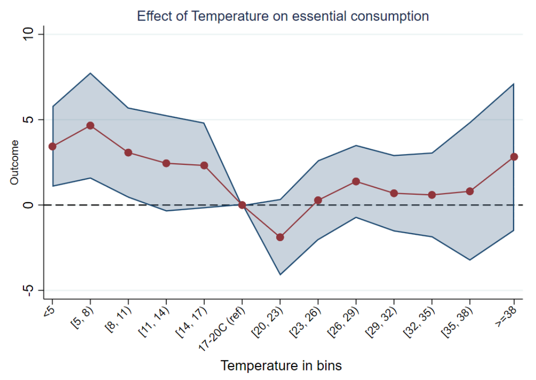


(e) Panel E: Effect on Eating Outside

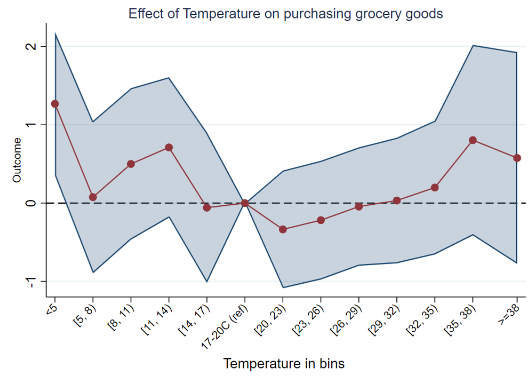
Figure A.2.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for fixed effects for county, holiday, year–month, and day.

A.3 Controlling for College Enrollment Status

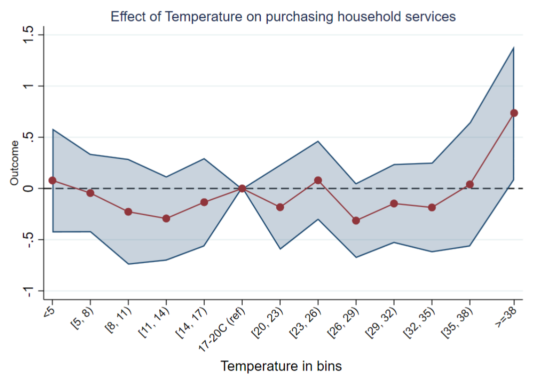
Essential Consumption: Robustness Using Additional Control for Being a Student



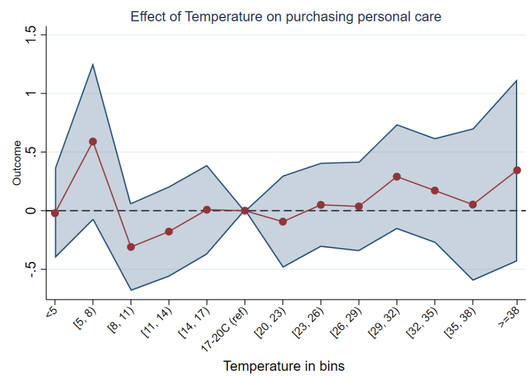
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



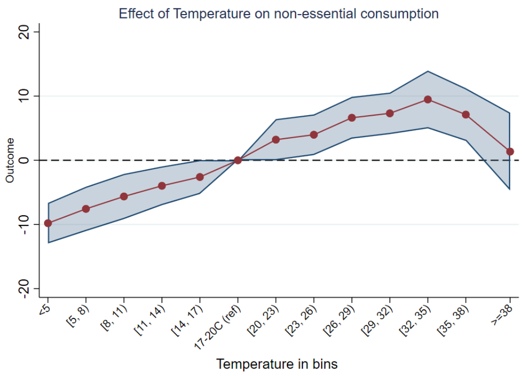
(c) Panel C: Effect on Household Services Purchase



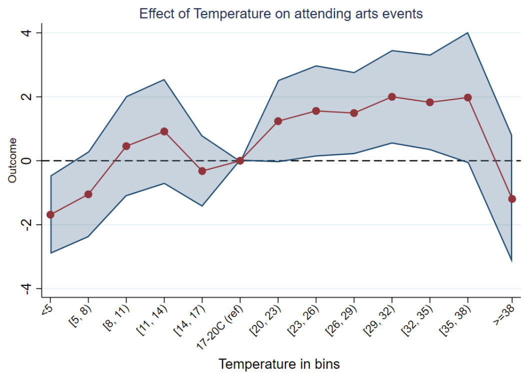
(d) Panel D: Effect on Personal Care Purchase

Figure A.3.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, a dummy for being a student, and fixed effects for county, holiday, year–month, and day.

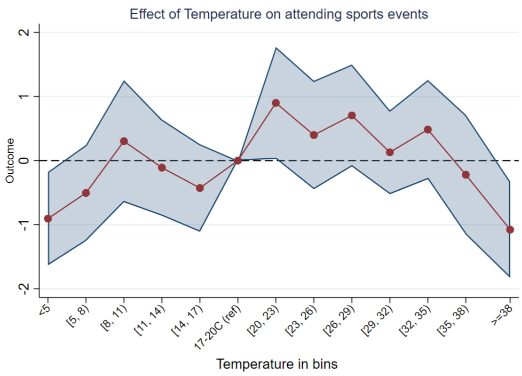
Non-essential Consumption: Robustness Using Additional Control for Being a Student



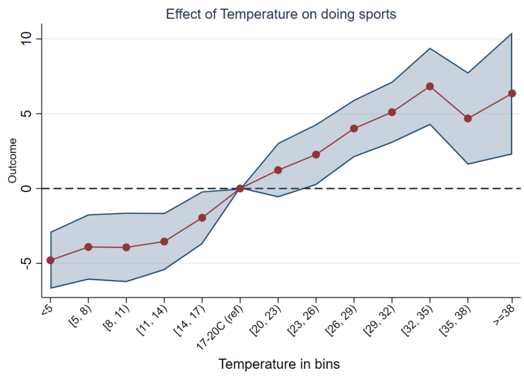
(a) Panel A: Effect on Non-Essential Goods Purchase



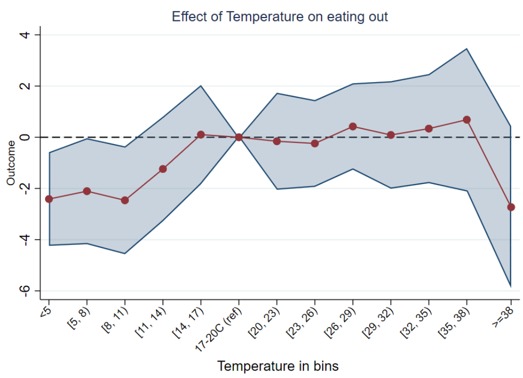
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports

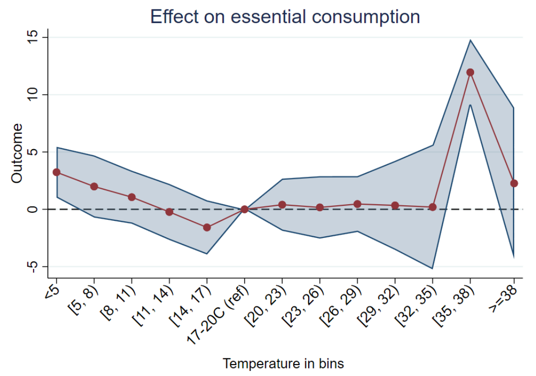


(e) Panel E: Effect on Eating Outside

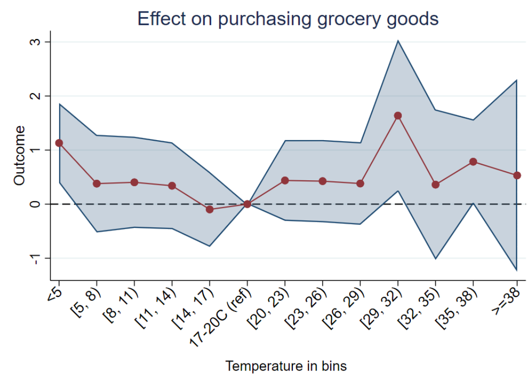
Figure A.3.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, a dummy for being a student, and fixed effects for county, holiday, year–month, and day. The status of enrollment in college and school serves as an additional control.

A.4 Robustness Using Average Temperature

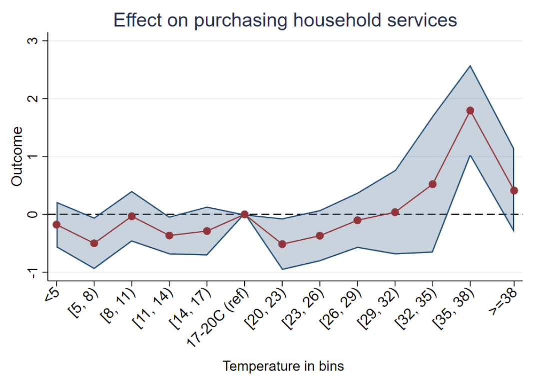
Essential Consumption: Robustness Using Average Temperature



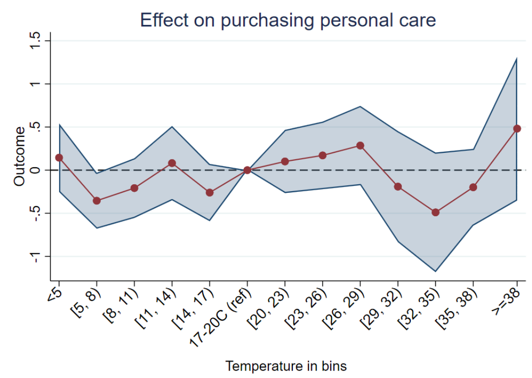
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



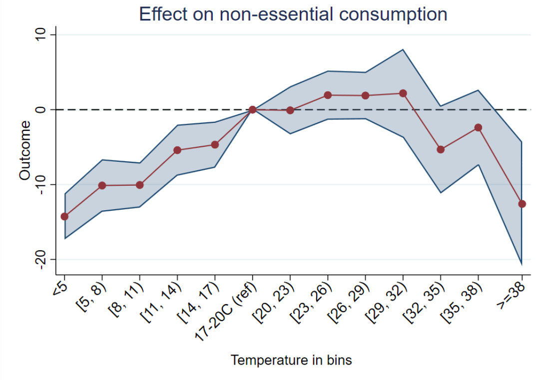
(c) Panel C: Effect on Household Services Purchase



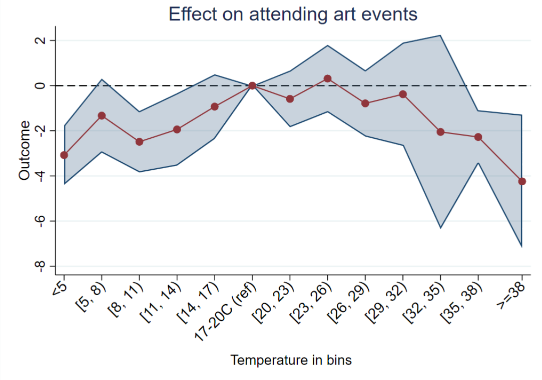
(d) Panel D: Effect on Personal Care Purchase

Figure A.4.1: Essential Consumption Activities Across Average Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

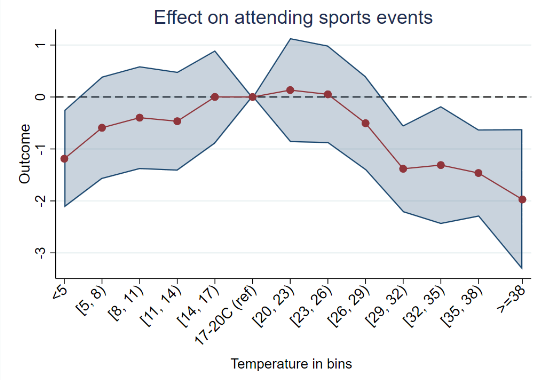
Non-essential Consumption: Robustness Using Average Temperature



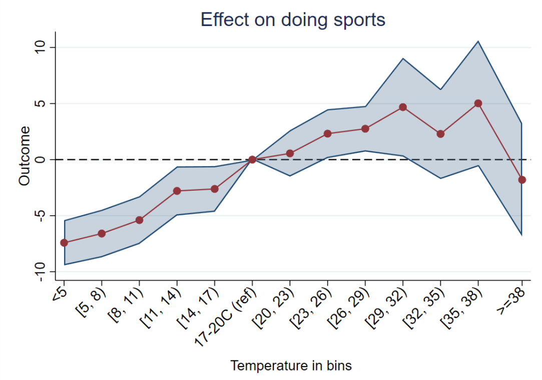
(a) Panel A: Effect on Non-Essential Goods Purchase



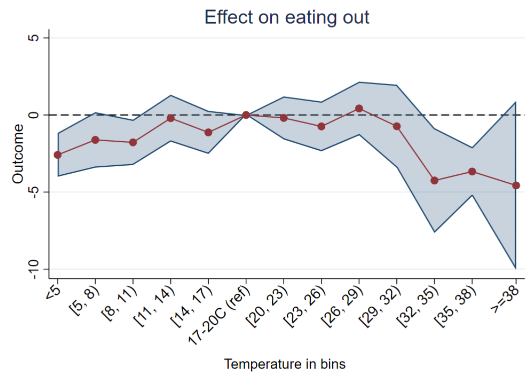
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports

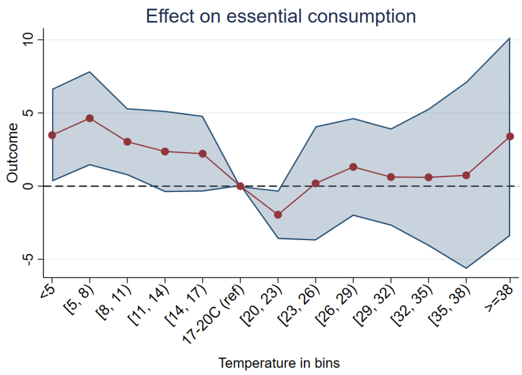


(e) Panel E: Effect on Eating Outside

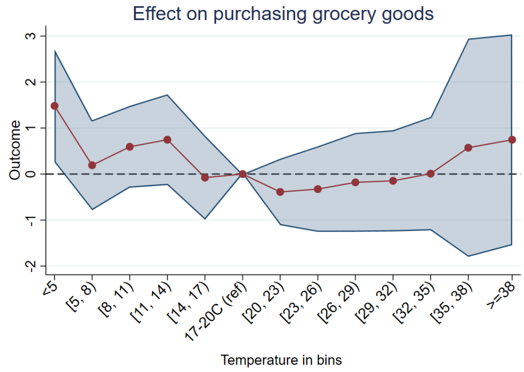
Figure A.4.2: Non-Essential Consumption Activities Across Average Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

A.5 Robustness Using State-level Clustering for the Error

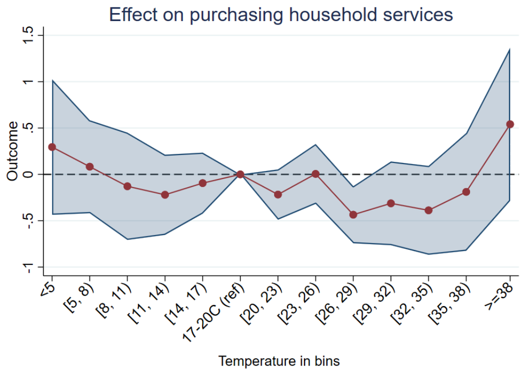
Essential Consumption: Robustness Using State-level Clustering



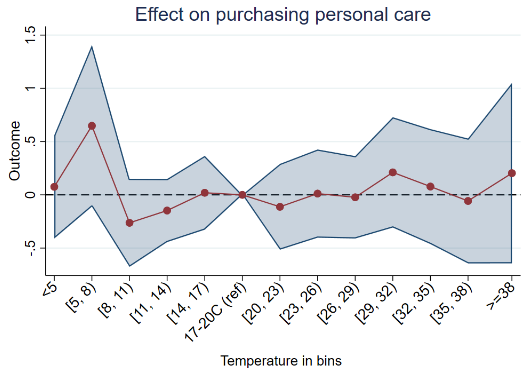
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



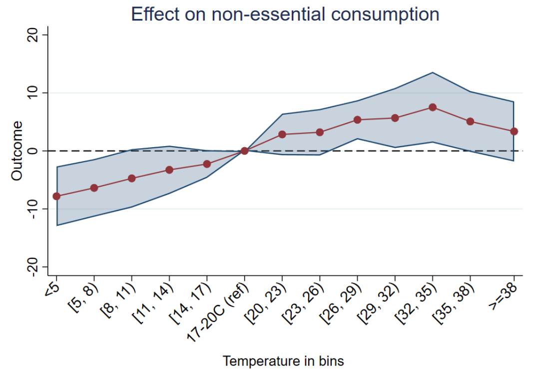
(c) Panel C: Effect on Household Services Purchase



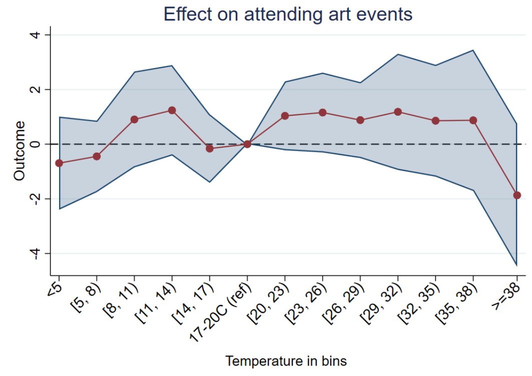
(d) Panel D: Effect on Personal Care Purchase

Figure A.5.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the state level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

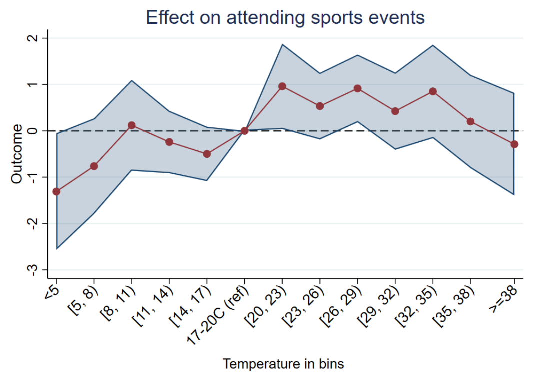
Non-Essential Consumption: Robustness Using State-level Clustering



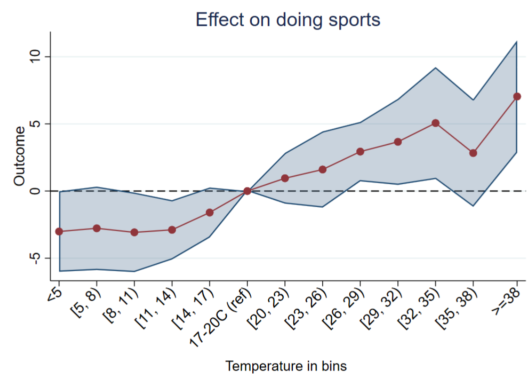
(a) Panel A: Effect on Non-Essential Goods Purchase



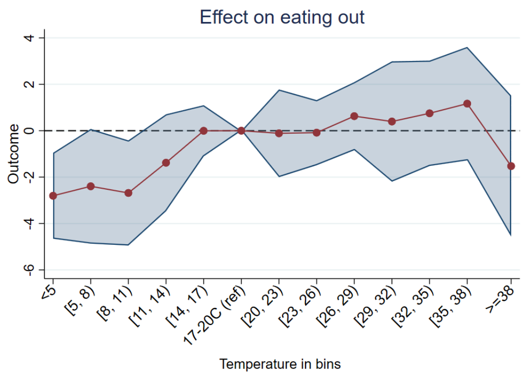
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports

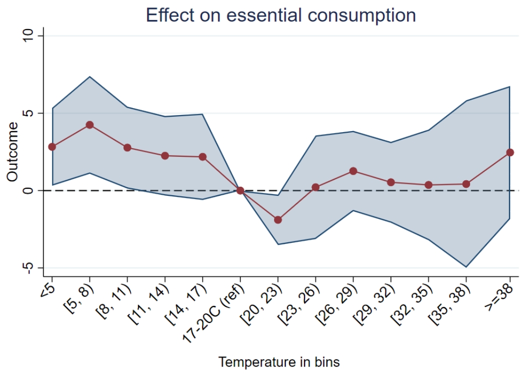


(e) Panel E: Effect on Eating Outside

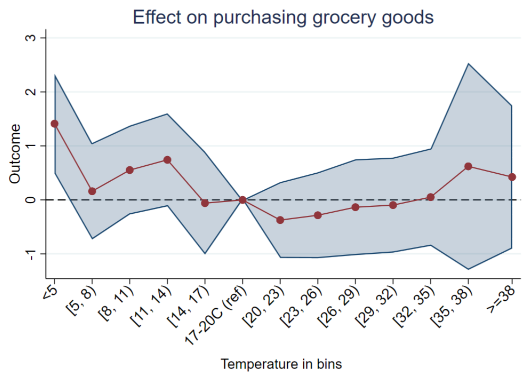
Figure A.5.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the state level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

A.6 Robustness Using Season Fixed Effect and Clustering at State Level

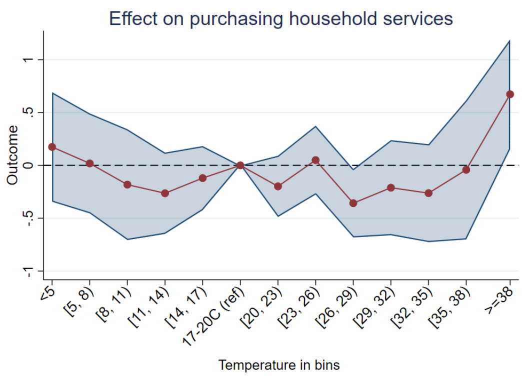
Essential Consumption: Robustness with Season Fixed Effect and State-level Clustering



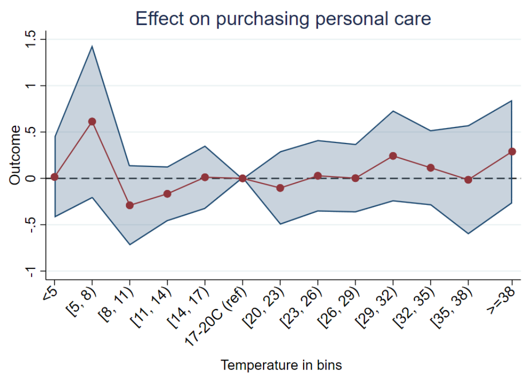
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



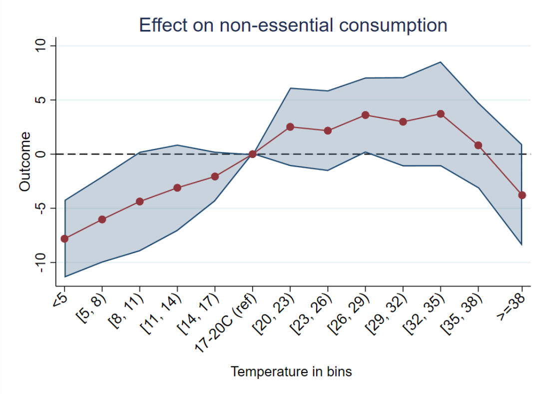
(c) Panel C: Effect on Household Services Purchase



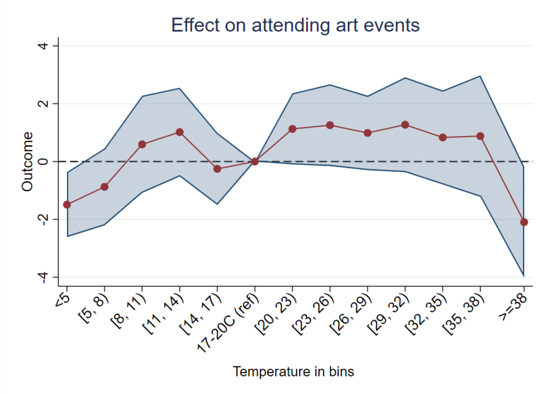
(d) Panel D: Effect on Personal Care Purchase

Figure A.6.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the state level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, season, year–month, and day.

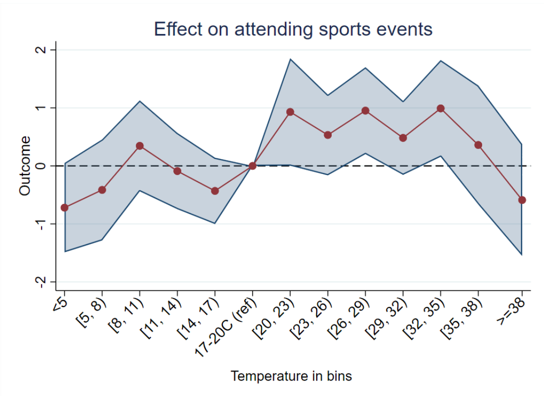
Non-Essential Consumption: Robustness with Season Fixed Effect and State-level Clustering



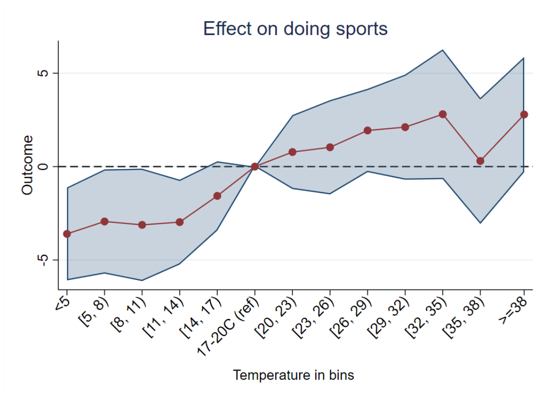
(a) Panel A: Effect on Non-Essential Goods Purchase



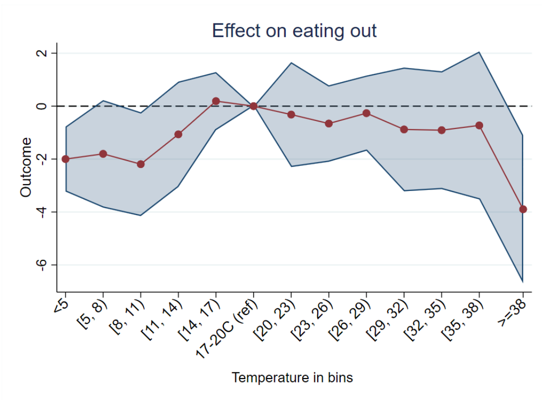
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports

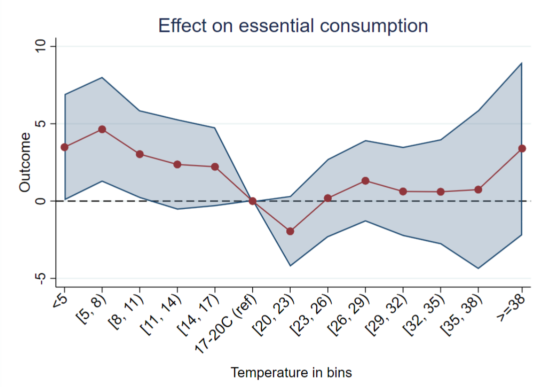


(e) Panel E: Effect on Eating Outside

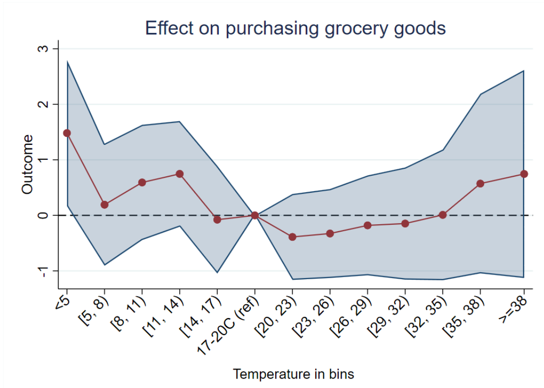
Figure A.6.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the state level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, season, year–month, and day.

A.7 Robustness Using Additional Temperature Control

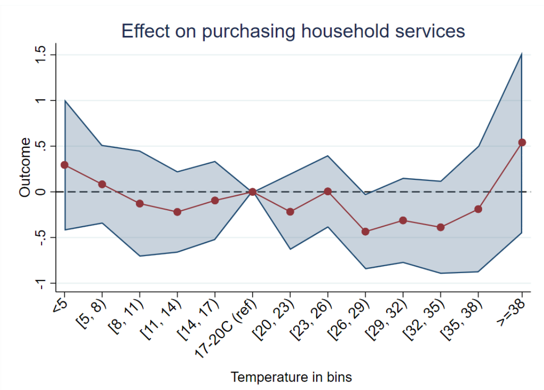
Essential Consumption: Robustness Using Additional Temperature Control



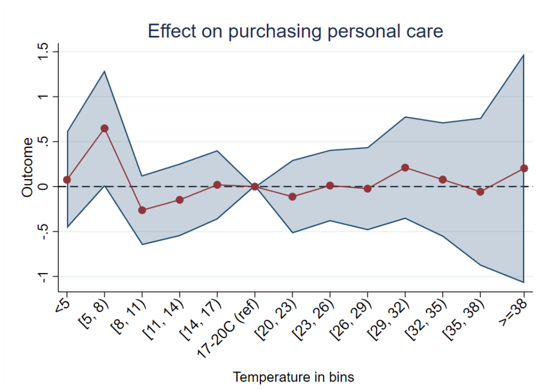
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



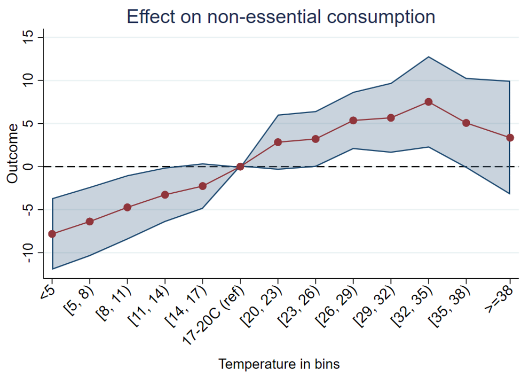
(c) Panel C: Effect on Household Services Purchase



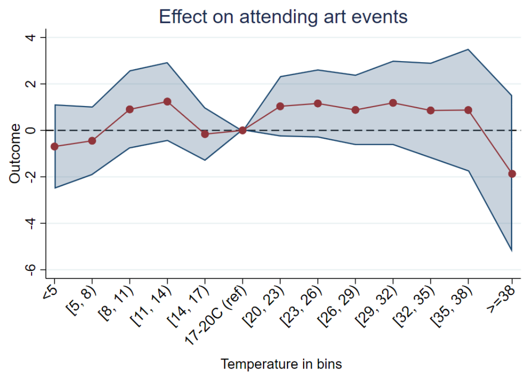
(d) Panel D: Effect on Personal Care Purchase

Figure A.7.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the effects on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day. The minimum temperature for that day serves as an additional control.

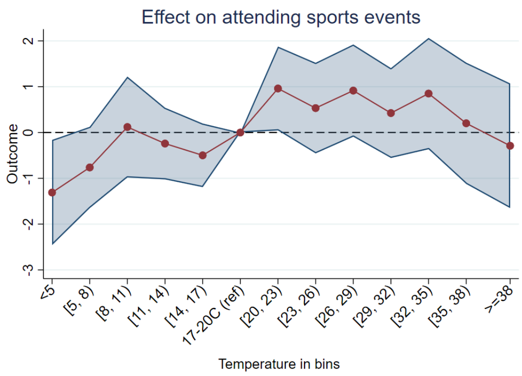
Non-essential Consumption: Robustness Using Additional Temperature Control



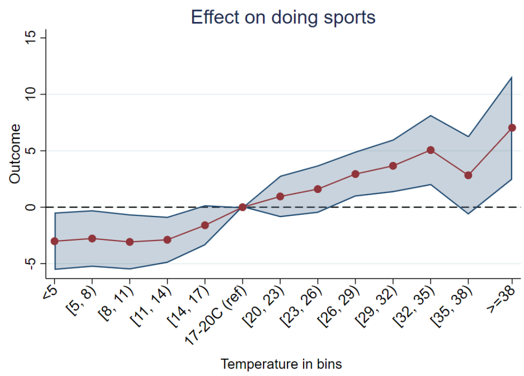
(a) Panel A: Effect on Non-Essential Goods Purchase



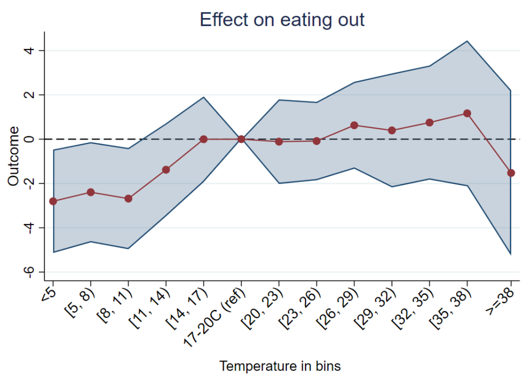
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports

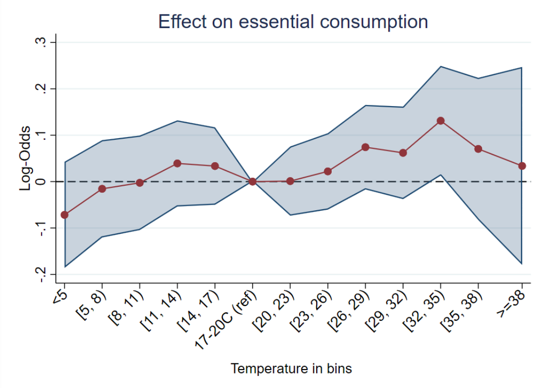


(e) Panel E: Effect on Eating Outside

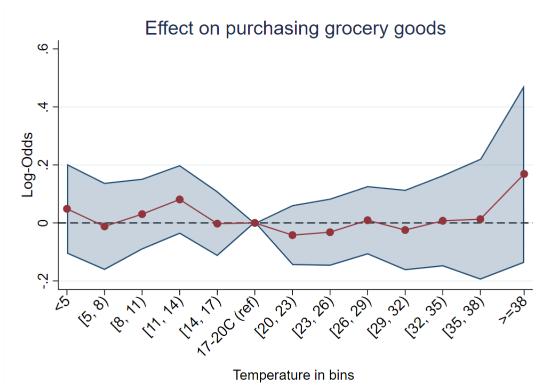
Figure A.7.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the effects on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, as well as minimum temperature and fixed effects for county, holiday, year–month, and day.

A.8 Robustness Using Logistic Regression

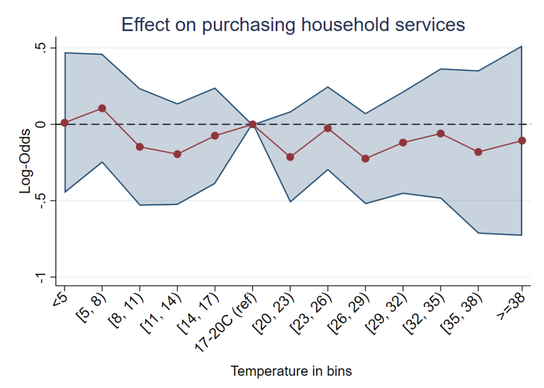
Essential Consumption: Robustness Using Logistic Regression



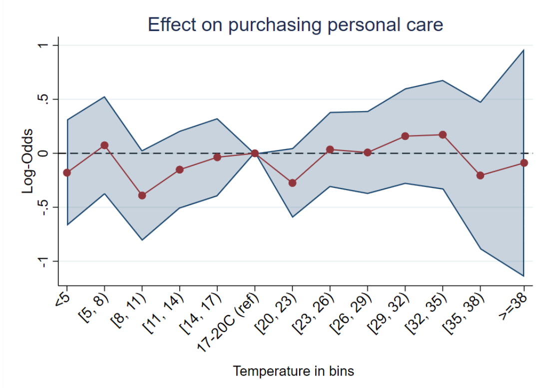
(a) Panel A: Effect on Overall Essential Goods Purchase



(b) Panel B: Effect on Grocery Purchase



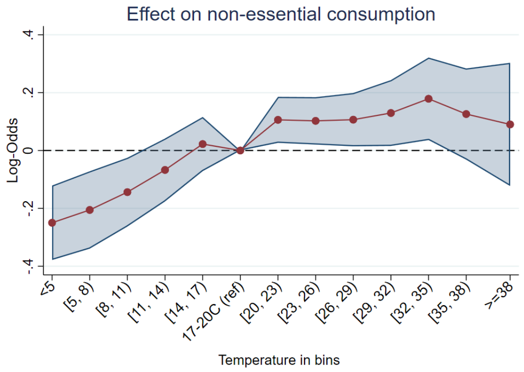
(c) Panel C: Effect on Household Services Purchase



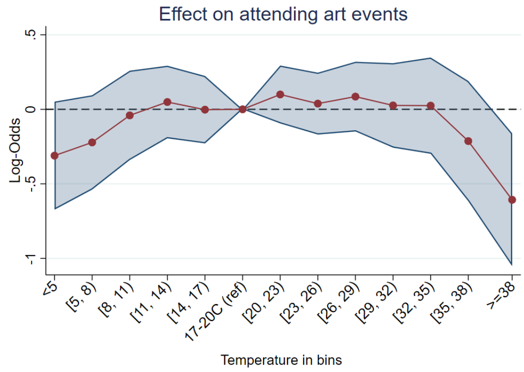
(d) Panel D: Effect on Personal Care Purchase

Figure A.8.1: Essential Consumption Activities Across Temperature Ranges. Panels A–D display the log odds of maximum temperature on overall goods purchase, grocery purchase, household services purchase, and personal care purchase. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day. The minimum temperature for that day serves as an additional control.

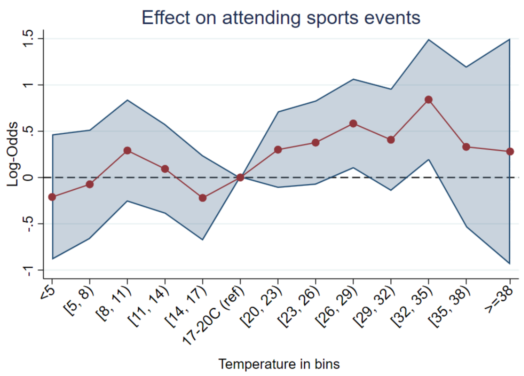
Non-essential Consumption: Robustness Using Logistic Regression



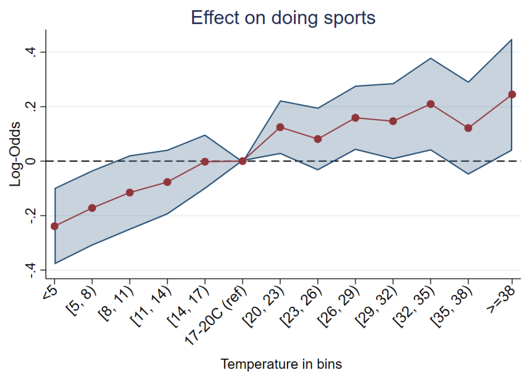
(a) Panel A: Effect on Non-Essential Goods Purchase



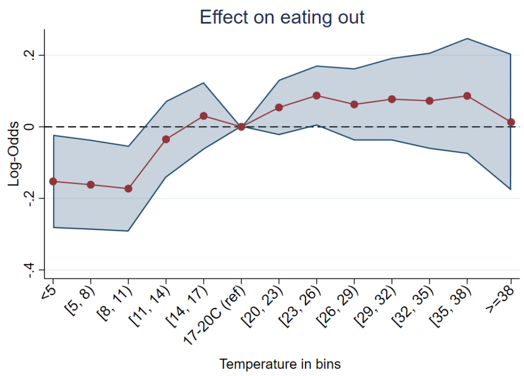
(b) Panel B: Effect on Attending Arts Related Events and Places



(c) Panel C: Effect on Attending Sports Events



(d) Panel D: Effect on Doing Sports



(e) Panel E: Effect on Eating Outside

Figure A.8.2: Non-Essential Consumption Activities Across Temperature Ranges. Panels A–E display the log odds of maximum temperature on non-essential goods purchase, attending arts-related events, attending sports events, doing sports, and eating outside, respectively. Shaded regions around each point estimate represent 95% confidence intervals based on clustered standard errors at the county level. Temperature bins are defined as: <5°C, 5–8°C, 8–11°C, 11–14°C, 14–17°C, 17–20°C (reference), 20–23°C, 23–26°C, 26–29°C, 29–32°C, 32–35°C, 35–38°C, and >38°C. All regressions control for age, a dummy for being female, a dummy for household having a minor, citizenship status, family income, rainfall, and fixed effects for county, holiday, year–month, and day.

A.9 Theoretical Implication

Theoretical Model: Substitution Between Essential and Non-Essential Consumption

This section attempts to rationalize my previous findings through a theoretical model that considers the substitution effect between essential and non-essential consumption. I start by assuming that the consumer gains utility from two consumption categories: C^H for total non-essential consumption and C^U for total essential consumption.

Given that time holds equal value to money, the consumer deals with time-based budget restrictions for consumption activities. Excluding the time allocated for rest and sleep, all available time can be divided into work and consumption periods. Therefore, with work time set aside, the consumer's remaining time should be dedicated to consuming different goods and services. This allocation is particularly significant as using time operates as a zero-sum game. Consequently, the consumer is confronted with the following budget constraint:

$$P^H C^H + P^U C^U = C$$

where P^H and P^U are the price of non-essential and essential consumption in terms of time, respectively, and C is the total time in minutes available for consumption.

The Lagrangian for the given problem can be written as:

$$\mathcal{L} = U(C^H, C^U) - \lambda(P^H C^H + P^U C^U - C)$$

where λ is the Lagrange multiplier.

Then I take the utility function for constant elasticity of substitution (CES), which is given by:

$$U(C^H, C^U) = \left[\alpha(C^H)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(C^U)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

To derive the substitution effect — the ratio of C^H to C^U — I maximize the utility function subject to the budget constraint. This can be done by taking the partial derivatives of the Lagrangian with respect to C^H and C^U and setting them equal to zero.

Taking the partial derivative of the Lagrangian with respect to C^H, we get:

$$\frac{\partial \mathcal{L}}{\partial C^H} = \left[\alpha(C^H)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(C^U)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \cdot \alpha(C^H)^{-\frac{1}{\sigma}} - \lambda P^H = 0$$

Similarly, taking the partial derivative with respect to C^U:

$$\frac{\partial \mathcal{L}}{\partial C^U} = \left[\alpha(C^H)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(C^U)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \cdot (1-\alpha)(C^U)^{-\frac{1}{\sigma}} - \lambda P^U = 0$$

Dividing the two first-order conditions, we obtain:

$$\frac{\alpha(C^H)^{-\frac{1}{\sigma}}}{(1-\alpha)(C^U)^{-\frac{1}{\sigma}}} = \frac{P^H}{P^U}$$

Rearranging:

$$\frac{C^H}{C^U} = \left(\frac{\alpha}{1-\alpha} \cdot \frac{P^U}{P^H}\right)^{\sigma}$$

Taking the natural logarithm of both sides yields:

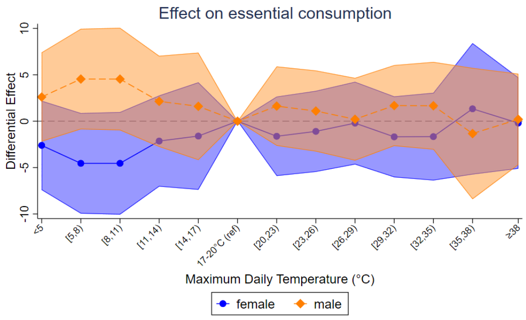
$$\ln\left(\frac{C^H}{C^U}\right) = \sigma \ln\left(\frac{P^U}{P^H}\right) + \ln\left(\frac{\alpha}{1-\alpha}\right)$$

This expression shows that the elasticity of substitution σ governs how sensitive the relative consumption allocation is to changes in the relative time-price of consuming non-essential versus essential goods.

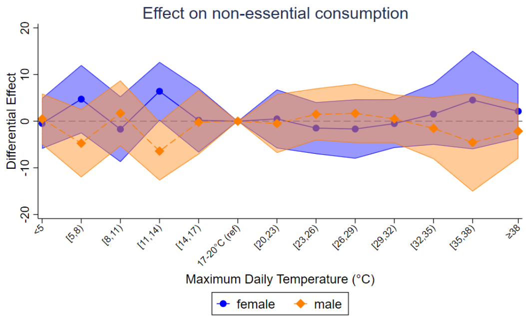
Thus, to estimate this effect, I then ran the regression with an assumption for the relative price of non-essential and essential goods, as shown above. Generally, extreme temperatures make non-essential Consumption more costly, while essential Consumption is less elastic, as people still need to do it even in bad weather.

Therefore, the relative price increases with extreme temperatures. Thus, I have used the standard deviation from the average mild temperature as a proxy for the relative price of the non-essential and Consumption goods. I suppose the mild temperature to be 18 °C. Using the above regression with longs and fixed effects and controls used in 2.1 , I found a significant negative relationship between essential and nonessential clustering of the error at the county level.

A.10 Heterogeneity by Various Demographic Characteristics

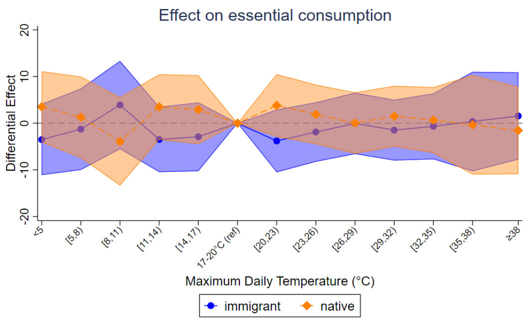


(a) Panel A: Effect on Essential Consumption by Sex (Female vs. Male)

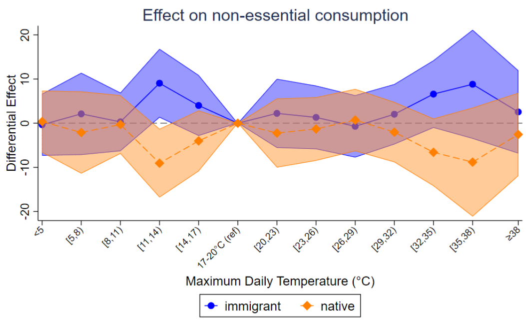


(b) Panel B: Effect on Non-essential Consumption by Sex (Female vs. Male)

Figure A.10.1: Heterogeneous Effects of Temperature by Sex. Panels A–B show the heterogeneous effects for females versus males on time spent in essential and non-essential Consumption, respectively. Regressions control for age, sex, citizenship status, family income, race, rainfall, and fixed effects for county, holiday, year–month, and day. Shaded bands are 95% confidence intervals (clustered by county).

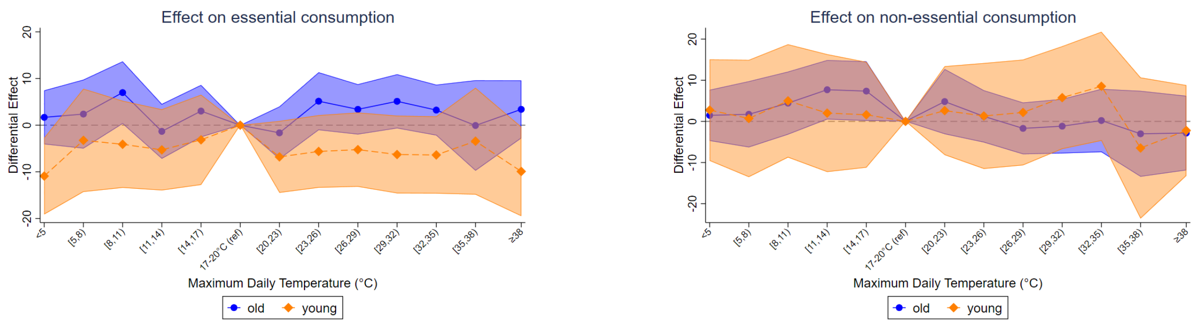


(a) Panel A: Effect on Essential Consumption by Citizenship (Native vs. Naturalized)



(b) Panel B: Effect on Non-essential Consumption by Citizenship (Native vs. Naturalized)

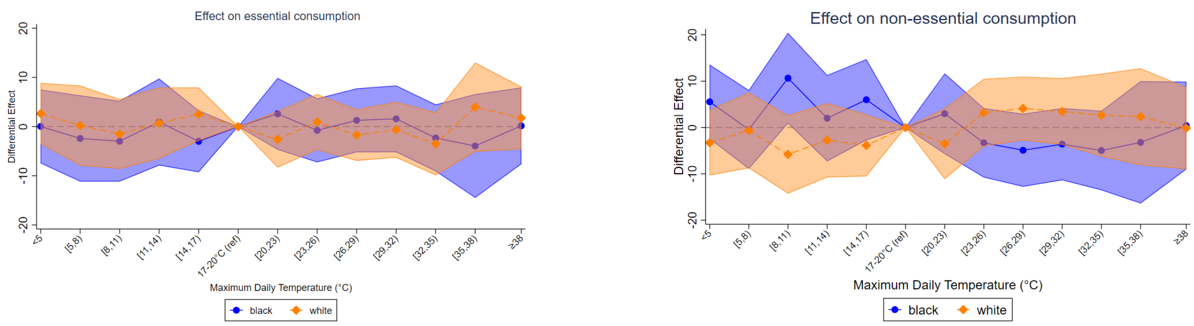
Figure A.10.2: Heterogeneous Effects of Temperature by Citizenship Status. Panels A–B show the heterogeneous effects for natives (U.S.-born and abroad) versus citizens-by-naturalization on time spent in essential and non-essential Consumption, respectively. Regressions control for age, sex, citizenship status, family income, race, rainfall, and fixed effects for county, holiday, year–month, and day. Shaded bands are 95% confidence intervals (clustered by county)



(a) Panel A: Effect on Essential Consumption by Age (Below 25 vs. ≥ 65)

(b) Panel B: Effect on Non-essential Consumption by Age (Below 25 vs. ≥ 65)

Figure A.10.3: Heterogeneous Effects of Temperature by Age Group. Panels A–B show the heterogeneous effects for "young" (below 25) versus "old" (65 and above) on time spent in essential and non-essential Consumption, respectively. Regressions control for age, sex, citizenship status, family income, race, rainfall, and fixed effects for county, holiday, year–month, and day. Shaded bands are 95% confidence intervals (clustered by county).



(a) Panel A: Effect on Essential Consumption by Race (Black vs. White)

(b) Panel B: Effect on Non-essential Consumption by Race (Black vs. White)

Figure A.10.4: Heterogeneous Effects of Temperature by Race. Panels A and B show the heterogeneous effects for Black versus White individuals on time spent in essential and non-essential Consumption, respectively. Regressions control for age, sex, citizenship status, family income, race, rainfall, and fixed effects for county, holiday, year–month, and day. Shaded bands are 95% confidence intervals (clustered by county).

A.11 Regarding the Use of Generative AI

I have used ChatGpt, Gork, Deepseek, Gemini, and Perpelexity during this research to write codes for analysis and LaTeX, especially Chatgpt. Additionally, I have utilized Gork and Grammarly to enhance my writing and grammar, such as suggesting appropriate transitions between sentences. I used the other AIs less frequently for cross-validation on the same task mentioned above and searching for literature. Finally, I have prompted ChatGPT to write the model using constant elasticity for my Theoretical Framework used in Appendix A.9.