Heat Exposure and Dietary Choices

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Heat waves are expected to become both more frequent and more intense globally as a consequence of climate change. Alongside the direct effects of heat on health (Basagaña et al., 2011; Hajat and Kosatky, 2010), humans' behavioral responses and adaptations to heat may themselves affect health, especially as these responses become more frequent. Understanding the effects of heat on behavior and decision-making is therefore essential to ascertain the full scope of possible health consequences of climate change.

I hypothesize that heat influences dietary choices through several possible channels. First, heat exposure can influence immediate preferences, making certain foods more (e.g. ice cream) or less (e.g. hot soup) palatable. Second, heat can make exposed individuals more averse to the physical exertion and utility costs of cooking, inducing them to purchase more convenient, ready-to-eat foods. Third, heat may influence food purchases by increasing the difficulty of transporting or storing certain types of foods, especially frozen foods. Fourth and finally, heat may increase demand for beverages, which are typically not nutrient-dense; this may be especially problematic for lower-income households who may need to reduce food purchases to compensate. In all of these cases, I hypothesize heat has a demand-side effect on dietary choices independent of supply-side effects, which are better understood (Battisti and Naylor, 2009).

This proposal bridges two literatures: the effect of heat on behavior and decision-making, and the behavioral determinants of dietary choices. Heat has been shown to increase crime (Hsiang et al., 2013) and conflict (Burke et al., 2015), time use (Graff Zivin and Neidell, 2014), cognitive performance (Zivin et al., 2018), and temperament (Baylis, 2015). In an interview with *Rolling Stone*, Solomon Hsiang summarized this literature as "growing evidence of a psychological mechanism that is impacted by heat, although we can't yet say exactly what that is" (Goodell, 2019). Dietary choices have also been linked to psychological mechanisms, including temptation and self-control (List and Samek, 2015) as well as stress and mental well-being (Oliver et al., 2000). Given that heat affects behavior and temperament, and behavior and temperament in turn affect dietary choices, it is natural to hypothesize that heat influences dietary choices. I intend to determine whether or not this is true, and if so, tease out the underlying mechanisms.

To study this hypothesis, I use the Nielsen HomeScan Consumer Panel dataset, which is available from 2004 to 2017, in conjunction with weather data covering the United States over the same time period. Households in the panel record the products they buy at grocery, convenience, department, and specialty stores, the prices of those products, and household member demographics. The panel includes data on more than 4.5 million unique product UPCs, over 2 million of which are grocery products, and a nationally representative sample of about 60,000 U.S. households. I link this consumption data with daily weather measures from the GHCN-Daily dataset maintained by the National Oceanic and Atmospheric Association (NOAA), which offers high spatiotemporal res-

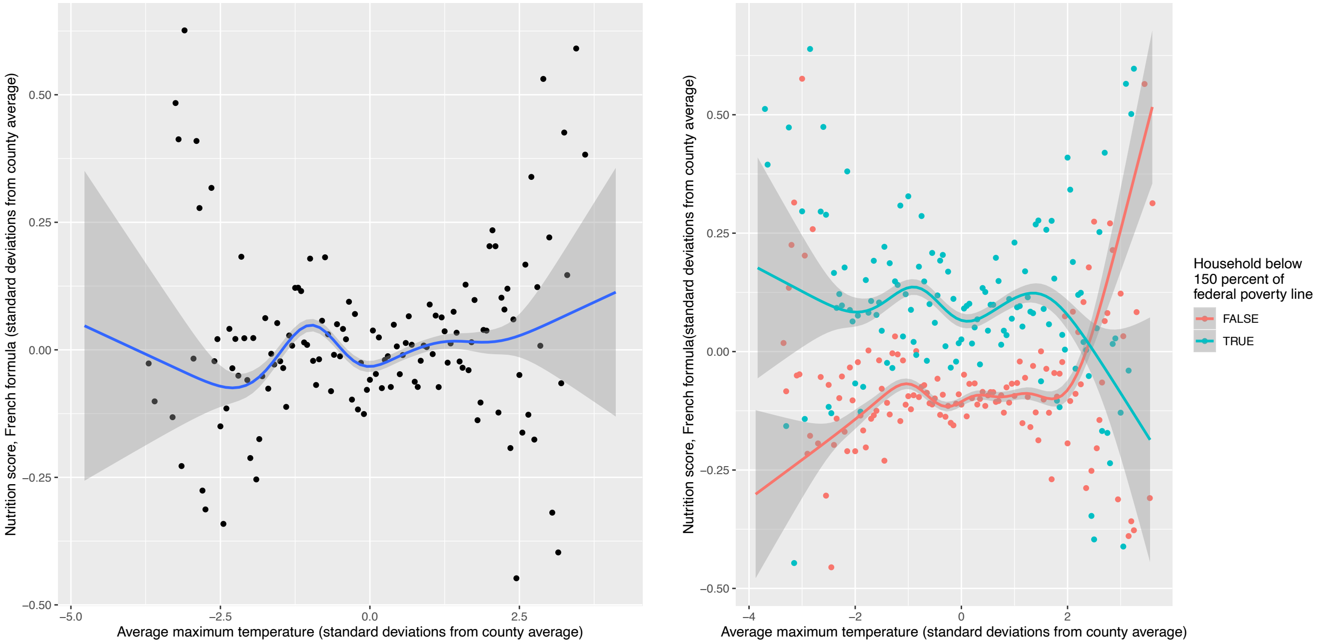

Figure 1: Nutri-Score and Heat

(a) All Households

(b) Heterogeneity by Household Income

Note: Higher values of the Nutri-Score correspond to lower nutritional quality. The score assigns positive points to less healthy components (e.g. saturated fat) and negative points to more healthy components (e.g. proportion of fruits and vegetables).

olution data from thousands of weather stations across the United States. To quantify the effects of heat on nutrition, I link the UPC-level HomeScan panel data to the open-access OpenFoodFacts nutrition facts database.

To causally identify the effect of heat on dietary choices, I use within-county variation in heat incidence and within-household variation in food purchases. This eliminates confounders such as differences in tastes, population characteristics, spatial variation in food availability or prices, or other geographic sources of heterogeneity.[1] I also restrict my analysis to summer months to avoid seasonal confounders such as the holiday season. I also intend to use the demographic information to conduct analyses of heterogeneity based on household income, household member occupations, age, and urban/rural status to determine population-specific effects of heat on nutrition and form policy implications.

Preliminary Findings

Figure 1 shows the relationship between summer temperatures and the Nutri-Score, a measure of grocery products' nutritional quality that was adopted in France in 2016. The score assigns positive points to less healthy nutritional components (e.g. total calories, saturated fat, sugars,

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[1] One limitation this does not address is the possibility that firms respond to heat by running advertising campaigns or promotions for specific foods.

sodium) and negative points to more healthy components (e.g. fruits, vegetables, nuts, protein, fiber). Thus less healthy foods are assigned higher values. The monthly county-level Nutri-Score reported in Figure 1 is an average of product scores weighted by the percentage of consumed calories associated with that product. All figures include temperature-binned scatter plots and a (non-binned) fitted generalized additive model (GAM) with thin-plate regression spline smoothing and a corresponding 95% confidence interval. I use GAMs to represent the relationship between heat and various outcomes to flexibly allow for nonlinearity without specifying bins, breakpoints, or polynomial degrees, which introduce misspecification concerns.

Subfigure (b) of Figure 1 shows the revealed preferences of higher-income households respond differently to heat shocks than lower-income households. The weighted-average Nutri-Score increases significantly for households with income above 150 percent of the federal poverty line, primarily because these households buy more dairy and deli products (shown in Figure 2). For households below 150 percent of the federal poverty line, the Nutri-Score decreases on average as dairy and deli purchases decline. However, this is largely due to an increase in expenditure on beverages (shown in Figure 3), including alcoholic beverages, which are not required to report nutrition facts on their packaging in the United States and thus do not have a Nutri-Score. Substituting beverages for food purchases may be especially problematic for food-insecure households because beverages are rarely nutrient-dense and many are high in “empty calories” from added sugars.

Even if the household only purchases more bottled water, their nutritional outcomes may be adversely affected if the household is budget-constrained and must purchase less food as a result. Table 1 and Figure 4 show evidence that this is true for lower-income households, especially in counties with a high risk of lead exposure as measured by Vox Media and the Washington State Department of Health[2]. Column 2 of Table 1 shows that, on average, an additional US$1 spent on bottled water reduces expenditure on all other categories by US$0.41 for higher-income households and US$0.55 for lower-income households, consistent with the idea that lower-income households forego more of other types of consumption as a result of increased bottled water purchases. Column 3 uses two-stage least squares (2SLS) to estimate the effect of an increase in bottled water expenditure induced by heat, finding a significant difference between higher-income and lower-income households in the same direction as the estimates in column 2. Figure 4 shows that the increase in bottled water expenditure induced by heat is larger in counties with a higher risk of lead exposure[3]. In sum, lower-income households who are more likely to rely on bottled water for their sanitary drinking water needs, such as those at a higher risk of lead exposure, may be particularly susceptible to food insecurity during heat waves.

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[2] See `https://www.vox.com/a/lead-exposure-risk-map`. I classify a county as “higher lead exposure risk” if its highest-risk census tract has a risk level of 9 or 10.

[3] Note that the measure of lead exposure risk used takes several possible sources into account, not exclusively drinking water.

Figure 2: Department Expenditure Shares and Heat

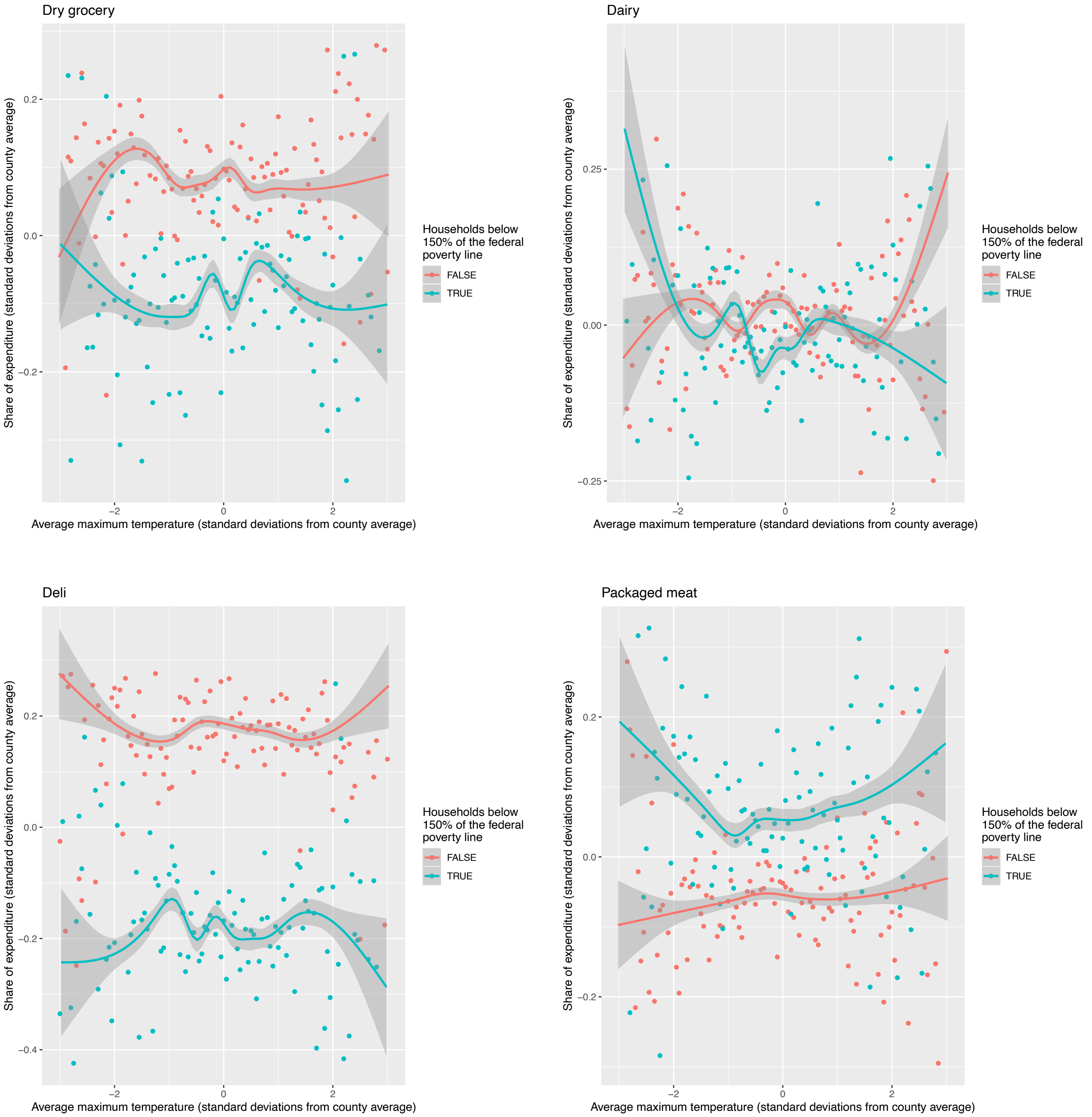
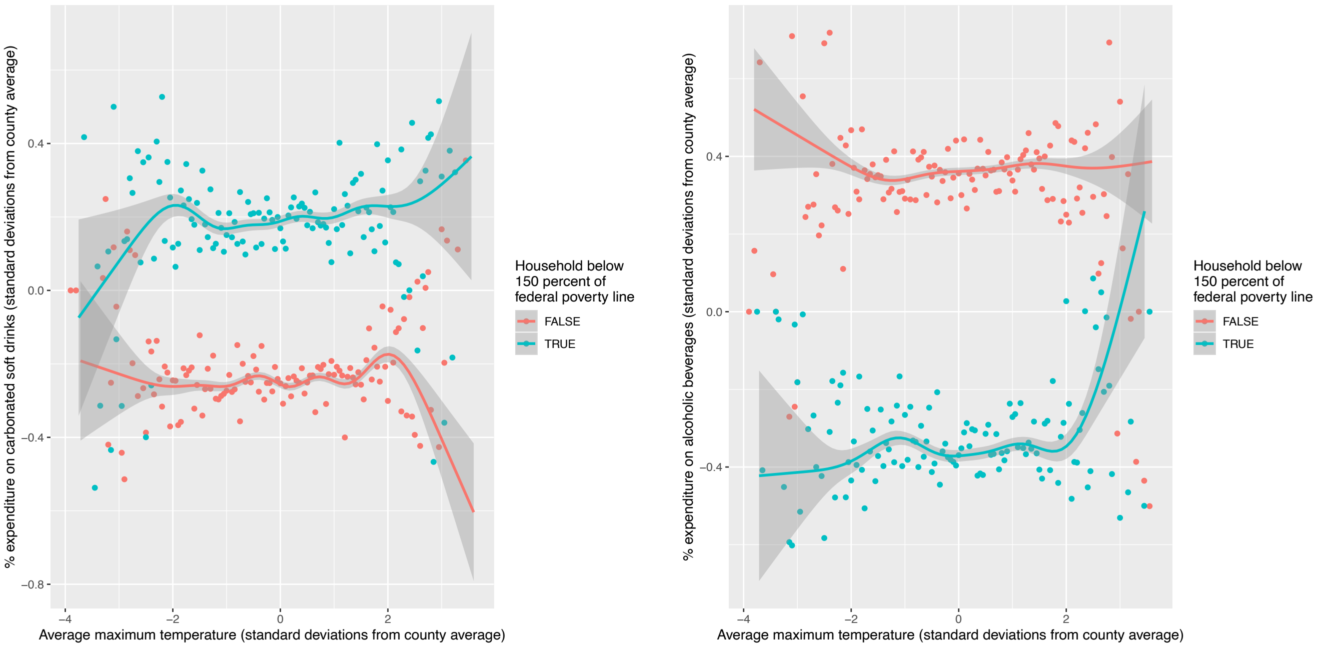


Figure 3: Beverage Expenditure Shares and Heat

(a) All Beverages (b) Bottled Water



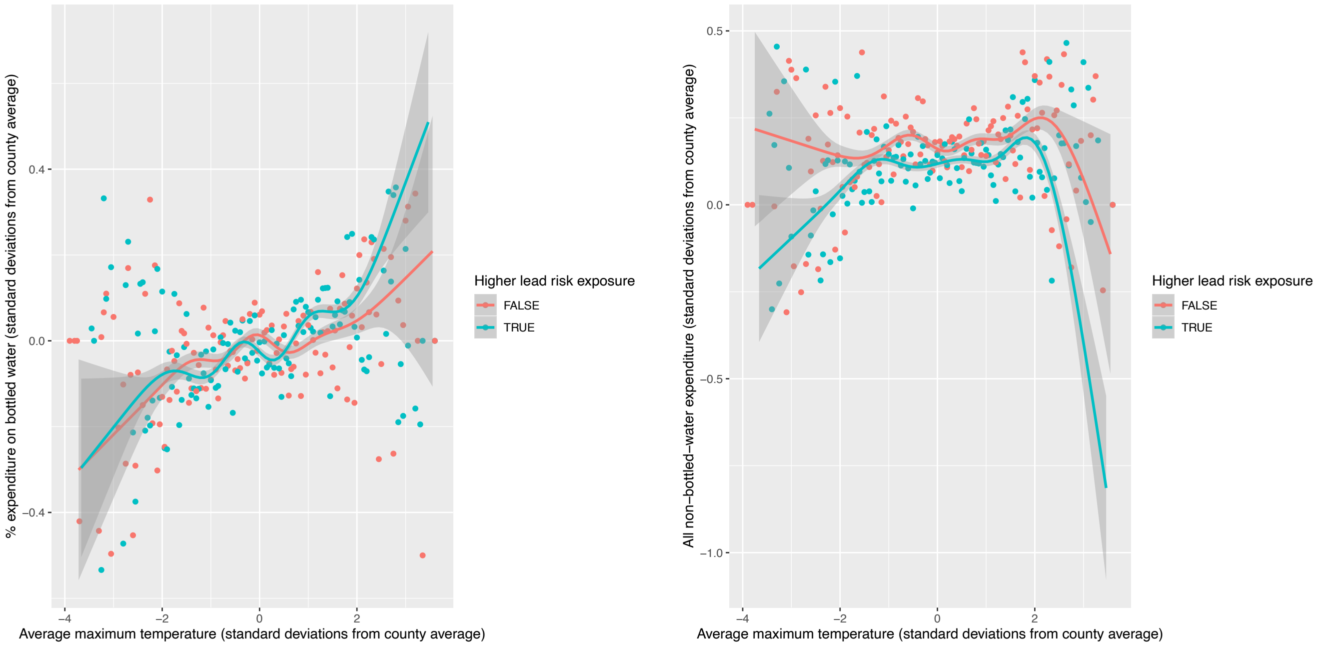
(c) Carbonated Soft Drinks (d) Alcoholic Beverages

Table 1: Effect of Increased Spending on Bottled Water on All Other Grocery Expenditures

	Dependent variable:		
	Total expenditure (USD), all categories except bottled water		
	(1) OLS	(2) OLS	(3) 2SLS
Monthly average maximum temperature (standard deviations from county-month average)	5.325 (6.466)		
Monthly average maximum temperature × Households below 150% of federal poverty line	-6.797^{**} (3.206)		
Bottled water expenditure (USD)		-0.410^{***} (0.147)	
Bottled water expenditure × Households below 150% of federal poverty line		-0.138^{***} (0.028)	
Bottled water expenditure, fitted values (regressed on temperature)			0.066 (0.776)
Bottled water expenditure, fitted values × Households below 150% of federal poverty line			-0.082^{***} (0.031)
Households below 150% of federal poverty line	8.321 (6.001)	62.783^{***} (12.544)	42.534^{***} (12.431)
Observations	190,262	190,570	190,262
R^2	0.999	0.999	0.999
County-year fixed effects	Yes	Yes	Yes

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
County-clustered standard errors in parentheses

Figure 4: Lower-Income Household Beverage Expenditures and Heat by Lead Exposure Risk



(a) Bottled Water Expenditure Share

(b) Expenditure on All Other Categories

References

Xavier Basagaña, Claudio Sartini, Jose Barrera-Gómez, Payam Dadvand, Jordi Cunillera, Bart Ostro, Jordi Sunyer, and Mercedes Medina-Ramón. Heat Waves and Cause-specific Mortality at all Ages. Epidemiology, 22(6):765–772, 2011. ISSN 10443983.

David S. Battisti and Rosamond L. Naylor. Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat. Science, 323(5911):240–244, January 2009. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.1164363.

Patrick Baylis. Temperature and temperament: Evidence from a billion tweets. Energy Institute at HAAS working paper, 2015.

Marshall Burke, Solomon M. Hsiang, and Edward Miguel. Climate and Conflict. Annual Review of Economics, 7(1):577–617, August 2015. ISSN 1941-1383. doi: 10.1146/annurev-economics-080614-115430.

Jeff Goodell. Can We Survive Extreme Heat?, August 2019.

Joshua Graff Zivin and Matthew Neidell. Temperature and the Allocation of Time: Implications for Climate Change. Journal of Labor Economics, 32(1):1–26, January 2014. ISSN 0734-306X. doi: 10.1086/671766.

Shakoor Hajat and Tom Kosatky. Heat-related mortality: a review and exploration of heterogeneity. Journal of epidemiology and community health, 64(9):753, 2010.

Solomon M. Hsiang, Marshall Burke, and Edward Miguel. Quantifying the Influence of Climate on Human Conflict. Science, 341(6151):1235367, September 2013. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.1235367.

John A. List and Anya Savikhin Samek. The behavioralist as nutritionist: Leveraging behavioral economics to improve child food choice and consumption. Journal of health economics, 39: 135–146, 2015.

Georgina Oliver, Jane Wardle, and E. Leigh Gibson. Stress and Food Choice: A Laboratory Study. Psychosomatic Medicine, 62(6):853, November 2000. ISSN 0033-3174.

Joshua S. Graff Zivin, Yingquan Song, Qu Tang, and Peng Zhang. Temperature and High-Stakes Cognitive Performance: Evidence from the National College Entrance Examination in China. Working Paper 24821, National Bureau of Economic Research, July 2018.