Global Warming and Obesity: The Effect of Ambient Temperature on BMI

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Dedicated to my parents: Bina & Sunil

Abstract

Previous research has shown that ambient temperature affects human metabolism and behavior. Inspired by these findings, this study examines the effect of lagged annual temperatures in the United States on average reported BMI. The results indicate that higher temperatures in the future will lead to increases in average BMI. A conservative estimate suggests that a 1 °C increase in temperature sustained for 10 years would result in a 0.15 unit increase in average BMI and an additional $15.5 billion in annual health care expenditure.

JEL classification: Q5; Q54; I1; I10

Keywords: Climate Change; Global Warming; Obesity

I. Introduction

Empirical studies have predicted that rising temperatures due to climate change will have wide–ranging effects in the coming decades, including increased prevalence of civil wars in Africa, changes in infectious disease occurrence, and widened global income inequality (Burke, Hsiang, & Miguel, 2015; Wu, Lu, Zhou, Chen, & Xu, 2016; Burke, Miguel, Satyanath, Dykema, & Lobell, 2009). Some evidence suggests that rising temperatures may also affect average human body composition, in particular body fat percentage, because of the influence of ambient temperature on human metabolism and behavior. Obesity is among the leading causes of global morbidity and mortality, and a greater understanding of how climate change will affect its prevalence will potentially improve efforts to combat it (Abdelaal, Roux, & Docherty, 2017). The empirical strategy utilized in this study exploits the exogenous nature of annual fluctuations in air temperature to capture the causal effect of ambient temperature on body mass index (BMI). This strategy is used to test the hypothesis that, on average, higher temperatures in the United States cause increases in BMI.

The remainder of the paper is organized as follows: Section II reviews the relevant literature, Section III describes the data used, Section IV outlines the empirical methods, Section V describes the results, and Section VI includes a discussion of the results and some concluding remarks.

II. Literature Review

Several biological studies have explicitly demonstrated that human metabolism responds to changes in ambient temperature. Dauncey (1981) confined subjects to a whole-body calorimeter for periods of thirty hours at a time and found that setting the temperature to 22 degrees Celsius (°C) resulted in greater energy expenditure than a temperature of 28 °C. Over the last few decades, this finding that exposure to a mildly cold environment results in a higher metabolic rate has been replicated in controlled, experimental settings over a wide range of temperatures for subjects of varying gender, age, and body composition (Vanooijen, Vanmarkenlichtenbelt, Vansteenhoven, & Westerterp, 2004; Warwick & Busby, 1990; Westerterp-Plantenga, Lichtenbelt, Cilissen, & Top, 2002; Westerterp-Plantenga, Lichtenbelt, Strobbe, & Schrauwen, 2002; Wijers, Saris, & Lichtenbelt, 2007). Lans et al. (2013) found that cold acclimation among subjects over a period of ten days resulted in an increase in the rate of nonshivering thermogenesis, along with an increase in brown adipose tissue (BAT) activity. BAT is a thermogenic tissue, and its primary function is endogenous heat production. Yoneshiro and Saito (2014) and Hanssen et al. (2016) found similar effects of temperature on energy expenditure and BAT recruitment. These experimental findings suggest a specific biological mechanism through which mild cold exposure increases energy expenditure, namely increased BAT activity.

Thermoregulation is energetically costly, and colder temperatures require that the body generate additional heat to maintain homeostasis. Conversely, exposure to warmer temperatures mitigates the need for endogenous heat production. On average, humans must maintain a core temperature within a narrow range of 0.2 °C above and below 37 °C , and approximately two-thirds of the energy expended as part of the average human's resting metabolic rate—and 40% of all energy expenditure—is devoted to heat production (Landsberg, 2012; Lam & Ravussin, 2016). More specifically, an individual must face the cost of thermoregulation whenever the ambient temperature is outside of the thermoneutral zone (TNZ), the range of temperatures for which only minimal endogenous heat production is required to maintain a normal core temperature. For the average clothed person, the TNZ lies between 20.3 and 23 °C (Daly, 2013). Although there is evidence that energy expenditure increases after exposure to mild cold stress, this can be compensated for by people adjusting their behavior to reduce their exposure, such as wearing winter clothes or increasing their home's heating. There is also evidence that people eat more when exposed to cooler temperatures in laboratory settings (Johnson, Mavrogianni, Ucci, Vidal-Puig, & Wardle, 2011). Thus, it is possible that all of the increased energy expenditure in cooler environments due to higher rates of thermogenesis is fully compensated for, resulting in no change in the overall energy balance.

Another mechanism through which ambient temperature affects body weight is by influencing the likelihood that people spend time outdoors for recreational activities. Obradovich and Fowler (2017) found that survey respondents report declines in physical activity during unusually cold and or unusually warm weather. In particular, participation in physical activities rises until approximately 28–29 °C, beyond which participation declines. Physical activity, of course, affects body weight by playing a central role in an individual's rate of energy expenditure.

Additionally, Bhattacharya, Deleire, Haider, and Currie (2013) found that low–income families living in the United States respond to unusually cold weather by reducing spending on food, and as a result consuming fewer calories, in order to increase spending on heating. Finally, ambient temperature has been shown to have effects on other factors that may potentially influence body weight at the population level, such as the level and rate of economic productivity and rates of migration (Dell, Jones, & Olken, 2012; Cattaneo & Peri, 2015). However, while these factors may affect body composition, they most likely do so indirectly, and it is not obvious what the mechanisms or directions of the effects would be.

In terms of the overall effect of ambient temperature on body weight, Yang et al. (2015) and Valdes et al. (2014) found that people who live in warmer regions of South Korea and Spain, respectively, tend to have higher body mass indexes after controlling for various social, economic, and health indicators. Daly (2014) found that people who live with indoor temperatures above the thermoneutral zone, which he defined as above 23 °C, had lower body weights compared to those who lived in lower temperatures, suggesting that physiological cooling is also energetically costly. Voss, Webber, Scher, and Atkinson (2013) examined the correlation between mean temperature and the prevalence of obesity in the United States and found a positive correlation up to around 20 °C, after which they found a decrease in obesity rates. Scheffer et al. (2013) found no statistically significant association between indoor temperature and BMI among children between the ages of three months and 11 years. Bo et al. (2011) studied a cohort of individuals six years after an initial interview and found that people who lived with higher indoor temperatures were more likely to be obese. The current state of the literature suggests that temperature and body weight are positively associated with each other, although there are some studies that provide evidence that BMI begins to decline once the temperature exceeds approximately 20 °C. The most significant difference between the approach used in this paper and those used in the other studies described above is that this study exploits exogenous variation in annual temperatures within geographic regions, in this case U.S. states and territories. This general framework, which will be described in greater detail in Section IV, has been used in previous studies to examine how outcomes of interest are affected by temperature, including civil war in Africa, economic growth, and human mortality (Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2012; Shi et al., 2016;). The main benefit of this approach is that it does not have the same concerns of endogeneity that previous studies that have examined the relationship between temperature and BMI are subject to.

III. Data

The Behavioral Risk Factor Surveillance System (BRFSS) is a continuously conducted health survey administered by the Centers for Disease Control and Prevention (CDC) in the United States from 1984 to present. Each year, the CDC reports data regarding health conditions, behaviors related to health, and use of medical services. Respondents' heights and weights, which are reported in the survey, can be used to calculate BMI, which is strongly correlated with measures of body fat (Jelena et al., 2016; Luke et al. 1997; Ranasinghe et al., 2013). The first BRFSS survey in 1984 included respondents living in 15 states; since 1991, the number of states and territories represented has been between 48 and 54. Figure 1 below summarizes the number of respondents surveyed in the BRFSS each year. From 1984 to 2010, the CDC has used post-stratification to weight the survey data such that it is representative of the state or territory population in terms of age, race, gender, and geographic region. In 2011, they changed their methodology from post-stratification to raking, which makes comparisons between data collected before 2011 to data from after problematic. For this reason, this study uses weighted survey data from 1984 to only 2010. In addition to height and weight, race, ethnicity, age, and sex of respondents are made available by the CDC.

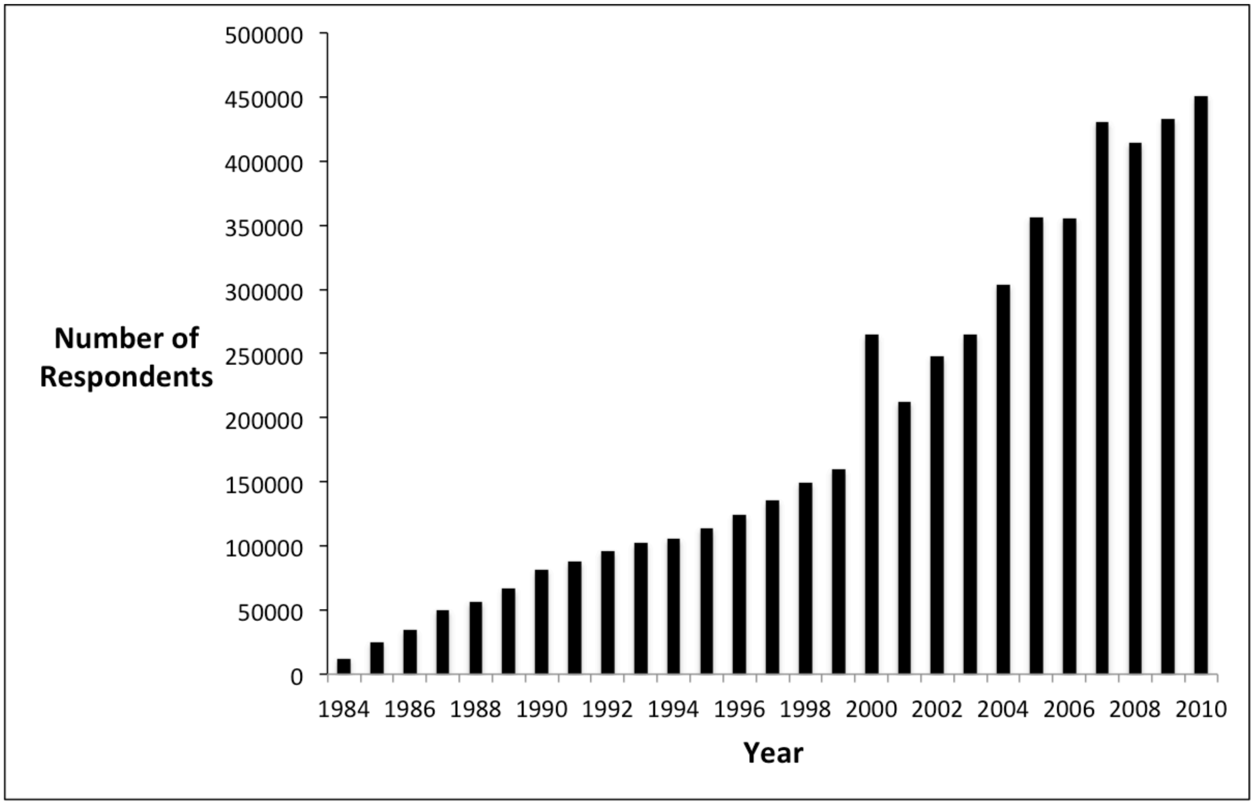

Figure 1. Number of BRFSS respondents by year, 1984-2010

Survey data were collapsed to the state-year level and merged with collapsed temperature data from the Global Historical Climatology Network-Monthly (GHCNM) temperature dataset, which contains monthly data from 1,628 weather stations in the United States. The GHCNM is compiled from 31 source datasets, and its developers account for inhomogeneity in mean temperature series caused by non-climatic factors that could bias the observed data, such as station moves and instrument changes. The developers of the dataset also remove data of low quality if there are concerns that the source dataset is unreliable or incomplete. The resulting adjusted values for monthly mean temperature were used for this study. Finally, real GDP per capita for states and territories in the United States was obtained from the U.S. Bureau of Economic Analysis.

Figure 2 depicts the mean temperature and BMI for each state and territory in 2010. The trend resembles the positive correlation between body mass index and temperature reported by Voss, Webber, Scher, and Atkinson (2013).

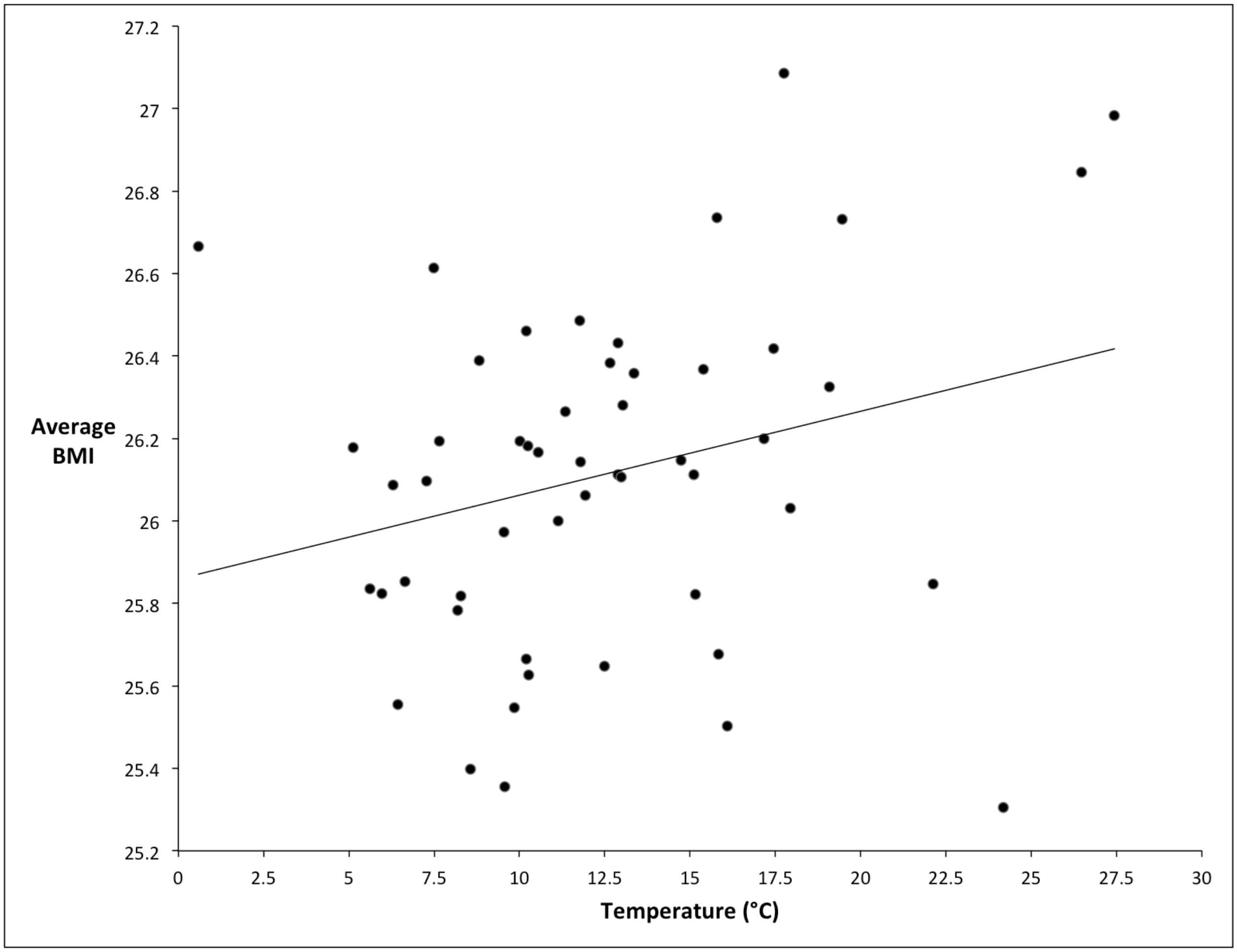

Figure 2. Body mass index and temperature by state/territory, 2010

Figure 3 depicts changes in average BMI from 1984 to 2010. The clear upward trend has been written about extensively by others (Flegal, Carroll, Kuczmarski, & Johnson, 1997; Mokdad et al., 1991; Ogden et al., 2006). Figure 4 is a histogram of temperatures in the United States from 1984 to 2010. It appears that the vast majority of temperatures fall between 5 and 20

°C, which is below the average human TNZ. This suggests that increases in temperature, both small and large, should lead to higher BMIs if changes in thermoregulation costs are a significant factor in the relationship between ambient temperature and body composition.

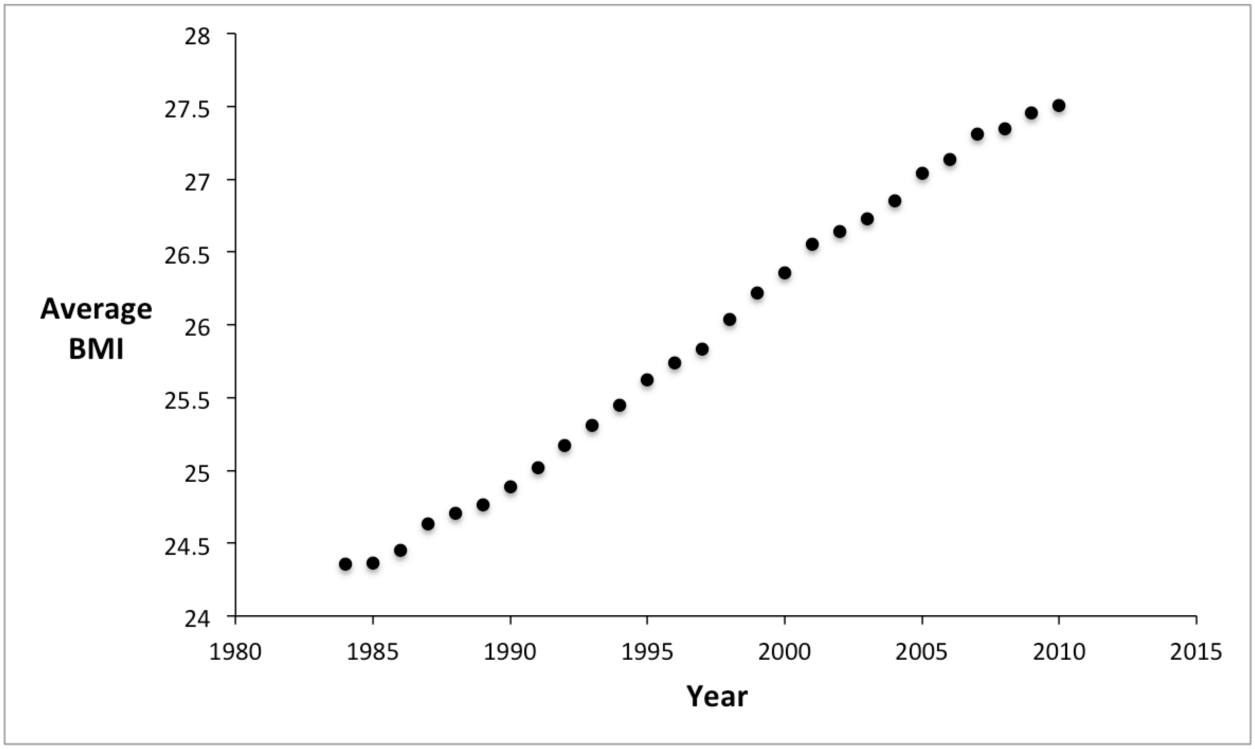

Figure 3. Average BMI in the United States, 1984-2010

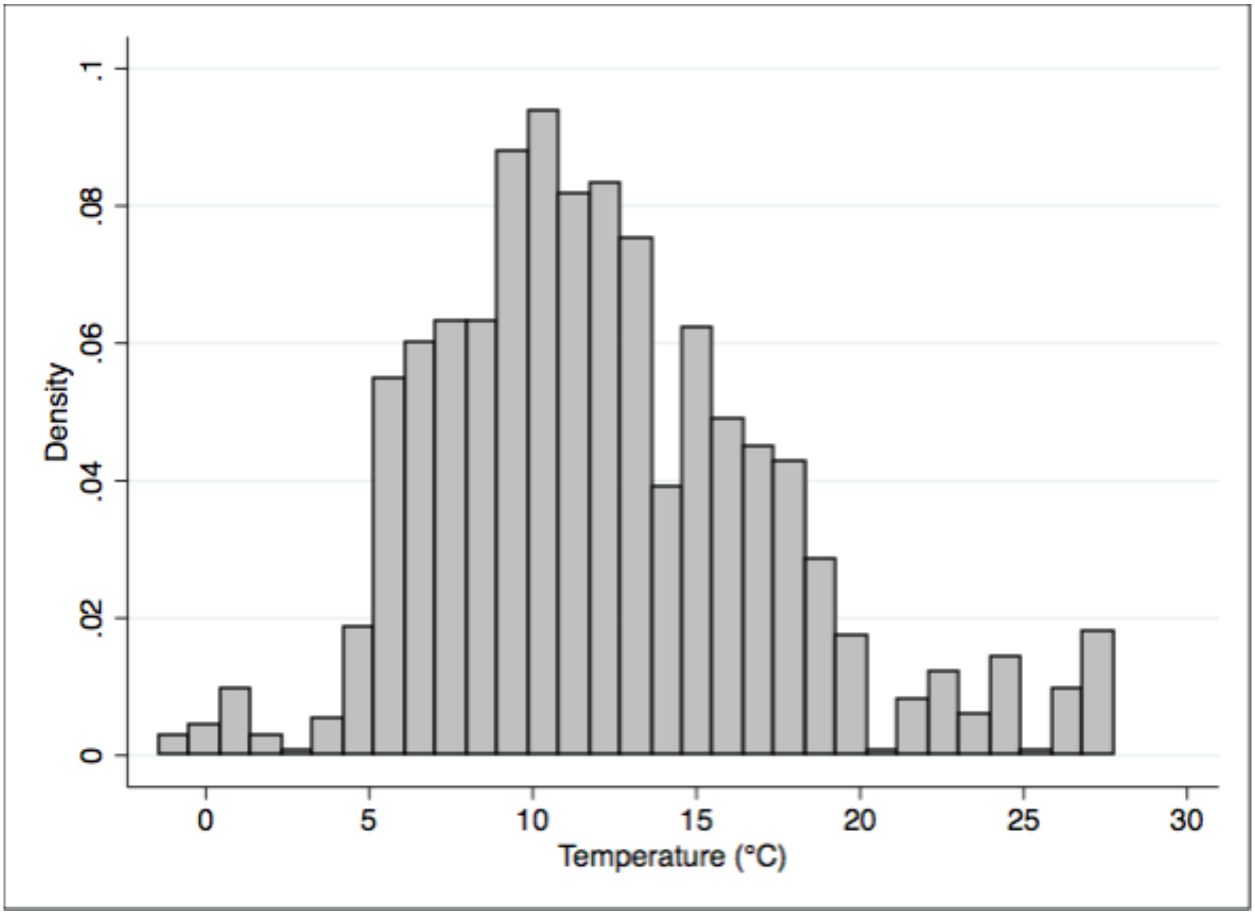

Figure 4. Frequency of annual temperatures in the United States, 1984-2010

IV. Empirical Strategy

The objective of the study is to measure the causal effect of temperature on BMI, and the empirical strategy outlined below achieves this by exploiting the fact that short-term fluctuations in temperature can be assumed to be exogenous. The baseline set of regressions are of the form

$$(1)\ BMI_{i,t} = \beta_0 + \beta_1 Temp_{i,t-x} + \beta_2 Temp^2_{i,t-x} + \beta_{3,t}\theta_t + \beta_{4,i}\theta_i + e_{it}$$

They use a lagged annual temperature variable and its square as the main explanatory variables of interest and average annual BMI as the outcome variable. θ_t and θ_i are state and year fixed effects, respectively. In (1), i refers to the state or territory and t is the year. X is an integer between 1 and 10, and it signifies the number of years the temperature is lagged by. Finally, e_{it} is the error term. Another set of regressions controls for racial and ethnic composition, sex, average

age, and GDP by adding the following variables to (1): percentage of respondents who are black, percentage of respondents who are white, percentage of respondents who are Hispanic, percentage of respondents who are male, the average respondent age, and the real GDP per capita of the state or territory. Controlling for these characteristics allows for a slight relaxation of the assumption that temperature fluctuations are exogenous and provides a robustness check.

The next set of regressions replaces lagged annual temperatures in (1) with lagged averages of temperatures over variable lengths of time. They are of the form

$$(2)\ BMI_{i,t} = \beta_0 + \beta_1 Temp_{i,t,x} + \beta_2 Temp^2_{i,t,x} + \beta_{3,t}\theta_t + \beta_{4,i}\theta_i + e_{it}$$

where x is the number of years that the temperature is averaged over and ranges from 1 to 10. Thus, when x equals 1, the temperature used is the temperature from the previous year, and when x equals 10, the temperature used is the average temperature over the last 10 years. As with lagged variables, the regressions summarized in (2) were run again after adding the control variables for demographics and GDP described above.

The last set of regressions uses temperature leads, rather than lags. They are of the form

$$(3)\ BMI_{i,t} = \beta_0 + \beta_1 Temp_{i,t+x} + \beta_2 Temp^2_{i,t+x} + \beta_{3,t}\theta_t + \beta_{4,i}\theta_i + e_{it}$$

where the temperature used is from x years in the future. X varies from 1 to 10. (3) provides a falsification test; by assumption, future temperature should not effect BMI, and if it does, this suggests a problem with the empirical framework or its execution.

V. Results

Table 1 summarizes the results from (1) as described in Section IV. Standard errors are clustered at the state level. Coefficient estimates for the temperature and temperature-squared terms are both significant at the 0.05 level for lags between 5 and 8 years and for just the temperature-squared term for 3 and 4 year lags. These results suggest that there is a robust, causal relationship between temperature and BMI. Concavity of a quadratic function is determined by the sign of the coefficient on the x^2 term. In this case, all of the coefficients for temperature-squared terms are positive, which suggests that the relationship is concave up. A concave up quadratic function has a global minimum, and the value of the temperature that minimizes BMI is reported as x_0 in Table 1. Values for x_0 were calculated by setting the first derivative with respect to temperature of functions of the form

$$BMI = \beta_1 Temp + \beta_2 Temp^2$$

equal to zero, where β_1 and β_2 are the calculated coefficients for temperature and temperature-squared, respectively. X_0 is the turning point for the concave up function that relates BMI and temperature, and thus these results suggest that deviations in temperature from x_0 in either direction result in increases in BMI.

Table 1. Effect of lagged annual temperature on BMI, 1 to 10 year lags

Dependent variable is BMI					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag
Temperature	-0.0311	-0.0171	-0.0533*	-0.0467	-0.0503**
	(0.0297)	(0.0318)	(0.0271)	(0.0293)	(0.0224)
$(\text{Temperature})^2$	0.00187	0.00121	0.00261**	0.00297**	0.00340***
	(0.00152)	(0.00136)	(0.00113)	(0.00118)	(0.000935)
x_0 (°C)	8.32	7.07	10.2	7.86	7.40
Observations	1,223	1,202	1,179	1,148	1,113
R-squared	0.967	0.965	0.964	0.963	0.963
Number of States/Territories	53	53	53	53	53
Year FE	YES	YES	YES	YES	YES

Dependent variable is BMI					
	(6)	(7)	(8)	(9)	(10)
VARIABLES	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag
Temperature	-0.0588**	-0.0608***	-0.0576***	-0.0490**	-0.0303
	(0.0222)	(0.0211)	(0.0211)	(0.0244)	(0.0278)
$(\text{Temperature})^2$	0.00298***	0.00255**	0.00286***	0.00192	0.000334
	(0.00110)	(0.000992)	(0.000996)	(0.00126)	(0.00114)
x_0 (°C)	9.87	11.9	10.1	12.8	45.4
Observations	1,075	1,031	984	935	885
R-squared	0.961	0.959	0.955	0.952	0.947
Number of States/Territories	53	53	53	53	53
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 summarizes the results from (3), which serves as a falsification test for the empirical model. The lack of statistically significant results in Table 2 suggests that the trends reported in Table 1 are not spurious but reflect a real causal relationship between ambient temperature and BMI.

Table 2. Effect of annual temperature leads on BMI, 1 to 10 year leads

Dependent variable is BMI					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Year Lead	2 Year Lead	3 Year Lead	4 Year Lead	5 Year Lead
Temperature	-0.0457**	-0.0129	-0.0210	-0.0324	0.00997
	(0.0217)	(0.0229)	(0.0225)	(0.0218)	(0.0193)
$(\text{Temperature})^2$	0.00151	0.000137	-0.000126	0.000544	-0.00135
	(0.000993)	(0.00108)	(0.00104)	(0.00111)	(0.00102)
Observations	1,185	1,132	1,079	1,026	975
R-squared	0.966	0.966	0.965	0.962	0.960
Number of States/Territories	53	53	53	52	52
Year FE	YES	YES	YES	YES	YES

Dependent variable is BMI	(6)	(7)	(8)	(9)	(10)
VARIABLES	6 Year Lead	7 Year Lead	8 Year Lead	9 Year Lead	10 Year Lead
Temperature	-0.00317	-0.0387*	-0.0215	-0.0261	-0.00250
	(0.0182)	(0.0206)	(0.0230)	(0.0172)	(0.0253)
$(\text{Temperature})^2$	-0.000632	0.000411	-0.000245	0.000180	-0.00160
	(0.00120)	(0.000940)	(0.00101)	(0.000738)	(0.00135)
Observations	923	872	821	770	719
R-squared	0.956	0.953	0.949	0.943	0.934
Number of States/Territories	52	51	51	51	51
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 3 summarizes the results from the regressions described by (2) in Section IV. Rather than lagged annual temperatures, these regressions use averages of lagged temperatures over periods of time ranging from 1 to 10 years. The results are consistent with the trends seen in Table 1. These results provide some insight into how prolonged periods of elevated temperatures due to climate change will affect BMI.

Table 3. Effect of lagged moving averages of temperature on BMI, 1 to 10 year averages

Dependent variable is BMI	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Year Average	2 Year Average	3 Year Average	4 Year Average	5 Year Average
Temperature	-0.0311	-0.0489	-0.0922	-0.133	-0.167*
	(0.0297)	(0.0487)	(0.0713)	(0.0963)	(0.0992)
$(\text{Temperature})^2$	0.00187	0.00353	0.00573*	0.00859**	0.0115**
	(0.00152)	(0.00225)	(0.00322)	(0.00427)	(0.00441)
Observations	1,223	1,199	1,172	1,139	1,102
R-squared	0.967	0.966	0.966	0.965	0.965
Number of States/Territories	53	53	53	53	53
Year FE	YES	YES	YES	YES	YES

Dependent variable is BMI	(6)	(7)	(8)	(9)	(10)
VARIABLES	6 Year Average	7 Year Average	8 Year Average	9 Year Average	10 Year Average
Temperature	-0.225**	-0.295**	-0.361***	-0.399***	-0.387**
	(0.109)	(0.121)	(0.132)	(0.139)	(0.150)
$(\text{Temperature})^2$	0.0141***	0.0179***	0.0213***	0.0227***	0.0210***
	(0.00488)	(0.00563)	(0.00632)	(0.00651)	(0.00670)
Observations	1,062	1,017	969	920	870
R-squared	0.964	0.963	0.960	0.957	0.953
Number of States/Territories	53	53	53	53	53
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, Tables 4 and 5 constitute robustness checks for the main sets of regressions described above. The regressions summarized in Table 4 are the same as those in Table 1, except for the addition of variables for racial composition, age, sex, and GDP. Similarly, Table 5 adds these control variables to the regressions in Table 3. The addition of these control variables does not significantly affect the overall trends of the results, suggesting that the assumption of temperature fluctuations being exogenous was appropriate.

Table 4. Effect of lagged annual temperature on BMI, 1 to 10 year lags (with controls)

Dependent variable is BMI					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag
Temperature	-0.0385	-0.0125	-0.0409*	-0.0293	-0.0354
	(0.0260)	(0.0309)	(0.0240)	(0.0295)	(0.0230)
$(\text{Temperature})^2$	0.00211	0.000548	0.00171	0.00210	0.00253**
	(0.00131)	(0.00135)	(0.00106)	(0.00125)	(0.00100)
x_0 (minimum)	9.12	11.4	12.0	6.98	7.00
Observations	1,165	1,165	1,166	1,133	1,096
R-squared	0.970	0.970	0.970	0.969	0.968
Number of States/Territories	51	51	51	51	51
Year FE	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES

Dependent variable is BMI					
	(6)	(7)	(8)	(9)	(10)
VARIABLES	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag
Temperature	-0.0489**	-0.0594***	-0.0632***	-0.0450*	-0.0364
	(0.0214)	(0.0196)	(0.0202)	(0.0242)	(0.0236)
$(\text{Temperature})^2$	0.00239**	0.00238**	0.00284***	0.00174	0.000964
	(0.00103)	(0.000944)	(0.00103)	(0.00124)	(0.00101)
x_0 (minimum)	10.2	12.5	11.1	13.0	18.9
Observations	1,056	1,011	963	914	864
R-squared	0.967	0.965	0.963	0.960	0.957
Number of States/Territories	51	51	51	51	51
Year FE	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Effect of lagged moving averages of temperature on BMI, 1 to 10 year averages (with controls)

Dependent variable is BMI	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Year Average	2 Year Average	3 Year Average	4 Year Average	5 Year Average
Temperature	-0.0385	-0.0442	-0.0840	-0.111	-0.137
	(0.0260)	(0.0450)	(0.0650)	(0.0887)	(0.0952)
$(\text{Temperature})^2$	0.00211	0.00250	0.00431	0.00628	0.00851**
	(0.00131)	(0.00209)	(0.00297)	(0.00397)	(0.00420)
Observations	1,165	1,164	1,164	1,131	1,094
R-squared	0.970	0.970	0.970	0.969	0.969
Number of States/Territories	51	51	51	51	51
Year FE	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES

Dependent variable is BMI	(6)	(7)	(8)	(9)	(10)
VARIABLES	1 Year Average	7 Year Average	8 Year Average	9 Year Average	10 Year Average
Temperature	-0.190*	-0.268**	-0.353***	-0.387***	-0.388***
	(0.108)	(0.115)	(0.117)	(0.121)	(0.132)
$(\text{Temperature})^2$	0.0108**	0.0147***	0.0186***	0.0198***	0.0189***
	(0.00475)	(0.00517)	(0.00531)	(0.00536)	(0.00568)
Observations	1,054	1,009	961	912	862
R-squared	0.968	0.967	0.965	0.963	0.959
Number of States/Territories	51	51	51	51	51
Year FE	YES	YES	YES	YES	YES
Demographic Controls	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VI. Discussion

Figure 5 depicts functions of the form

$$BMI = \beta_1 Temp + \beta_2 Temp^2$$

where β_1 and β_2 are the reported coefficients for temperature and temperature-squared, respectively, in Table 1. The four curves correspond to the four regressions that had statistically significant coefficients at the 0.05 level for both temperature and temperature-squared. A constant was added to each function in order to make the value of BMI equal 0 when temperature equals x_0.

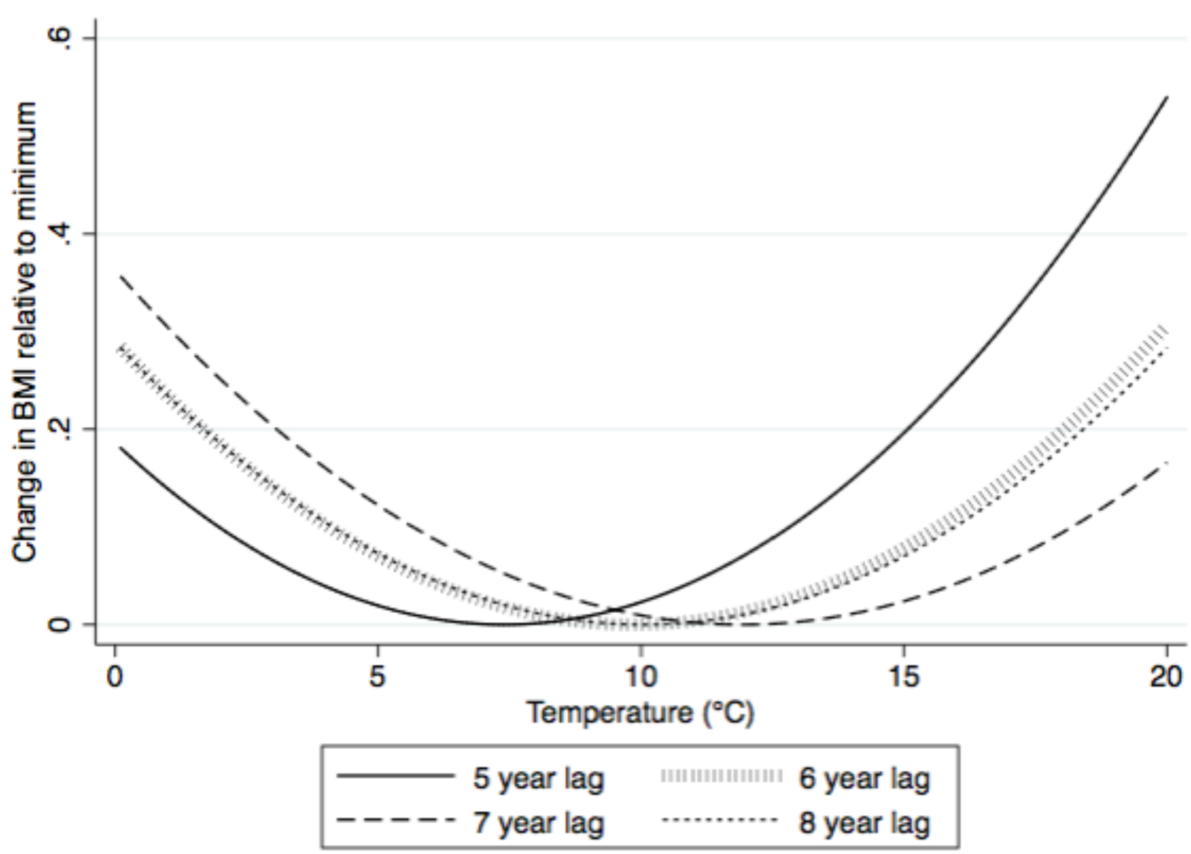

Figure 5. Predicted changes in BMI due to changes in temperature

The shapes of these curves provide some insight into what mechanisms may be involved in the relationship between temperature and BMI. If the main mechanism through which temperature affects BMI were the fact that thermoregulation costs vary depending on ambient temperature, one would expect the relationship to be concave down. We would expect for BMI to be maximized around a narrow range of temperatures corresponding to the TNZ and for deviations in temperature in either direction to result in higher BMIs. An opposite relationship is suggested by these findings, since the predicted curves are concave up. This is more consistent with a behavioral mechanism, such as the one described by Obradovich and Fowler (2017). If, as Obradovich and Fowler (2017) suggest, there is a range of temperatures in which people are most likely to spend time outside doing physical or recreational activities, and deviations in temperature in either direction result in decreases in outside activity, this would suggest that the opposite is true for BMI—that is, BMI is minimized at a range of temperatures and deviations in either direction result in higher BMIs.

The lagged nature of the relationship between temperature and BMI also supports a behavioral mechanism. For example, suppose that higher temperatures on average result in people spending less time outside. First, it is possible that these changes in behavior are lasting if people's behavior is habit-forming. Thus, even if the fluctuation in temperature were temporary, there could be effects on behavior, and thus BMI, several years into the future. The effect on BMI may not be apparent until several years in the future because small changes in behavior lead to small changes in BMI, and enough time must pass with the behavioral change in place in order to have any noticeable effect. Second, there might be network effects involved if an individual is more likely to exhibit a behavior if the people around them exhibit the behavior. For example, people may spend more or less time outside depending on how the people they interact with spend their time. If this is the case, then one would expect changes in behavior to diffuse among the population gradually over time even after the initial temperature fluctuation. While these results are suggestive of a behavioral mechanism, it is difficult to say with any confidence what the actual underlying mechanism is. Moreover, Obradovich and Fowler (2017) found that physical recreation does not begin to decrease until temperatures reach 28–29 °C. In contrast, this study's findings suggest that the turning point lies significantly below this level, as seen by the reported values of x_o in Table 1. Thus, while these findings are potentially consistent with a general behavioral mechanism, they do not align with either of the two major mechanisms proposed initially. Further research is needed to better understand the underlying mechanisms.

While it is unclear precisely through which mechanism temperature affects BMI based on the results of this study, it is possible to interpret the direction and magnitude of the overall effect in the context of rising temperatures due to climate change. The results suggest that higher temperatures in the future will lead to, on average, higher BMIs in the United States. The temperatures that minimize the estimated quadratic functions that are reported as x_o in Table 1 range from 7.4 to 11.9 °C for regressions that had statistically significant coefficients at the 0.05 level for both temperature and temperature-squared. Since these quadratic functions are concave up, they predict that, in response to a uniform rise in temperatures, any person whose baseline average temperature is below x_o is expected to lose weight, and anyone whose baseline temperature is above x_o will gain weight. The average annual temperature in the United States from 1984 to 2010 was 12.2 °C, which suggests that more people would gain weight than lose weight in response to a rise in average temperature.

The results summarized in Table 3 also give some insight on the predicted magnitude of change in BMI in the United States due to sustained rises in temperature because of global warming. For example, using the results from regression 6 in Table 3, an increase of 1 °C would result in an increase in average BMI of $[\beta_1(T+1) + \beta_2(T+1)^2] - [\beta_1 T + \beta_2 T^2]$, where β_1 and β_2 are the reported coefficients for temperature and temperature-squared, respectively, and T is the average national temperature. Evaluating this expression for the appropriate values (β_1 = -0.225, β_2 = 0.0141, and T = 12.2), results in a predicted change in BMI of 0.13 units. Using coefficients from regressions 7, 8, 9 and 10 in Table 3 results in estimated changes in BMI of 0.16, 0.18, 0.19, and 0.15, respectively, for every 1 °C increase in temperature. Wang et al. (2006) demonstrated that a one unit increase in BMI is associated with a 4% increase in medical costs and a 7% increase in pharmaceutical costs, while Raebel et al. (2004) found a 2.3% increase in medical spending. For the purposes of rough calculation, one can assume that a unit increase in BMI results in a 3.15% increase in medical spending, the average of the two estimates. Assuming that a sustained increase of 1 °C over ten years would result in an increase in BMI of 0.15 units, as predicted by regression 10 in Table 3, this implies a 0.47% increase in medical spending. According to the Centers for Medicare and Medicaid Services, total U.S. health care expenditure was $3.3 trillion in 2016, and thus a 0.47% increase would be equal to an annual cost of $15.5 billion. This analysis does not take into account the fact that health care costs are rising over time, making it an extremely conservative estimate. Based on a probability forecast of carbon dioxide emissions and temperature change, Raftery, Zimmer, Frierson, Startz, and Liu (2017) found that the likely range of the increase in average global temperature by the year 2100 is 2.0–4.9 °C. Thus, even a conservative estimate of the temperature effects of climate change suggests an increase in annual health care spending of several tens of billions of dollars due to increases in BMI. The purpose of this calculation is not to provide a precise estimate, but rather to demonstrate that, based on the results of this study, the costs of rising obesity due to global warming will not be negligible and should be taken into account when assessing the effects of climate change and what policies should be enacted in response.

Additional research is needed to further elucidate the relationship between ambient temperature and BMI. As noted above, while these results provide some insight on the direction and magnitude of the effect of temperature on BMI, one can only speculate on what the underlying mechanisms are. Additionally, it is likely that the effects vary depending on an individual's baseline BMI or other characteristics, as well as other weather changes that may accompany climate change. This also warrants further research. One potential methodology that would be appropriate for future research is the use of a distributed lag model to jointly test the effect of past and current temperatures on current BMI, rather than one lagged temperature at a time. Finally, this empirical model can be applied to study other health outcomes of interest. For example, Table 6 summarizes the results of a regression that tests the effect of annual temperature and annual temperature-squared on a measure of mental health. The results of regression 1 indicate that higher temperatures lead to reports of worse mental health, and these results appear to be robust to the addition of control variables for race, age, sex, and GDP. Additional research is required to better understand this relationship, as well as other ways in which global warming will affect human health.

Table 6. Effect of annual temperature on days of poor mental health per month

Dependent variable is mental health VARIABLES	(1) Average Annual Temperature	(2) With Demographic Controls
Temperature	-0.103**	-0.139***
	(0.0410)	(0.0452)
$(\text{Temperature})^2$	0.00518**	0.00695***
	(0.00240)	(0.00253)
Observations	842	834
R-squared	0.286	0.319
Number of States/Territories	53	51
Year FE	YES	YES
Demographic Controls	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VII. References

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