Title: **Increasing Ambient Temperature Reduces Emotional Well-Being**

Authors: Clemens Noelke[a,1], Mark McGovern[b], Daniel Corsi[c], Marcia P. Jimenez[d], Ari Stern[e], Ian Sue Wing[e], Lisa Berkman[f]

Affiliations: [a]Heller School for Social Policy and Management, Brandeis University, Waltham, MA 02453, USA; [b]Queen's Management School, Queen's University, Belfast, BT9 5EE, United Kingdom; [c]Clinical Epidemiology Program, Ottawa Hospital Research Institute, 725 Parkdale Avenue, Ottawa ON K1Y 4E9, Canada; [d]School of Public Health, Brown University, 121 South Main Street, Providence, RI 02912, USA; [d]Department of Earth and Environment, Boston University, 675 Commonwealth Avenue, Boston, MA 02215, USA; [f]Center for Population and Development Studies, Harvard University, 9 Bow Street, Cambridge, MA 02138, USA

[1]**Corresponding Author:** Clemens Noelke, Institute for Child, Youth and Family Policy at the Heller School for Social Policy and Management, Brandeis University, Waltham, MA 02453, USA. Tel.: +1-781-736-8748. Email: cnoelke@brandeis.edu.

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INCREASING AMBIENT TEMPERATURE REDUCES EMOTIONAL WELL-BEING

Abstract

This study examines the impact of ambient temperature on emotional well-being in the U.S. population aged 18+. The U.S. is an interesting test case because of its resources, technology and variation in climate across different areas, which also allows us to examine whether adaptation to different climates could weaken or even eliminate the impact of heat on well-being. Using survey responses from 1.9 million Americans over the period from 2008 to 2013, we estimate the effect of temperature on well-being from exogenous day-to-day temperature variation within respondents' area of residence and test whether this effect varies across areas with different climates. We find that increasing temperatures significantly reduce well-being. Compared to average daily temperatures in the 50 to 60°F (10 to 16°C) range, temperatures above 70°F (21°C) reduce positive emotions (e.g. joy, happiness), increase negative emotions (e.g. stress, anger), and increase fatigue (feeling tired, low energy). These effects are particularly strong among less educated and older Americans. However, there is no consistent evidence that heat effects on well-being differ across areas with mild and hot summers, suggesting limited variation in heat adaptation.

Introduction

While the empirical link between heat exposure and mortality rates is well-established (Curriero et al., 2002; Deschênes & Greenstone, 2011; Gasparrini et al., 2015; Kovats & Hajat, 2008), little is known about the effect of heat exposure on mental health. Previous studies have focused on suicide mortality and indicate that heat exposure is associated with increased suicide rates (Basagaña et al., 2011; Kim et al., 2016; Maes, De Meyer, Thompson, Peeters, & Cosyns, 1994; Page, Hajat, & Kovats, 2007; Qi, Hu, Page, & Tong, 2015). One study has found an impact of heat exposure on hospital admissions for mental and behavioral disorders (Hansen et al., 2008). Related research in psychology and economics has suggested that heat exposure reduces emotional wellbeing (Keller et al., 2005), increases interpersonal aggression (Anderson & Anderson, 1998; Anderson & Bushman, 2002) and diminishes life satisfaction (Connolly, 2013; Denissen, Butalid, Penke, & van Aken, 2008; Lucas & Lawless, 2013; Schwarz & Clore, 1983). Together, these findings indicate that heat exposure may adversely impact mental health and that global climate change, by increasing exposure to extreme heat, could similarly have negative consequences for mental health (Berry, Bowen, & Kjellstrom, 2010).

In this study, we use survey data on 1.9 million Americans to examine the impact of ambient temperatures on emotional well-being. Our main goal is to provide evidence of a psychological link between heat exposure and emotional well-being, which could contribute to the impact of heat on mental health. Furthermore, while previous research focused on hospital admissions and suicide mortality, we obtain an estimate of the sub-clinical impact of ambient temperatures on individual's emotional well-being and quality of life in the U.S. population.

Finally, we explore empirically whether adaptation to hotter climates could potentially mitigate the effect of heat exposure on emotional well-being.

Direct exposure to ambient heat likely affects emotional well-being by causing heat stress and exhaustion (Kovats & Hajat, 2008), which is experienced as intrinsically unpleasant (Frederick & Loewenstein, 1999). Heat exposure may also alter mental states through thermo-sensitive physiological processes (Leon & Bouchama, 2015; Page et al., 2007). Emotional well-being may diminish because individuals are forced to stay indoors for extended periods, have to alter their daily schedules and face increased cooling expenditures, e.g., due to running air conditioners (Deschênes, 2012). Our outcome measure therefore captures potential well-being losses due to direct heat exposure and opportunity costs caused by heat avoidance.

Our data allow us to explore whether adaptation to heat exposure could lower the adverse effect of heat on emotional well-being. The U.S. represents a good test-case because of its diverse climate conditions, mobile population and available technology. Local climate conditions are a robust predictor of where in the U.S. Americans chose to live (Albouy, Graf, Kellogg, & Wolff, 2013). At least some Americans chose to live in areas with local climate conditions that optimally fit their preferences, e.g., areas with neither very cold winters nor extremely hot summers. Climate-driven migration therefore represents one mechanism of adaptation (Albouy et al., 2013; Deschênes & Moretti, 2009). Second, heating and cooling technologies like air conditioners are widely available (Barreca, Clay, Deschênes, Greenstone, & Shapiro, Forthcoming) so that individuals can avoid exposure to hazardous temperatures and can adjust indoor climates to subjectively optimal levels.

Residential mobility and technology therefore allow individuals to move to and adapt to local climates. While these conditions exist in other developed countries too, the U.S. is a good test case because climate conditions vary more across regions, which provides useful identifying variation while keeping many other factors, e.g. available technology, constant. We exploit this identifying variation to test whether adaptation to local climates could perhaps mitigate or even eliminate any impact of ambient temperature on emotional well-being.

Finally, the issue of adaptation is relevant to understanding the future impact of global warming on well-being. If further adaptation occurs, the future impact of increased heat exposure due to global climate change may not result in a net well-being loss. Conversely, if we find that heat lowers well-being by the same amount across areas with mild and hot summers, this could be interpreted as evidence that adaptive potentials have been exhausted and that there is little room for further heat adaptation. In this case, it is more likely that the future impact of increased heat exposure will result in a net well-being loss.

Materials and Methods

We used the Gallup G1K dataset, which is based on telephone surveys of a random sample of 1,000 Americans that is conducted on 350 days per year. Our observation period covers the years 2008 to 2013. Our analysis included all measures explicitly referencing emotional well-being on the day prior to the day of interview. Specifically, respondents were asked "Did you experience the following feelings a lot of the day yesterday?" before interviewers went through the following list: enjoyment, worry, sadness, stress, anger, and happiness. We also included the following additional questions: "Did you smile or laugh a lot yesterday?”, “Did you have enough energy to get things done yesterday?”, “Were you treated with respect all day yesterday?”, and “Did you feel well-rested yesterday?”. For each item, respondents could chose to answer “yes”, “no”, “don’t know”, or refuse to answer. Individuals in the last two response categories were dropped, reducing sample size by 4%, which resulted in a final sample of 1,854,746 individuals. The items included in the analyses were originally developed to capture hedonic well-being (Kahneman & Krueger, 2006), but are very similar to items used in common epidemiologic self-report mental health scales (see Appendix, p. 7., for further details).

We recoded the well-being measures into binary variables that took the value 1 for “yes” responses indicating the presence of positive feelings or the value 0 for “no” responses indicating the presence of negative feelings, i.e. the value 1 indicates reports of positive or absence of negative feelings. We performed principal component analysis on all ten items. The first component explained 53% of the total variation. Predicted scores of this component form our aggregate index of emotional well-being. After oblique rotation, we obtained three distinct components that jointly explained 74% of the total variation, and which we labeled positive emotions (happiness, enjoyment, smiling/laughter), negative emotions (anger, stress, worry, sadness, not treated with respect), and fatigue (well-rested, enough energy). The predicted scores for these components were also analyzed as dependent variables. All indices are standardized (mean = 0, standard deviation = 1). Further details on the index construction and results from principal components analysis are available in the Appendix (p. 4).

We linked the G1K survey to temperature data using information on the day of interview and respondents' self-reported zip codes. Respondents' zip codes were linked to Zip Code Tabulation Areas (ZCTAs) and, in combination with data on interview dates, matched to 24-hour average daily temperature records from the North American Land Data Assimilation System (NLDAS-2) forcing files, which provide hourly estimates of air temperature (K) 2 meters above ground level on a 0.125 x 0.125 degree grid. Air temperature is the main predictor of interest; total hourly precipitation and relative humidity (calculated from temperature, pressure and specific humidity) were included as control variables for robustness checks. For each respondent in our sample, we calculated the daily 24-hour average values of these variables at the centroid of the ZCTA. Our main exposure variable is 24-hour average temperature in respondents' ZCTA of residence on the day prior to the day of interview, which is the day to which outcome measurements refer.

To model the relationship between temperature and well-being, we used ordinary least squares (OLS) regression with sampling weights provided by Gallup and standard errors adjusted for clustering of respondents within ZCTAs. Because individuals residing in different areas differ in ways that are likely to be correlated with well-being and local temperatures, we control for area of residence fixed effects.(Burke, Hsiang, & Miguel, 2015) To reduce computation time, rather than controlling for >32,000 ZCTA fixed effects, we control for commuting zone fixed effects in our baseline specification. Specification checks (see Appendix, p. 16) show that this restriction does not affect temperature estimates. Using information on the county of residence, we identify individual commuting zones, which are similar to Metropolitan Statistical Areas defined by the U.S. Census Bureau, but include rural counties, too. We observe 691 commuting zones. The resulting estimates are immune to biases resulting from unmeasured time-constant determinants of well-being shared by individuals residing in the same commuting zone. Furthermore, seasonal factors, e.g. variation in sunlight exposure(Buscha, Forthcoming), are correlated with well-being and temperature and therefore flexibly controlled for. The modeling approach closely follows recent contributions in climate economics (Burke et al., 2015; Deschênes & Greenstone, 2011).

Specifically, we estimate variants of the following model, where we use subscripts i to denote individuals, j to denote commuting zones ($j = 1, \dots, 691$), m to denote survey months ($m = 1, \dots, 12$), s to denote contiguous US states ($s = 1, \dots, 48$), c to denote calendar weeks ($c = 1, \dots, 312$) and y to denote calendar years ($y = 2008, \dots, 2013$):

$$Y_{ijmscy} = \alpha_{jm} + \sum_{k=1}^{7} \beta_k T_k + \lambda_{sy} + \mu_c + X\gamma + \varepsilon_{ijmscy}$$

The continuous temperature variable is split into a categorical variable with eight bins, denoted T_k, with seven temperature coefficients β_k to be estimated. For β_k to have a causal interpretation, we assume that the correlation between temperature dummies and the idiosyncratic error term ε is zero conditional on the other covariates, i.e., within ZCTAs, day-to-day variation of temperatures is uncorrelated with unmeasured determinants of well-being.

To make this assumption more plausible, we flexibly control for both location of residence and season fixed effects by including α_{jm} commuting zone by month fixed effects, i.e.

one fixed effect per commuting zone and survey month. Our baseline model also adjusts for λ_{sy} state by calendar year fixed effects to capture unobserved state- and year-specific well-being shocks, e.g., caused by the recession unfolding during the observation period, which could induce a spurious correlation between temperature and well-being. Furthermore, we adjust for μ_c calendar week fixed effects, i.e. one fixed effect per year and calendar week, to adjust for common year- and week-specific events that could affect well-being across the US, such as holidays or election outcomes, and be correlated with temperature. Finally, X is a matrix of additional covariates. In the baseline model, X only includes weekday fixed effects. For specification checks reported in the Appendix (p. 16), we add socio-demographic and climate control variables. We show that our results are consistent across multiple specifications, which suggests that the day-to-day temperature variation within respondent's areas of residence is as good as randomly assigned.

Our baseline model does not impose a particular functional form on the temperature effect. In the Appendix, we report results from analyses using temperature polynomial functions. None of our conclusions was substantially affected by functional form issues, and we discuss the main issues behind different modeling approaches in the Appendix (p. 23). We also explored whether lagged or future temperature values affect well-being after temperature on the day of interview is conditioned on, but found no evidence that this is the case (Appendix, p. 11).

To test for heat adaptation, we compared the well-being temperature response functions across U.S. regions defined by summer climate. For each ZCTA, we calculated the average summer temperature (June, July, August) during the five years preceding the year of interview.

We then generated an indicator variable classifying each respondent as living in an area with above median or below median summer time temperatures. We added this indicator variable to the baseline model and also added interactions between this indicator and all other variables in the baseline model.

Our null hypothesis is that the temperature well-being response function is constant across different climate regions. In turn, we interpret significant differences in the response function as evidence supporting adaptation, specifically if we find a significantly weaker effect of heat on well-being among individuals living in areas with typically hot compared to mild summers. This testing approach faces the challenge that average summer temperature and heat exposure are positively correlated. We observe much fewer extreme heat exposures in areas with mild compared to areas with hot summers (Appendix Table A10). Our tests therefore have less statistical power in the tails of the temperature distribution compared to the center. Similarly, it becomes more difficult to identify the correct functional form of the temperature effect in the tails of the temperature distribution. The Appendix (p. 23) discusses these analyses further, explores issues of statistical power, functional form and reports results from additional tests. However, the additional evidence is consistent with the evidence and conclusions drawn here.

Results

Figure 1A shows OLS estimates from our baseline model of the effect of exposure to temperatures within 10°F intervals on the aggregate index of emotional well-being. The response function shows the estimated change in well-being due to a day spent in a given temperature interval relative to a day spent in the reference interval of 50 to 60°F (10 to 16°C). While temperatures from 20 to 70°F (-7 to 21°C) have no effect, exposure to one day averaging 70-80°F (21 to 27°C) reduces well-being by 1.6% of a standard deviation ($p<0.01$). Days above 90°F (32°C) reduce well-being by 4.4% of a standard deviation ($p<0.01$). Very cold days (less than 20°F or -7°C) are associated with a 3.1% of a standard deviation well-being increase ($p<0.01$). These results are robust to the inclusion of an extensive set of demographic, socio-economic, and health control variables, ZCTA fixed effects, and controls for relative humidity and precipitation (Appendix, p. 16).

We observe significant reductions in well-being during hot temperatures for all three sub-components of well-being (Figure 1, B-D). Positive emotions (Figure 1, C) exhibit the least consistent temperature response: heat effects are no longer statistically significant after adjusting for all potential confounders (Appendix, p. 16), while moderately cold (20 to 40°F), but not very cold (<20°F) days are associated with slight reductions in well-being. Negative emotions (Figure 1, D) and fatigue (Figure 1, B) respond in a similar way as aggregate emotional well-being. The fatigue component shows the strongest association with temperature.

To test if temperature effects on emotional well-being vary across different sub-populations, we added group indicator variables to the baseline regression model and interacted the group indicator with the temperature indicator variables. Joint *F*-tests on the interaction terms indicate that age ($p<0.001$) and education ($p<0.001$) are significant moderators, but yield no evidence of effect moderation by gender ($p=0.89$). While temperature effects on 18-45 year-olds are small and fail to reach statistical significance at conventional levels (Figure 2, A), we observe well-being enhancing effects of very cold temperatures and more sizeable negative effects of moderately hot and very hot days among individuals aged 46+ (Figure 2, B). Education is also an important moderator. Less educated individuals are more sensitive to temperature variation, experiencing larger decreases (increases) in well-being at high (low) temperatures (Figure 2, C). Heat effects do not reach statistical significance for individuals with more than a high school degree (Figure 2, D).

To put these effect sizes in perspective, we computed unadjusted well-being gaps by gender and education. Compared to men, women's levels of well-being are 11% of a standard deviation lower ($p<0.001$), which is consistent with gender gaps in morbidity (Case & Paxson, 2005) and life satisfaction (Stevenson & Wolfers, 2009). Reflecting enduring socio-economic differentials in health and well-being (Mirowsky & Ross, 2003), levels of well-being are 7% (11%) higher among individuals with a bachelor (graduate) degree compared to individuals with a high school degree. This suggests that the estimated magnitude of the transitory reduction in well-being during very hot days is substantial, particularly among older and less educated Americans.

Figure 3 displays the marginal effects of exposure to temperatures in a given interval relative to the reference interval of 50-60°F (10 to 16°C) for areas with mild and hot summers. We display 95% confidence intervals as grey areas for mild summer areas, and as dashed lines for hot summer areas. Consistent with adaptation to heat in hot summer areas, the effect of temperatures in the 80-90°F range on well-being is weaker in areas with hot vs. mild summers ($p<0.05$). However, the effects of exposure to temperatures above 90°F are nearly identical across areas, as are the effects of other temperature exposures. A joint F-test on the interaction terms between climate area and temperature suggest that observed differences in temperature responses across areas are not statistically significant (p-value = 0.26).

Discussion

Our results indicate that ambient temperatures in excess of 70°F, and especially above 90°F, significantly reduce emotional well-being. The magnitude of these effects appears meaningful when compared to well-being gaps between genders and education groups. We found no consistent evidence suggesting that individuals living in areas with mild and hot summers respond differently to heat exposure, suggesting a limited role for heat adaptation to mitigate the impact of heat on well-being in the contemporary U.S.

Heat-related well-being losses are likely generated in part by direct heat exposure through thermo-sensitive physiological mechanisms resulting in sleep disturbance, exhaustion, and heat stress (Kovats & Hajat, 2008). These may trigger fatigue, or alter mental states resulting in reduced emotional well-being (Keller et al., 2005) or increased aggression (Anderson & Bushman, 2002; Hsiang, Burke, & Miguel, 2013; Ranson, 2014). Furthermore, by potentially diverting time and money away from activities and investments that increase well-being, defensive investments (e.g., air conditioning) and avoidance behavior (e.g. substituting indoor activities for time spent outside) may also reduce well-being (Deschênes & Greenstone, 2011; Zivin & Neidell, 2014).

Our results support the existence of a psychological link between heat exposure and mental health that could be a contributing factor behind the association between heat exposure and suicide mortality (Kim et al., 2016; Maes et al., 1994; Page et al., 2007; Qi et al., 2015). Furthermore, our results are consistent with and provide evidence of mechanisms mediating the effect of temperature on economic activity and interpersonal aggression. U.S. studies have found that county-level income and hours worked in occupations with high weather exposure decrease with increasing temperatures (Deryugina & Hsiang, 2014; Zivin & Neidell, 2014). We show that heat exposure increases reports of fatigue, suggesting that heat may lower economic output by reducing productivity (Heal & Park, 2013). Furthermore, we find that heat exposure increases negative emotions, e.g. feelings of anger, which could contribute to the observed association between heat and interpersonal aggression (Anderson & Bushman, 2002; Hsiang & Burke, 2013; Hsiang et al., 2013).

Our results also indicate that relative to temperatures in the 50 to 60°F range, very cold temperatures reduce both negative emotions and fatigue. Low temperatures may reduce negative emotions by reducing aggressive feelings and arousal(Anderson & Bushman, 2002), which is consistent with research indicating a lower incidence of violent crime at cold temperatures (Ranson, 2014). Cold, especially unusually cold days relative to seasonal norms, may also be perceived as invigorating (Anderson & Anderson, 1998). This “bracing cold” effect might explain the fatigue-reducing impact of very cold days.

Future research should clarify the mechanisms that put less educated and older Americans at risk, which would facilitate the implementation of polices to protect those most vulnerable to heat exposure. At present, there are several candidate explanations for these disparities, such as pre-existing health conditions (older and less educated Americans; Mirowsky

& Ross, 2003), greater exposure to heat due to lack of adequate air conditioning (less educated), and increased probability of working outdoors (less educated; Zivin & Neidell 2014). With the share of older Americans in the overall population and economic inequalities on the rise, it is important to better understand how these processes are intertwined with exposure risks and vulnerability to climate change.

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FIGURES

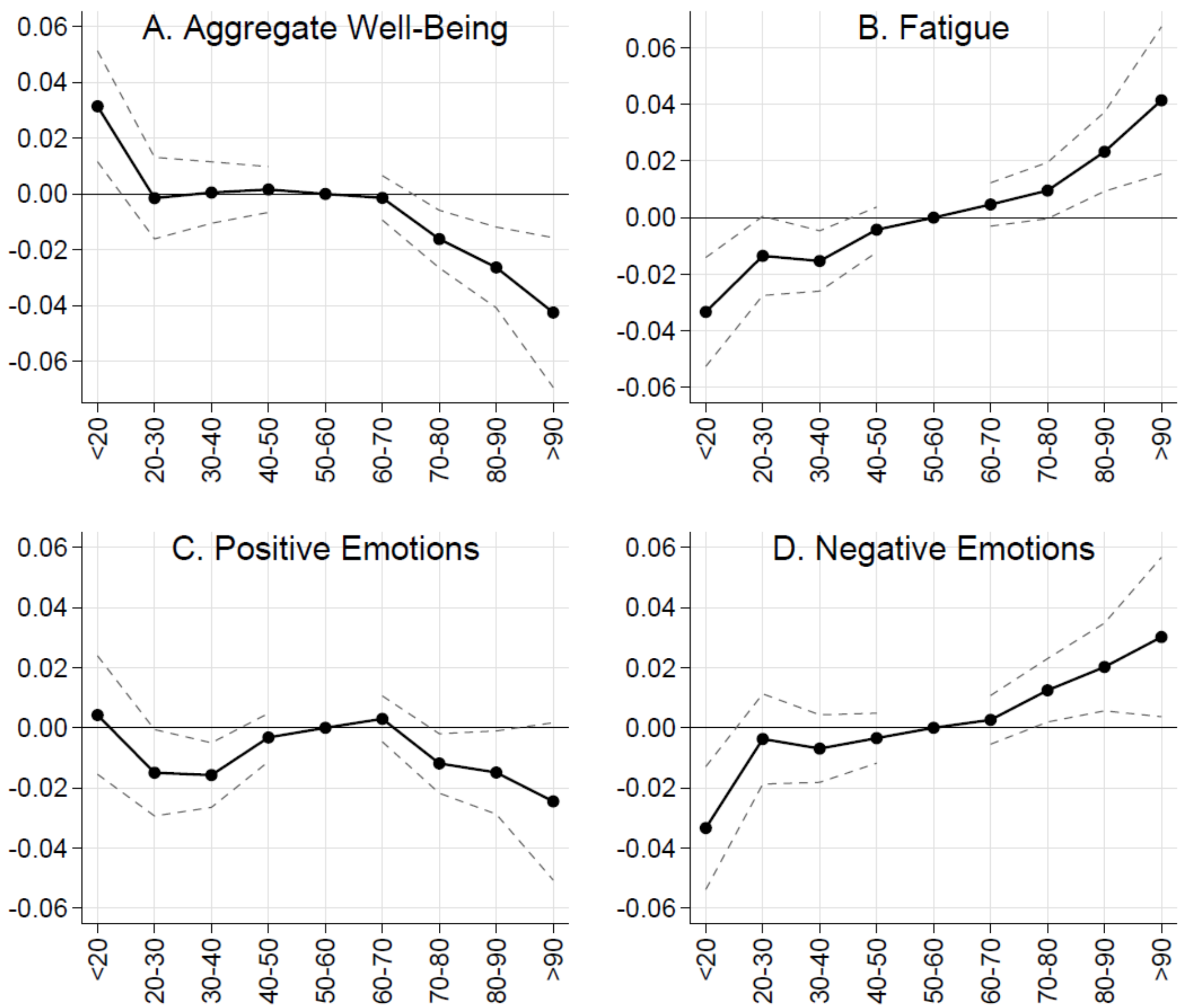


Figure 1. The effect of temperature exposure (°F) on emotional well-being on the day prior to the respondent's interview. Panel **A** shows the temperature response of the aggregate well-being index. Panels **B**-**D** show results for its components: fatigue (**B**), positive emotions (**C**), and negative emotions (**D**). To facilitate interpretation, we reversed the response scale for fatigue (**B**) and negative emotions (**D**) so that a positive temperature effect indicates increased fatigue or reports of negative emotions. Well-being measures (y-axes) are standardized with mean zero and standard deviation one. Temperature exposure (x-axes) is measured as the 24-hour average daily temperature on the day prior to the respondent's interview in their zip code tabulation area (ZCTA). Each panel shows the estimated effect (with 95% confidence intervals, dashed lines) of being exposed to temperatures in a given interval relative to the reference interval of 50 to 60°F.

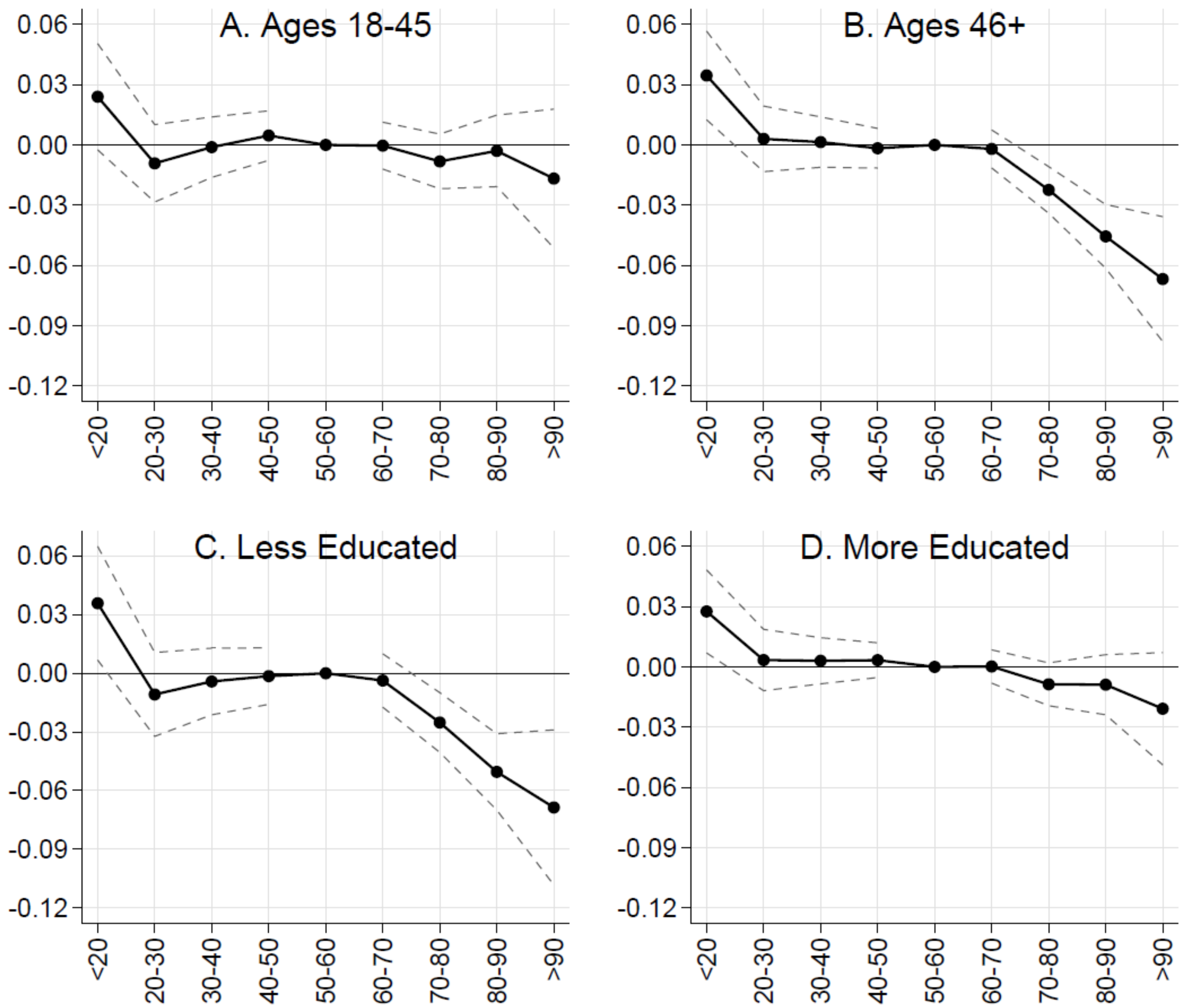


Figure 2. The effect of temperature exposure (°F) on emotional well-being on the day prior to the respondent's interview, stratified by younger (ages 18-45, Panel **A**), older (ages 46+, Panel **B**), less educated (max. high school degree, Panel **C**) and more educated (more than a high school degree, Panel **D**) populations. The well-being index (y-axis) is standardized with mean zero and standard deviation one. Temperature exposure (x-axis) is measured as the 24-hour average daily temperature on the day before the respondent's interview in their zip code tabulation area (ZCTA). Each panel shows the estimated effect (with 95% confidence intervals) of being exposed to temperatures in a given interval relative to the reference interval of 50 to 60°F.

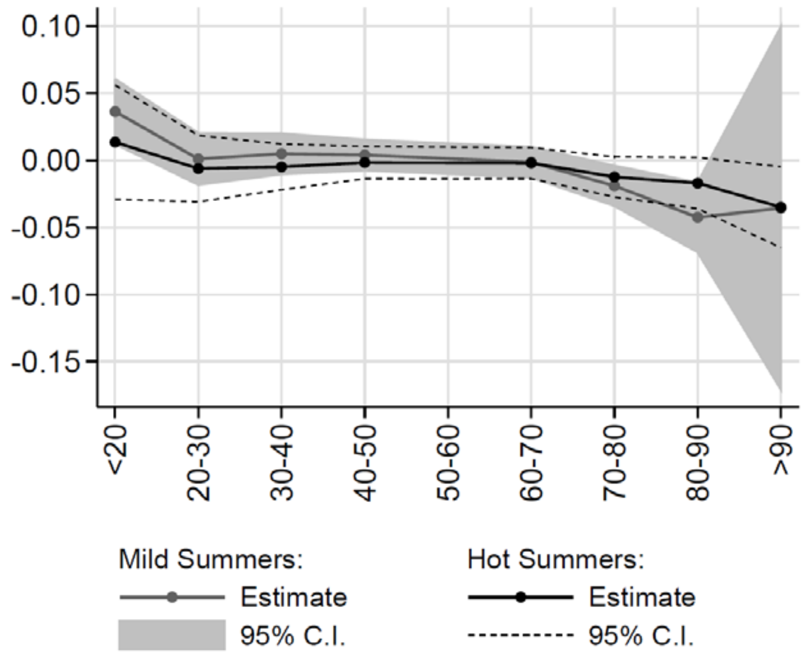


Figure 3. The effect of temperature exposure (°F) on emotional well-being on the day prior to the respondent's interview by average summer temperature in respondent's zip code tabulation area (ZCTA). Well-being (y-axis) is standardized with mean zero and standard deviation one. Temperature exposure (x-axis) is measured as the 24-hour average daily temperature on the day prior to the respondent's interview in their ZCTA. Marginal effects of being exposed to temperatures in a given interval relative to the reference interval of 50 to 60°F (10 to 16°C) for areas with mild and hot summers are displayed. 95% confidence intervals are shown as grey areas for mild summer areas and dashed lines for hot summer areas.

INCREASING AMBIENT TEMPERATURE REDUCES EMOTIONAL WELL-BEING

APPENDIX

Data, Methods and Additional Results

FURTHER DETAILS ON DATA AND VARIABLE CONSTRUCTION

Gallup Data

Since 2008, Gallup has conducted a daily survey of 1,000 Americans aged 18+. We use data from this survey for the period from 2008-13. Around 250 interviewers conduct computer assisted live telephone interviews with randomly sampled respondents on 350 days per year. In addition to registered landline phones, the sampling frame also includes cell phones to improve representativeness. 400 cell phone and 600 landline surveys are completed daily. The cell-phone numbers are selected by random digit dialing. Up to three calls are made to a given number at different times of the day, if initial contact attempts are unsuccessful. After contact is made, a random method is used to select respondents within households. Interviews are conducted in Spanish if respondents only speak Spanish.

51% of the calls resulted in contacts with eligible candidates. If candidates agreed to an interview, the completion rate was 91%. The CASRO response rate (completed interviews divided by number of eligible individuals for whom contact was attempted) is 11%, which is in line with major non-governmental phone surveys (Kohut, Keeter, Doherty, Dimock, & Christian, 2012). To account for nonresponse and disproportionalities in selection, Gallup weights the data on a daily basis. Weights are calculated to match targets from the U.S. Census Bureau by age, sex, race and ethnicity, education, region and population density of self-reported location. Finally, the data are also weighted to match national targets of phone status (cell phone only, cell phone with unlisted land line, land-line only etc.). The weighted sample is representative of 90% of the U.S. population. Despite the sampling limitations, available evidence suggests that the estimates of population parameters are not compromised; for example, the survey predicted recent midterm and presidential election results within an acceptable margin of error and also aligns closely with other surveys in terms of predicting changes in health insurance coverage due to the Affordable Care Act in 2014 (Claxton, Levitt, Brodie, Garfield, & Damico, 2014; Gallup, 2014a, 2014b). Furthermore, the robustness checks below indicate that individual characteristics such as education and health are not correlated with the temperature exposure variable, partially alleviating concerns about bias due to selective survey response.

The survey includes standard demographic variables, zip code of respondents' residence and other geographical identifiers, detailed information on health and well-being, and other topical variables. Our outcome is based on respondents' self-assessed well-being on the day prior to the survey. We included all available measures of subjective emotional well-being that explicitly reference emotional well-being on the day prior to the day of interview. We excluded well-being measures that were not date-specific, e.g. measures of life satisfaction and measures of physical well-being, e.g. suffering from allergy symptoms on the day prior to the survey.

We analyzed ten measures of individual self-assessed well-being on the day prior to the day of interview. Respondents are asked "Did you experience the following feelings a lot of the day yesterday?" and then interviewers go through the following list: enjoyment, worry, sadness, stress, anger, and happiness. We also included the following items: "Did you smile or laugh a lot yesterday?", "Did you have enough energy to get things done yesterday?", "Were you treated with respect all day yesterday?", and "Did you feel well-rested yesterday?". For each item, respondents can answer yes, no, don't know, or refuse to answer. We recoded the binary variables to equal 1 to indicate yes-responses to positive feelings and no-responses to negative feelings and zero otherwise.

After dropping respondents not reporting to reside in the contiguous US, the initial sample size was 1,934,910. We then dropped individuals with missing zip code information and individuals whose zip code could not be assigned to a county in the contiguous US, which reduced the sample to 1,898,583 observations. Finally, we dropped individuals who responded "don't know" or who refused to answer to the well-being questions, which reduced the sample to 1,854,746, a loss of 80,164 observations or 4% of the initial sample.

For robustness checks, we used an extensive set of covariates. All variables are entered as categorical indicators with an additional category for missing values. The results are robust to dropping individuals with missing information on the covariates. The variables are: gender (2 categories), age (82), race (5), education (6), marital status (6), number of children (5), as well as 6 binary indicators for health conditions. Table A1 includes descriptive information on these variables as well as the dependent variables used in the analysis.

Principal Components Analysis

We calculated a tetrachoric correlation matrix for the ten well-being items selected for analysis. Table A2 summarizes the tetrachoric correlations between the items. All items are at least moderately correlated (minimum 0.3), suggesting that there is sufficient shared information to be extracted in a principal component analysis. We then performed principal component analysis. The first three components had Eigenvalues of 5.3, 1.2 and 0.8, respectively. The first component explained 53% of the total variation. We obtained the predicted scores for the first component, which we refer to as the 'subjective well-being index'. Retaining the first three components, which explained 74% of the total variation, we performed an oblique factor rotation, which yielded a clearly interpretable component structure. Results from varimax rotation yielded a very similar structure. The resulting three components had eigenvalues of 4.3, 4.0 and 2.6. Items querying positive emotions and querying negative emotions loaded onto two different components that we label ‘positive emotions’ and ‘negative emotions’, respectively, and the two items querying energy levels or tiredness formed a third component that we label ‘fatigue’. Factor loadings for the un-rotated and rotated solutions are shown in Table A3.

Table A1. Descriptives Analysis Sample, Sample Percentages Unless Otherwise Noted.

Variable		%	Variable		%
Well-Being Index, mean (std. dev.)		0.0 (1.0)	*Week* mean (std. dev.)*		26.3 (14.8)
Negative Emotions Index, mean (std. dev.)		-0.1 (1.0)	*Age in Years* mean (std. dev.)*		47.7 (17.7)
Positive Emotions Index, mean (std. dev.)		-0.1 (1.0)	*Women*		51.9
Fatigue Index, mean (std. dev.)		-0.1 (1.0)	*Race*	*White*	74.9
Felt Enjoyment Yesterday		84.8		*Other*	3.5
Felt Happiness Yesterday		88.4		*Black*	11.1
Smiled/Laughed a Lot Yesterday		82.6		*Race Asian*	1.9
Felt Sadness Yesterday		17.6		*Hispanic*	8.6
Felt Worry Yesterday		31.7	*Education*	*Less than high school*	10.9
Felt Stress Yesterday		39.9		*High school*	29.5
Felt Anger Yesterday		13.8		*Technical/Vocational school*	6.1
Felt Treated with Respect Yesterday		92.1		*Some college*	22.8
Felt Well-Rested Yesterday		70.6		*College graduate*	17.3
Enough Energy To Get Things Done Yesterday		85.9		*Postgraduate work or degree*	13.5
Year	*2008*	16.8	*Marital Status*	*Single, never married*	22.2
	2009	16.7		*Married*	54.6
	2010	16.7		*Separated*	2.2
	2011	16.5		*Divorced*	9.5
	2012	16.6		*Widowed*	7.0
	2013	16.6		*Domestic partnership*	4.5
Month	*January*	8.5	*Number of Children in Household*	*0*	62.4
	February	7.8		*1*	15.1
	March	8.7		*2*	13.4
	April	8.3		*3*	5.9
	May	8.5		*4 or more*	3.1
	June	8.4	*Any Health Problems That Limit Activity*		21.6
	July	8.5	*Ever Been Diagnosed with*	*High Blood Pres.*	30.0
	August	8.8		*High Cholesterol*	26.4
	September	8.4		*Diabetes*	10.9
	October	8.6		*Heart Problems*	4.2
	November	8.1		*Asthma*	11.6
	December	7.4		*Cancer*	7.2

Note: All entries are sample percentages (percentage of respondents with a given response) unless otherwise noted. *Age and week are entered as categorical variables into the analysis.

Table A2. Tetrachoric Correlations between Well-Being Measures.

	Enjoyment	Happiness	Smile / Laughter	Sadness	Worry	Stress	Anger	Treated with Respect	Well-Rested	Enough Energy
Enjoyment	1.00									
Happiness	0.82	1.00								
Smile/Laughter	0.73	0.73	1.00							
Sadness	0.50	0.50	0.45	1.00						
Worry	0.47	0.42	0.40	0.70	1.00					
Stress	0.48	0.38	0.38	0.58	0.76	1.00				
Anger	0.39	0.33	0.35	0.56	0.55	0.56	1.00			
Treated with Respect	0.46	0.40	0.39	0.40	0.42	0.50	0.56	1.00		
Well-Rested	0.53	0.43	0.42	0.39	0.45	0.52	0.34	0.42	1.00	
Enough Energy	0.53	0.48	0.44	0.47	0.44	0.40	0.30	0.30	0.57	1.00

Source: Gallup G1K, own calculations.

Table A3. Factor Loadings from Principal Components Analysis

	Un-rotated	After Oblique Rotation			
	Component 1 ‘Emotional Well-Being Index’	Component 1 ‘Negative Emotions’	Component 2 ‘Positive Emotions’	Component 3 ‘Fatigue’	Uniqueness
Enjoyment	0.82	0.06	**0.83**	0.12	0.15
Happiness	0.76	-0.03	**0.92**	0.03	0.15
Smile/Laughter	0.73	0.00	**0.89**	-0.02	0.21
Sadness	0.77	**0.65**	0.14	0.15	0.36
Worry	0.77	**0.78**	-0.07	0.26	0.24
Stress	0.76	**0.80**	-0.09	0.25	0.24
Anger	0.67	**0.88**	0.06	-0.22	0.27
Treated with Respect	0.66	**0.66**	0.28	-0.22	0.42
Well-Rested	0.69	0.18	0.13	**0.68**	0.30
Enough Energy	0.67	0.02	0.22	**0.75**	0.24
Eigenvalue	*5.3*	*4.3*	*4.0*	*2.6*	

Source: Gallup G1K, own calculations.

Comparison of Well-Being Index to Epidemiologic Mental Health Scales

While developed to measure hedonic or experiential well-being (Kahneman & Krueger, 2006), the items included in our index of emotional well-being are very similar to items used in common self-reported epidemiologic mental health scales. Concerning the fatigue component, lacking energy to get things done, not being able to "get going", or feeling exhausted or worn out are considered to potentially indicate mood disorders or mental health problems. For example, the widely used 20-item Center for Epidemiologic Studies Depression (CES-D) Scale includes "I felt that everything I did was an effort", "I could not get going" in both the 20-item long and the 8-item short form. The Kessler 10-item psychological distress scale (Kessler et al., 2002) includes the item "During the last 30 days, about how often did you feel tired out for no good reason?", "During the last 30 days, about how often did you feel that everything was an effort?" The Rand 36-item health survey covering both physical and mental health includes the items "How much of the time during the past 4 weeks…", "…Did you feel full of pep?", "…Did you have a lot of energy?", "…Did you feel worn out?".

Positive and negative emotions are also routinely recorded as indicators of mental health or mood problems. Similar to the positive/negative emotion items in the G1K, the CES-D Depression scale includes items like "I was happy", "I felt sad", "I felt depressed", and also "People were unfriendly", which is similar to the item "Were you treated with respect all day yesterday?" in the G1K. The Kessler distress scale also includes items tapping depressed mood, vigilance and worry: "During the last 30 days, about how often did you feel": (a) "unhappy", (b) "sad or blue", (c) "depressed", (d) "angry", (e) "happy", (f) "worried about things that were not really important", (g) "worried about things that were not likely to happen".

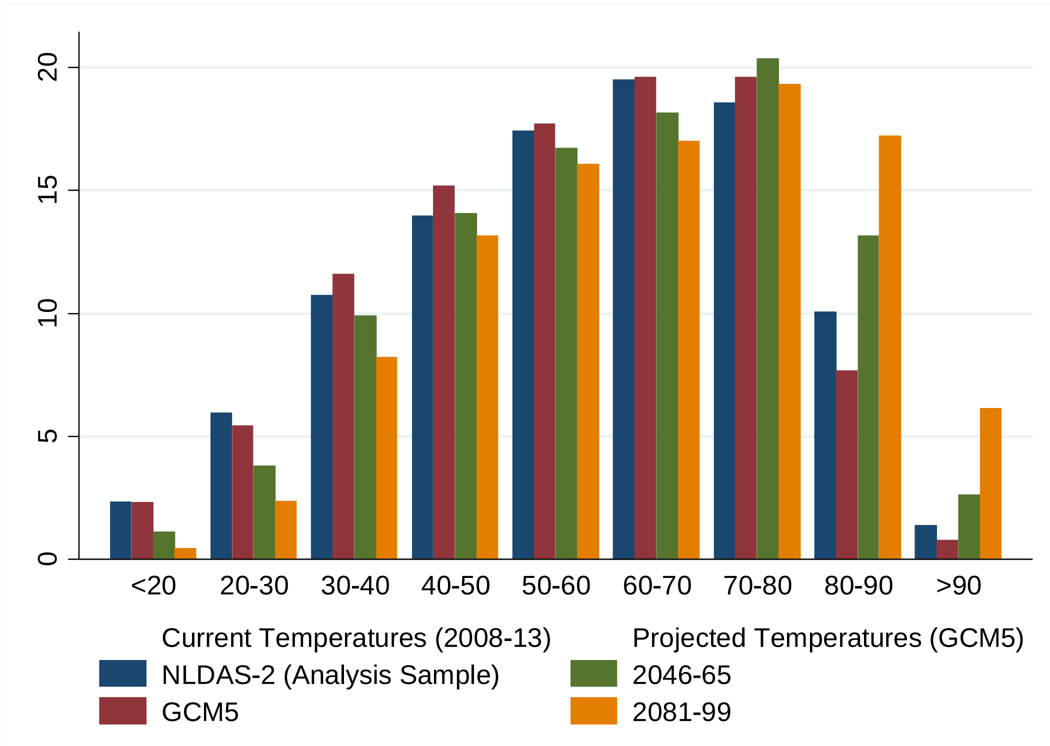
Climate Data

Meteorological variables for the multivariate analysis are taken from the North American Land Data Assimilation System (NLDAS-2) primary forcing files, which provide hourly fields of 2m above ground air temperature (K), surface pressure (Pa), 2m specific humidity (kg kg^{-1}), and hourly total precipitation (kg m^{-2}) on a 0.125° grid. The NLDAS-2 data were acquired as part of the mission of NASA's Earth Science Division and are archived and distributed by the Goddard Earth Sciences (GES) Data and Information Services Center (http://disc.sci.gsfc.nasa.gov/hydrology/data-holdings). Air temperature is the predictor of interest in our exposure calculations; total hourly precipitation and relative humidity (calculated from temperature, pressure and specific humidity) were included as control variables in some specifications. For each respondent in our sample, we calculated the daily 24-hour average values of these variables at the centroid of the reported ZCTA on the day prior to the interview.

As an additional reference, we also show data on 3-hourly temperature fields simulated by five earth system models (ESMs) from the Coupled Model Intercomparison Project, Phase 5 (CMIP5): GFDL-CM3, INMCM4, MIROC5, MPI-ESM-LR, and CNRM-CM5. Models' gridded fields were first interpolated spatially to county boundaries, and average daily temperatures calculated for each county over three periods 2008-13 (current), 2046-2065 (mid-century) and 2081-2099 (end-of-century). For each ESM, the time-averaged pattern of exposure for individuals in each county was then calculated as the proportion of the total days in each period for which temperatures fell into in different intervals.

Figure A1 summarizes the spatially and temporally averaged temperature data from the different sources. The blue bars (NLDAS-2, Analysis Sample) show the distribution of the temperature exposure in the multivariate analyses using sampling weights. Red bars show the distribution of the temperature variable in the projections, averaged over ESMs. Green and yellow bars show the projected temperature distribution for mid- and end-of-century, averaged over ESMs.

Figure A1. Current Temperatures and Projected Temperatures.



Source: Gallup G1K, NLDAS-2 and projections from five earth system models.

The multivariate analyses also use total precipitation and relative humidity as a control variables. We calculated relative humidity according to the following formula:

Relative Humidity: $RH = 100*(E/E_S)$

Saturated Vapor Pressure at a Given Temperature: $E_S=6.1094*\exp((17.625*T_C)/(T_C+243.04))$

Vapor Pressure: $E=(SH*P)/(0.622+SH*(1-0.622))$

T_C = Temperature in Degrees Celsius

SH = 2-m above ground specific humidity (kg/kg)

Table A4 summarizes the distribution of relative humidity and precipitation in the analysis sample. Both variables have been transformed into categorical variables.

Table A4. Climate Control Variables, Sample Percentages.

Relative Humidity (%)	<10	0.1	Precipitation (kg/m2)	0.00	28
	[10-20)	1.4		(0.00-0.05)	31.9
	[20-30)	2.7		[0.05-0.10)	9.9
	[30-40)	3.6		[0.10-0.20)	11.7
	[40-50)	4.9		[0.20-0.30)	6.8
	[50-60)	9.3		[0.30-0.40)	4.2
	[60-70)	19.7		[0.40-0.70)	5.2
	[70-80)	32.9		>=0.70	2.3
	[80-90)	22.5			
	>=90	2.9			

Source: Gallup G1K, NLDAS-2.

Data Linkage

To link the gridded NLDAS-2 climate data to the Gallup data, we make use of respondents' self-reported zip codes. Each zip code shares the same numeric identifier as its zip code tabulation areas (ZCTAs), which are defined by the Census Bureau by aggregating census blocks that use the same zip code. The Census Bureau also provides information on the latitude and longitude of each ZCTA centroid. We used the 2010 Census Gazetteer files for ZCTA information. We then take the grid point in the NLDAS-2 data that is closest to respondents' ZCTA centroids to measure ambient climate individuals were exposed to. Specifically, we used the grid point with minimal distance to the centroid, where distance was calculated using the Haversine formula (Sinnott, 1984) .

Using a 2010 cross-walk by the U.S. Department of Housing and Urban Development, we were able to identify respondents' county of residence using information from their ZCTAs. Finally, using a cross-walk linking counties to commuting zones, we identified the commuting zones respondents live in. Commuting zones are defined on the basis of commuting patterns recorded in Census data, i.e. using Census information on individuals' county of residence and the county in which they work. Commuting zones aggregate clusters of counties that form integrated local labor markets (Tolbert & Sizer, 1996). We observe 691 commuting zones. The median size of a commuting zone in our data set is 3,179 square miles, which corresponds to a square area with each side equal to 56 miles. 90% of the commuting zones were between 1,074 and 8,782 square miles large. By comparison, the average size of the 48 states forming the contiguous US is 64,997 square miles.

Specification of Temperature Variable

Consistent with recent work in climate economics (Barreca, Clay, Deschênes, Greenstone, & Shapiro, Forthcoming; Deschênes & Greenstone, 2011a, 2011b), we split the temperature variable into 10 °F bins to avoid imposing a functional form on the well-being temperature response function. Below, we also report results using more restrictive polynomial functions, which yield somewhat more precise estimates without altering any of the conclusions drawn in the main manuscript.

We also tested for lead, lagged or cumulative temperature effects, which have been reported for mortality (Deschênes & Moretti, 2009; Hajat, Armstrong, Gouveia, & Wilkinson, 2005). To test for such dynamic effects, we added leads and lags of temperature, averaged temperature exposure over multiple days, and replaced the categorical variable with temperature bin specific count variables, counting the number of days in the past week the temperature was in a given bin (Deschênes & Greenstone, 2011a). We found no evidence that future or lagged temperature affects well-being after temperature on the day the outcome was measured was controlled for. If there was a cumulative effect, we reasoned that averaging over multiple days (or counting exposure over multiple days) may capture such effects, but the resulting estimates were generally weaker both in size and significance than a simple specification using contemporaneous exposure only.

In other words, we found that the effect of temperature on well-being is strongest if measured contemporaneously. A contemporaneous link is implied by our theoretical framework. Direct heat exposure should lower well-being at the time of exposure. It is also implied by the way our dependent variable is measured, i.e., recording feelings on a specific day not over an extended period of time. It is not clear what mechanisms would cause temperature at time t-1 to have an effect on well-being, with temperature at t controlled. In research on the link between temperature and mortality, there is strong evidence of lag and lead effects of temperature exposure. However, the mechanisms affecting the outcomes considered here are likely different (e.g. mortality displacement) and may not apply to our context.

IDENTIFICATION AND ESTIMATION

All estimates were obtained using Ordinary Least Squares (OLS) regression using sampling weights provided by Gallup. Standard errors are adjusted for clustering of respondents within ZCTAs using the generalized Huber-White estimator (Angrist & Pischke, 2009).[1] We follow the empirical approach adopted in recent studies on the economic impact of temperature (Deschênes & Greenstone, 2011b; Hsiang, 2010; Schlenker & Roberts, 2009) that uses short-term variation of temperature within small geographic locations, a non-linear specification for the temperature variable, and flexible controls for secular trends and seasonal confounders.

In the following linear model, we use subscripts z, d and i to denote ZCTAs, days and individuals, respectively:

$$Y_{i,z,d} = \alpha_z + \lambda_d + \sum_{k=1}^{8} \beta_k T_{k,z,d} + \varepsilon_{i,z,d} \tag{S.1}$$

The parameters α_z are λ_d are ZCTA and calendar day fixed effects, and ε_{izd} is an idiosyncratic error term. In line with prior findings of a non-linear impact of temperature on health outcomes (Deschênes & Greenstone, 2011a), we split the continuous temperature variable into a categorical variable with eight bins, $T_{k,z,d}$, with the associated vector of coefficients, β_k, estimating the effect of an additional day of exposure to temperatures in each interval, relative to the reference interval of 50-60°F. For β_k to have a causal interpretation, we need to assume that the correlation between temperature dummies and the idiosyncratic error term is zero conditional on the other covariates, i.e., within ZCTAs, day-to-day variation of temperatures is uncorrelated with unmeasured determinants of well-being.

[1] We chose to cluster standard errors at the ZCTA level, because we expected a high degree of autocorrelation in the dependent variable among respondents living in the same area, as well as in terms of temperature exposure. We used alternate approaches to adjust for spatio-temporal autocorrelation, e.g. by clustering standard errors by groups defined by date, or state-year-month, or commuting zone-year-week. These tests revealed that our standard errors are rather conservative, and do not indicate the presence of spatial or temporal autocorrelation that could have biased our standard errors.

Our baseline model is in some ways more restrictive and in others more flexible than eq. (S.1). We impose restrictions to obtain a computationally tractable and parsimonious model. First, we do not condition on the full set of ZCTA fixed effects, but instead condition on commuting zone fixed effects, which reduces the elements of α from >32,000 to 691. Substantively, this assumes that compositional differences between residents of different ZCTAs within a commuting zone are uncorrelated with temperature, which is plausible given that commuting zones are small enough to have homogenous temperature conditions. We also conduct a robustness check to verify that this has no meaningful impact on our main results (Tables S5-8). Second, we collapse the full set of 2100 calendar days in the sample into week fixed effects (6 years × 52 weeks = 312 week FEs) and further add 6 dummy variables for weekdays. This assumes that net of day of the week effects, day-to-day variation in the level of well-being within any given week is uncorrelated with temperature.

We control for time-varying confounders in a more flexible way than eq. (S.1). First, we adjust for the impact of seasonally-varying confounding influences by conditioning on the full set of interactions between interview month and commuting zone. The temperature effects are therefore identified from variation around average monthly temperatures within commuting zones. We observe 691 commuting zones in our data, resulting in (691 commuting zones × 12 months) – 1 = 8291 parameters to be estimated, though only 8271 contain at least one observation. Second, we include interactions between state and year to capture state-specific year-to-year variation in well-being.

Temperature effects are therefore identified by variation relative to average temperatures observed in a given commuting zone and month. We ignore all variation in well-being that is due to commuting-zone specific month-to-month changes in average temperatures, because this variation is confounded with month-to-month changes in other influences on well-being, e.g., holiday and vacation seasons as well as variation in sunlight exposure. Moreover, if individuals are acclimatized to these area-specific monthly conditions, our estimated well-being effects are driven by variation in temperatures around the typical conditions individuals expect—and are prepared for.

To test for variation in the effect of temperature across demographic groups, we add a group indicator variable (e.g. a gender dummy variable), to the baseline model and include all interaction terms between the group indicator and the temperature dummies $T_{k,z,d}$. To evaluate whether group membership moderates the temperature effect, we perform a joint F-test on the coefficient estimates of the group-temperature interaction terms. While we used group indicators with multiple categories to explore the different ways of categorizing respondents by age, our final regressions collapse group identifiers into binary categories.

As a robustness check, we re-estimate the model including plausibly exogenous individual control variables (see Table A1, for descriptive statistics). These are age (90 categories), race (5 categories), education (6 categories), marital status (6 categories), number of children in household (5 categories), and binary categorical indicators of sex, self-reported health problems that limit activity, and past diagnosis of high blood pressure, high cholesterol, diabetes, heart problems, asthma, or cancer.

Finally, below we report additional results using more restrictive model specifications (Table A12). These results illustrate that more restrictive model specifications also reproduce the baseline estimates. None of these checks yields evidence suggesting that omitted variable bias affects our estimated temperature effects. Consistent with other longitudinal studies (Barreca et al., Forthcoming; Deschênes & Greenstone, 2011a, 2011b) temperature variation over short periods of time within small geographic areas appears to be as good as randomly assigned.

RESULTS FROM ADDITIONAL ROBUSTNESS CHECKS

The following tables report the main results from OLS regressions of well-being on temperature. Table A5 contains the results for the aggregate emotional well-being index, Tables A6-A8 contain the results for the components of well-being: negative emotions, positive emotions, fatigue. Columns M1 include results from the baseline model that were also visually displayed in Fig. 1 and that underlie the simulations in Fig. 3 and Fig. 4 in the main text. Estimates in columns M2 adjust for climate controls (relative humidity and precipitation). Estimates in columns M3 adjusts for ZCTA fixed effects (FE) instead of commuting zone FE and state-by-month FE rather than commuting zone-by-month FE.

Estimates in column M4 also adjust for individual covariates. Because our data are survey-based, selective non-response may be a concern. For example, one possibility is that individuals who are particularly affected by hot temperatures are less likely to respond to the survey, in which case our estimated heat effects would be downwardly biased. To explore this possibility, we controlled for individual level socio-economic and health measures to assess whether there is selection into the sample that is correlated with temperature exposure on the day prior to the interview. Adjusting for an extensive set of individual level covariates has virtually no effect on coefficient estimates.

Table A9 includes results from OLS linear probability models estimating the effect of temperature on each of the ten well-being measures. For this analysis, we recoded the binary variables to equal 1 for yes-responses and 0 otherwise. All estimates are based on the baseline covariate specification. Significance levels are generally lower compared to the results based on the indicators derived from the principal components analyses. One explanation is that by combining information from several indicators, we reduce measurement error in the dependent variable and increase precision in temperature impact estimates. By the same token, more accurate measures of well-being such as those proposed by Kahneman and Krueger (Kahneman & Krueger, 2006) would be expected to yield even more precise estimates.

Table A5. Temperature and Well-Being, Robustness Checks.

Temperature in °F	% of Sample	M1 = Baseline	M2 = M1 + Climate Controls	M3 = M2 + ZCTA FE	M4 = M3 + Individual Covariates
<20	2.3	0.031**	0.027*	0.017	0.019
		(0.010)	(0.010)	(0.010)	(0.010)
[20-30)	6.0	-0.001	-0.005	-0.010	-0.006
		(0.007)	(0.008)	(0.007)	(0.007)
[30-40)	10.7	0.001	-0.003	-0.004	-0.003
		(0.006)	(0.006)	(0.006)	(0.006)
[40-50)	14.0	0.002	0.000	-0.001	0.000
		(0.004)	(0.004)	(0.004)	(0.004)
[50-60) = Reference Group	17.4				
[60-70)	19.5	-0.001	-0.001	0.003	0.003
		(0.004)	(0.004)	(0.004)	(0.004)
[70-80)	18.6	-0.016**	-0.016**	-0.011*	-0.012*
		(0.005)	(0.005)	(0.005)	(0.005)
[80-90)	10.1	-0.026***	-0.027***	-0.020**	-0.020**
		(0.007)	(0.008)	(0.007)	(0.007)
>=90	1.4	-0.043**	-0.044**	-0.033*	-0.034*
		(0.014)	(0.014)	(0.013)	(0.013)
Commuting Zone FE		Yes	Yes		
Month FE		Yes	Yes	Yes	Yes
Commuting Zone x Month FE		Yes	Yes		
ZCTA FE				Yes	Yes
State x Month FE				Yes	Yes
State-Year FE		Yes	Yes	Yes	Yes
Day of the Week FE		Yes	Yes	Yes	Yes
Climate Controls			Yes	Yes	Yes
Individual Controls					Yes

*** p<0.001, ** p<0.01, * p<0.05. Note: FE = Fixed Effects. ZCTA = Zip code Tabulation Area. Climate controls = Relative humidity, precipitation. Individual Controls: age, gender, race, education, marital status, number of children, self-reported health problems that limit activity, and past diagnosis of high blood pressure, high cholesterol, diabetes, heart problems, asthma, or cancer. Column 1: in-sample distribution of the temperature exposure variable. Column 2: estimates of the well-being temperature response function from the baseline model graphed in Figure 1. Columns 3-5: robustness checks. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

Table A6. Temperature and Negative Emotions, Robustness Checks.

Temperature in °F	% of Sample	M1 = Baseline	M2 = M1 + Climate Controls	M3 = M2 + ZCTA FE	M4 = M3 + Individual Covariates
<20	2.3	0.033**	0.033**	0.029**	0.029**
		(0.010)	(0.011)	(0.011)	(0.010)
[20-30)	6.0	0.004	0.003	-0.000	0.003
		(0.008)	(0.008)	(0.008)	(0.008)
[30-40)	10.7	0.007	0.006	0.004	0.005
		(0.006)	(0.006)	(0.006)	(0.006)
[40-50)	14.0	0.003	0.003	0.002	0.003
		(0.004)	(0.004)	(0.004)	(0.004)
[50-60) = Reference Group	17.4				
[60-70)	19.5	-0.003	-0.003	-0.001	-0.000
		(0.004)	(0.004)	(0.004)	(0.004)
[70-80)	18.6	-0.012*	-0.013*	-0.011	-0.011*
		(0.005)	(0.005)	(0.005)	(0.005)
[80-90)	10.1	-0.020**	-0.022**	-0.017*	-0.016*
		(0.007)	(0.008)	(0.007)	(0.007)
>=90	1.4	-0.030*	-0.034*	-0.028*	-0.026*
		(0.014)	(0.014)	(0.013)	(0.013)
Commuting Zone FE		Yes	Yes		
Month FE		Yes	Yes	Yes	Yes
Commuting Zone x Month FE		Yes	Yes		
ZCTA FE				Yes	Yes
State x Month FE				Yes	Yes
State-Year FE		Yes	Yes	Yes	Yes
Day of the Week FE		Yes	Yes	Yes	Yes
Climate Controls			Yes	Yes	Yes
Individual Controls					Yes

*** p<0.001, ** p<0.01, * p<0.05. Note: FE = Fixed Effects. ZCTA = Zip code Tabulation Area. Climate controls = Relative humidity, precipitation. Individual Controls: age, gender, race, education, marital status, number of children, self-reported health problems that limit activity, and past diagnosis of high blood pressure, high cholesterol, diabetes, heart problems, asthma, or cancer. Column 1: in-sample distribution of the temperature exposure variable. Column 2: estimates of the well-being temperature response function from the baseline model graphed in Figure 1. Columns 3-5: robustness checks. The dependent variable is one of the three components extracted in a principal components analysis of 10 well-being items, querying respondents' emotional well-being on the day prior to the interview. It is standardized with mean zero and standard deviation one. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

Table A7. Temperature and Positive Emotions, Robustness Checks.

Temperature in °F	% of Sample	M1 = Baseline	M2 = M1 + Climate Controls	M3 = M2 + ZCTA FE	M4 = M3 + Individual Covariates
<20	2.3	0.004	-0.004	-0.018	-0.017
		(0.010)	(0.010)	(0.010)	(0.010)
[20-30)	6.0	-0.015*	-0.021**	-0.027***	-0.025**
		(0.007)	(0.007)	(0.007)	(0.007)
[30-40)	10.7	-0.016**	-0.020***	-0.023***	-0.021***
		(0.005)	(0.006)	(0.005)	(0.005)
[40-50)	14.0	-0.003	-0.005	-0.006	-0.005
		(0.004)	(0.004)	(0.004)	(0.004)
[50-60) = Reference Group	17.4				
[60-70)	19.5	0.003	0.003	0.008*	0.007
		(0.004)	(0.004)	(0.004)	(0.004)
[70-80)	18.6	-0.012*	-0.010*	-0.005	-0.006
		(0.005)	(0.005)	(0.005)	(0.005)
[80-90)	10.1	-0.015*	-0.013	-0.006	-0.007
		(0.007)	(0.007)	(0.007)	(0.007)
>=90	1.4	-0.024	-0.023	-0.010	-0.013
		(0.013)	(0.014)	(0.013)	(0.013)
Commuting Zone FE		Yes	Yes		
Month FE		Yes	Yes	Yes	Yes
Commuting Zone x Month FE		Yes	Yes		
ZCTA FE				Yes	Yes
State x Month FE				Yes	Yes
State-Year FE		Yes	Yes	Yes	Yes
Day of the Week FE		Yes	Yes	Yes	Yes
Climate Controls			Yes	Yes	Yes
Individual Controls					Yes

*** p<0.001, ** p<0.01, * p<0.05. Note: FE = Fixed Effects. ZCTA = Zip code Tabulation Area. Climate controls = Relative humidity, precipitation. Individual Controls: age, gender, race, education, marital status, number of children, self-reported health problems that limit activity, and past diagnosis of high blood pressure, high cholesterol, diabetes, heart problems, asthma, or cancer. Column 1: in-sample distribution of the temperature exposure variable. Column 2: estimates of the well-being temperature response function from the baseline model graphed in Figure 1. Columns 3-5: robustness checks. The dependent variable is one of the three components extracted in a principal components analysis of 10 well-being items, querying respondents' emotional well-being on the day prior to the interview. It is standardized with mean zero and standard deviation one. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

Table A8. Temperature and Fatigue, Robustness Checks.

Temperature in °F	% of Sample	M1 = Baseline	M2 = M1 + Climate Controls	M3 = M2 + ZCTA FE	M4 = M3 + Individual Covariates
<20	2.3	0.033**	0.032**	0.034**	0.036***
		(0.010)	(0.010)	(0.010)	(0.010)
[20-30)	6.0	0.014	0.013	0.014*	0.017*
		(0.007)	(0.007)	(0.007)	(0.007)
[30-40)	10.7	0.015**	0.014*	0.015**	0.017**
		(0.005)	(0.006)	(0.005)	(0.005)
[40-50)	14.0	0.004	0.004	0.004	0.004
		(0.004)	(0.004)	(0.004)	(0.004)
[50-60) = Reference Group	17.4				
[60-70)	19.5	-0.005	-0.005	-0.002	-0.003
		(0.004)	(0.004)	(0.004)	(0.004)
[70-80)	18.6	-0.010	-0.010	-0.007	-0.008
		(0.005)	(0.005)	(0.005)	(0.005)
[80-90)	10.1	-0.023**	-0.024**	-0.022**	-0.022**
		(0.007)	(0.007)	(0.007)	(0.007)
>=90	1.4	-0.041**	-0.041**	-0.038**	-0.040**
		(0.013)	(0.014)	(0.013)	(0.013)
Commuting Zone FE		Yes	Yes		
Month FE		Yes	Yes	Yes	Yes
Commuting Zone x Month FE		Yes	Yes		
ZCTA FE				Yes	Yes
State x Month FE				Yes	Yes
State-Year FE		Yes	Yes	Yes	Yes
Day of the Week FE		Yes	Yes	Yes	Yes
Climate Controls			Yes	Yes	Yes
Individual Controls					Yes

*** p<0.001, ** p<0.01, * p<0.05. Note: FE = Fixed Effects. ZCTA = Zip code Tabulation Area. Climate controls = Relative humidity, precipitation. Individual Controls: age, gender, race, education, marital status, number of children, self-reported health problems that limit activity, and past diagnosis of high blood pressure, high cholesterol, diabetes, heart problems, asthma, or cancer. Column 1: in-sample distribution of the temperature exposure variable. Column 2: estimates of the well-being temperature response function from the baseline model graphed in Figure 1. Columns 3-5: robustness checks. The dependent variable is one of the three components extracted in a principal components analysis of 10 well-being items, querying respondents 'emotional well-being on the day prior to the interview. It is standardized with mean zero and standard deviation one. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

Table A9. Temperature and Well-Being, Results for Ten Well-Being Measures.

Temperature in °F	Enjoyment	Happiness	Smiled or Laughed	Sadness	Worry	Stress	Anger	Treated with Respect	Well Rested	Enough Energy
<20	-0.001	0.003	-0.001	-0.009*	-0.004	-0.010*	-0.010**	0.006*	0.024***	0.007*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)
[20-30)	-0.005*	-0.002	-0.008**	-0.002	0.005	0.001	-0.003	0.002	0.012***	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
[30-40)	-0.004*	-0.002	-0.008***	-0.001	0.000	-0.002	-0.002	0.002	0.010***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
[40-50)	-0.001	-0.001	-0.002	-0.001	0.000	0.002	-0.003	0.001	0.004*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
[50-60) = Ref.										
[60-70)	0.002	0.000	0.001	-0.000	0.000	0.002	0.001	-0.000	-0.003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
[70-80)	-0.003	-0.004*	-0.003	0.002	0.001	0.005	0.004*	-0.003*	-0.008**	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
[80-90)	-0.005*	-0.005*	-0.002	0.005*	0.004	0.011**	0.003	-0.005*	-0.011***	-0.007**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
>=90	-0.006	-0.011*	-0.004	0.009	0.005	0.020**	0.008	-0.003	-0.017**	-0.013**
	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.004)	(0.006)	(0.004)

*** p<0.001, ** p<0.01, * p<0.05. Note: Temperature exposure is defined as the 24-hour average daily temperature in degrees Fahrenheit (°F) on the day before interview in respondents' Zip code Tabulation Area (ZCTA). The dependent variables are ten measures of well-being. Respondents were asked "Did you experience the following feelings a lot of the day yesterday?" and interviewers went through the following list: enjoyment, worry, sadness, stress, anger, and happiness. We also included the following items: "Did you smile or laugh a lot yesterday?", "Did you have enough energy to get things done yesterday?", "Were you treated with respect all day yesterday?", and "Did you feel well-rested yesterday?". For each item, respondents can answer yes, no, don't know, or refuse to answer. We coded the binary variables to equal 1 for yes-responses and 0 otherwise. All estimates use the baseline model specification (see Table A5), are obtained using OLS regression and use sampling weights provided by Gallup. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS2.

FURTHER TESTS FOR HEAT ADAPATION

The basic logic of our empirical test is to compare the well-being temperature response functions across U.S. regions defined by summer climate. We split the sample into two groups at the median of average summertime temperature reported in respondents' ZCTA over the five years preceding the year of interview. For respondents interviewed in 2010, average summer-time temperature is measured as the average of daily temperatures for the months June, July and August over the years from 2005 to 2009. Our null hypothesis is that the temperature well-being response function is constant across different climate regions. In turn, we interpret significant differences in the response function as evidence supporting adaptation, specifically if we find a significantly weaker effect of heat on well-being among individuals living in areas with typically hot compared to mild summers.

Data

The following analysis use the same data and sample as the analyses described above. In addition, we calculated, for each ZCTA, the five-year average summer temperature, as the average of daily 24-hour temperatures for the months of June, July and August over five years. Temperature data are taken from the NLDAS-2 (see Data & Methods in main manuscript). Each respondent was matched with the average summer time temperature of the preceding five years in his or her ZCTA. For example, a respondent observed in July 2008 was assigned the average summer temperature in her ZCTA for the period 2003-2007. Implicit in this choice is the assumption that the experience and memory of recent summers is central for how adapted individuals to summer time heat exposure on a day-to-day basis. We report analyses using two groups or climate areas, splitting the sample at the median of ZCTA-specific, average summer temperature. We refer to the resulting groups as the mild (below median) or hot (at or above median) summer areas/groups below.

Our testing approach faces the challenge that average summer temperature and heat exposure are positively correlated. If we split the sample into areas with hot summers and areas with mild summers, we will observe much fewer extreme heat exposures in areas with mild compared to areas with hot summers. Table A10 shows the distribution of the sample across the two groups. In the mild summer sample, the top bin has 462 observations. Our tests therefore have less statistical power in the tails of the temperature distribution compared to the center. Similarly, it becomes more difficult to identify the correct functional form of the temperature effect in the tails of the distribution. This particularly applies to the mild summer sample at temperatures above 90°F. To improve efficiency, we use more parsimonious covariate specifications and parametric specifications of the temperature variable.

Table A10. Distribution of observations across climate areas.

Temperature in °F	Mild Summers (average temperatures <75°F)	Hot Summers (average temperatures >75°F)
<20	38,907	6,683
[20-30)	85,443	26,657
[30-40)	130,533	67,891
[40-50)	154,148	109,277
[50-60)	185,042	142,591
[60-70)	198,649	162,047
[70-80)	141,677	196,783
[80-90)	20,169	162,574
>=90	462	25,213

Source: Gallup G1K, NLDAS-2.

Table A11 shows that daily temperatures in the hot summer sample are on average around 11°F, or 6°C, higher than in the mild summer sample. This difference in summertime temperatures across the two samples exceeds the projected increase in U.S. surface temperatures until the end of century in many scenarios.

Table A11. Sample average temperatures in degrees Fahrenheit across climate areas.

	Mild Summers (average temperatures <75°F)	Hot Summers (average temperatures >75°F)
Year-round	52.0	63.7
June, July, August	70.5	81.7

Note: Based on respondents' average of 24-hour average temperature exposure in analysis sample, using sampling weights. Source: Gallup G1K, NLDAS-2.

Model Specification

In the following analyses, temperature variables and control variables are specified to have different effects across the climate groups we distinguish. If we allow all parameters to vary across groups, this would roughly double the number of estimated parameters, some of which may not be well identified. To address this issue and to improve overall efficiency, we explored whether it was possible to recover the estimates from the baseline model using a more restricted covariate specifications. Our goal was to obtain a more parsimonious model, yielding more efficient estimates of temperature on well-being. This in turn should increase the likelihood of finding significant differences in the well-being temperature response functions across climate and therefore evidence supporting adaptation. Here and elsewhere, the models are estimated using Ordinary Least Squares with the sampling weights provided, and standard errors that allow for arbitrary residual correlation within ZCTAs.

Column 1 of Table A12 reports the baseline model results visually displayed in Figure 1 in the main manuscript. The following columns report results from more restrictive models. A separate row lists the number of parameters (including a constant) estimated for each model.

Model 2 replaces state by year fixed effects with census-division by year fixed effects, which saves 239 parameters. Model 3 replaces the year by week fixed (i.e. one fixed effect per year and calendar week) effects with year fixed effects and week fixed effects, saving another 255 parameters. M4 drops the census division by year fixed effects, saving another 48 parameters. Finally, M5 conditions on commuting zone fixed effects instead of commuting zone by month fixed effects.

Table A12. Temperature and Well-Being, Restricting the Number of Control Variables.

Temperature in °F	% of Sample	M1	M2	M3	M4	M5
<20	2.3	0.0315**	0.0319**	0.0310**	0.0300**	0.0190*
[20-30)	6.0	-0.0015	-0.0015	-0.0009	-0.0016	-0.0099
[30-40)	10.7	0.0005	0.0004	0.0011	0.0010	-0.0068
[40-50)	14.0	0.0016	0.0014	0.0028	0.0028	-0.0007
[50-60) = Reference Group	17.4					
[60-70)	19.5	-0.0014	-0.0013	-0.0008	-0.0009	-0.0010
[70-80)	18.6	-0.0162**	-0.0163**	-0.0160**	-0.0162**	-0.0170***
[80-90)	10.1	-0.0263***	-0.0264***	-0.0247***	-0.0250***	-0.0293***
>=90	1.4	-0.0425**	-0.0428**	-0.0407**	-0.0400**	-0.0386***
Number of parameters		8881	8642	8387	8339	761
Year x Week FE		Yes	Yes			
State x Year FE		Yes				
Commuting Zone x Month FE		Yes	Yes	Yes	Yes	
Commuting Zone FE						Yes
Weekday FE		Yes	Yes	Yes	Yes	Yes
Year FE					Yes	Yes
Week FE				Yes	Yes	Yes
Census Division x Year FE			Yes	Yes		

*** p<0.001, ** p<0.01, * p<0.05. Note: FE = Fixed Effects. Column 1: in-sample distribution of the temperature exposure variable. Column 2: Estimates from baseline model graphed in Figure 1, and listed in Table A5. Columns 3-5 report results from models with fewer covariates. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

Replacing the state-year fixed effects with census division fixed effects (and later dropping census division fixed effects altogether) barely influences results (column M2). Specification M5 only conditions on 51 dummy variables for calendar week, 6 week-day fixed effects, 6 year fixed effects and 698 commuting zone dummies, reducing the total number of parameters by 8,339. It nearly succeeds in recovering the estimates from the baseline model. The effects in the most extreme temperature categories are a bit smaller, but these differences are negligible.[2] Most importantly, our goal was to determine whether a more efficient parsimonious model with reduced confidence intervals would still produce unbiased point estimates for the heat effects, which specification M5 accomplishes in the full sample. To assess whether restrictions are consequential, we repeated the analysis in the following section using both specification M2, which produces estimates that are virtually identical to the baseline model, and specification M5.

Results

For our first test, we employed the analysis sample used in the main model and adopted covariate specifications M2 and M5 identified in the preceding section. We added the climate zone indicator variable distinguishing mild and hot summers and interacted it with all other covariates, including interactions with the temperature variables. We then conducted a joint F-tests on the estimated interaction effects between temperature and climate area variable. The

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[2] Another consideration influencing our choice was that any model that we tried that was less restrictive than M5 resulted in computational problems when simulating the temperature well-being response function with confidence intervals using the margins command in Stata.

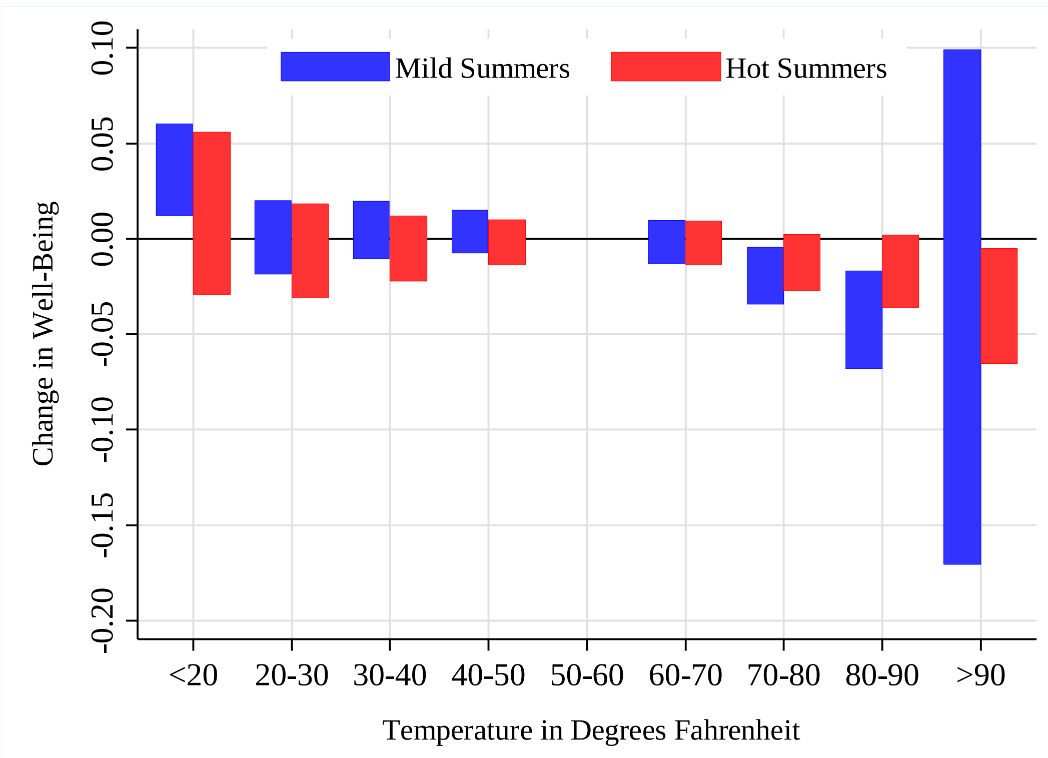
resulting test answers the question whether the temperature response function differs across areas in a way that cannot be attributed to sampling variability.

Figure A2 graphs the 95% confidence intervals around the group-specific marginal effects, using specification M2 (see preceding section). The data presented here is identical to the data shown in Figure 3 in the main manuscript. Confidence intervals are of central interest here because the main issue is whether the response functions for temperature effects vary for reasons other than the uncertainty introduced by sampling. Again, the reference group is exposure to temperatures in the 50-60°F range. The effect of temperature in the 80-90°F degree range differs across samples in a manner that is consistent with adaptation. Moreover, the 95% confidence intervals just barely include 0 for exposure to 70-80°F and 80-90°F in the hot summer sample.

However, there is no formal evidence that the response functions differ; none of the F-tests we performed yielded evidence suggesting that they do. For example, testing whether the effect of exposure to 70-80°F and 80-90°F differs across groups, i.e. the two effects most suggestive of adaptation, we obtained an F-statistic of 1.29 with a p-value of 0.27. Figure S2.1 also reveals that because of the low number of observations (see Table A10), the confidence interval for exposure to very hot days (>90°F) in the mild summer sample is very wide. This illustrates that effects in this part of the temperature distribution are more difficult to identify, which we will further examine below.

While we failed to find evidence of adaptation using conventional statistical tests within the modeling framework adopted for the main analysis, we found this difference intriguing enough to conduct further analyses that address two main concerns. First, we wanted to explore whether our conclusions would differ if we adopted a more parsimonious covariate specification. Second, we wanted to explore whether binning the temperature variable into 10 degree bins affects our results, and in particular whether a continuous temperature variable would yield more efficient estimates. The categorical temperature variable does not utilize variation within temperature bins to identify the effect of temperature on well-being, which could result in tests for adaptation that are too conservative.

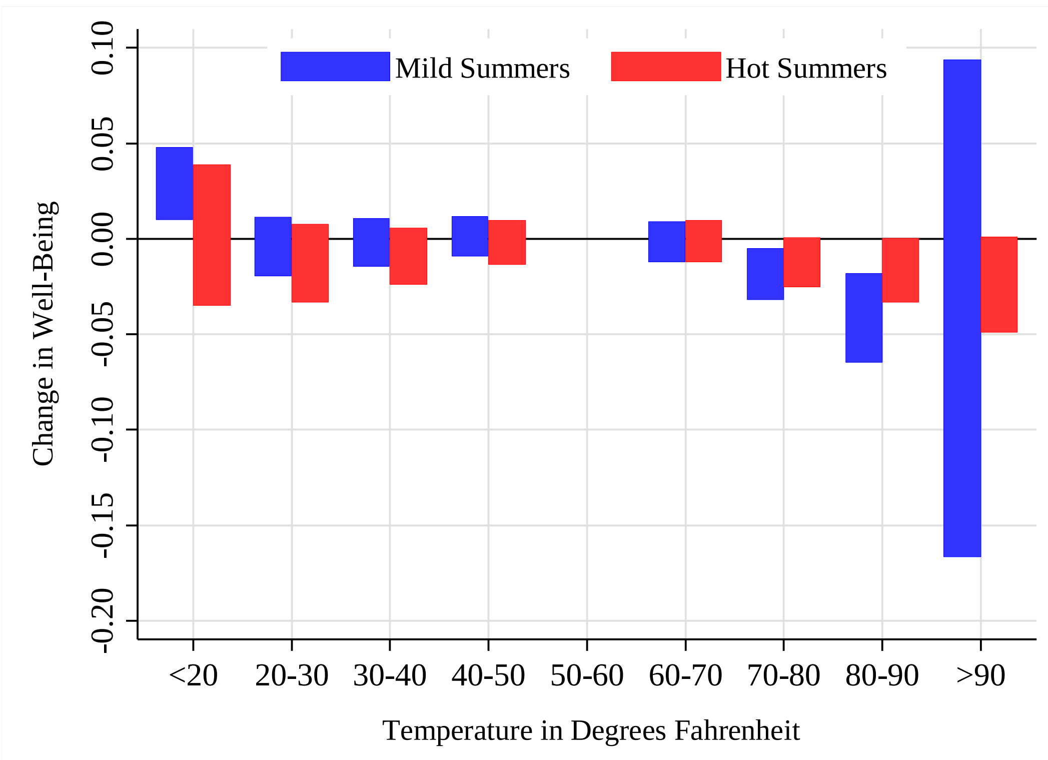
Figure A2. Temperature Exposure (°F) and Emotional Well-Being, Interactions Between Temperature and Local Climates, Covariate Specification M2 (see Table A12).



Note: The bars represent 95% confidence intervals around the marginal effect of temperature exposure on well-being relative to the exposure level of the reference group (50 to 60°F). Estimates were stratified by climate area, grouping respondents into areas with mild (<75°F) and hot (>75°F) summers. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. The covariate specification is described in Table A12. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

We therefore repeated the preceding analysis using specification M5 identified in the preceding section, which uses less than 10% of the number of parameters that specification M2 (see Figure S2.1 and preceding section) uses. Figure S2.2 reports the confidence intervals around the marginal effects for both climate groups. The 95% confidence intervals for all heat exposure effects in the hot summer sample just cross 0. The respective p-values of the coefficient estimates are around 0.06.

Figure A3. Temperature Exposure (°F) and Emotional Well-Being, Interactions Between Temperature and Local Climates, Restricted Covariate Specification M5 (see Table A12).



Note: The bars represent 95% confidence intervals around the marginal effect of temperature exposure on well-being relative to the exposure level of the reference group (50 to 60°F). Estimates were stratified by climate area, grouping respondents into areas with mild (<75°F) and hot (>75°F) summers. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. The covariate specification is described in Table A12. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

While estimates appear qualitatively very similar to those in Figure S2.1, closer inspection of the estimates indicates that some but not all confidence intervals are marginally smaller than in Figure S2.2.[3] Still, there is no formal evidence of adaptation. For example, testing whether the effect of exposure to 70-80°F and 80-90°F differs across groups, we obtained an F-statistic of 1.50 with a p-value of 0.22.

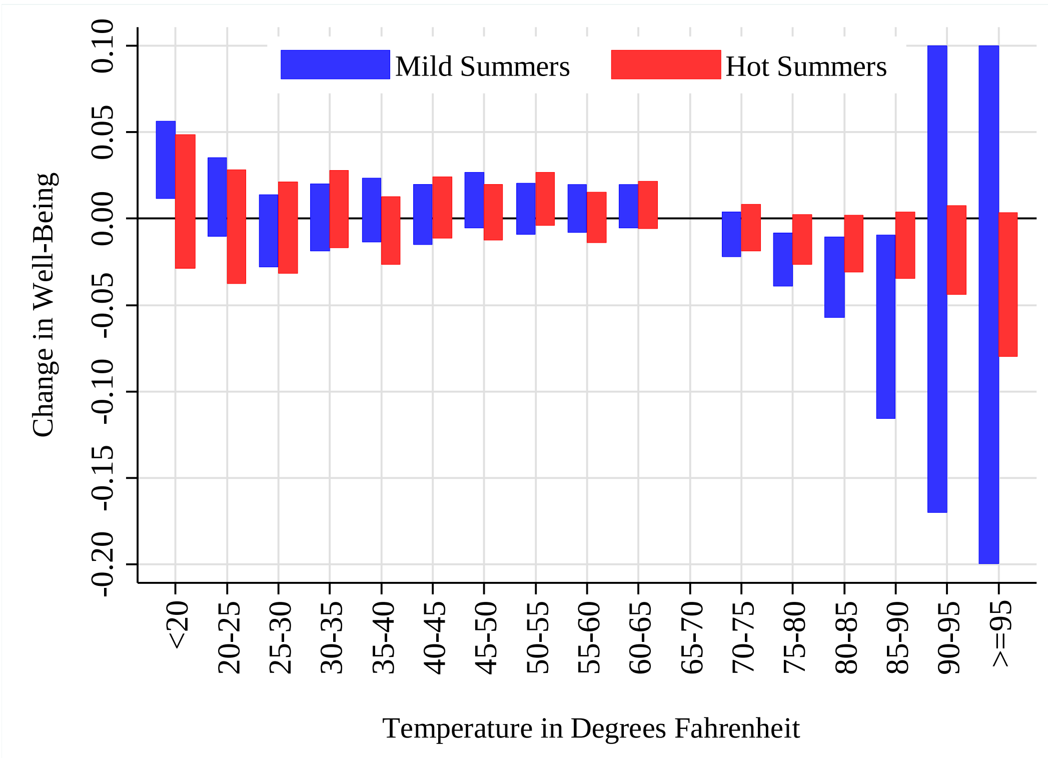
Before conducting a parametric analysis, we want to explore the functional form of the well-being temperature response function further. For Figure S2.3, we repeated the preceding analysis except that we binned the temperature variable into 5 degree instead of 10 degree bins. This reduced the number of observations in each bin and resulted in wider confidence intervals. In particular, the confidence intervals for exposure to very hot days in the mild summer sample expanded substantially. To facilitate the visual display of results, we truncated the estimated effect for exposure to temperatures above 90°F for the mild summer group at -0.2 and 0.1 respectively.

This further illustrates the problem that temperature effects estimated in the tails of the temperature distribution, in particular in the right tail for the mild summer sample, are based on relatively few observations. This not only increases confidence intervals, but also creates difficulty in identifying the functional form of the temperature effect. Figure S2.3 illustrates this by showing how well-being seems to diminish seemingly as a linear function of temperature in

[3] If the covariates we dropped predict the outcome variable well for one of the groups, the increase in residual variation could increase estimated standard errors and widen confidence intervals.

the mild summer sample between the reference group and the 85-90°F bin. Beyond that point, we lack observations to make a more definitive assessment about the functional form of the temperature effect.

Figure A4. Temperature Exposure (°F) and Emotional Well-Being, Interactions Between Temperature and Local Climates, 5°F Temperature Exposure Bins, Restricted Covariate Specification M5 (see Table A12).



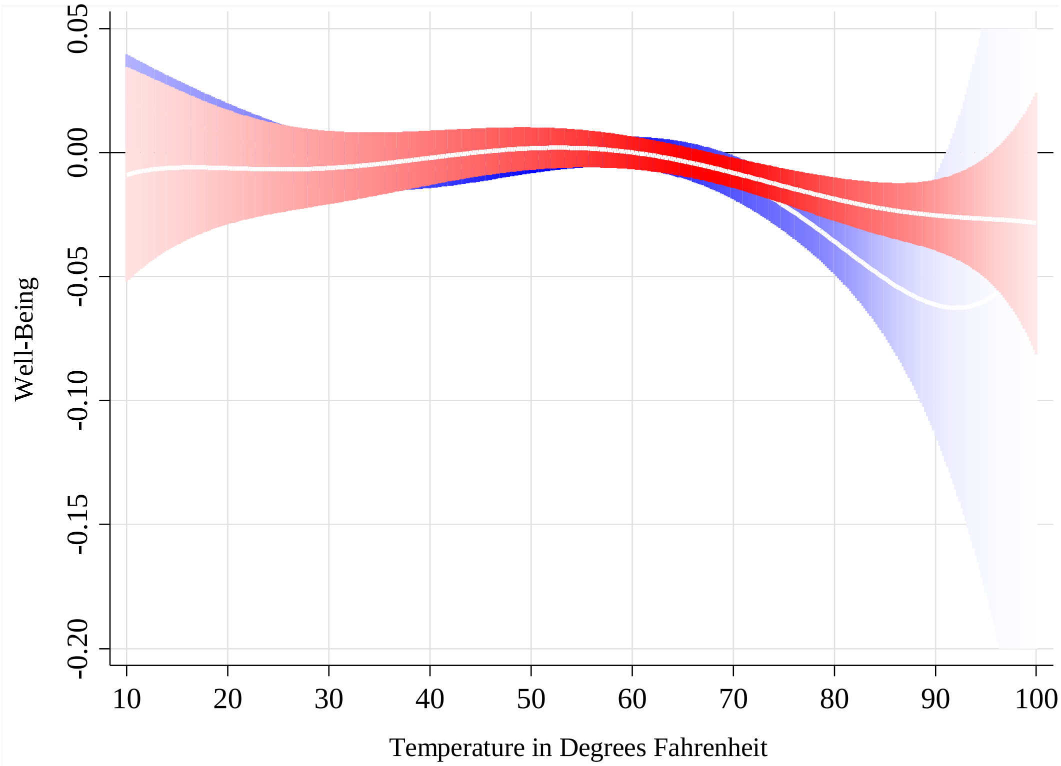
Note: The bars represent 95% confidence intervals around the marginal effect of temperature exposure on well-being relative to the exposure level of the reference group (65 to 70°F). Estimates were stratified by climate area, grouping respondents into areas with mild (<75°F) and hot (>75°F) summers. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. The covariate specification is described in Table A12. Standard errors are adjusted for clustering at the ZCTA level. To facilitate visual display, we truncated the confidence interval for exposure to temperatures above 90°F for the mild summer group at -0.2 and 0.1 respectively. Source: Gallup G1K and NLDAS-2.

For the following analyses, we use the restricted covariate specification and replaced the binned temperature variable with a continuous temperature variable and higher order temperature polynomials. We again add the climate group dummy variable and its interactions with all other variables to the model and performed joint F-tests to see whether the well-being temperature response function differs significantly across groups. We then simulate predicted means and 95% confidence intervals to visualize the temperature effects over the full temperature distribution from 10 to 100°F, keeping all other variables at their sample means. One should keep in mind that in the mild summer sample, we only observe 462 observations at temperatures above 90°F, an only 52 observations at temperatures above 95°F.

Figures S2.4 and S2.5 below visualize the continuous temperature well-being response function across the two climate areas. Both show simulated mean well-being at a given temperature with a 95% confidence interval. Following Hsiang, confidence intervals were drawn in a manner that adds “graphical weight” to the areas of the figure where confidence intervals are smallest, i.e. where we have the greatest certainty about the underlying population parameter if we were to repeat our estimation on multiple successive samples (Hsiang, 2013).

The predicted means are shown in white, embedded within their respective confidence intervals. The confidence intervals are shown in color, with color saturation at each temperature inversely proportional to the width confidence interval. Inverse proportionality implies that, at each temperature, the same amount of color or ink is used to draw the confidence interval. In areas where confidence intervals are small, this amount of ink is used on a small vertical area, producing high color saturation. In areas where confidence intervals are wide, the same amount of ink has to be used to color a larger vertical area, and therefore the resulting color saturation is low.

Figure A5. Temperature Exposure (°F) and Emotional Well-Being, Interactions Between Temperature and Local Climates, Sixth Order Temperature Polynomial, Restricted Covariate Specification M5 (see Table A12).



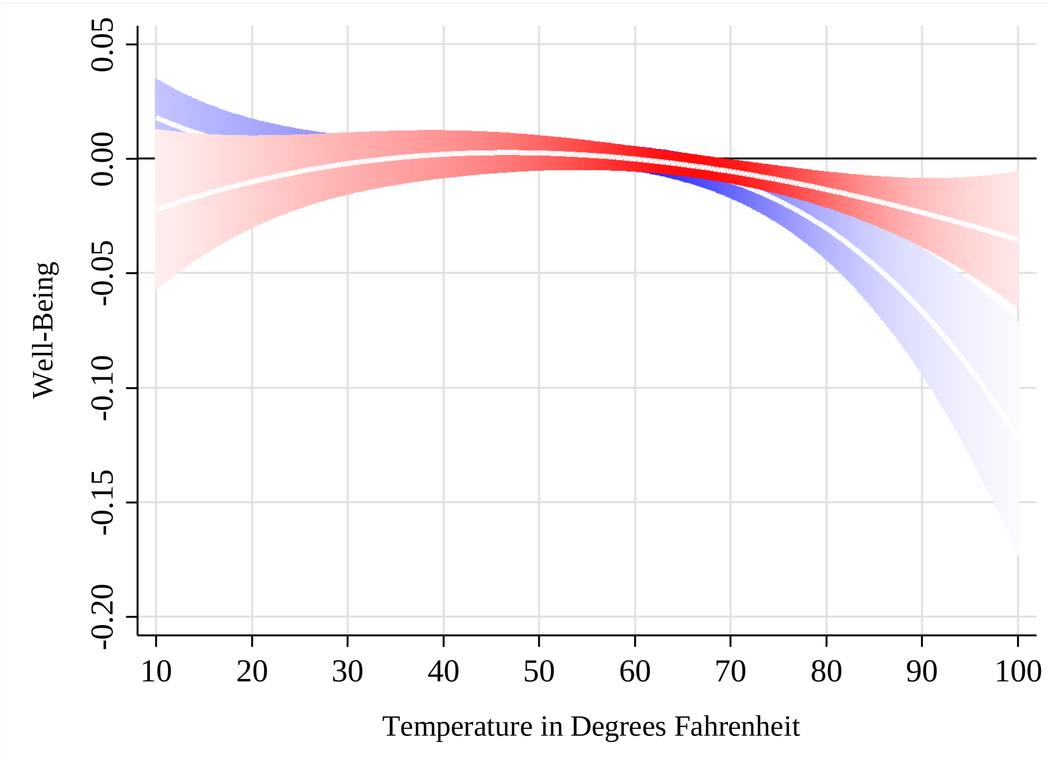
Note: The figure shows predicted means and 95% confidence intervals from a regression of well-being on a sixth order temperature polynomial. Confidence intervals are visually weighted as a function of their width, with lower color saturation at greater widths (Hsiang, 2013). Estimates were stratified by climate area, grouping respondents into areas with mild (<75°F) and hot (>75°F) summers. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. The covariate specification is described in Table A12. Standard errors are adjusted for clustering at the ZCTA level. To facilitate visual display, we truncated the confidence interval for exposure to temperatures above 90°F for the mild summer group at -0.2 and 0.1 respectively. Source: Gallup G1K and NLDAS-2.

Using a sixth order polynomial, joint F-test on the interactions between climate group dummy and temperature polynomials indicate no significant difference (p-value = 0.21). The well-being temperature response functions are statistically indistinguishable up until 60°F (Figure S2.5). Then well-being seems to decline faster with temperature in the mild summer sample, but confidence intervals also widen rapidly. Moreover, there is some evidence of non-linearity beyond 90°F. This may be specific to our sample, but illustrates the general point that it is difficult to identify the functional form in this part of the covariate distribution.

Once we restrict the functional form to a third order polynomial (Figure S2.6), we detect statistically significant differences. The more restrictive functional form results in much smaller confidence intervals in the mild summer sample at high temperatures. A joint F-Test on the interaction between climate group variable and temperature polynomials indicates a statistically significant difference ($p<0.05$). However, well-being also declines with temperature in the areas with hot summers. Despite the fact that the underlying population should be well adapted to heat in this region if adaptation is to occur at all, we nevertheless observe a negative effect of temperature on well-being.

Finally, we explored whether a more conservative model selection criterion would lead to different conclusions. Despite the power issues noted, we are more likely to find evidence for adaptation using joint F-tests as sample size increases. We therefore also considered the Bayesian Information Criterion (BIC). In situations where an F-test would support the addition of further parameters, i.e. an interaction between climate and temperature, BIC tends to prefer more restrictive specifications with fewer parameters.

Figure A6. Temperature Exposure (°F) and Emotional Well-Being, Interactions Between Temperature and Local Climates, Third Order Temperature Polynomial, Restricted Covariate Specification M5 (see Table A12).



Note: The figure shows predicted means and 95% confidence intervals from a regression of well-being on a third order temperature polynomial. Confidence intervals are visually weighted as a function of their width, with lower color saturation at greater widths (Hsiang, 2013). Estimates were stratified by climate area, grouping respondents into areas with mild (<75°F) and hot (>75°F) summers. The dependent variable is a well-being index with mean zero and standard deviation one. The index is the first principal component extracted from ten measures querying respondents' emotional well-being on the day prior to the interview. Temperature is measured as the 24-hour average temperature in degrees Fahrenheit (°F) on the day before the interview. All estimates were obtained using OLS regression and use sampling weights provided by Gallup. The covariate specification is described in Table A12. Standard errors are adjusted for clustering at the ZCTA level. Source: Gallup G1K and NLDAS-2.

Table A13 reports statistics from goodness of fit tests. Each row contains statistics from a different model. In the upper (lower) section, the temperature effect has been specified as a 3rd order (6th order) polynomial. The baseline model (=M1) only includes the temperature polynomial, commuting zone fixed effects, year fixed effects, week fixed effects and day of the week fixed effects. M2 adds the climate zone indicator variable and an interaction between climate zone indicator and the respective temperature polynomial. Model 3 contains interactions between the climate zone indicator and all other covariates in the model. Column 1 contains p-values from a joint F-test on the interaction between the climate zone indicator and temperature polynomials (also reported above). Column 2 contains the BIC for the respective model, and column 3 contains the change in BIC relative to the baseline model (M1). A smaller BIC generally indicates a better fit.

Table A13. Interactions Between Temperature and Local Climates: Testing Model Fit Using Different Temperature Polynomials.

	P-Value*	BIC	Change in BIC relative to Baseline
Third Order Temperature Polynomial			
M1: Baseline		5404823	
M2: Baseline + climate area interactions	0.039	5404851	28
M3: Fully interacted	0.012	5405096	273
Sixth Order Temperature Polynomial			
M1: Baseline		5404819	
M2: Baseline + climate area interactions	0.300	5404865	46
M3: Fully interacted	0.210	5405113	248

Note: * p-value from joint F-test on interactions between climate zone indicator and temperature polynomial. Source: Gallup G1K and NLDAS-2.

We observe that the baseline model for the 6th order polynomial specification has the lowest BIC. Moreover, using either the 3rd or 6th order polynomial specification, we would prefer the baseline model to the models which allow for an interaction between climate and temperature. Using a conservative criterion for model selection, we would therefore favor the baseline specification and omit climate area specific temperature effects. Using BIC to guide model selection, we therefore find no evidence for adaptation.

Discussion

The weight of the evidence does not suggest that the effect of temperature on well-being differs across regions with mild and hot summers. Using the Bayesian Information Criterion as a guide model selection, we find no evidence of improved model fit if we allow for an interaction between climate and temperature. Using joint F-tests, we also find no evidence that the temperature effects differ by climate area if we use a semi-parametric or flexible polynomial specification for the temperature variable. Only the most restrictive model we estimate, both in terms of covariates controlled and functional form of the temperature variable, yields some evidence in favor of adaptation.

Using a third-order polynomial, we find that the temperature effect is significantly weaker in the hot summer sample according to a joint F-test ($p<0.05$). This evidence is consistent with lower levels of adaptation in areas with mild summers, and could imply untapped capacity for adaptation in these areas that, if it is realized, might weaken the well-being response to heat levels observed in areas with hot summers. However, using BIC, we would prefer a model without a climate-temperature interaction. Another problematic aspect of this analysis is the implied functional form assumption (Schlenker & Roberts, 2009). This particularly applies to the mild summer subsample, for which we lack observations at high temperatures to test whether or not a chosen functional form is an accurate representation of the data. In Figure A6, we effectively extrapolate the temperature effect into parts of the temperature distribution where we have very little data, by imposing a curvilinear functional form. Analyses that make use of a more flexible functional form at high temperatures (Figure A4, A5) suggest that the functional form may well be different from the one imposed by the 3rd order polynomial.

Our testing approach is limited by a lack of observations at very high temperatures in the mild summer sample, which in turn limits our ability to reliably determine the functional form of the temperature effect, and therefore to assess whether these effects indeed differ at high temperatures. However, our test is also stacked in favor of finding adaptation in several ways. First, we used F-tests to determine whether effects differ across very large (~900,000 observations) subsamples. Second, we adopted restrictive model specifications, both in terms of covariates controlled and the functional form of the temperature variable. Third, the difference in temperatures across our climate zones was larger than the expected increase in temperatures due to global climate change during our projection period. Even if we had found consistent evidence for adaptation, we could not be sure that adaptation would occur if the expected increase in temperatures due to global warming would provide a weaker incentive for adaptation than the difference in temperatures across our climate zones.

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