Temperature and Temperament: Evidence from a billion tweets

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Abstract

What is the welfare cost of environmental stress? The change in amenity values resulting from temperature increases may be a substantial unaccounted-for cost of climate change. Without an explicit market for climate, prior work has relied on cross-sectional variation or survey data to identify this cost. This paper presents an alternative method of estimating preferences over nonmarket goods which accounts for unobserved cross-sectional and temporal variation and allows for precise estimates of nonlinear effects. Specifically, I create a rich panel dataset on hedonic state: a geographically and temporally dense collection of updates from the social media platform Twitter, scored using a set of both human- and machine-trained sentiment analysis algorithms. Using this dataset, I find strong evidence of a sharp declines in hedonic state above and below 20°C (68°F). This finding is robust across all measures of hedonic state and to a variety of specifications.

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1 Introduction

Acute environmental stressors like typhoons, hurricanes, and other marked changes in the external environment are known to have large economic costs (Hsiang and Jina 2014). However, slower-moving changes in the environment, such as temperature increases due to climate change, tend to have subtler economic effects. The empirical climate impacts literature has set out to estimate the size of these effects, largely focusing on estimating the indirect impacts of climate change, *e.g.*, temperature-induced changes in income, crime, or natural disasters.

Because temperature is a nonmarket good, estimating the "direct" impacts of climate change has proven to be more challenging[1]. Prior work has estimated that individuals would be willing to pay between 1% and 3% of their incomes to avoid a one °F increase in summer temperatures (Cragg and Kahn 1997; Sinha and Cropper 2015; Albouy, Graf, Kellogg, and Wolff 2013). However, these costs are almost exclusively identified using cross-sectional variation in climate and therefore rely on important assumptions about unobservable variation in climate preferences. A separate literature uses subjective well-being surveys in order to estimate preferences for temperatures. While these papers do not estimate costs directly, they are able to account for some unobserved cross-sectional variation by controlling for time-invariant characteristics in space (Levinson 2012; Feddersen, Metcalfe, and Wooden 2012), but yield conflicting results due to limited statistical power.

This paper demonstrates a new method to estimate preferences over nonmarket

[1] "Direct" here refers to the hypothesized welfare impact of changing average daily temperature while holding the indirect impacts of temperature constant. This can also be viewed as the amenity value of changes in climate.

goods using an approach that addresses both the identification and statistical power concerns described above. I construct a geographically and temporally dense collection of more than a billion geocoded social media updates from the online platform Twitter. To estimate preferences for temperature, I code each tweet using a set of sentiment analysis algorithms designed to extract hedonic state from natural languag.[2]. The density of my dataset allows me to resolve identification concerns by accounting for correlated unobservables at the county, neighborhood, and even individual level with an extensive set of fixed effects and while simultaneously accounting for unobserved state-specific seasonal variation.

I define hedonic state as a one-dimensional measure of mood ranging from negative to positive[3]. The four measures I use span a range of sentiment analysis techniques designed to elicit mood from natural language. Two measures are specified using expert- and crowd-sourced dictionaries that map words to numerical scores. A third measure scores tweets by whether or not they contain profanity. The final measure trains a machine-learning algorithm using those Twitter updates that contain emoticons, *e.g.*, ":)" or ":(", to predict the emotional content of the full set of tweets. I validate these measures by demonstrating their change across days of the week and, following Card and Dahl (2011), their response to nearby NFL teams' wins or losses.

Using geographical information attached to the Twitter updates, I match these

[2]Since climate change is projected to manifest primarily as changes in average temperature for most of the world (IPCC 2014), I focus specifically on temperature as the environmental variable. Still, this approach generalizes to many other similar phenomena that are experienced heterogeneously across space and time.

[3]The definition of emotional state, mood, and other measures of affective well-being are active areas of research. See Russell (1980) or Kahneman, Diener, and Schwarz (1999) for more details on these definitions.

measures of emotional state to daily weather conditions at the precise location of the user. My identifying assumption is that temperature realizations are as good as random after accounting for spatial and seasonal fixed effects. Allowing temperature to enter the econometric model flexibly, I find strong evidence of a sharp decline in hedonic state above and below 20°C (68°F). The difference in hedonic state between 20-25°C (68-77°F) and 30-35°C (86-95°F) is significant and comparable in size to the average difference in hedonic state between Sundays and Mondays.

I conduct a series of robustness checks to further explore the results and to test for potential sources of bias. First, I demonstrate consistent effects in both direction and standardized magnitude across all measures of hedonic state, indicating that the results are not driven by measure design. I additionally confirm that the observed effects are not generated by correlated compositional changes in the sample across temperatures by estimating a model with individual fixed effects. Next, I examine heterogeneity in the response by hour of day and document that warmer temperatures are strongly dispreferred in the morning, weekly preferred in the afternoon, and weakly dispreferred in the evening. Following Albouy, Graf, Kellogg, and Wolff (2013), I also document heterogeneity in the effects by season. I combine estimates of regional temperature response functions and downscaled climate projection data to project the effects of changes in temperature on hedonic state under scenarios with and without adaptation. Finally, following prior work, I implement a back-of-the-envelope calculation of the monetary costs implied by the changes in hedonic state I estimate.

The paper proceeds as follows: sections 2 and 3 sketch the conceptual framework and review the related literature. Section 4 describes the data and sentiment analysis algorithms I use, while section 5 lays out the empirical approach and identifying assumptions. Section 6 reports the baseline results, section 7 documents robustness checks and extensions, and section 8 concludes.

2 Conceptual framework

A simple conceptual framework helps illustrate the problem of estimating the costs of climate change. Consider a representative consumer with a utility function defined over temperature T, a composite of goods whose consumption utility is affected by temperature c_T, and a composite of goods whose consumption utility is unaffected by temperature c_N. Let this consumer choose the quantity of c_T and c_N she consumes, subject to their prices p_T and p_N and income I. T is assumed to be determined exogenously[4] and as a result does not enter the budget constraint. The consumer's problem is as follows:

$$\max_{c_T, c_N} U = U(T, c_T, c_N) \text{ s.t. } p_T c_T + p_N c_N \leq I$$

To maximize utility, the consumer chooses c_T^* and c_N^* optimally such that $\frac{\partial U}{\partial c_T} = \lambda p_T$ and $\frac{\partial U}{\partial c_N} = \lambda p_N$, where λ is the shadow value of relaxing the budget constraint by one unit. Note that c_N^* is implicitly a function of T through the budget constraint, since changes in T may alter c_T^*. Consider two types of exogenous shocks: a change

[4] A two-period model would allow consumers to choose T by changing location, in doing so alter the prices and utility value of both c_T and c_N. I focus on the simpler model for clarity.

in T and a change in I.

$$\begin{aligned}\frac{dU}{dT} &= \frac{\partial U}{\partial T} + \frac{\partial U}{\partial c_T^*}\frac{\partial c_T^*}{\partial T} + \frac{\partial U}{\partial c_N^*}\frac{\partial c_N^*}{\partial T} \\ \frac{dU}{dI} &= \frac{\partial U}{\partial c_T^*}\frac{\partial c_T^*}{\partial I} + \frac{\partial U}{\partial c_N^*}\frac{\partial c_N^*}{\partial I}\end{aligned}$$

Combining these, the monetary cost of a unit change in temperature is the compensating variation x that keeps the consumer on her original indifference curve:

$$\frac{dU}{dT} + x\frac{dI}{dT} = 0$$
$$\frac{\partial U}{\partial T} + \frac{\partial U}{\partial c_T^*}\frac{\partial c_T^*}{\partial T} + \frac{\partial U}{\partial c_N^*}\frac{\partial c_N^*}{\partial T} + x\left[\frac{\partial U}{\partial c_T^*}\frac{\partial c_T^*}{\partial I} + \frac{\partial U}{\partial c_N^*}\frac{\partial c_N^*}{\partial I}\right] = 0$$

In principle, a researcher could estimate x using a choice experiment in which consumers are asked to state their willingness to pay to avoid a degree rise in average temperature. In reality, multiple market failures make this design infeasible. First, information is not perfect: the costs of climate change are incompletely understood even by researchers in the field, and likely less so by the average consumer (IPCC 2014). Moreover, even with perfect information, present-day consumers may have a discount function that is inappropriate to capture the full costs of climate change, since those costs will likely be endured mostly by generations who have yet to be born[5]. Third, the choice experiment as presented suffers from a collective action problem, since the benefits of climate change mitigation are spread across the entire world, while the implied cost would be born by the respondent alone.

[5]The problem of how to properly account for the preferences of future generations remains a topic of active debate. See Stern (2006) and Nordhaus (2007) for two views of this question.

Instead, in practice, the literature estimates the effect of temperature on different sectors of the economy and calculates the cost of climate change to be the sum of the value of the projected changes in those sectors. As an example, let c_T^C be crime risk, which has been documented by Ranson (2014) to increase in temperature. Researchers estimate $\frac{\partial c_T^C}{\partial T}$ and multiply by estimates of willingness to pay to avoid crime. Integrated Assessment Models (Hope 2006; Nordhaus and Sztorc 2013; Antoff and Tol 2014) and the Social Cost of Carbon (Interagency Working Group on Social Cost of Carbon 2013) aggregate $\frac{\partial c_T}{\partial T}$ for all possible impacts, then multiply by expected temperature changes to obtain the net benefit of climate change[6].

The climate impacts literature has historically focused on estimating $\frac{\partial c_T}{\partial T}$, which I refer to as the "indirect" effects of climate change. Because these effects on welfare are driven through other factors, measuring indirect impacts relies on the combination of measurement of preferences for these indirect factors and predicted changes in these factors due to climate change, but not measurement of direct preferences for temperature itself. This paper instead measures $\frac{\partial U}{\partial T}$, the "direct impacts" of climate change. $\frac{\partial U}{\partial T}$ can be thought of as the amenity value of temperature, or the marginal change in hedonic state associated with a marginal change in temperature[7].

[6]For more complete descriptions of the construction of the IAMs or the SCC, see the listed citations or the summary in Diaz (2014). This framework does not imply that the net benefit must be less than zero, but most current estimates find this to be the case empirically.

[7]It is reasonable to argue that this paper too examines an "indirect impact", since psychological changes, for example, could be viewed as a kind of mechanism. I use the term "direct" here to refer to mechanisms in which weather alters individuals' day-to-day experience of the world. I make use of the fact that the main drivers of hedonic state are an individual's underlying hedonic state and transient changes in the state of the world (Kahneman and Krueger 2006). This suggests that the primary effects I observe are likely to correspond closely with the prior literature's definition of amenity value.

3 Background

Economists have studied the economic impacts of climate change for more than two decades (Nordhaus 1991; Cline 1992), but the recent availability of panel datasets and advanced econometric techniques have made possible the identification of the causal effects of changes in temperature on a wide variety of outcomes (Dell, Jones, and Olken 2014), the results of which are used to project the economic impacts of climate change.

Early work in the climate impacts literature focused on identifying the effects of changes in climate on agricultural output (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005; Deschênes and Greenstone 2011). One notable finding from this literature is that the response function of yields to temperature changes contains important non-linearities: yields tend to increase slightly up to a threshold, after which they decrease sharply, implying severe negative effects on yields under many climate change scenarios (Schlenker and Roberts 2009).

Recently, scholars have directed their attention to non-agricultural impacts of climate change. Dell, Jones, and Olken (2012) use country-level data to identify the effect of weather variation on aggregate economic outcomes, and find that higher temperatures reduce economic growth in poor countries. Using county-level data on U.S. incomes, Deryugina and Hsiang (2014) conduct a similar analysis in the United States and document the negative impacts of warm weekday temperatures on county income, and provide suggestive evidence that these effects are driven by changes in the productivity level of basic economic units such as workers and crops. Burke, Hsiang, and Miguel (2015b) expand these findings to the global scale, providing evidence that economic productivity declines in high temperatures for both rich and poor countries.

Other work has examined the effect of temperature on economic productivity. Graff Zivin and Neidell (2014) study the effect of temperature on time allocation using county-level data, finding that the quantity allocated to labor decreases in higher temperatures. In related work, Graff Zivin, Hsiang, and Neidell (2015) study the effect of temperature on cognitive performance, using a panel of test scores to find statistically significant decreases in math (but not reading) performance when the temperature rises above 79°F.

A substantial literature has examined the relationship between climate and conflict. Burke, Hsiang, and Miguel (2015a) conduct a meta-analysis of the available estimates and find that one standard deviation increase in temperature increases interpersonal and intergroup violence by 2.4% and 11.3%, respectively.

Other work has looked at the relationship between temperature and electricity usage, or load. Auffhammer and Mansur (2014) review the existing literature and document the need for additional panel data studies to properly control for unobserved cross-sectional variation. Existing panel data studies, such as Deschênes and Greenstone (2011) find a significant increase in energy consumption due to high temperatures using state-level averages, while Auffhammer and Aroonruengsawat (2011) use detailed billing data from California to document within-state heterogeneity in load responses.

Individuals without access to air conditioning are more susceptible to the effects of temperature changes. Understanding the adoption of temperature-regulating technology informs predictions about future effects of climate change. Auffhammer (2013) uses a two-stage model to estimate both intensive and extensive margin increases in air conditioning due to climate change. In related work, Davis and Gertler (2015) study air conditioner adoption in Mexico, predicting close to full adoption within a few decades primarily due to income growth rather than changes in climate.

Climate-induced changes in mortality have been studied by Deschênes and Greenstone (2011) and **Barreca2013b**, among others. The first estimates a 3% increase in the age-adjusted mortality rate in the United States, while the second documents the importance of air conditioning in mitigating the temperature-mortality relationship observed in the first half of the 20th century.

Many of the estimates described contribute, directly or indirectly, to aggregate measures of the total cost of climate change produced by summary reports (Stern 2006; Houser et al. 2014) and integrated assessment models (IAMs), which in turn are inputs to the United States government's estimate of the social cost of carbon (Interagency Working Group on Social Cost of Carbon 2013). In particular, three IAMs are used to construct this estimate. They are the Dynamic Integrated Climate-Economy Model (Nordhaus and Sztorc 2013), or DICE, the Climate Framework for Uncertainty, Negotiation, and Distribution (Antoff and Tol 2014), or FUND, and the Policy Analysis of the Greenhouse Effect (Hope 2006), or PAGE. IAMs integrate economic and ecological models to weigh the costs and benefits of global warming[8]. The link between warming and damages (or benefits) is modeled in each using either a single damage function or a set of damage functions.

[8]For a detailed review of the three IAMs listed, see Diaz (2014) or Rose (2014).

DICE uses a global damage function that is built from separate, sector-level damage functions. The author uses a time of use survey to value nonmarket amenities, resulting in a quadratic damage function between temperature and amenity value. This formulation estimates net benefits from changes in amenity value that actually exceed the total market impacts in the United States (Nordhaus and Boyer 2000). PAGE includes damage functions for both economic and noneconomic changes, the parameters of which are generated from the findings of the third IPCC report (Hope 2006), which did not include nonmarket amenity values directly (IPCC 2001). FUND uses a set of damage functions, but these do not include a separate function for nonmarket amenities (Antoff and Tol 2014).

That the direct effect of climate change could entail a significant welfare impact follows from the observation that people have preferences over weather. Still, estimating these preferences and the cost associated with shifting the temperature distribution has been challenging, due primarily to the fact that there is no market for temperature. Two main approaches have emerged, the first using hedonic price models and the second using life satisfaction surveys.

The hedonic price approach recovers willingness-to-pay (WTP) for climate amenities by comparing cross-sectional differences in wages and climate amenities after controlling for other covariates; for an early example, see Hoch and Drake (1974). Cragg and Kahn (1997) model the locational choices of migrants and find that movers are willing to pay about about 1.5% of annual income for an additional one °F in winter and -1.2% of annual income for an additional one °F in summer[9]. Sinha and

[9] The authors split results up by age and estimate different of WTP. Estimates are the unweighted average of the estimates in Table 7 of Cragg and Kahn (1997), adjusted for a one °F increase and

Cropper (2015) also look at migration decisions using a discrete model of location choice to estimate the rate of substitution between wages and climate amenities. The authors estimate that the marginal WTP for a one °F increase is between 1% and 5% of income in winter, and between -3% and -1.5% of income in summer. Finally, Albouy, Graf, Kellogg, and Wolff (2013) use a hedonic framework and data from the 2000 census to find a marginal WTP for a one °F increase in winter to be between 0.5% and 1% of income, and in summer between -2.5% and -1% of income[10].

The hedonic approaches described above are appealing because they identify implicit demand for climate using households' observed choices on where to live. Using estimates of the differential between wages and costs of living, they are also able to back out a WTP for climate. However, because the models estimate the effect of climate characteristics, which are mostly stable across time, the coefficients are identified using cross-sectional variation. This approach requires the assumption that there is no unobserved variation that is correlated with both climate and with the differential between wages and costs of living, an assumption that may be violated by cultural norms, geographic factors, or other unobserved amenities.

The survey approach uses surveys of subjective well-being (SWB) to estimate preferences over temperature. These surveys ask respondents to assess their well-being on a single dimensional scale (Diener 2000; Dolan, Peasgood, and White 2008). Kahneman and Krueger (2006) and Mackerron (2012) discuss the merits and weaknesses of these studies: a common challenge is that measurements of SWB are by

divided by the annual household income of the movers in their sample.

[10] I take the estimates of MWTP for a day at 40°(80°) F from Table 3 in Albouy, Graf, Kellogg, and Wolff (2013) and divide by the distance between 40 (80) and 65 to get the MWTP for one degree at that temperature.

definition subjective and likely to include unobserved variation across time and space. For example, responses to questions about one's well-being may depend on regional dialects or norms, or could be driven by the interaction between the interviewer and the interviewee, which may itself be affected by temperature.

The estimates of the effect of temperature on SWB vary widely within the literature. Most studies use cross-sectional variation or follow a very small group of individuals over time[11]. Only two control for unobservable cross-sectional variation using panel data models. Levinson (2012) uses 6,035 surveyed individuals from the General Social Survey to find a inverse-U shaped relationship between temperature and happiness, though the paper is primarily focused on the effects of pollution. Feddersen, Metcalfe, and Wooden (2012) use nearly 100,000 observations from Australian SWB surveys to compare the effects of short-term weather and long-term climate on life satisfaction. Since individuals are observed more than once in their data, they are able to control for individual fixed effects for some specifications. They find that weather affects reported life satisfaction through solar exposure, barometric pressure, and wind speed, but they do not find impacts from changes in temperature itself.

The mixed results in this literature suggest that statistical power is constrained by

[11] Howarth and Hoffman (1984) collect data from 24 Canadian male university students over a period of 11 days and find that higher temperatures improve hedonic state. Keller et al. (2005) study the effect of weather on both cognition and hedonic state and find that pleasant weather, *i.e.* moderate temperature or barometric pressure, is associated with higher hedonic state, although they find that higher temperatures in the summer are associated with lower hedonic state. Dennisenn, Butalid, Penke, and Van Aken (2008) also find that higher temperatures reduce hedonic state, while Klimstra et al. (2011) follow nearly 500 adolescents and find large individual differences in their responses to hedonic state. Lucas and Lawless (2013) find little effect of temperature on hedonic state using state-level data.

the combination of the high variance in SWB responses driven by non-temperature factors and relatively small sample sizes. Most studies in this area have either relied heavily on small sets of repeated samples, which limits external validity, or large sets of non-repeated samples, which raises concerns about unobserved cross-sectional variation.

Temperature preferences are likely to be correlated with unobservable factors that vary across both space and time, and may be small relative to preferences for other goods and services. To control for both geographic and temporal variation while maintaining sufficient power to identify small, non-linear effects would require a prohibitively expensive survey of subjective well-being.

In lieu of conducting such a survey, I use sentiment analysis algorithms to detect hedonic state from a large set of Twitter data. Sentiment analysis is a natural language processing technique designed to elicit subjective feeling from textual data. There are a small number of a studies in computer science and computational linguistics that have used sentiment analysis techniques on Twitter data. Dodds and Danforth (2010) create an dictionary-based algorithm that scores individual tweets using a mapping of more than ten thousand English words to scores of hedonic state. The authors demonstrate that although the algorithm can misclassify individual sentiments, it produces accurate results in aggregate (Mitchell et al. 2013). Other work uses machine learning techniques to predict the sentiment of tweets (Pak and Paroubek 2010). Related work has used sentiment analysis on Twitter data to predict economic outcomes of interest. Bollen, Mao, and Zeng (2011) find that collective hedonic state can help predict the stock market, Eichstaedt et al. (2015) use measures of county-level hedonic state to predict heart disease mortality, and Gerber (2014) shows that local Twitter hedonic state can improve local predictions of crime. To my knowledge, no studies have used sentiment-analyzed Twitter data in a causal setting.

By collecting a large, geographically and temporally detailed dataset, I am able to account for unobserved variation across both time and space. The size of my sample and the empirical techniques I use allow me to precisely estimate the effect of temperature in the midst of substantial unrelated variation in hedonic state. Additionally, I am able to identify non-linearities in the temperature response function and previously unexplored dimensions of heterogeneity.

4 Data

I generate four measures of hedonic state using data from Twitter and match these to weather data at the tweet level. Table 1 describes sample characteristics. The first panel shows the count, mean, median, minimum, and maximum of the measures of hedonic state I describe later in this section, the second and third panel describe the weather data used, and the fourth panel summarizes the number of tweets by individual, grid cell, and county in the data.

Table 1: Sample characteristics

	Count	Mean	Median	Min	Max
Measures of hedonic state					
Expert	1,077,127,397	0.37	0.38	-5.00	5.00
Crowd-sourced	1,083,068,307	5.51	5.51	1.30	8.44
Profanity	1,083,498,783	0.94	0.94	0.00	1.00
Emoticon	1,083,498,783	0.79	0.80	0.00	1.00
PRISM weather					
Min temperature (F)	943,724,684	53.6	58.0	-33.9	99.3
Mean temperature (F)	943,724,684	63.3	68.4	-22.9	108.7
Max temperature (F)	943,724,684	73.1	78.3	-17.3	123.9
Precipitation (mm)	943,724,684	3.0	0.0	0.0	318.3
QCLCD weather					
Proportion overcast	918,921,992	0.2	0.1	0.0	1.0
Visibility (km)	918,921,992	15.3	15.7	0.2	132.1
Relative humidity	918,921,992	59.6	60.4	2.1	100.0
Station pressure	918,921,992	29.2	29.4	19.9	30.8
Wind speed	918,921,992	7.7	7.3	0.0	74.7
Twitter updates per ...					
Individual	10,227,302	87	9	1	240,045
PRISM grid cell	519,942	2,084	14	1	20,849,368
County	3,102	307,508	33,276	44	45,557,251

Notes: First panel shows statistics for the measures of hedonic state, second and third panels for the weather datasets. For first through third panel, one observation is a single Twitter update. First column in the fourth panel is the total number of individuals, grid cells, and counties in the sample. Second through fifth columns are the means, medians, minimums, and maximums of the count of Twitter updates by individuals, grid cells, and counties, respectively.

4.1 Twitter data

Created in 2006, Twitter is a social networking site built around the public[12] exchange of short (<140 characters) Twitter updates. Since its founding, Twitter has become one of the most popular social media platforms worldwide, with 288 million active users sending over 500 million tweets per day[13].

Twitter's Streaming API[14] is designed to give developers access to the massive amount of data generated on the Twitter platform in real-time. Starting in June 2014, I began collecting geolocated Twitter updates from within the continental United States using a client that is continuously connected to the Streaming API[15] I collect the vast majority of geolocated tweets produced within my sample period, which ends in December 2015.

Geo-located tweets are those for which the user has consented to have his or her location information shared. The location information is either produced using the exact latitude and longitude of the user if the tweet is sent from a phone, or from a reverse-geocoding algorithm that derives the latitude and longitude from location information entered by the user. In principle, Twitter limits the total number of tweets delivered through the Streaming API to 1% (Morstatter, Pfeffer, Liu, and Carley 2013) of the total tweets created. Since I request only geolocated tweets from within the United States, this rarely comes to more than 1% of the total tweets

[12] Tweets are in the public domain.

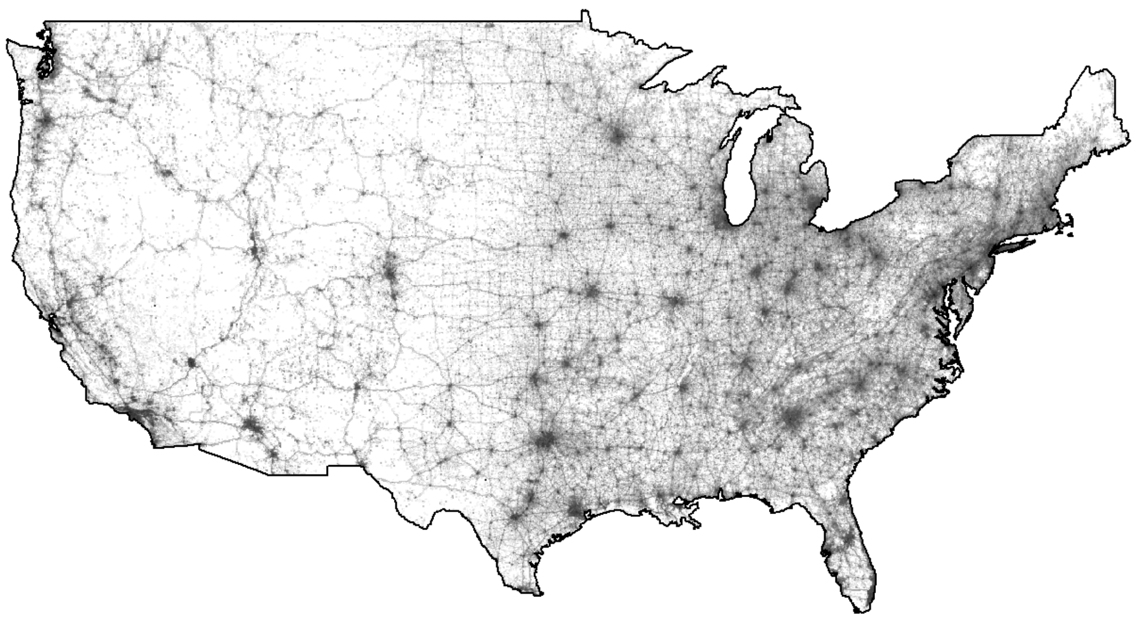
[13] Population summary statistics from `https://about.twitter.com/company`.

[14] `https://dev.twitter.com/streaming/overview`.

[15] There are two gaps, from June 26th to July 12th, 2014, and from September 18th to October 27th, 2014, corresponding to periods of time when the streaming client was unable to connect to the Streaming API.

worldwide (geocoded and otherwise). Over the course of the sample I collect, the percentage of missed tweets is fewer than 0.01% of the total available. Figure 1 is a map of Twitter update density where the shading for each pixel represents the log of the total number of tweets in the dataset for each grid cell, a 4 km^2 area. The distribution of tweets closely resembles the population distribution in the United States.

Figure 1: Tweet density



Notes: Darker areas represent higher levels of activity. Each pixel is a 4 km $\times$ 4 km grid cell, colored to represent the total recorded number of tweets in that grid cell over the sample period. Color is on a $\log_{10}$ scale.

To construct a measure of hedonic state, I generate measures of hedonic state from the text of the Twitter updates in the dataset. Because no single measure of hedonic state will perfectly capture the hedonic state of the individual at time of update, I construct four separate measures of hedonic state from the text in the

Twitter updates: Expert, Crowd-sourced, Profanity, and Emoticon measures.

Table 1 shows the raw measures of hedonic state in the sample. Count is the total counts of Twitter updates in the dataset, irrespective of whether or not covariate data was obtained for those tweets.[16] Note that although the Profanity and Emoticon scores are binary variables and thus would be expected to have median zero or one, the table displays the median of the average measure in a grid-cell day, weighted by count of tweets. The descriptive statistics are constructed using the raw measures, but the difference in means and scales suggests that standardization will be useful for empirical comparison. As such, the measures are standardized (mean zero and unit standard deviation) for the empirical estimation described in section 5. The fourth panel shows the number of tweets per individual, grid cell, and county in my dataset over the entire sample. There is considerable variation in the tweet volume across these groups. Los Angeles county, for example, is responsible for more nearly 5% of the sample, while a single user accounts for nearly a quarter million tweets[17].

Table 2 shows the correlations between the four measures. As expected, all of the measures are positively correlated with each other, reflecting general agreement. Some of the correlations are low, particular those between the Profanity measure and the other measures, likely reflecting the considerable differences in the ways these measures are constructed. The complexity of measuring hedonic state, as demonstrated by the relatively limited agreement of the measures presented here, suggests the importance of considering the effects across all measures rather than

[16] A proportion of tweets in my sample came from locations just outside the continental United States, which is outside the range of the meteorological data I use.

[17] I do not include users with more than 10,000 tweets over the sample period in the analysis.

Table 2: Measure correlations

	Expert	Crowd-sourced	Emoticon	Profanity
Expert	1.00			
Crowd-sourced	0.59	1.00		
Emoticon	0.35	0.31	1.00	
Profanity	0.39	0.19	0.12	1.00

Notes: Table displays correlations between the four measures of hedonic state within the sampling frame.

just one. I next detail the construction of each measure.

4.1.1 Expert measure

The Expert measure is constructed using an expert-created dictionary that maps words to scores of hedonic state. The AFINN-111 dictionary contains 2,477 words scored using integers between -5 and 5, where -5 indicates negative hedonic state and 5 indicates positive hedonic state. The dictionary focuses on words that are indicative of hedonic state, and was created by Nielsen (2011) to analyze language typically used in microblogging. The dictionary is refined from an earlier dictionary built by psychologists to assess the affective state (the psychological equivalent concept to hedonic state) of written texts (Bradley and Lang 1999). The measure is constructed using the following procedure:

1. Tweets are cleaned of extraneous punctuation, URLs, hashtags, and other nonsense characters.
2. Tweets are checked for weather-related stopwords to avoid a mechanical correlation generated by individuals discussing aberrant weather patterns. If a stopword is found, the given tweet is scored as missing.

3. For each word in a tweet that matches an entry in the AFINN dictionary, the corresponding measure of hedonic state is retrieved.
4. The overall score for a given tweet is the average score for word matched in step 3. If no words in the tweet matched to the dictionary, then the measure is scored as missing.

Let $j = 1..J$ index words w_j in a cleaned tweet and let $k = 1..K$ index the tuples (w_k, s_k), which are the word-score pairings in the dictionary. The Expert measure E^E for a given tweet is:

$$E^E = \frac{\sum_{j=1}^{J} \sum_{k=1}^{K} \mathbb{1}[w_j = w_k] \times s_k}{\sum_{j=1}^{J} \sum_{k=1}^{K} \mathbb{1}[w_j = w_k]}$$

The AFINN-111 dictionary is specifically designed to include only words that are indicative of emotional state. For example, the tweet "happy anniversary mom and dad" has five words, but only "happy" is included in the AFINN-111 dictionary, and has rating $s_{\text{happy}} = 3$. The overall score for the tweet is just the average across scored words, which in this case is just $E^E = 3$ for this tweet, since only "happy" was scored. Similarly, the tweet "i can't watch matt cry" is given $E^E = -1$, since the word "cry" has $s_{\text{cry}} = -1$.

4.1.2 Crowd-sourced measure

The Crowd-sourced measure E^C is constructed in a similar manner, but the dictionary used is that provided by and described in Dodds and Danforth (2010). The authors crowd-source a dictionary of more than 10,000 words using the Mechanical Turk service, which outsources tasks to external users. Users were asked to rate each word on a scale from 1 to 9, where 1 indicated negative emotional state and 9 indicated positive emotional state, and scores were averaged across users to get a single score for each word.

Unlike the Expert-measure, the Crowd-sourced measure scores most commonly-used words regardless of whether they are likely to be indicative of underlying hedonic state. Taking the same example tweets from the section above, "happy anniversary mom and dad" has $E^C = 6.976$, since the words in the tweet have scores of 8.3, 6.7, 7.64, 5.22, and 7.02, respectively. "i can't watch matt cry" has $E^C = 4.428$ with word scores of 5.92, 3.42, 5.7, 5.26, and 1.84 for each word in the tweet, respectively. More examples of words with positive, neutral, and negative sentiment are available in the appendix.

4.1.3 Emoticon measure

While lexical affinity approaches such as the Expert and Crowd-sourced methods are frequently used in the sentiment analysis literature, they can be sensitive to the particular word-sentiment score mapping chosen by the researcher. To complement these approaches, I construct a measure of hedonic state that classifies tweets as positive or negative using a small set of assumptions and machine learning techniques.

Emoticons are text-based facsimiles of common facial expressions. In general, emoticons can indicate positive moods, e.g. ":)" or ":-)", or negative moods, e.g. ":(" or ":-(". One possible approach would be to limit the sample to tweets that contain either a positive or a negative emoticon. However, since emoticons appear in only about 2% of the sample, this approach substantially limits power. Since most

Twitter updates with emoticons contain words as well, researchers in computational linguistics have employed machine learning techniques to leverage the subset of tweets with both emoticons and words to predict the sentiment of the entire set of tweets (Go, Bhayani, and Huang 2009; Kouloumpis, Wilson, and Moore 2011).

I collect a training dataset consisting of all tweets containing either positive or negative emoticons. For this training dataset, I code the hedonic state as binary and assume its polarity (1 if positive, 0 if negative) is indicated by the attached emoticon. For a full list of the emoticons used to collect this dataset, see the appendix. Next, I train an effective, computationally efficient machine learning classifier, Multinomial Naïve Bayes[18], to estimate whether particular words are more likely to be associated with positive or negative emoticons. Finally, I use this classifier to compute the Emoticon measure E^M of the population of tweets.

Developing a predictive model as described above could be done using a variety of tools, ranging in complexity from ordinary least squares to ensemble techniques that incorporate multiple machine-learning algorithms. I select Naïve Bayes because it is equally effective and computationally much more efficient than other standard approaches complex machine learning techniques for text classification tasks (Go, Bhayani, and Huang 2009)[19].

[18] I use the scikit-learn implementation of the Multinomial Naive Bayes classification algorithm (Pedregosa et al. 2011).

[19] I also test other machine learning classification algorithms. To do so, I train different classifiers using a random subsample of the training set of tweets with emoticons, then cross-validate the predicted sentiment classification using the remainder of the training set. I test Multinomial Bayes, Stochastic Gradient Descent (SGD), and Support Vector Machines (SVM), and find that Multinomial Bayes performs as well or better as SGD and SVM, which are more complicated techniques. For detailed descriptions of Stochastic Gradient Descent and Support Vector Machines, see Pedregosa et al. (2011). I find that Multinomial Bayes achieves an accuracy of around 80%, which matches the observed percentage with which human raters of sentiment tend to agree (Wilson,

Naïve Bayes uses Bayes' Theorem to estimate the probability that a given word (called a unigram) or set of words (called bigrams, trigrams, etc.) are associated with a particular sentiment. Multinomial Naïve Bayes is a variation of this technique demonstrated to which work well with collections of words such as tweets. Pang, Lee, and Vaithyanathan (2002) report that unigrams perform as well or better than bigrams, and described the Naïve Bayes classification as follows: sentiment class $s^* \in \{0,1\}$ is assigned to tweet d, where

$$s^* = \arg\max_s P(s|d)$$
$$P(s|d) = \frac{P(s)\prod_{m=1}^{M} P(w_m|s)}{P(d)}$$

$P(s|d)$ is the probability that tweet d has sentiment s. w_m represents a particular unigram (word) out of a total of M possible words. $P(s)$ is the overall average sentiment, estimated in the training set, while $P(w_m|s)$ is the likelihood of observing word w given sentiment s, estimated in the training set. Laplacian smoothing is used to ensure that $P(w_m|s) \neq 0$. $P(d)$ is the probability of observing a particular tweet d, but since it is a scalar it does not affect the choice of s^* and is therefore not included in the estimation procedure. The predicted sentiment obtained from the represent a simple scoring system: tweets whose content is predicted to be positive are scored 1, while those with negative content are scored 0.

Wiebe, and Hoffmann 2005).

4.1.4 Profanity measure

Finally, to provide a measure with a more intuitive interpretation, I compile a list of more than 300 profanities and scored each tweet for the presence or absence of these profanities[20]. In the sentiment analysis literature, this approach is called a "keyword spotting" approach. I calculate the Profanity measure as follows: $E^P = \mathbb{1}[\text{Profanity} \notin \text{Tweet}]$. The assumption that drives the Profanity measure is that, in general, profanities indicate negative hedonic states. To align with the other measures, note that I code tweets without profanities as 1.

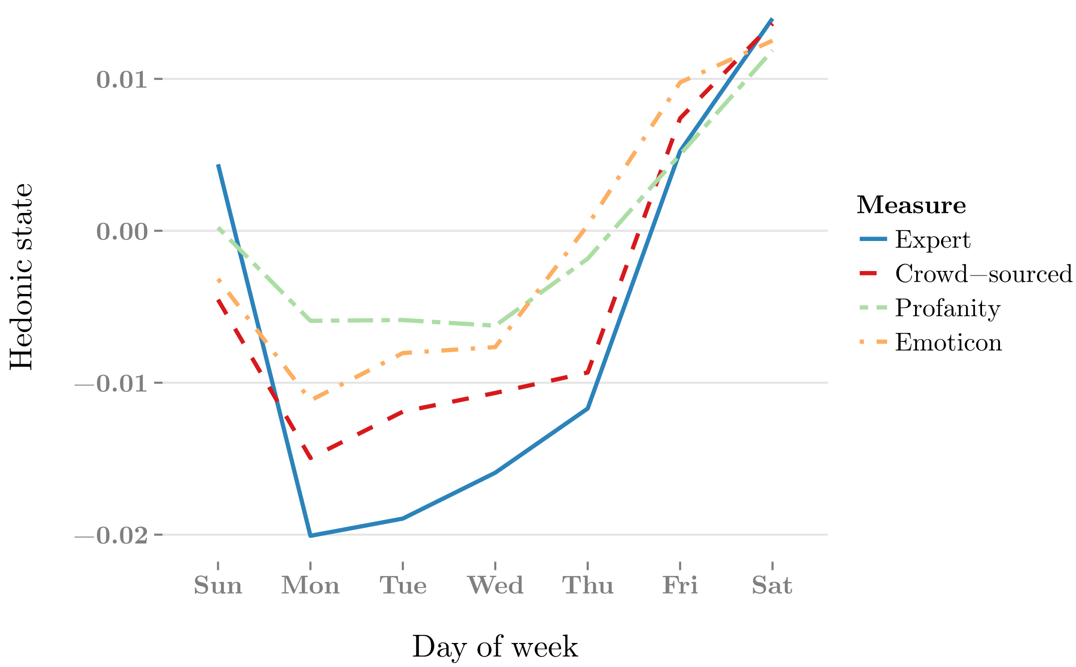
4.1.5 Validation exercises

I conduct a series of validation exercises to tie the measures to phenomena that most readers will find intuitive. Figure 2 shows the measures by day of week. Since the raw measures use different scales, I standardize such that all have mean = 0 and standard deviation = 1. The weekly variation in matches prior work (Dodds et al. 2011) and common intuition: weekends and Fridays are preferred to non-Friday weekdays, with the lowest measures of affect occuring on Mondays and the highest on Saturdays. To calibrate the results later in the paper, it is useful to note that the average difference in sentiment score between Sunday and Monday is approximately 0.01σ across measures.

Following Card and Dahl (2011), I conduct a separate validation exercise using 2014 National Football League (NFL) game outcomes. Twitter users within 80 kilometers of an NFL stadium are matched to their home team, and their average hedonic

[20] List of profanities available from `http://www.noswearing.com/dictionary`, which maintains a comprehensive database of swear and curse words.

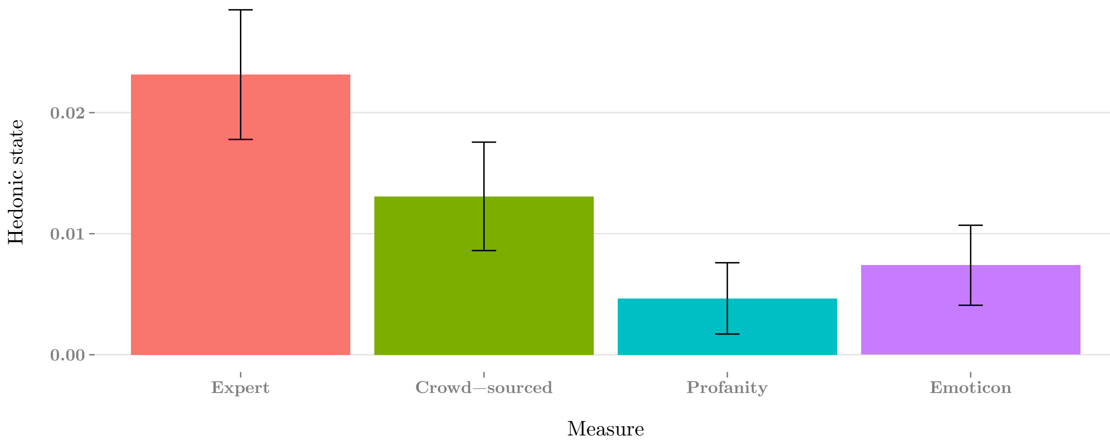
Figure 2: Hedonic state by day of week



Notes: Each line shows the average hedonic state for each measure described in section 4 by day of week. Measures are standardized to have zero mean and unit standard deviation. Sample excludes major U.S. holidays.

state in the remainder of a day following a win or loss is measured. The results are shown in Figure 3. The difference between a win and a loss is approximately 0.01σ across all measures, though the difference is larger in the Expert measure and smaller in the Profanity measure. This corresponds roughly to the difference in hedonic state observed between Sundays and Mondays.

Figure 3: Effect of nearby NFL team win on hedonic state



Notes: Height of bars is the change in hedonic state after a win by an National Football League (NFL) team within 80 kilometers. Hedonic response is estimated using the four measures of hedonic state described in section 4. Measures are standardized to have zero mean and unit standard deviation. Sample includes areas within 80 kilometers of an NFL team on Sundays and Mondays during the 2014 season, which ran from September to December. Error bars are the 95% confidence intervals, estimated using two-way cluster robust standard errors on county and day-of-sample.

4.2 Weather data

This work focuses primarily on the effects of temperature, but some specifications include other weather variables such as precipitation, cloud cover, humidity, and wind speed.

4.2.1 Temperature and precipitation

I use daily data on minimum temperature, maximum temperature, and precipitation at 4 km^2 grid cell across the contiguous United States. These data are from PRISM Climate Group's AN81d dataset and are produced using the Parameter-elevation

Relationships on Independent Slopes Model, which interpolate measurements from more than 10,000 weather stations (Daly et al. 2002). The data capture a high degree of both spatial and temporal heterogeneity in weather. The second panel in Table 1 describes sample statistics for the PRISM data, weighted by tweet volume.

4.2.2 Other weather data

Prior work suggests that other weather variables besides temperature and precipitation may be important determinants of hedonic state (Dennisenn, Butalid, Penke, and Van Aken 2008; Levinson 2012). I collapse hourly data on proportion of day that was overcast, visibility in kilometers, relative humidity, station pressure, and wind speed from 2,162 weather stations included in the Quality Controlled Local Climatological Data (QCLCD) data from NOAA to the daily level. I drop any station-months in which more than 10% of the observations were missing. To fill in the remaining observations, I compute the inverse-distance weighted quantile of a given measure from nearby stations and estimate the value of that measure for the station with the missing data using the cumulative distribution function of that station. This gives me a balanced panel of weather station observations. I then use inverse distance weighting to impute these measures of weather on a grid similar to that of the PRISM data. Maps of average daily measurements from within my sampling frame are available in the appendix. All measures of weather show substantial geographic and temporal heterogeneity. The third panel in Table 1 describes sample statistics for the QCLCD data, weighted by tweet volume.

5 Empirical specification

I estimate a panel fixed effects model to identify the effect of temperature on hedonic state. As is standard in the climate impacts literature, the model is identified under the assumption that temperature is as good as random after accounting for unobserved cross-sectional and seasonal variation (Dell, Jones, and Olken 2014). To this end, I include PRISM grid cell and state-by-month of year fixed effects in my empirical specification. Following prior work that estimates marked non-linearities in weather impacts across multiple economic outcomes (Schlenker and Roberts 2009; Ranson 2014; Graff Zivin, Hsiang, and Neidell 2015), I estimate the effects on hedonic state as a non-linear function of temperature by including temperature in the model using a set of ten °F bins. Following standard practice, 20-25°C is the omitted category, such that the coefficient on, say, 30-35°C should be interpreted as the effect on hedonic state caused by replacing a 20-25°C with a day which has an maximum daily temperature of between 30-35°C (**Barreca2013b**; Albouy, Graf, Kellogg, and Wolff 2013). The empirical model I estimate is given by:

$$\overline{E}_{gd} = \sum_{b \neq 20\text{-}25}^{B} \beta_b T_{gd}^{b} + f(P)_{gd} \phi_{cmy} + \phi_d + \varepsilon_{gd} \qquad (1)$$

Let g, c, s, d, m, y index grid cell, county, state, day, month, and year, while b is an index over temperature bins. $\overline{E}_{gd}$ is the grid cell-day average of one of the four measures of hedonic state described in section 4. Because my temperature measure varies at the grid cell-day, taking the grid-cell day average of the hedonic state measures and weighting by the total number of tweets in that grid-cell day produces the same point estimates and standard errors as would be estimated using a model where each observation represented a single tweet (Wooldridge 2002), while reducing computation time substantially.

T^b_{gd} is a dummy variable $= 1$ if the maximum daily temperature in a grid cell falls within the associated five degree bin b. I estimate a similar model with precipitation in bins as the primary right-hand side variable, where the zero precipitation bin is the omitted category. $f(P)_{gd}$ is a flexible function of daily precipitation.

The county by month-of-sample fixed effects ϕ_{cmy} control for unobservables within each county-month. For example, individuals with higher income tend to have higher levels of life satisfaction (Easterlin 2001) and may be inclined to locate in areas with generally pleasant climate. By including ϕ_{cmy}, I identify the coefficients of interest using within-cell variation over time. I also include date fixed effects ϕ_d to account for national trends in weather, *e.g.*, the well-known seasonal variation of human emotion and seasonal changes in weather.

The coefficients β_b are identified using within-grid cell variation in weather that is not absorbed by state-month fixed effects and map out a non-linear response function between temperature and hedonic state. To allow for spatial and temporal correlation in the data, I cluster the standard errors two ways, by state (48)[21] and by week of sample (50)[22].

[21]I exclude Alaska and Hawaii due to limitations of the Twitter Streaming API and because the PRISM weather data are confined to the continental United States.

[22]I also run a model that allows for spatial correlation up to 16 km and temporal correlation of up to 7 days using spatial standard errors as described by Conley (2008) and implemented using code from Hsiang (2010). The standard errors are smaller than those obtained using the two way clustering described here, suggesting that the confidence intervals presented here may be conservative.

6 Baseline results

Using the econometric model specificied above, I document sharp declines in hedonic state above and below 20°C. For expositional clarity, this section presents these results in two formats: first, I tabulate results for two of the measures using increasingly robust sets of fixed effects, the last of which reflects the model described in equation (1). Next, I plot the point estimates and standard errors to visually represent the response of hedonic state to daily temperature. Because each outcome measure $\overline{E}_{gd}$ is standardized to have mean zero and unit standard deviations, the point estimates β_b represent the change in the conditional mean of hedonic state, measured in standard deviations, expected as a result replacing a day having maximum temperature between 20-25°C (the omitted bin) with a day having maximum temperature within the corresponding temperature bin. For example, the coefficient for 35-40°C represents the change in hedonic state caused by replacing a 20-25°day with a 35-40°day.

Each column in Tables 3 and 4 displays point estimates and standard errors for increasingly robust sets of fixed effects and controls. Column (1) is the ordinary least squares (OLS) estimate, which finds a large negative effect of high temperatures, estimating that the difference between 20-25°day and a 35-40°day is equivalent to seven times the difference in hedonic state observed between Sundays and Mondays. This model also documents mixed evidence of effects in colder temperatures, though the sign of point estimates are inconsistent across measures: negative for the Expert measure and positive for the Emoticon measure. However, the coefficients in this model likely suffer from the classical omitted variables bias problem: without controls, endogenous sorting, regional lexical norms, income levels, and seasonal variation in temperature and hedonic state all likely correlate with both temperature and hedonic state. For example, the northern United States tends to be more affluent and experiences lower average temperatures. If affluence has a positive effect on hedonic state, this would introduce a downward bias in the coefficients on high temperatures.

Table 3: Effect of temperature on hedonic state (Expert measure)

	(1)	(2)	(3)	(4)
Max temperature T				
$T \leq 0$	-0.015^{**}	-0.012^{**}	-0.017^{***}	-0.009^{***}
	(0.006)	(0.005)	(0.005)	(0.002)
$T \in (0,5]$	-0.009^{*}	-0.004	-0.008	-0.007^{***}
	(0.005)	(0.004)	(0.005)	(0.002)
$T \in (5, 10]$	-0.006	0.002	-0.007^{**}	-0.007^{***}
	(0.004)	(0.003)	(0.003)	(0.001)
$T \in (10, 15]$	0.007	0.011^{***}	-0.002	-0.003^{***}
	(0.004)	(0.004)	(0.003)	(0.001)
$T \in (15, 20]$	0.012^{***}	0.011^{***}	0.0001	-0.001
	(0.003)	(0.002)	(0.002)	(0.001)
$T \in (25, 30]$	-0.014^{***}	-0.010^{***}	-0.003^{**}	-0.002^{***}
	(0.002)	(0.002)	(0.001)	(0.001)
$T \in (30, 35]$	-0.033^{***}	-0.018^{***}	-0.008^{***}	-0.007^{***}
	(0.003)	(0.003)	(0.001)	(0.001)
$T \in (35, 40]$	-0.037^{***}	-0.027^{***}	-0.013^{***}	-0.011^{***}
	(0.005)	(0.003)	(0.002)	(0.001)
$T \geq 40$	-0.015	-0.032^{***}	-0.014^{***}	-0.013^{***}
	(0.010)	(0.007)	(0.003)	(0.002)
Grid cell-days (m.)	20.7	20.7	20.7	20.7
Twitter updates (m.)	527	527	527	527
County FE	No	Yes	Yes	Yes
State × m-y FE	No	No	Yes	Yes
Date FE	No	No	No	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Dependent variable is the average standardized (mean zero, unit standard deviation) Expert measure of hedonic state for a grid cell-day. Independent variables are dummies for temperature (in °F) bins. Each column is a separate regression, coefficients represent the change in standard deviations of hedonic state between a day within the associated temperature bin and a day with temperature $T \in [20,25)$, the omitted category. Coefficients are estimated conditional on the fixed effects and controls listed. Grid cell-days is the count of observations in the regressions in millions. Twitter updates is the count the number of Twitter updates aggregated into the grid cell-days in millions.

Table 4: Effect of temperature on hedonic state (Emoticon measure)

	(1)	(2)	(3)	(4)
Max temperature T				
$T \leq 0$	0.006	-0.012^{***}	-0.014^{***}	-0.011^{***}
	(0.005)	(0.004)	(0.003)	(0.002)
$T \in (0,5]$	0.010^{**}	-0.004	-0.005^{*}	-0.007^{***}
	(0.004)	(0.004)	(0.003)	(0.001)
$T \in (5,10]$	0.014^{***}	0.004	-0.004^{**}	-0.007^{***}
	(0.004)	(0.003)	(0.002)	(0.001)
$T \in (10,15]$	0.020^{***}	0.013^{***}	-0.002	-0.004^{***}
	(0.004)	(0.003)	(0.002)	(0.001)
$T \in (15,20]$	0.017^{***}	0.013^{***}	0.0002	-0.001
	(0.003)	(0.002)	(0.001)	(0.001)
$T \in (25,30]$	-0.015^{***}	-0.013^{***}	-0.004^{***}	-0.003^{***}
	(0.003)	(0.002)	(0.001)	(0.001)
$T \in (30,35]$	-0.044^{***}	-0.022^{***}	-0.011^{***}	-0.008^{***}
	(0.004)	(0.003)	(0.001)	(0.001)
$T \in (35,40]$	-0.071^{***}	-0.032^{***}	-0.015^{***}	-0.013^{***}
	(0.005)	(0.004)	(0.002)	(0.002)
$T \geq 40$	-0.061^{***}	-0.045^{***}	-0.020^{***}	-0.017^{***}
	(0.013)	(0.008)	(0.003)	(0.003)
Grid cell-days (m.)	25.3	25.3	25.3	25.3
Twitter updates (m.)	1056.3	1056.3	1056.3	1056.3
County FE	No	Yes	Yes	Yes
State × m-y FE	No	No	Yes	Yes
Date FE	No	No	No	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Dependent variable is the average standardized (mean zero, unit standard deviation) Emoticon measure of hedonic state for a grid cell-day. Independent variables are dummies for temperature (in °F) bins. Each column is a separate regression, coefficients represent the change in standard deviations of hedonic state between a day within the associated temperature bin and a day with temperature $T \in [20,25)$, the omitted category. Coefficients are estimated conditional on the fixed effects and controls listed. Weather controls include day-level measures of temperature range, cloudiness, visibility, station pressure, relative humidity, and average wind speed. Grid cell-days is the count of observations in the regressions in millions. Twitter updates is the count the number of Twitter updates aggregated into the grid cell-days in millions.

To account for unobservables in space, column (2) adds county-level fixed effects ϕ_c, standard in the climate impacts literature (Dell, Jones, and Olken 2014). These point estimates are identified using within-county fluctuations in temperature, and document smaller (in magnitude) effects in of high temperature and more consistenty negative effects of cold temperatures than the OLS estimates. These results suggests that unobserved variation in space was likely responsible for some portion of the OLS estimates. However, this model continues to find substantial positive effects associated with temperatures between 10 and 20°C, which contrasts with intuition and prior evidence.

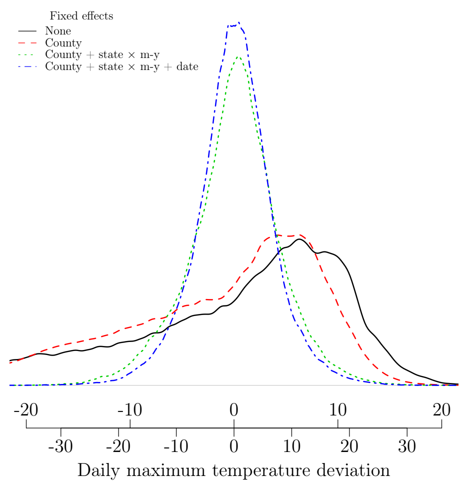
To control for seasonal variation, column (3) adds state-by-month of sample fixed effects ϕ_{smy}, allowing for differential seasonal trends by states. This specification not only accounts for unobservable seasonal effects, but also allows those seasonal effects to differ by state. The addition of these controls to the model produces estimates that are more in line with intuition: days with maximum temperature from 20-25°C are preferred to all other days, while increasingly extreme days on either side are found to be increasingly dispreferred.

Finally, column (4) adds date fixed effects ϕ_d to account for within-month correlation between hedonic state and temperature. While controlling by seasonality using month fixed effects aligns with the extant literature (Auffhammer, Hsiang, Schlenker, and Sobel 2013), it is possible that, for example, trends in hedonic state may mean that moods in early March tend to be higher than in late March, for example, which would spuriously correlate with within-month temperature trends. This model reflects equation (1) and is my preferred specification. Empirically, adding these fixed effects does not qualitatively alter the results, however.

A concern with fixed effects models is that accounting for additional unobservables wipes out much of the useful variation in the data and can frequently result in measurement error overwhelming the model (Angrist and Pischke 2008). This kind of classical measurement error would result in attenuated estimates, which do not appear to be an issue with the models I estimate. Still, I plot the distribution of the residual variance used for these models in Figure 4 as a method of demonstrating the amount of variance used to estimate the model as additional fixed effects are added. Notably, both the OLS and the model in column (2) displayed skewed distributions for temperature, while the addition of seasonal fixed effects results in residuals whose distribution resembles a normal distribution but reduces the variance in the distribution substantially.

Turning to Figure 5, the four measures of hedonic state all strongly reject the null of no effect of temperature on hedonic state, and provide strong evidence of a negative relationship between hedonic state and maximum daily temperatures both above and below 20°C. The left panels of Figure 5 capture the results from column (4) in Tables 3 and 4, while the right panels document results for the Crowd-sourced and the Profanity measures. All measures reflect the same qualitative findings, with the possible exception of the Profanity measure, which does not find significant changes in hedonic state in lower temperatures. A possible explanation for this is that aggressive behavior, which is most captured lexically using profanity, is not additionally reduced by colder temperatures (Ranson 2014), while depressive behavior, which would be missed by the Profanity measure but captured by the other measures, could still

Figure 4: Residual variance in daily maximum temperature

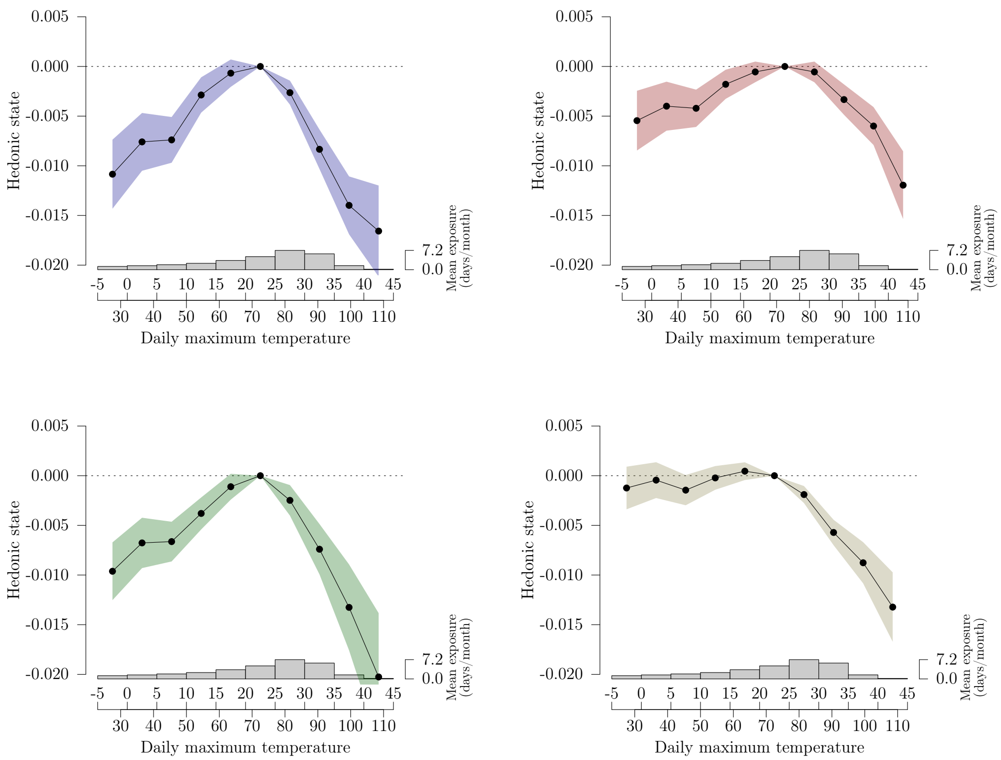


Notes: Kernel densities of the residuals from regression of hedonic state on temperature bins using four different econometric models. First model does not include fixed effects, second adds county fixed effects, third adds state by month of sample fixed effects, and fourth adds day of sample fixed effects.

increase.

The negative relationship between temperature and hedonic state both above and below a 20-25°C "bliss point" resembles that estimated by Albouy, Graf, Kellogg, and Wolff (2013) and other work in the locational choice literature, who find that individuals would pay to avoid warm temperatures in summer and cold temperatures in winter. All measures estimate that the difference between a 20-25°C day and a 35-40°C day to be approximately 0.01σ, and three of the measures find a similar difference between a less than 0°C day and a 20-25°C day. As a point of comparison, these differences are roughly comparable to the average difference in hedonic state between tweets sent on Sunday versus tweets sent on Monday (see Figure 2).

Figure 5: Effect of temperature on hedonic state



Notes: Plots represent the hedonic response to temperature, where each plot uses a different measure of hedonic state described in section 4. Measures are standardized to have zero mean and unit standard deviation. Each point estimate is the difference in the average grid cell-day hedonic state for the associated five °C temperature bin relative to the 20-25°C (68-77°F) bin (the omitted category), conditional on grid cell and state by month fixed effects and weighted by the number of tweets in a grid cell-day. 95% confidence intervals estimated using two-way cluster robust standard errors on county and day-of-sample.

7 Robustness checks and extensions

This section extends the baseline results with a series of robustness checks and extensions: I account for possible endogenous selection into sample using individual fixed effects, examine seasonal differences in responses to temperature, disaggregate the response by hour of day, project future changes in hedonic state as a result of climate change both with and without adaptation, and use a preliminary method to estimate a willingness-to-pay for temperature from these data.

7.1 Accounting for endogenous sample selection

Including county fixed effects in the empirical model accounts for sorting into preferred climates. In this respect, model (1) is highly robust to unobserved variation. However, since participation in Twitter is a choice on the part of a given user, failing to account for potential endogeneity of Twitter participation may induce a sample selection bias (Heckman 1979). In this setting, the selection bias of greatest concern is compositional sorting: samples of tweets at different temperatures may reflects different sets of users with different unobservable characteristics. For example, if individuals with higher or lower native affect become more likely to compose Twitter updates in different temperatures, the coefficients could be capturing this compositional change in the sample rather than a change in average hedonic state.

Since the data I collect include an identifier for the tweet creator, I control for compositional sorting in my sample using user fixed effects. To do so, I estimate the following model:

$$E_{id} = \sum_{b \neq 20\text{-}25}^{B} \beta_b T_{gd}^b + \phi_i + \phi_d + \varepsilon_{id} \tag{2}$$

This model substitutes user fixed effects, ϕ_i, for the county fixed effects, ϕ_c, in model

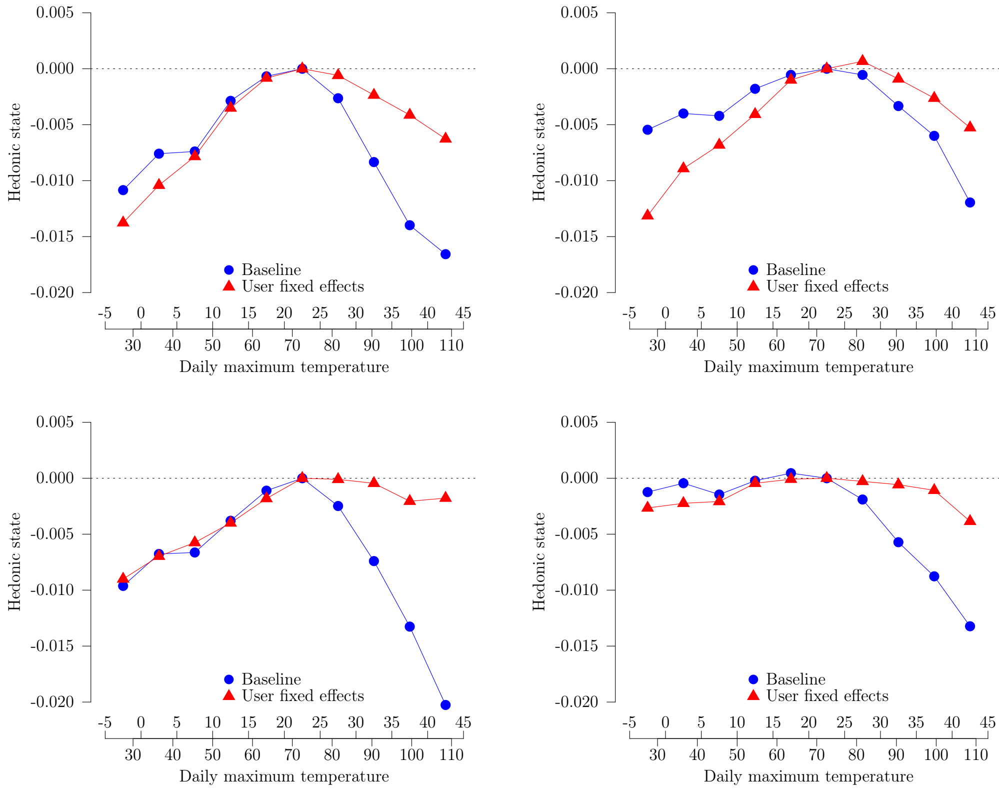
()1)[23]. The model requires the use of the entire unaggregated sample of observations in my dataset; because the right-hand side of model (2) includes variation at the individual level, it not possible to compute the same coefficients using grid cell-day averages. Let i and d be the user and date a status update was sent, respectively. E_{it} is one of the four measures of hedonic state. For computational reasons, I use a 20% subsample of users to estimate the following results: they are robust to multiple subsample selection.

To compare the results from models (1) and (2), I overlay the estimates from each model in Figure 6. I find qualitatively similar results for the measures, although the estimates for higher temperatures are attenuated in the individual fixed effects model relative to the baseline model. It is possible that this is evidence of some compositional sorting at higher temperatures, but more likely the result of measurement error driven using a sparser source of variation. The negative response to cold temperature is nearly identical between models, suggesting that the source of the differential is heterogenous in temperature.

To further examine this possibility, Figure 7 plots the volume of tweets by temperature, using a model similar to (1), but with the log of the count of tweets in grid cell-day as the outcome variable. After accounting fixed effects, I find that tweet volume is higher on days with higher temperature, and that the change in volume is more pronounced in low temperatures. This is suggestive evidence that composi-

[23] A possible concern with model (2) is that the same individual tweeting from different locations may be endogenously determined with weather, *e.g.* a family choosing to vacation in California to avoid a cold snap in Minnesota. To address this bias, I estimate a specification that also includes PRISM grid cell fixed effects alongside the individual fixed effects. The results are qualitatively the same.

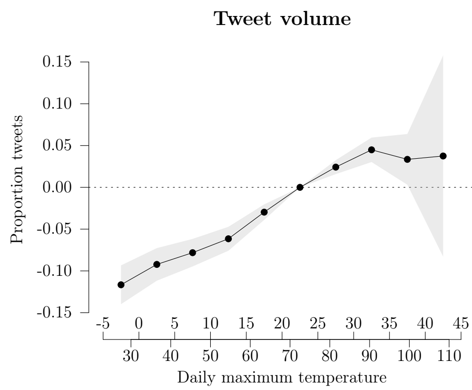
Figure 6: User and grid cell fixed effects comparison



Notes: Plots compares the hedonic response to temperature across two statistical models, one with county and one with user fixed effects. Both models include date fixed effects. Each point estimate is the difference in the average grid cell-day hedonic state for the associated five °C temperature bin relative to the 20-25°C (68-77°F) bin (the omitted category). 95% confidence intervals estimated using two-way cluster robust standard errors on county and day-of-sample.

tional sorting is unlikely to be driving the results in Figure 6, since we would expect the temperatures with the greatest change in the volume of tweets to also reflect the most compositional sorting.

Figure 7: Volume of tweets by temperature



Notes: Plot estimates the effect of temperature on tweet volume, after conditioning on county, state by month, and date fixed effects. Outcome variable is the natural log of tweets, coefficients approximate the proportional change in tweets induced by replacing a 20-25°C day with a day in the given temperature bin.

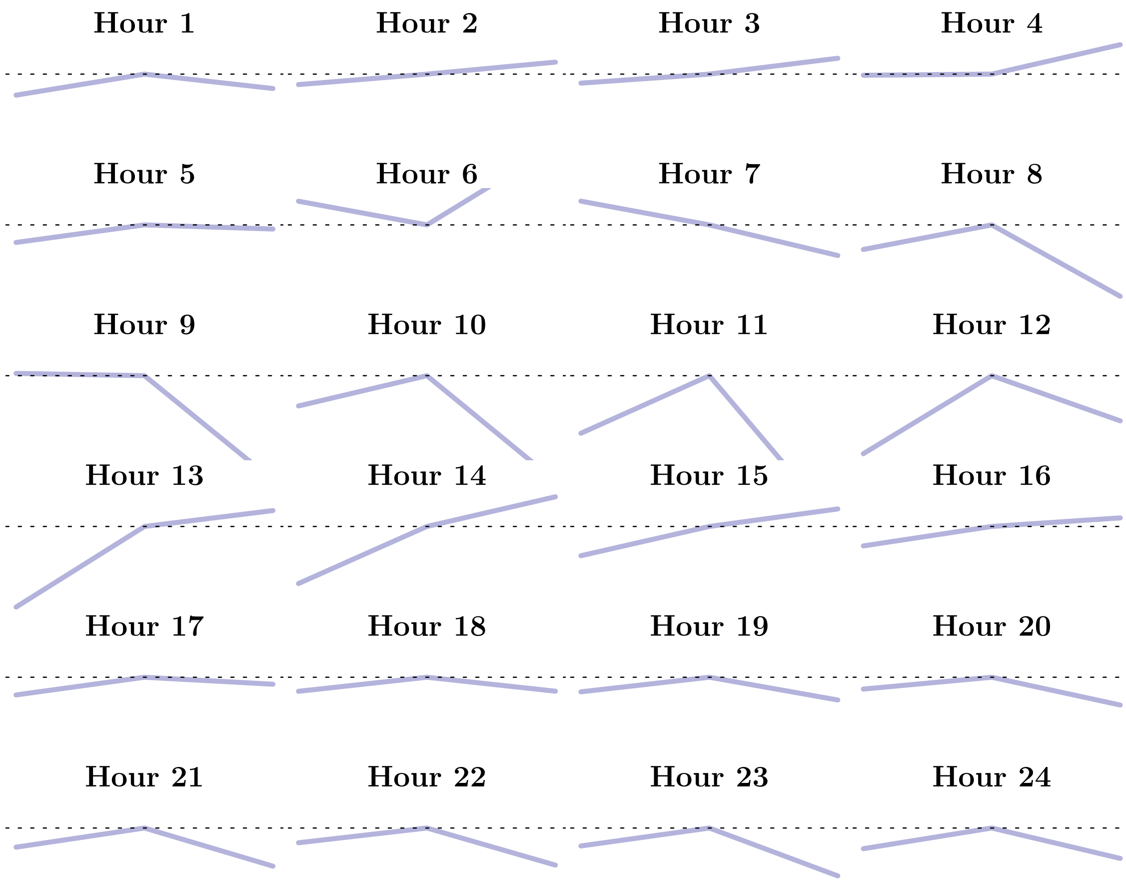
7.2 Effect by hour of day

To better understand how temperature affects hedonic state, I compare the effect of temperatures across different hours of the day. To do so, I replace the PRISM weather data with the hourly station-level data from QCLCD described in section 4. Using this level of details allows me to investigate the extent to which daytime and/or nighttime temperatures are driving the observed effects on hedonic state. To estimate this model, I simplify the bins by using a piecewise linear function in temperature with a break at 20°C and allow this function to differ by how of day. More precisely, I estimate the following econometric model:

$$E_{gdh} = \gamma_1 \min(T_{gdh}, 20) + \gamma_2 \max(20 - T_{gdh}, 0) + \phi_c + \phi_{smy} + \phi h + \mu_{gdh} \qquad (3)$$

This model adds hour of day fixed effects ϕ_h to control for spurious correlated variation in mood over the course of the day and weather patterns, and is identified by comparing tweets within a given hour in the same grid cell on warm days to tweets within the same hour on cooler days, after accounting for geographic and seasonal variation. γ_1 and γ_2 are the coefficients of interest, where the first represents the linearized response up to 20°C, and the second represents the response about 20°C. Figure 8 plots the piecewise linear functions for each hour of the day for the Expert measure. For nearly every hour, hedonic state increases in temperature up to the 20°midpoint. Above 20°, sharp negative decreases in temperature are observed for the morning hours until around 1 PM, when a slight positive relationship between temperature and mood can be observed until about 4 PM. This abates in the evening, when small negative effects of higher temperatures are observed.

Figure 8: Response by hour of day (Expert measure)



Notes: Each plot captures the fitted piecewise linear function of hedonic state in temperature for one hour of the day, with a breakpoint imposed at 20°C. Model includes county, state by month of sample, and hour fixed effects. Standard errors clustered by county by month of sample and date.

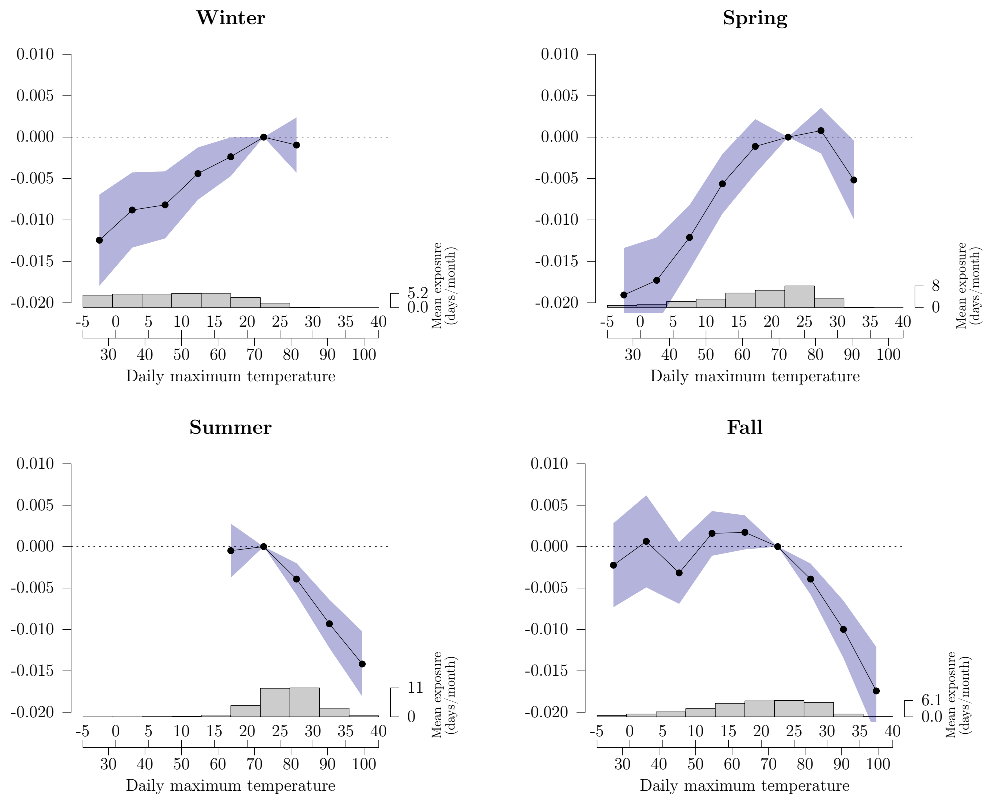
7.3 Heterogeneity in response by season

Model (1) estimates an average response function over the entire year. Pooling the response over the entire year could mask seasonal heterogeneity in the response, since individuals may respond differently to a relatively warm day in winter than they would in summer. Indeed, results obtained by other researchers suggest that people are willing to pay for lower temperatures in summer and higher temperatures in winter. To test this in my data, I specify a model that allows for the effects of temperature to differ seasonally:

$$\overline{E}_{gd} = \sum_{b \neq 20\text{-}25}^{B} \sum_{s \neq 1}^{\text{Seasons}} \beta_b^s T_{gd}^b \times \mathbb{1}[\text{Season} = \text{s}]_m + \phi_c + \phi_{smy} + \varepsilon_{gd} \tag{4}$$

Figure 9 documents the response function by seasons for the Expert measure. In general, colder temperatures are dispreferred in the winter but viewed with ambivalence in the fall, while the relationship between high temperatures and hedonic state is uniformly negative across seasons. This evidence suggests that preferences for temperature differ seasonally in a way that reflects observed willingness to pay for housing (Albouy, Graf, Kellogg, and Wolff 2013). These results are consistent across all measures.

Figure 9: Seasonal response heterogeneity



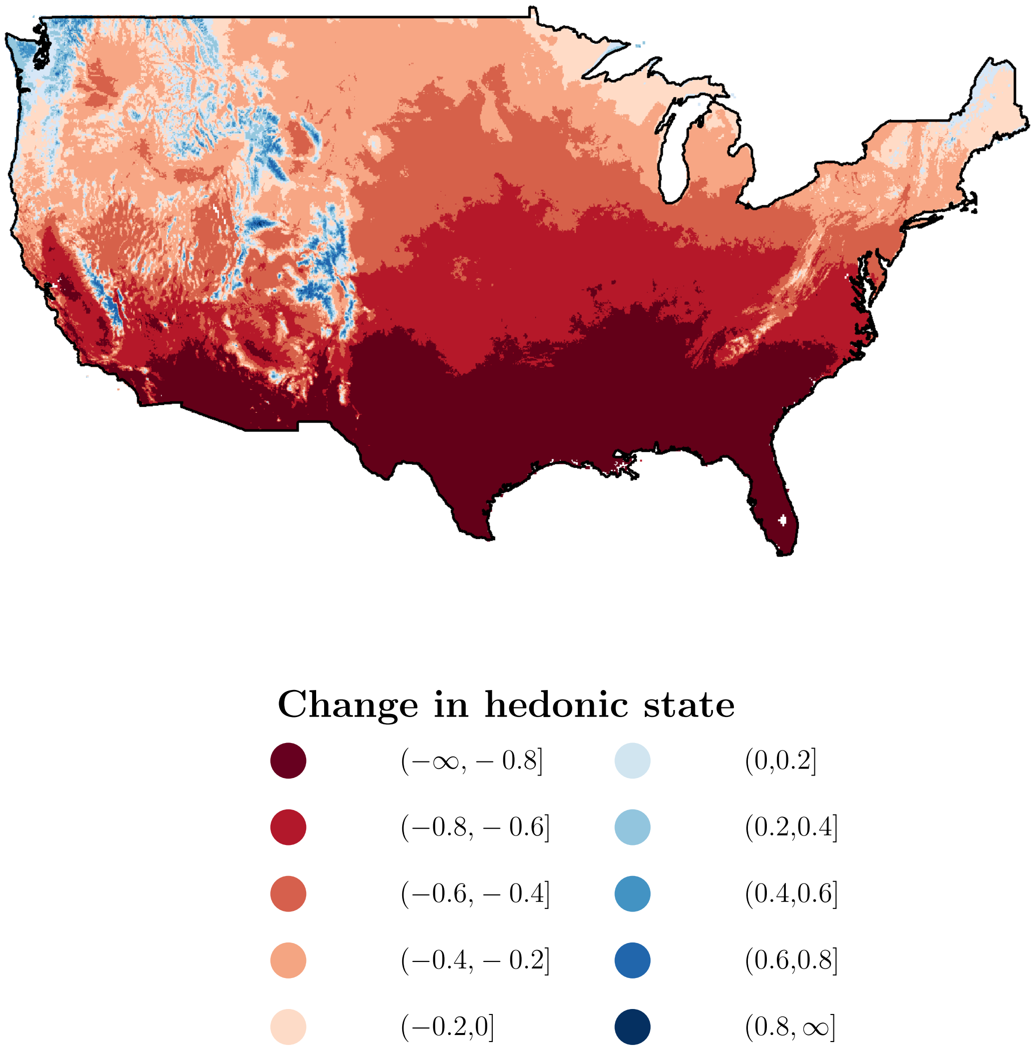
Notes: Plots illustrate hedonic response to high temperatures by hour of day. Measures of hedonic state are as described in section 4 and standardized to have zero mean and unit standard deviation. Sample is limited to days with average daily temperature greater than 20°C. Each point is the coefficient from a separate regression of hedonic state on the daily temperature where the sample is limited to observations in corresponding hour, conditional on county, state by month, and date fixed effects and weighted by the number of tweets in a grid cell-day. 95% confidence intervals estimated using two-way cluster robust standard errors on county and day-of-sample.

7.4 Climate projections

The projected effects of climate change are, on average, an increase in the mean and variance of the climate distribution. To better understand the future impacts of climate change on hedonic state, I combine the estimates documented above with projected changes in United States climate. The thought experiment I perform is as follows: if the predicted end-of-century effects of climate change were to take place tomorrow, how should we expect hedonic state to change? By using downscaled climate data, I am able to account for likely geographic heterogeneity in climate impacts and observe how different regions of the United States may be affected. I emphasize that these projection exercises are not meant to be direct predictions of future changes in hedonic state but are instead meant to illustrate ways in the which the amenity costs of temperature could be differentially altered in the United States. I conduct two projection exercises, with and without accounting for adaptation.

First, I use the average response function across the United States as the basis of projection, holding that response function constant over time. The projected damages are products of the coefficients estimated in Figure 5 and the expected change in the number of days in a given bin, summed over all bins. The result of this exercise is mapped in the top left panel of Figure 10. In general, southern areas of the United States experience the greatest losses of hedonic state. This finding is driven by the findings of the climate models, which predict a large increase in the number of very hot days in this region. Because the most severe impacts of hedonic state are found in higher temperatures, these regions are most profoundly affected.

Figure 10: Projected changes in hedonic state (no adaptation)

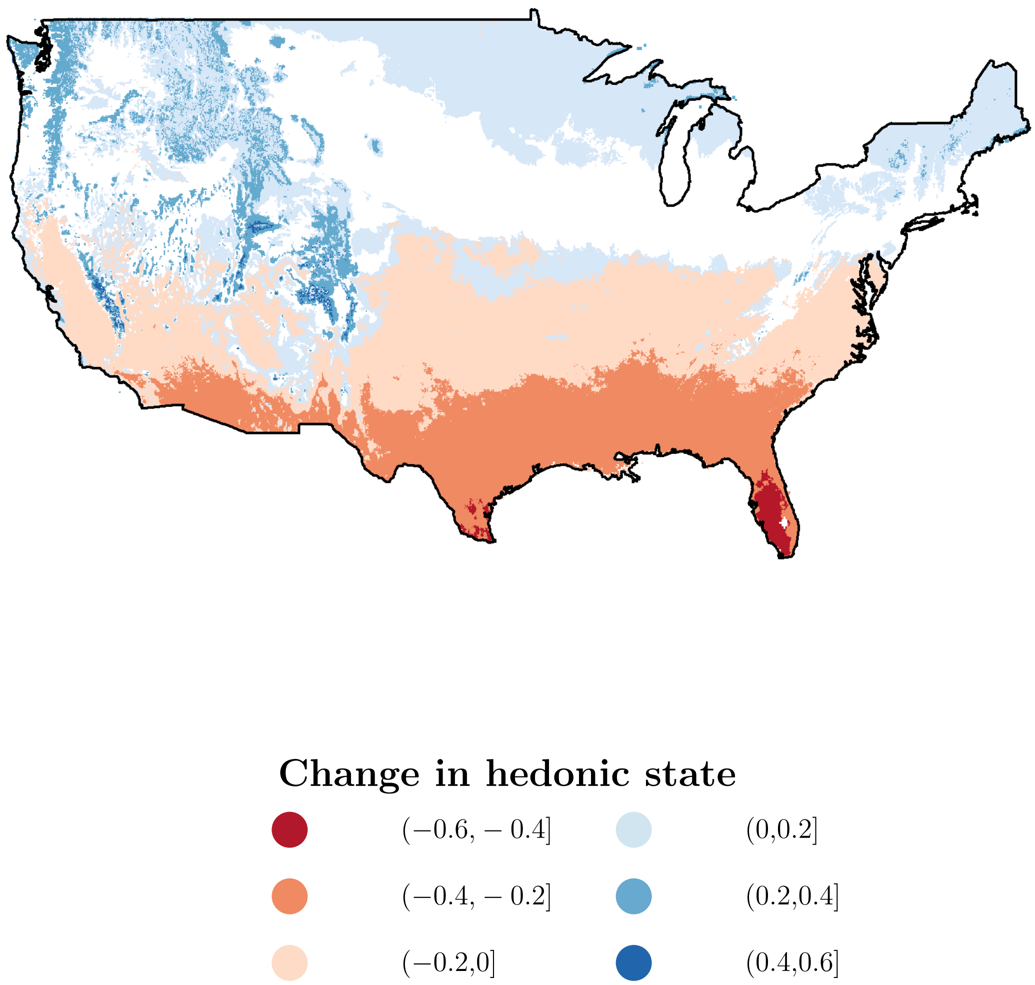


Notes: Darker areas represent larger (in absolute values) annual changes in hedonic state, as measured using the Expert measure described in section 4. Projected changes are computed by taking the difference in the average annual days in a given temperature bin between climate model output of 2086-2099 and 2000-2019, multiplying by the corresponding coefficients in Table 3, and then summing the products. Each pixel is a 4 km $\times$ 4 km grid cell, colored to represent the predicted annual change in standard deviations of hedonic state.

The extent to which individuals adapt to changing climate regimes is an important input to understanding the cost of climate change (**Barreca2013b**; Burke, Hsiang, and Miguel 2015a). Since hedonic state is known to adapt to changes in circumstances, it is possible that the hedonic response to temperature could fully adjust to changes in the mean of the climate distribution. Put another way, if the change in hedonic state due to temperature is solely a function of the distance from the mean temperature, then the change in the mean of the climate distribution will have no effect on welfare. With sufficient data, one way to test for this possibility would be to use a long differences approach similar that implemented by Burke and Emerick (2015).

Because my data are a much shorter time series, I provide suggestive evidence of future adaptation by estimating separate temperature response functions for areas with different climates. Next, I allow areas to adapt to a new temperature regime by adopting a response function of their new quintile, using the historical quintile breaks. To fix ideas, suppose that there is a county in Minnesota in the lowest historical daily average temperature quintile. After allowing for climate change, this county would now fall into the second lowest quintile using the historical temperature cutoffs. I project the effect of climate change using the response function of the second lowest quintile, which would, for example, include Kansas. This exercise allows Minnesota's response function to adjust to look more like Kansas' response function. Figure 11 contains this final projection exercise. This map suggests that the most affected regions are likely to be in the northern part of the country.

Figure 11: Projected changes in hedonic state (with adaptation)



Notes: Darker areas represent larger (in absolute values) annual changes in hedonic state, as measured using the Expert measure described in section 4. Projected changes are computed by taking the difference in the average annual days in a given temperature bin between climate model output of 2086-2099 and 2000-2019, multiplying by the corresponding coefficients in Table 3, and then summing the products. Each pixel is a 4 km $\times$ 4 km grid cell, colored to represent the predicted annual change in standard deviations of hedonic state.

I emphasize that these projections are reliant on strong assumptions, in particular regarding future technological change, migration, and adaptation. I attempt to provide a margin for adaptation, both past and future, in the second and third exercises. With that in mind, these estimates suggest large changes in hedonic state due to climate change. Returning to the calibration exercise, for some areas this change would be the equivalent of replacing every Saturday and Sunday in a year with a Monday. Given the strong assumptions required to obtain this estimate, I instead focus on the regional differences in the projected outcomes produced by varying aggregation levels and allowances for adaptation. This setting is likely not the only area in which these regional differences are important, and suggests the importance of both accounting for these differences and using them to infer adaptation behavior.

7.5 Estimating a willingness-to-pay for temperature

The evidence provided thus far demonstrates a clear relationship between hedonic state and temperature. However, to compare the magnitude of these cost of changes in hedonic state to the magnitude of costs in other sectors, it is necessary to convert the changes in hedonic state into monetary damages.[24] Following prior work, I present a *highly preliminary* method for this conversion. I emphasize that this method relies on strong assumptions and should be interpreted as a back-of-the-envelope calculation at best.

The technique I use follows Train (2002) and Levinson (2012), the latter of which

[24]Conversion into a monetary cost is also important for inclusion in Integrated Assessment Models (Hope 2006; Nordhaus and Sztorc 2013; Antoff and Tol 2014) or the social cost of carbon (Interagency Working Group on Social Cost of Carbon 2013).

implements it to estimate the monetary cost of changes in air quality on reported life satisfaction. I estimate the following model:

$$\overline{E}_{gd} = \beta T^b_{gd} + \gamma I_b + \phi_{sm} + \varepsilon_{gd} \tag{5}$$

The major addition to the model is I_b, Census Block Group median income in thousands. β can be interpreted as the change in hedonic state induced by a one °F change in temperature, while γ is the change in hedonic state associated with a $1,000 dollar increase in the income of an individuals Census Block Group.

I estimate and totally differentiate the above, holding $dE = 0 \rightarrow \frac{\partial I}{\partial T} = -\frac{\hat{\beta}}{\hat{\gamma}}$. This estimate can be interpreted as the willingness to substitute between a degree of temperature change and $1,000 increase in median income. The results of this regression are displayed in Table 5. Computing the willingness to substitute across all four measures yields estimates of $548, $875, $2096, and $816 for the Expert, Crowd-Sourced, Emoticon, and Profanity measures, respectively. These estimates are largely driven by the size of the denominator γ, and constitute a 1-2% change in income relative to the median in my sample, which is in line with other results estimated in the locational choice literature.

Table 5: Estimating a WTP for temperature

	Expert	Crowd-sourced	Emoticon	Profanity
Mean temperature	-0.000492*	-0.000746*	-0.000784*	0.000607**
	(0.000227)	(0.000297)	(0.000296)	(0.000186)
Income ($1,000)	0.000897***	0.000853*	0.000374	-0.000744**
	(0.000136)	(0.000331)	(0.000288)	(0.000236)
Grid cell-days	17,986,266	15,059,391	18,460,020	18,460,020

Notes: Each column contains coefficients from a regression of a measure of hedonic state on temperature and median Census block group income. Measures of hedonic state described in section 4 and are standardized to have mean zero and unit standard deviation. All regressions include state by month fixed effects and are weighted by the number of tweets in a grid cell-day. 95% confidence intervals estimated using two-way cluster robust standard errors on county and day-of-sample.

I emphasize that this procedure requires two strong assumptions. First, it requires that $dE = 0 \Rightarrow dU = 0$, or that holding hedonic state constant is equivalent to holding utility constant. Second, it requires that within state, between-Census Block Group differences in income are as good as random. The results of this exercise should be interpreted with appropriate caution.

8 Discussion

This paper explores the relationship between temperature on hedonic state as a way to understand preferences for day-to-day temperature. The existing literature estimates large costs due to the change in amenity value driven by climate change, but does so by relying on cross-sectional variation. In this paper, I document a method that allows researchers to estimate preferences over nonmarket goods while accounting for a wide range of unobservable variation across both space and time. I accomplish this by constructing a dataset of text updates from the social media platform Twitter, which I code using human and machine-trained sentiment analysis algorithms from computational linguistics. I combine this geographically and temporally detailed measure of hedonic state with finely gridded weather data to flexibly estimate the effect of weather on mood. I find that hedonic state is unaffected by cooler temperatures, but declines sharply above 20°C. In terms of magnitudes, I estimate a difference of about 0.01σ between a day with mean temperature of 20-25°C (68-77°F) and a day with 30-35°C (86-95°F), which is roughly the average difference between observed hedonic state on Sundays relative to Mondays. These results are net of short-term adaptation, *e.g.* air conditioning. Since my data are from the United States, where air conditioner penetration rates are among the highest in the world, it is likely that the relationship between temperature and hedonic state may be even more pronounced in other countries.

The negative effects of warm temperatures strongly resemble qualitative results documented using other approaches. However, the lack of a similar distaste for extremely cold temperatures, even in winter, remains a puzzle. I speculate that this apparent contradiction may illuminate a key difference between *ex ante* preferences for temperature and *ex post* hedonic responses to different temperatures. One important factor may be the relative margins for adjustment to low and high temperatures: cold days can be easily adapted to through additional clothing, but no such margin exists for hot days. Similarly, the greater penetration of heating equipment, relative to air conditioning, could play a role.

The results obtained in section 6 should be interpreted with some caution. First, users of Twitter are a selected sample, though a large one. Moreover, users who choose to enable geolocation services may be yet different from the Twitter user-base at large. The adaptive nature of hedonic state could also imply that the costs of climate change could be overstated by this analysis, though section 7.4 accounts for this possibility and negative impacts remain. Finally, the nature of the results presents challenges to monetary conversion: how much social welfare does the loss of one standard deviation of hedonic state represent? The preliminary method I demonstrate in section 7.5 provides one view, but relies on strict assumptions.

Nevertheless, this paper makes several contributions to the literature. It introduces a new methodology and data source to estimate preferences over nonmarket goods while accounting for possible unobservable cross-sectional and seasonal variation. It demonstrates how an appropriate use of sentiment analysis and machine-learning algorithms can enhance the econometric analysis of large datasets, estimates the relationship between temperature and hedonic state across multiple dimensions of heterogeneity, and suggests a psychological channel through which other impacts of climate change may operate. Additionally, this paper is one of the first to employ social media data in a rigorous causal framework. The projection exercise I conduct is unique in the literature in that I use both aggregated and disaggregated response functions to project future damages, showing that the use of disaggregated response functions and allowing areas to adapt over time substantially modifies the qualitative implications of the projection exercise. Broadly, this work provides supporting evidence that changes in the amenity value of climate are an important component of the overall costs of climate change.

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