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Temperature and Tempers: Heats impact on Mood and Language

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Temperature and Tempers: Heat's Negative Impact on Language and Mood

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Abstract: Temperatures above 20° Celsius have shown to adversely impact human behavior, leading to increased aggression and violence. Climate change will contribute to both the magnitude and severity of this pattern as temperatures continue their rise. Contributions to this field of research have only recently begun to analyze online behavior and language as a proxy for hedonic state, or well-being. From a development perspective this study is relevant since the poor tend to live in some of the warmest regions on earth, and would thus be disproportionately impacted by increased temperatures. We use several sources of data; U.S. based daily statewide temperature data from 2016 through 2017, as well as localized viewer chat data from a live video streaming website. We will sort chatting comments looking for key words (i.e. hate speech, swearing, etc.), and with the use of a word rating system we then assess the overall mood of the chatters contingent on high temperature readings on the precise day of the communications. After controlling for spatiotemporal fixed effects, we find strong evidence that hedonic state decreases above 20°c.

I. Introduction & Problem Statement.

What are the effects of temperature on human behavior and language, and what might be the underlying causes of this behavior? An extensive literature ties temperatures above 20° Celsius with increased irritability and aggressiveness, and unfortunately these behaviors reinforce violence and conflict. While there is no scientific consensus on why this occurs, there are no shortage of theories. A short list would include: a biological shift in the brain when exposed to increased heat, population density and the underlying economics and wealth of a region. Whatever the cause, the equivalent of a five degree Fahrenheit increase in an average USA county over a month is estimated to raise the odds of personal violence such as assault, murder and domestic violence by 4%, and the risk of riots or ethnic violence by 14% (Hsiang et al., 2013).

Coinciding with the turn of the twenty-first century and the increasingly impactful world-wide effects of climate change, there has been great interest in studying the effect of temperature on the brain and human behavior. Of the three distinct qualities of climate change, rising temperature, drought and heavy rainfall, current studies show that rising temperature has the greatest effect on human behavior and conflict (Miguel, et al, 2014). As reported by the NOAA (National Oceanic and Atmospheric Association), four of the last six years have been the hottest ever recorded in the U.S. (see *Figure 7* for average annual temperatures over the last 140 years). A study by the IPCC (Intergovernmental Panel on Climate Change) in 2007 expects that the U.S. will see an increase of between 3.6° and 7.2° degrees Celsius by 2100 (IPCC, 2007). Thus, the impact of climate change and its estimated increased heating of the planet is concerning not only for the impact on the environment, but also as it relates to humans' overall state of well-being.

This study will seek to provide further evidence relating the impact of heat on one's overall mood and use of language by analyzing online chat discussions and mapping them to daily weather patterns. I will use chat data from a live streaming video website, as well as weather data from the NOAA. I will also use the AFINN-111 word lexicon as a means of assessing specific key words found within our chat data sample by matching key works to their associated "well-being rating". Due to language and data limitations discussed further herein, our study will be limited to the U.S. and will cover a ten months between May of 2016 and September of 2017.

After assessing approximately 3.4MM chat messages and controlling for the fixed effects of both time and weather variants, as well as employing the use of clustered standard errors at the state level, our findings suggest that hedonic states decrease -1.6% at the 25° Celsius level, -3.7% at 30° Celsius level and -4.0% at the 30° Celsius level when compared to our base temperature of 20° Celsius.

II. **Literature Review**

We will first briefly discuss the economic theory relating climate change as an externality. We will then discuss the impact that temperature has on brain function. After a brief overview of online behavior and definitions, we will turn our attention to economic studies that have analyzed the impact of temperature on human behavior.

Climate Change as an Externality

Climate change is a significant negative externality, affecting all inhabitants of earth. Although no one individual is solely responsible, humankind as a whole is clearly experiencing a lasting impact. Economists theorize that there are several ways to address externalities through laws, taxes or assignment of property rights (Cornes, et al, 1986). Attempts to reduce emissions and internalize the externality vis-à-vis treaties (laws), carbon taxes or carbon permits (property rights) are all underway, with limited success.

From an economic standpoint, greenhouse gas (GHG) emissions are negative externalities and potentially represent the biggest market failure the world has seen. Every person and country produce GHGs at varying levels, and thus these externalities are not localized in nature. *Figure 7* summarizes the estimated range of increases in temperature relative to preindustrial times (around 1850), were the world to stabilize at the given concentration of GHGs in the atmosphere measured in ppm CO2e (Wang et al, 2014).

The absence of consistent goals by nations of the world has caused a coordination failure to adequately respond to climate change, since the impacts on the climate and vulnerabilities from climate change vary considerably among nations. In fact, the rules of the game appear to operate exactly in opposition of what is required. Those that have the greatest impacts on the climate – the most industrialized nations with the exception of the United States –

are estimated to have a lower impact than many developing nations (Ricke, et al, 2018). This certainly doesn't mean that we cannot beat climate change, though it helps us understand just how daunting the task of tackling climate change will be.

Biological Impact of Temperature on the Human Brain

Flaring tempers and cranky attitudes are common side effects of a hot and muggy summer day. Could it be that your brain is having a difficult time managing the heat from the surrounding environment? Our brain and body are effective at cooling us down when we overheat. The hypothalamus is a small region of the brain located at the base, near the pituitary gland. While it's comparatively small in size, it plays an outsized role in many important functions, including regulating our core body temperature. The hypothalamus works with other parts of the body's temperature-regulating system, such as the skin, sweat glands and blood vessels — the vents and heat ducts of our body's heating and cooling system. The brain acts as the conductor in this complex process.

The human brain is considered a metabolically "expensive" organ with intense heat production. It is sensitive to fluctuations in temperature with regards to its functional activity and energy efficiency. "The brain comprises only 2% of human body mass, yet accounts for 25% of the body's total glucose utilization and 20% of oxygen consumption" (Wang, et al , 2014). The brain's ability to work efficiently is highly temperature-dependent. Hence, the brain's ability to regulate its own temperature may define its capability to carry out its core functions (Yu et al, 2012).

The average brain temperature of humans is less than 1°C higher than body temperature (Wang et al., 2014). Medical studies are showing a fundamental understanding of temperature dynamics in the brain and the interactions between temperature, cerebral blood flow, regional brain activity and neural activity (Wang et al, 2014). It has been reported that cerebral functional activities are temperature-dependent and brain temperature acts as an active factor in regulating brain activity and function. For example, 70% of information that is normally retained during memory encoding is lost at approximately 34-35°C body temperature (Holland et al, 1986). During temperature fluctuations, production of neurotransmitters and hormones like serotonin and melatonin in the body is altered (Abbas, Khan & Helaluddin, 2011). Thus, a person's mood, similar to human body temperature and brain temperature, is variable and highly influenced by both biological processes and the physical environment (Jonc & Murphy, 1993).

Online Behavioral Trends and Definitions

With an abundance of online platforms to comment and offer opinions, one can find almost any point of view they desire. Online behavior can often take on a toxicity in its viewpoints that one does not normally encounter in-real-life. In cyberspace, someone who feels hidden from view behind the safety of their computer screen might behave in a way that they otherwise may lack the courage offline. This behavior is referred to as online disinhibition (Suler, 2004), or the lack of inhibition one feels when communicating online as opposed to in person. This can have both negative and positive impacts; unsightly online behavior can limit employment opportunities and can have lasting implications on personal relationships. Conversely, this may also have beneficial impacts if it helps draw someone outside of their comfort zone to reasonably speak their mind. Individuals actively participating in the labor market are increasingly managing their professional online profiles by verifying their job histories as well as deleting embarrassing posts. Unfortunately, historical online dalliances are difficult, if not impossible, to erase entirely. Anonymous postings can also be unmasked from websites with lax privacy rules leading to "online outing".

Toxic disinhibition occurs when someone uses hostile language, swears or uses threats (Suler, 2004). This study analyzes online disinhibition as it relates to ambient temperature increases. Previous studies attempting to find a definitive correlation between high temperatures and violence have shown mixed results. A known issue in using criminal data is that over long periods of time criminal activity might be displaced. Such displacement might occur when an increased police presence is felt in one area and not another or when a curfew is mandated. Such efforts are seen to simply push criminal activity from one location to another, and do not actually try to alter the root causes of crime. Offenders who are displaced simply shift to more advantageous places. (Hesseling, 1994). This study is not affected by such displacement concerns since the activity of watching online video content and socializing online via chatting is generally conducted indoors and usually does not contain a criminal element.

Ambient Temperature, Aggressive behavior and Hedonic State

The list of potential variants leading to reduced hedonic levels is long: hours of sunlight, income level and policing levels to name a few. As previously discussed, ambient temperature should also be included as a factor. Craig A. Anderson, from Iowa State University, was one the first to study the impact on how increased temperatures beyond 20° Celsius manifested into increased violent crime rates in the 1980's. This groundbreaking work has laid the foundation for additional analysis in this field, and by extension into related studies of temperature and its relationship to mood and the brain's biological function.

While there is little literature on how temperatures impact online social interactions, there is ample research on how heat impacts violent crime rates as well as cause general agitation. These historical studies aim to show a causal link between temperature and one's hedonic state, as well as the resulting implications climate change poses as a result of these findings. Such studies have shown that there is either a linear relationship between temperature and crime, or a curvilinear relationship that reaches a maximum point and then sees a diminishing relationship (Miguel, 2014). Understanding how this relationship changes as temperatures continue to rise in absolute terms is important since each have different theoretical implications, and pose differing levels of concern relating to climate change. Within the last ten years, there has been an explosion of new studies analyzing this relationship.

In the 1980's, laboratory studies showed a significant relationship between extreme heat and irritability and aggressiveness (Anderson, 1989). During this time a biochemical linkage between increased cortisol and catecholamine levels and increased aggressiveness was determined during times of extreme heat. These produce a "flight or fight" response, which can result in violent or aggressive behavior (Brenner et al, 1999). This initial research, mainly examining the biological implications of temperature shocks, provided the framework for future studies.

More homicides and violent crime occurs in the hottest regions of the world. There are 26 homicides per 100,000 people in Central America and 18 per 100,000 in Middle Africa, compared with 5 per 100,000 in Europe and North America, per the 2013 UN Global Homicide report. The report also identified regional differences as well, based on proximity to the equator: southern Europe has more murders than Scandinavia, and in the US, the

South has more overall crime than in the North (with the exception of Alaska that is an outlier). Also noted in the survey was a strong correlation of inequality to violence, especially in Africa and Central America (UN Global Homicide Report 2013). Both Europe and Oceania overall have seen a drop in homicide rates since 1955 while the Americas have seen wide fluctuations, with steady increasing trends since the 2000s.

A working paper series study entitled *Climate and Conflict*, by Ted Miguel, Soloman Hsiang and Marshall Burke aggregates 55 previous studies in the field. Written in October 2014, the average mean date of the studies examined was from 2012, demonstrating just how recent and prodigious such studies have become. They found that taken as a whole, most studies found a non-linear relationship between temperature and conflict. They also found that warmer weather overall leads to significantly more conflict than cooler weather.

Having access to such a vast amount of studies, they grouped the studies' findings into two categories; conflict between individuals, and conflict committed in group settings. They found that both of these settings to be markedly similar in nature and linear, post 20° Celsius, whether related to murder (individual) or gang violence (group setting). They consolidate the studies to draw overall conclusions using standardized effect sizes. They found that for every 1σ increase in temperature came a corresponding increase in individual conflict of 2.4%, and an increase in group conflict of 11.3% (Miguel, et al, 2014). They conclude that their findings are stronger in the aggregate than the individual studies since they are drawing upon all of the previous data, and are confident in their aggregation methodology of previous findings (Miguel, et al, 2014).

Aside from the work of the Miguel study where they summarized various studies and condensed the overall findings into one summarized paper, there are several important studies that on their own add valuable insights to the overall body of literature. We've selected several such studies, each offering an important contribution.

How does the body's core temperature impact our short term memory, alertness and irritability? One of the earliest studies of the body's core temperature's impact on mood and cognitive ability was conducted by R. L. Holland in 1985. They submerged volunteers into a water tank at 41°c and raised the subject's core temperatures up to 39°c. A series of tests were then performed as their subjects bodies cooled. At the elevated temperatures, the subjects could not recall memories from an hour earlier. They did not find that the elevated temperatures had an impact on verbal abilities or simple verbal logic problems. Though they did find that at the elevated temperatures the subjects performed tests at an increased speed of approximately 10%. Finally they found an overall decrease in alertness and an increase in irritability. It is difficult to draw firm conclusions from this study as there were certainly confounding factors such as dehydration levels, the type of task performed and the subjects overall ability to acclimate.

A classic study on temperatures and violence, by Gamble & Hess in 2012, investigated the link between the ambient daily temperatures in Dallas, Texas and the rates of daily violent crime over a seven year period from 1993 to 1999. They found convincing evidence that a u-shaped curvilinear relationship exists between crime and temperatures. Crime rates increased at a steady rate as temperatures exceeded 80°F degrees until reaching 90°F degrees, and then began to fall. They reason that once temperatures exceed a tolerable level, people retreat to the comfort of their air-conditioned homes. This study also controlled for time-varying factors other than weather that would cause variation in the data. They controlled for fixed effects of day of the week, holidays and season of the year. Interestingly, they found a disproportionate amount of violent crimes committed on weekends and holidays, when individuals are not generally occupied with work and have free time (Gamble et al, 2007).

Sporting events, especially those sports that tend to be more physical and are played outdoors, offer a great window of study into aggressive behavior at different temperatures. A 2015 study by Curtis Craig, et al, analyzed the impact of temperature fluctuations and aggression in NFL football penalties. The NFL operates in a highly aggressive environment and is the perfect environment for conducting such a study since it starts in the summer with training and ends in the winter during the Super Bowl. In US football, penalties help distinguish play that is considered aggressive but fair, and penalty play that is considered purposefully aggressive. This study allows for the impact of an inter-group setting to see if temperature shocks might have a snowball effect and spread within a team during play. Penalties for taunting, face masks, unnecessary roughness and unsportsmanlike conduct were all considered aggressive. They reviewed data from 2,376 games and found temperatures ranging from -1° F to 109° F. The mean temperature was 59.01° F. They found that ambient temperature was significantly associated with more aggressive penalties. They also found that temperature shocks had a significant impact on the home team, but not on the visiting team. This seems to suggest that playing in front of supportive home fans promotes an environment likened to peer group bullying. Of note for this study is the linear relationship between temperature and aggression. This makes sense since football games on the whole are played outside without the benefit of air-conditioning on particularly hot game days (Criag, et al, 2015).

How do the components of weather, namely high and low temperatures, humidity, amount of sunlight, etc. predict mood? A recent study by Bullock, Murray and Meyer (2017) supports the effect of temperature on mood from previous studies (Cao & Wei, 2005; Holland et al., 1985). They examined meteorological factors, such as atmospheric pressure, hours of sunshine, relative humidity, and daily maximum and minimum temperatures as better predictors of self-reported daily mood change in people diagnosed with bipolar disorder. The results showed that daily maximum temperature was the only meteorological variable to predict clinically-relevant mood change, with increases in temperature associated with greater odds of a transition into manic mood states (Bullock, et al, 2017). Hence, instead of saying that the weather affects our mood, this study suggests that it is more precise to say that temperature, which is a fragment of weather, influences our mood.

Our last study we discuss most closely resembles this paper, and relates temperature spikes to one's overall wellness, as determined by their online language. Patrick Baylis (2015) studied the impact of temperature on well-being by analyzing billions of tweets and scoring them using the AFINN-111 well-being model. Baylis analyzed data from 2008 to 2015, and employed a fixed effects model controlling for time and location, as we will also follow in this study. After controlling for fixed effects, he found no significant correlation between low temperatures (between 20°c and 40°c) and change in well-being, similar to the findings in this study. Baylis did find a significant correlation between temperatures greater than 20° Celsius and a drop in well-being. This increased dramatically from 21°c to 32°c degrees, from a -0.005 to -0.016 impact, per million twitter updates. Baylis reasons that during cold temperatures one can put on more clothes to warm up, but during times of increased heat one cannot escape soaring temperatures simply by removing all of their clothing (Baylis, 2015).

III. Methodology

Our location for this study is the United States. We chose the United States as our location since (1) the chat feature was initially launched in the U.S. in late 2015 and originated in English and (2) temperature fluctuations are vast within the U.S. at any point and can vary from the northern to southern regions by as much as 20°c on an average day (NOAA March 2018 Climate Report).

We are interested in observing the language used by chatters while online. From this universe of individuals, we sampled every 100th complete chat message and included it as part of our results, thus obtaining a 1% sample size. We then analyzed their chatting habits matching them to the AFINN-111 term dictionary (see *Appendix B* for word sample). This dictionary is a staple used in other behavioral studies (Baylis, et al) and contains 2,477 words scored between -5 and 5 relating to a persons' negative or positive hedonic state. Previous studies have shown that individual's sentiments may sometimes be misclassified, since this methodology for example would not interpret sarcasm, though in the aggregate the results were plausible (Mitchell, et al, 2013).

The AFINN-111 dictionary contains words that assist in categorizing one's emotional state. For example, "I'm unhappy today" has three words, but only one would be included in the AFINN-111 dictionary, "unhappy". "Unhappy" in this case would be included in the word score, and would receive a negative "-3", its AFINN-111 rating. The frequency of this word in our selected chat dialogues was then weighted based on its relative occurrence. The site allows its broadcasters to censor certain language at their own discretion. The vast majority of broadcasters select minimum censorship, Level 0 (See *Appendix B* for the site's Auto-mod Policy).

In order to observe how fluctuations in temperature impact online language sentiment, ten months of cross sectional panel data was collected between May and September 2016, and between May and September 2017. For each of the 295 days that fall within this period, chat data on the site was searched for every 100th message looking for an exact match of an AFINN-111 word. For each day and state, the number of times each AFINN-111 word occurred was included for our analysis. This procedure produced a sample size of 3,391,853 word matches over the 295 day period in question. The sentiment analysis was employed identically over space and time to our sample and is not subject to the same potential biases when surveys are used to gather sentiment analysis, though we are beholden to the efficiency and accuracy of the AFINN-111 lexicon.

Although there is a correlation between hot and cold weather throughout the US (i.e. Dallas, Texas is hot and Portland, Maine is cold), the *timing* of weather patterns is markedly random. After taking into account the fixed effects of both location and time of year, we believe to show causation between our direct and indirect variables. In an ideal world we would have two sets of populations and we would present a temperature shock to one, and use the other as a counterfactual. Since weather cannot be manipulated, this is not possible. Instead we use "control" population as separated in time just before the temperature shock, and the "treatment" population during and just after the shock. There the same population of individuals serves as both the treatment and control groups. Results are based on how a single population reacts to the shock, or increase in temperature. This is consistent with results found in studies examined by Miguel, et al 2014.

A. Data Collection

We will use temperature data obtained from the Daily Global Historical Climatology Network (GHCN-Daily) which is a subdivision of the NOAA National Climatic Data Center. From this site we pulled mean daily ambient temperature data for all 50 U.S. states as well as Washington D.C. The data includes surface minimum, maximum and total precipitation. The average for each state was then taken of temperature stations spread throughout the state that had at least 90% of reporting days between 1970 and 2010. Each state-day temperature observation reports only the stations with valid data for the day. The reported weather is a straight average over the stations.

Our second data source will be from a live streaming video platform. The platform is an interactive entertainment site that broadcasts channels of entertainers, who are referred to as broadcasters, usually playing video games. The site introduced "chat" in 2015, which allowed viewers to interact with each other online while watching content, as well as allowing them to interact directly with any broadcaster. The site monitors traffic for all of its broadcasters by hours watched, and based on geo-tagging, maintains viewership by precise location, worldwide. Regardless of device (i.e. desktop, mobile or console), a user is tagged based on location where they watch content. The site's demographic of users are young men on average between the ages of 16 and 30, representing 90% of its total viewership. We have collected data subsequent to the launch of the chat feature, from May 2016 through September 2017 for all 50 states as well as Washington D.C. *Figure (1)* shows the range of AFINN values by U.S. state used in our regression. *Figure (5)* shows the top 50 words matched to our sampling data with the log number of times occurring as well as their corresponding rating.

We inadvertently collected chat data located on several U.S Army bases around the world. These were easily identifiable and excluded from our analysis.

B. Hypothesis, Model and Variable Specification

Hypothesis

Our hypothesis is that rising temperatures cause a drop in hedonic state as evidenced by online discourse. The null hypothesis is that temperatures are not correlated with online behavior. Stated in formal terms, the hypothesis is as follows:

$$H_o : B_t = 0 \qquad H_a : B_t \neq 0$$

Model and Variable Specification

We have created several regression models in order to assess the overall impact of temperatures on language. The model's dependent variable will be the weighted average AFINN-111 quotient, or "Sumafinn", and will be for each state "s" measured at day "t". This is the overall AFINN-111 measurement that will range from -5 to +5 on any given day and U.S. state. A total of 3,391,853 words were a match and are included in the sample. A weighted average AFINN-111 score will be calculated by multiplying the word count by the associated score for that word and finally dividing by the number of words counted. Once the weighted average for each day is calculated, this represented15,606 weighted observations, encompassing 10 months of data for 51 locations (US States plus D.C.) for an average of 30 days per month (refer to *Table 1* for details relating to our data characteristics).

Our first independent variable is State-wide daily ambient high temperature, or "$hightemp_{st}$", measured in Celsius, for state "s" on day "t".

Using the above variables, we ran our first panel regression on the simple impact of daily high temperature readings on one's hedonic state, using robust standard errors. We then ran the same regression, but with the fixed effects of both location and time, including day-of-week, month, weekend, holiday and state. These represent the first two columns of data in *Table 2*. The fixed effects of location and time are represented by α_s and ∂_t, respectively. Finally, u_{sd} represents the error term of our equation.

(1) $\text{Sumafinn}_{st} = \beta_o + \beta_1 \text{highemp}_{st} + u_{st}$

(2) $\text{Sumafinn}_{st} = \beta_o + \beta_1 \text{highemp}_{st} + \alpha_s + \partial_t + u_{st}$

In order to assess the impacts over temperature ranges we have created temperature bands starting with our lowest temperature readings of 5°c and increasing each band by increments of 5°c. Accordingly, we have the following temperature bands:

C < 10 C [15,20) C [20,25) C [25,30) C [30,35) C > 35

For the remaining four regressions, the baseline temperature reading range between 15° and 20° will be omitted, and the remaining five bands will then be used as a comparison against this range. Hence, the interpretation of the dependent variable will be the unit change from the hedonic state between a day with the associated temperature bin and a day with temperature C [15,20), the omitted category (see *Table 2, columns (3) through (6)*). This range was chosen as the omitted category since previous studies have shown temperatures in this range to not have had a significant impact on aggressive behavior or language valance.

The remaining four regressions employ the use additional series of fixed effects in order to better understand and maximize the explanatory capacity of non-high temperature weather, space and time-varying factors. Standard errors are clustered at the state level for these remaining analyses. The first of these fixed effects models, equation (4), includes the impact of state-level factors. Equation (5) adds the fixed effects of time invariants, including day-of-week, month, weekend and holiday. There were three holidays in each year over the sample period, Memorial Day, the 4th of July and Labor Day. Finally, regression (6) adds the interactive term of state*month, which takes into account how both time and location interact with each other, accounting for seasonality of temperature by state.

The below list summarizes the remaining regressions used as part of our overall results:

$(3)\ Sumafinn_{st} = \beta_o + \beta_1 hdummytemp10_{st} + \beta_1 hdummytemp20_{st} + \beta_1 hdummytemp25_{st} + \beta_1 hdummytemp30_{st} + \beta_1 hdummytemp35_{st} + u_{st}$

$(4)\ Sumafinn_{st} = \beta_o + \beta_1 hdummytemp10_{st} + \beta_1 hdummytemp20_{st} + \beta_1 hdummytemp25_{st} + \beta_1 hdummytemp30_{st}\ \ \beta_1 hdummytemp35_{st} + \alpha_s + u_{st}$

$(5)\ Sumafinn_{st} = \beta_o + \beta_1 hdummytemp10_{st} + \beta_1 hdummytemp20_{st} + \beta_1 hdummytemp25_{st} + \beta_1 hdummytemp30_{st} + \beta_1 hdummytemp35_{st} + \alpha_s + \partial_t + u_{st}$

$(6)\ Sumafinn_{st} = \beta_o + \beta_1 hdummytemp10_{st} + \beta_2 hdummytemp20_{st} + \beta_3 hdummytemp25_{st} + \beta_4 hdummytemp30_{st} + \beta_5 hdummytemp35_{st} + \alpha_s + \partial_t + \Omega state*month + u_{st}$

In addition to these analyses we also performed several robustness checks which are described in section IV of this report.

IV. Results

Main Results

This section reports the main results of our findings. Each column in *Table 2* displays point estimates and standard errors for increasingly robust sets of fixed effects and controls as discussed in the methodology section. Column (1) and (2) uses the ordinary least squares method (OLS) without the use of temperature bands, which finds a relatively small negative effect of higher temperatures. The coefficients in this simplistic model are biased downward due to the overall weighed calculation of a single high temperature independent variable. The results from the subsequent analyses when the temperature bands are employed prove this theory to be true. The added use of fixed effects had no impact on this simple test case.

Columns (3) through (6) use the high temperature bands as previously described and are the main results of our study. Column (3) does not include any consideration for either time or location fixed effects. There may be differences in each region relating to language preferences, differing income levels or seasonal variations. For example, the northern United States tends to be more affluent and also experiences lower average temperatures. Column (3)'s results appear artificially inflated due to this omission.

To account for the aforementioned unobservables, column (4) adds U.S. State fixed effects and column (5) also adds time invariant fixed effects as previously discussed. The point estimate obtained at the T [20, 25) level is approximately 73% lower than in our original regression. For temperature bands beyond this range, results were 67% lower. Previous studies have found similarly uniform reductions in coefficients when accounting for location and time fixed effects.

Overall we find that, taking into account spatiotemporal fixed effects, significant reductions in hedonic state at the T [25,30) T [30,35) T > 35 levels. When compared to the base case, these three bands shows a reduction -2%, -3.8% and -4%, respectively, significant at the 1% level.

Just as in the 2007 Gamble study, we found a significant negative impact on hedonic state on weekends and holidays, when individuals are not generally occupied with work and have free time. This is likely a result of those who tend to watch the video platform on the weekend versus during the week. This should also help control for those individuals who primarily use chat on the weekends, as traffic spikes during this time anywhere from 25% to 50% more than during weekdays.

Notably, we did not see an increased degradation of hedonic state between our last two temperature bands, which implies that post T [30, 35) hedonic state does not get noticeably worse. This implies a consistent maximum degradation starting at T [30, 35). This is likely the case since the site's viewership is an approximately even mix between mobile and PC users, which can be viewed either anywhere (for mobile) or exclusively indoors under cooler conditions (for PC).

Figure 1 and *Figure 2* highlights the affinity score for each of the 51 locations in the study and the high temperature readings by state, respectively. The majority of the hottest states are the states with the lowest affinity score, but there were several notable exceptions. Texas, Arizona and Florida, the three hottest states, had affinity scores in the mid-range compared to other states. Acclimation to warm weather year round as well as an abundance of air-conditioning is likely impacting this result.

Figures 3 and *4* highlight the frequency of word matching from the AFINN-111 list. Figure 3 shows the log of times each of the top 50 words were found as part of our sample. Figure 4 looks at the same top 50 words, but compares the likelihood of usage of those words when temperatures are greater than 25° Celsius, mapped against the word's rating. This Figure clearly shows a decline in usage of words considered positive and a likelihood of negative word usage. The fitted line shows the estimated downward slope of word valance associated with this trend. To further illustrate the point that word ratings fall as temperature increases, the residuals of both the affinity scores and high temperatures have been plotted against each other. We clearly see from *Figure 4* that as temperatures rise, language tends toward a more negative state, as anticipated from our general results.

Figure 8, a non-parametric regression mapping hedonic state to our high temperature bands illustrates our findings nicely. One can see how as we increase temperatures beyond 25°c we see a continued decline in hedonic state.

Robustness Checks

As a robustness check, we added further controls for weather variants other than daily high temperatures, including both the low temperature reading for the day, or "lowtemp", as well as a precipitation reading, or "precip", again using clustered standard errors at the state level. Dummy variables were created for both of the weather variants, and the band method used with our high temperatures was again employed. For our low temperature readings, the following bands were assigned based on the stratification of the data:

C [0,5) C [5,10) C [10,15) C [15,20) C [20,25) C [30,35) C > 35

For our precipitation readings, the following bands were created:

P [0,3) P [3,6) P [9,12) P [12,15) P [15,18) P > 18

The following regression includes the newly created bands for "lowtemp" and "precip".

$$\text{Sumafinn}_{st} = \beta_o + \beta_1\text{hdummytemp10}_{st} + \beta_2\text{hdummytemp20}_{st} + \beta_3\text{hdummytemp25}_{st} + \beta_4\text{hdummytemp30}_{st} + \beta_5\text{hdummytemp35}_{st} + \alpha_s + \partial_t + \Omega\text{state*month} + \text{lowtemp} + \text{precip} + u_{st}$$

For simplicity the above equation shows the dummy variables for temperature related items once, though in the actual regression each dummy variable was included.

By adding these additional controls for low temperatures and precipitation we may introduce an endogeniety problem since temperature readings may influence precipitation totals. But doing so added virtually no point estimate impact to our model. Daily low temperature did, however, show a slightly positive impact on hedonic state in the point estimate. This is likely due to the imprecise nature of using state-wide data and not county level information.

Several extreme weather events happened over the sample period that impacted precipitation: hurricanes Matthew, Harvey and Maria. The strongest, costliest, and deadliest storm of the 2016 season was Hurricane Matthew, the southernmost Category 5 Atlantic hurricane on record and the first to reach that intensity since Felix in 2007. Matthew reached its highest intensity on October 1st, 2016 which falls outside of our data range, though in the lead up to the storm, precipitation readings climbed to maximum daily reading of between 40 and 60 cumulative inches of rain in the D.C. area, and its surrounding states. In 2017 both hurricanes Maria and Harvey occurred. Hurricane Harvey recorded between 30 and 50 cumulative inches of rain for several days in both Texas and Louisiana in August 2017. Hurricane Maria recorded 111 cumulative inches of rain in Florida on September 11, 2017. This was the highest precipitation reading during the sample period. We ran robustness check and compared the results with our final regression, (6). Results did not change from our previous regression which included all other spatiotemporal fixed effects.

Figure 5 highlights the outliers in precipitation readings, by showing the upper and lower quartiles of precipitation and readings outside of this range in dots, located well above the average ranges. Colorado, Wisconsin, and Vermont had the most low temperature outliers in our sample, and Arizona had the most high temperature outliers, as we would expect.

As noted earlier, temperature readings were determined at the state level. For large states, such as California and Texas, deviations from the daily mean high and low temperatures varied widely. A more precise measure of country level data would be preferred, but was not available due to confidentiality restrictions on the data. In order to test our overall country-wide results a final series of regressions were run that only included states with a limited amount of square miles, under 12,000. Nine states and the District of Columbia qualified for this final analysis. The majority of states that fit this criteria were located in the North East and would share similar demographics, social norms and are generally the wealthier of the US states. This robustness check added bias to our estimations, and when controlling for both time and location variants, results were inconclusive.

V. Summary and Conclusion

Does temperature influence mood and language? Results from this study and others suggest that it does. This study shows that when temperatures cross the 20° Celsius threshold that language becomes increasing more negative. Point estimates of hedonic state decreased between -2% and -4% depending on temperature ranges over 25°c, while controlling for time, location, and weather variants when compared to 20°c. Figure 5 depicts the increased likelihood of use of negative language above 25° Celsius, showing the top 50 words in the sample. Words associated with a positive language valance are on the decline and words associated with negative valance correspondingly increase. Our overall findings support that changes in our climate, and in particular increased heat, are an important component of the overall costs of climate change.

From a policy perspective, current building codes are increasingly calling for new construction of buildings to achieve their power sources from more environmentally friendly technologies, such as solar power. While this push to improve a building's environmental footprint will have lasting impacts on global warming, there is less uniform agreement of the requirement of cooling systems. As temperatures rise, it will become increasingly important to provide cooling systems in buildings where there is a greater potential for aggressive behavior. Examples of such buildings would include prisons, schools and places of work.

There is currently a debate in the economic community regarding the ability of citizens to acclimate to warmer temperatures, and further study is needed in this area. Since it is not possible to relocate entire populations to test one's ability to acclimate from colder to warmer temperatures, this presents a potential problem in ascertaining estimates of potential future conflict as temperatures increase further in years to come.

A final note of importance on the impact of online behavior is its link to increased levels of suicide. According to the World Health Organization, in the year 2020 approximately 1.53MM people will die from suicide. A 2013 study of suicide rates in South Korea found a significant association between social media and national suicide rates (Won et al, April

2013). If we indeed find that temperature increases lead to decreases in hedonic state and more negative online social discourse, an additional impact could be a further increase in suicide rates.

Research is beginning to shed light on current trends of online behavior relating to climate change. And as the LDCs catch up to the more developed nations of the world in terms of interconnectivity and speed, these studies should act as a warning of what's to come.

References

Anderson CA. Psychology Bulletin, *Temperature and aggression: Ubiquitous effects of heat on occurrence of human violence.* 1989; 106:74–96. [PubMed]

Baylis, Patrick, Energy Institute at Haas, *Temperature and Temperament: Evidence from a Billion Tweets*, November 2015. https://ei.haas.berkeley.edu/research/papers/WP265.pdf

Brenner, et al, 1998. The International Journal of Sports Medicine, pg. 130-143.

https://www.ncbi.nlm.nih.gov/pubmed/9562223

Cao, M., & Wei, J. (2005). Stock Market Returns: A Note on Temperature Anomaly. *Journal of Banking and Finance, 1559-1573.*

Cornes, Richard, Sandler, Todd, 1986, The Theory of Externalities, Public Goods and Club Goods

Craig et al, 2015. The Journal of Sport and Health Science, *The Relationship Between Temperature and Aggression in NFL Football Penalties*

https://www.sciencedirect.com/science/article/pii/S2095254615000022?via%3Dihub

Ely, Richard, American Economic Review: Papers & Proceedings 2008, http://www.aeaweb.org/articles.php?doi=10.1257/aer.98.2.

Gamble, Janet & Hess, Jeremy, 2012, *Temperature and Violent Crime in Dallas, Texas: Relationships and Implications of Climate Change*

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3415828/

Hessiling, Rene, 1994, "*Displacement A Review of the Empirical Literature*".

https://www.researchgate.net/publication/245948036_Displacement_A_review_of_the_empirical_literature

Hewitt, David, 2010, Current Climate Change Models May be Overly Optimistic, *Earth Times*

Holland, H. R., Sayers, J. A., Keating, W. R., & Davis, H.M., January 1986, Effects of Raised Body Temperature on Reasoning, Memory and Mood, *The Journal of Applied Physiology*.

Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the Influence of Climate on Human Conflict. *Science*, *341*(6151), 1212.

Huan Wang, Bonnie Wang,[3] Kieran P. Normoyle,[4,5] Kevin Jackson,[2] Kevin Spitler,[3] Matthew F. Sharrock,[4]Claire M. Miller,[4,6] Catherine Best,[7] Daniel

Llano,[2,5] and Rose Du[8] , Published online 2014 Oct 8, *Brain temperature and its fundamental properties: a review for clinical neuroscientists*

Jacob, et all. *"The Dynamics of Criminal Behavior: Evidence from Weather Shocks"*, September 2004 http://www.nber.org/papers/w10739.pdf

Miguel, Edward et al, "climate and conflict", NBER Working paper series,

http://www.nber.org/papers/w20598.pdf

National Centers for Environmental Information, 2015 – 2018 weather data, https://www.ncdc.noaa.gov/

Ricke, Catherine, Drouet, Lauren, September 2018, The Journal of Nature Climate Change, *Country-Level Social Cost of Carbon*

Suler, John (June 2004). "*The Online Disinhibition Effect*". *CyberPsychology & Behavior.* **7**: 321–326.

US Department of Justice, FBI Crime Reports. 2015 -2018. Available at https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/tables/table-43

US Energy Information Administration 2015 consumption data.

https://www.eia.gov/consumption/residential/data/2015/hc/php/hc7.5.php

UNODC (United Nations Office on Drugs and Crime) 2013. Global Study on Homicide

www.unodc.org/documents/gsh/pdfs/2014_GLOBAL_HOMICIDE_BOOK_web.pdf

Wang, H., Wang, B., Normoyle, K. P., Jackson, K., Spitler, K., Sharrock, M. F., ... & Du, R. (2014). Brain temperature and its fundamental properties: a review for clinical neuroscientists. *Frontiers in neuroscience.*

Won, et al. April 2013. PLOS. Predicting National Suicide Numbers with Social Media Data

http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0061809

Yu Y., Hill A. P., Mccormick D. A. (2012). Warm body temperature facilitates energy efficient cortical action potentials. PLoS Comput. Biol. 8:e1002456 10.1371/journal.pcbi.1002456

Tables, Figures & Appendices

Table 1: Sample Characteristics

	Count	Mean	Median	Min	Max	Standard Dev
Measures of Hedonic State	15,606	0.497	0.510	-0.593	1.780	0.167
Number of Days in Sample	295	295	295	295	295	n/a
Temperature Variables						
Min Temperatures	15,606	15.00	15.00	-2.79	26.50	1.15
Max Temperatures	15,606	27.90	28.00	6.09	41.31	5.52
Precipitation	15,606	3.03	3.05	0.00	111.43	5.30
Number of Chats	3,391,853	3,391,853	3,391,853	3,391,853	3,391,853	n/a
Number of AFINN Words	2,477	2,477	2,477	2,477	2,477	n/a
% of Total Chats Selected	1%	1%	1%	1%	1%	n/a

Table 2: Effect of Temperature on Hedonic State

	(1)	(2)	(3)	(4)	(5)	(6)
Daily Temperature T						
High temperature	-0.003 ***	-0.001 **				
	0.00	0.00				
T [0,15)			0.020	0.019	0.011	0.012
			(0.01)	(0.01)	(0.02)	(0.02)
T [20,25)			-0.017 *	-0.014 *	-0.004	-0.006
			(0.01)	(0.01)	(0.01)	(0.01)
T [25,30)			-0.026 **	-0.026 ***	-0.007	-0.010
			(0.01)	(0.01)	(0.01)	(0.01)
T [30,35)			-0.045 ***	-0.042 ***	-0.015 *	-0.019 **
			(0.01)	(0.01)	(0.01)	(0.01)
T > 35			-0.041 ***	-0.046 **	-0.015 *	-0.020 *
			(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.577 ***	0.530 ***	0.525 ***	0.523 ***	0.505 ***	0.508 ***
	(0.01)	(0.01)	(0.01)	(0.01)	0.00	(0.01)
State FE	No	Yes	No	Yes	Yes	Yes
Weekend FE	No	Yes	No	No	Yes	Yes
Holiday FE	No	Yes	No	No	Yes	Yes
Day of Week	No	Yes	No	No	Yes	Yes
Month	No	Yes	No	No	Yes	Yes
State x Month FE	No	No	No	No	No	Yes

Figures:

Figure 1 - Box-and-Whisper Plot Afinn Score to US State, Ascending Order

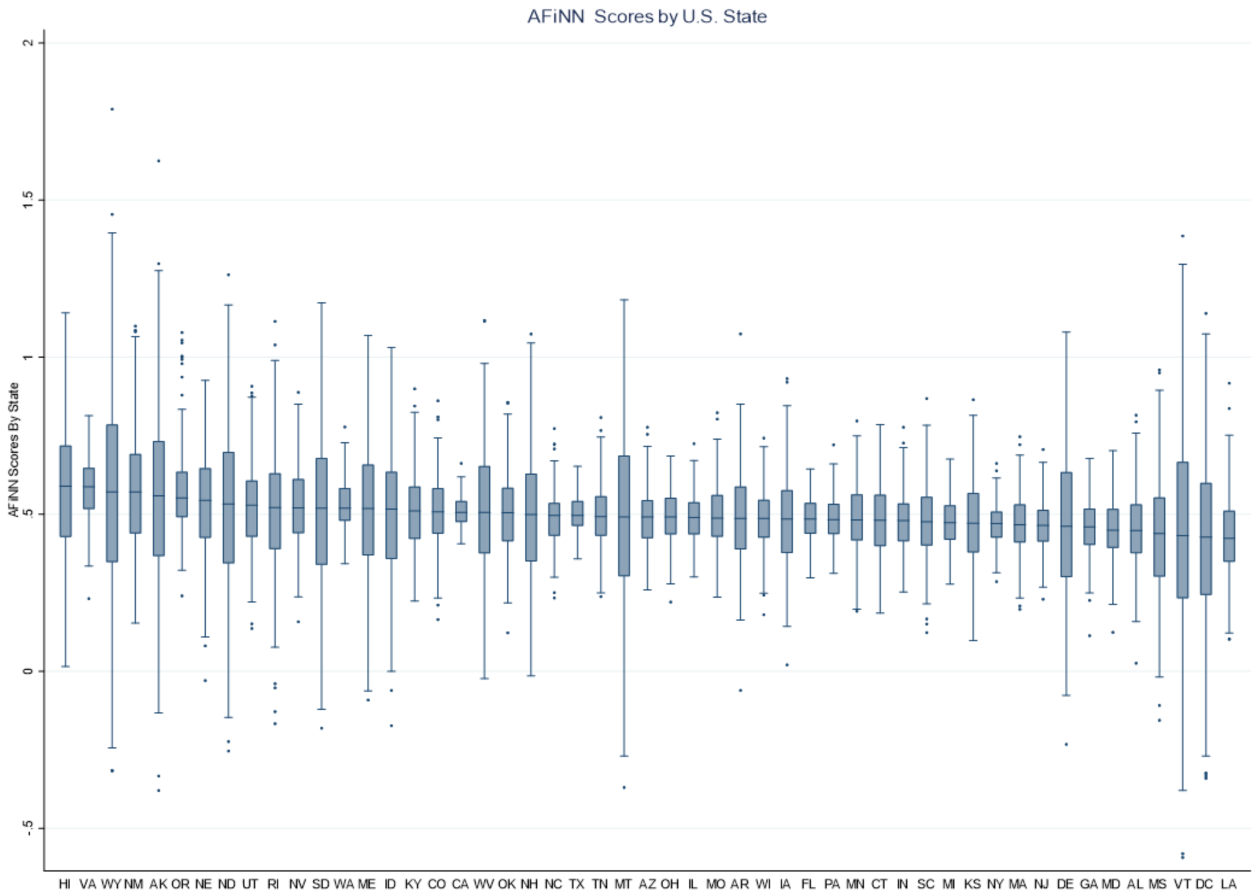


Figure 2 – High Temperature Readings by US State

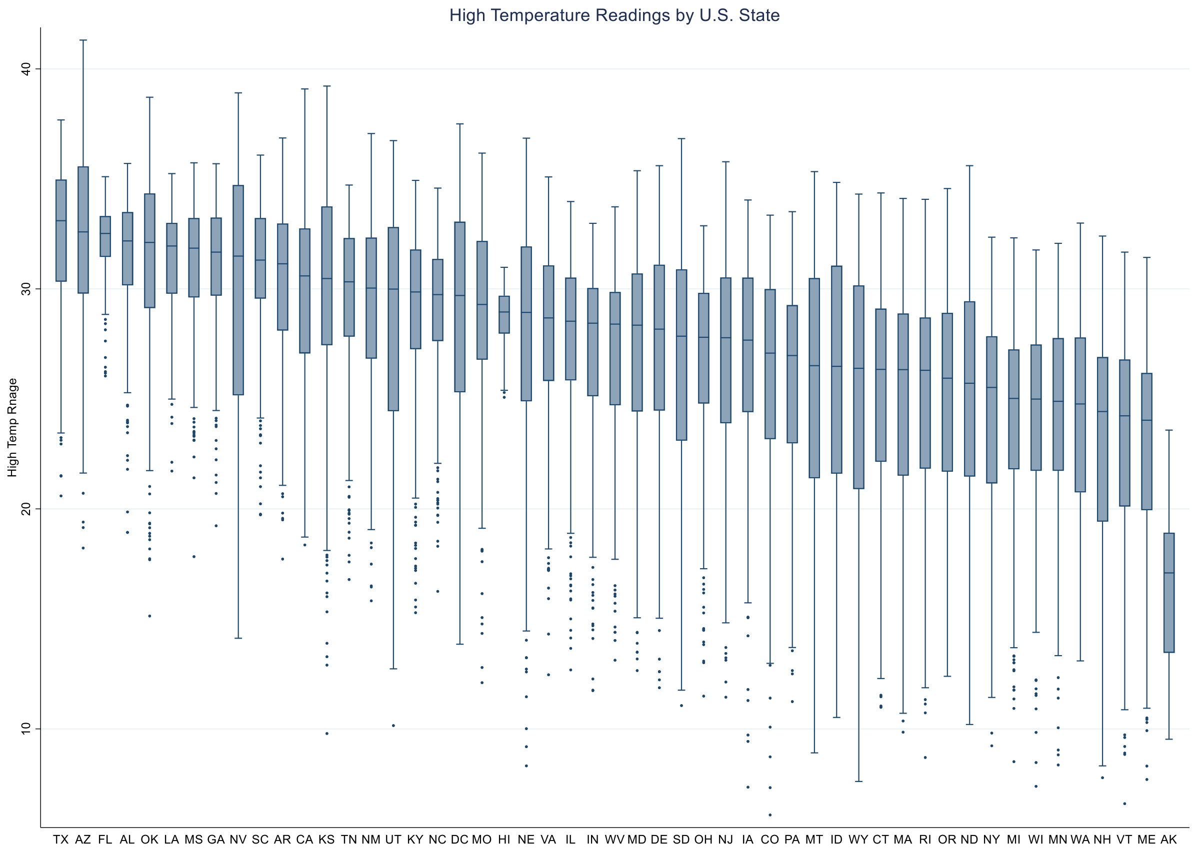


Figure 3 – AFINN Score Top 50 Words Found within Sample

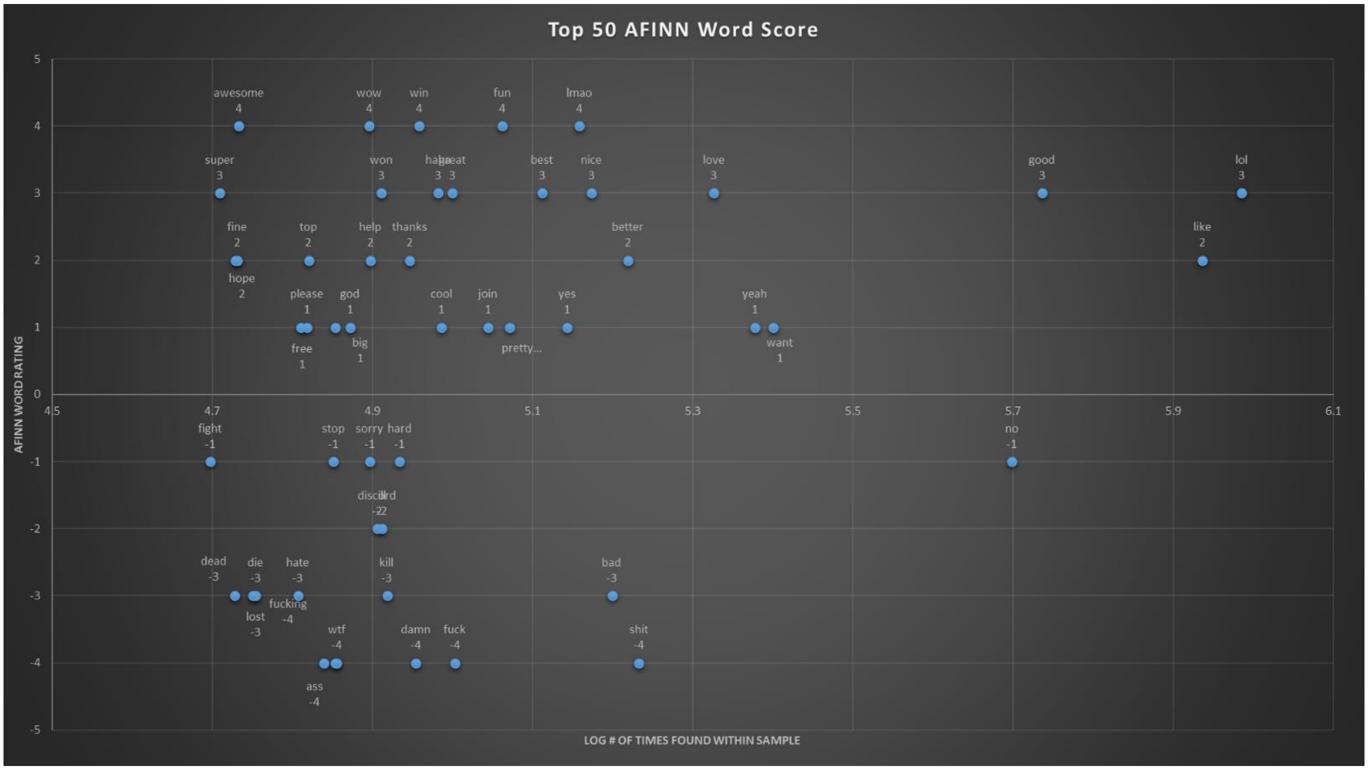


Figure 4 – Top 50 Words Frequency when temperature are greater than 25° Celcius

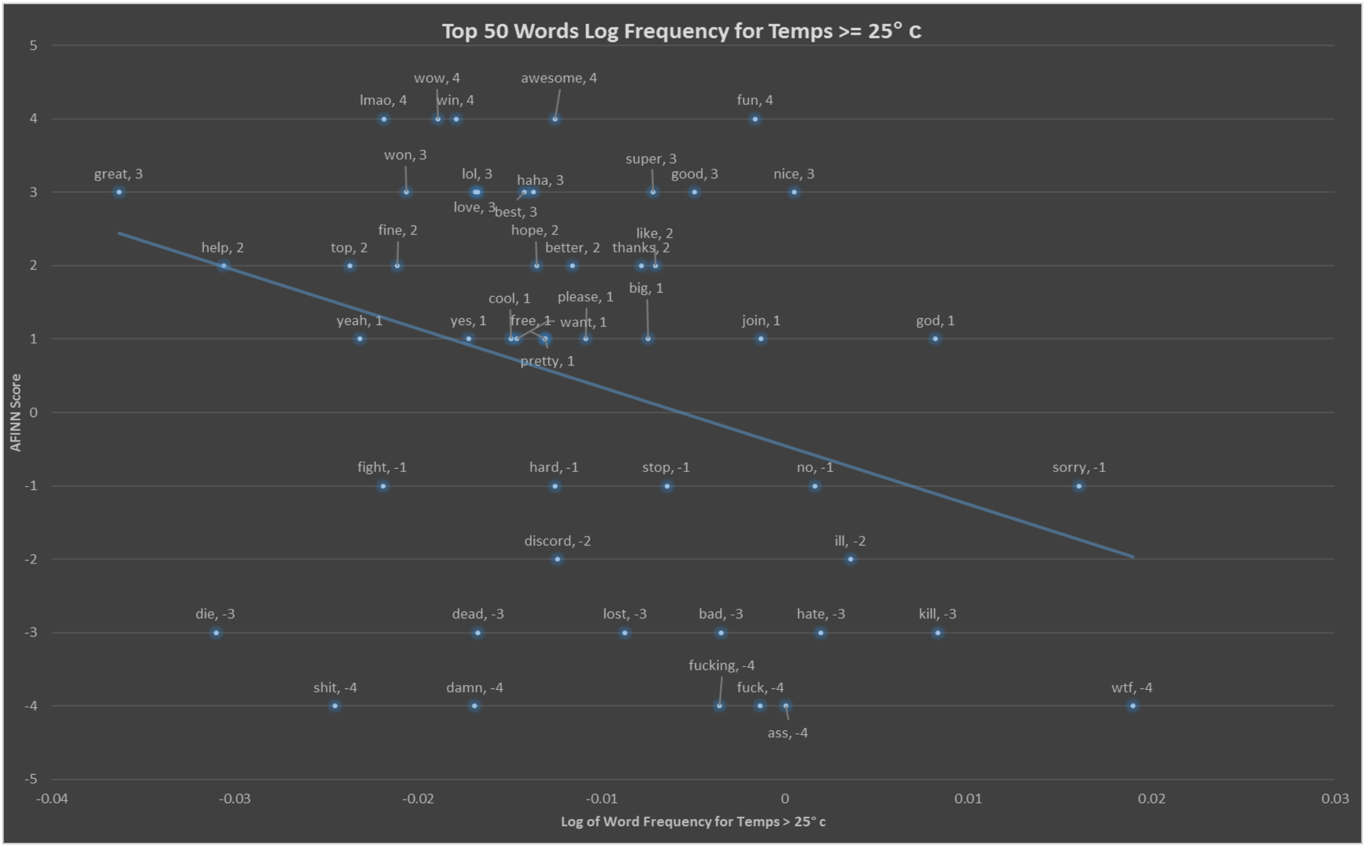


Figure 5 – Precipitation by US State

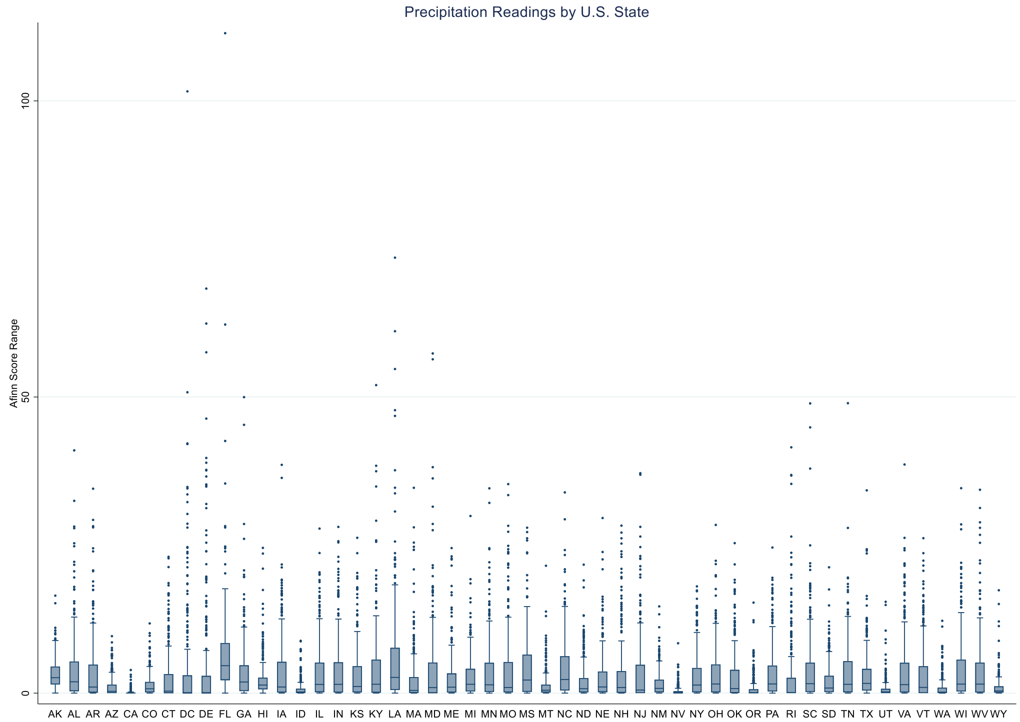


Figure 6 – Top 50 Words Frequency Residuals when temperature are greater than 25° Celcius

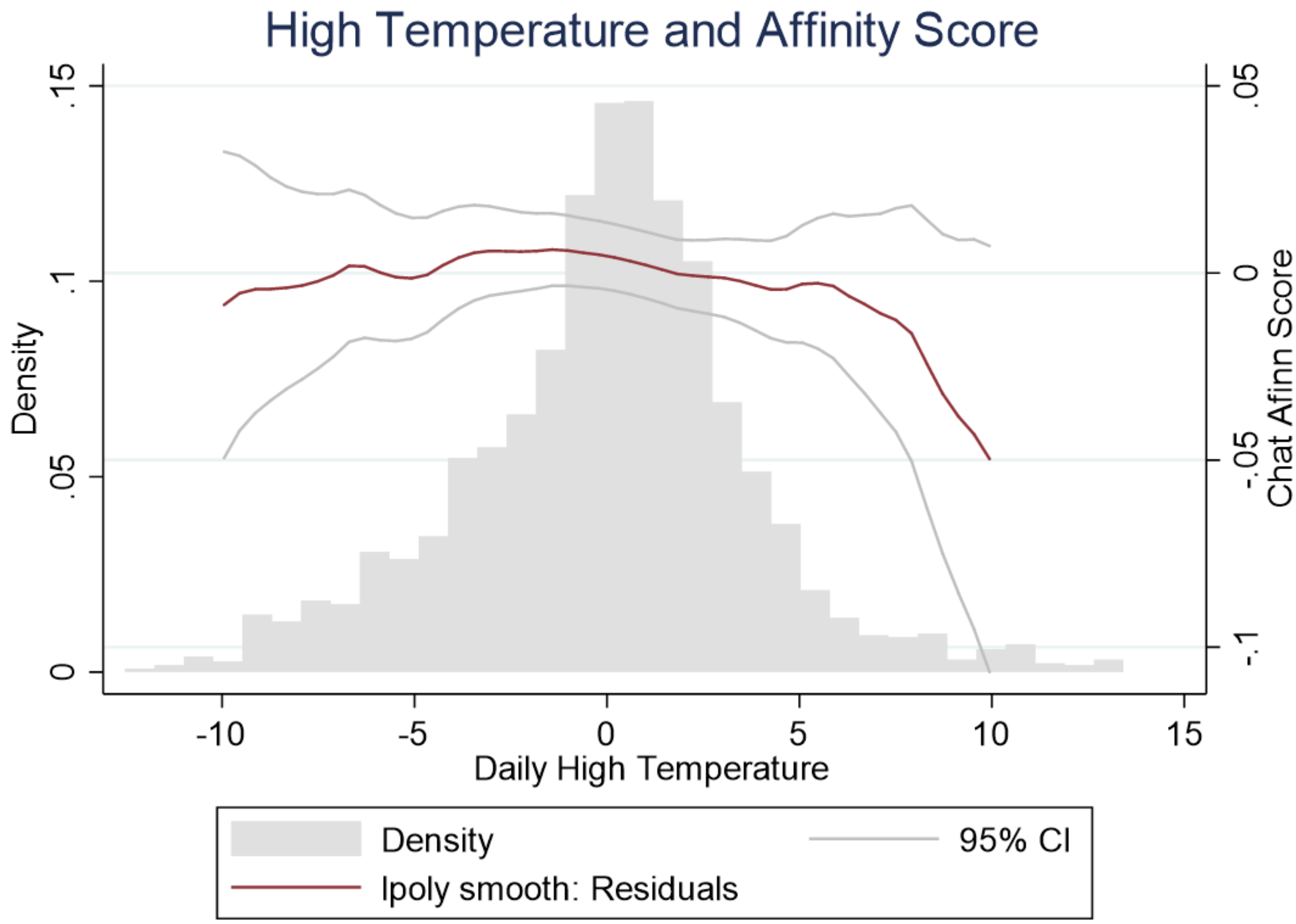
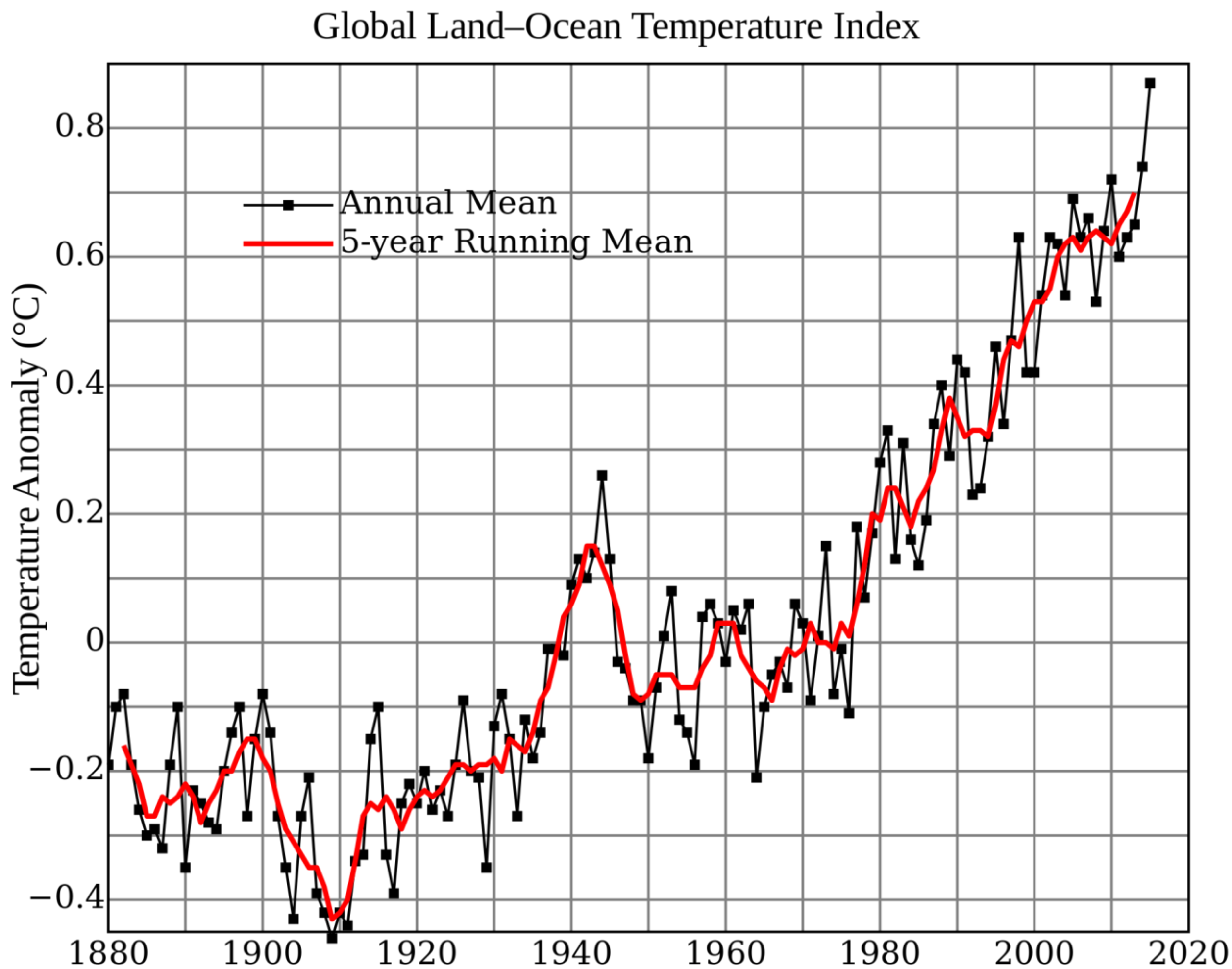
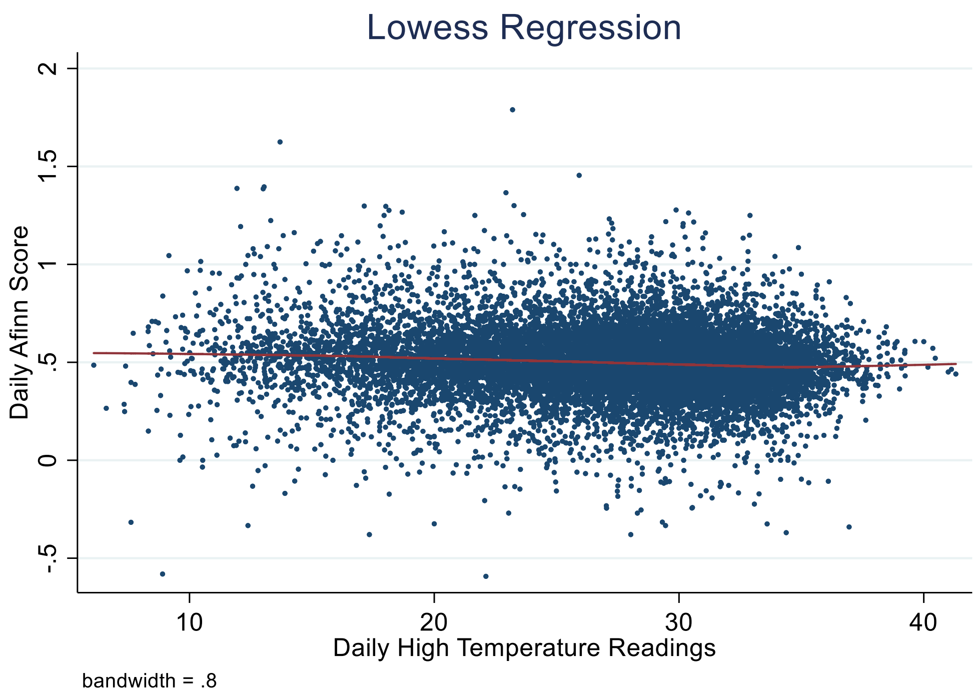


Figure 7 – Historical Mean Temperatures Since 1880



David Hewitt, 2010, *Earth Times*

Figure 8 – Non Parametric Regression



Appendix A – AutoMod Policy

Broadcasters can choose one of five levels for their AutoMod setting. Each level catches all words from the previous level, plus more. The higher the level, the more AutoMod will catch. You can see how strictly AutoMod will filter based on how many shields are displayed in each language category, from zero (a little) to four (a lot). The default AutoMod setting is 0 for all Broadcasters.

AutoMod language categories:

Identity language - Words referring to race, religion, gender, orientation, disability, or similar. Hate speech falls under this category.

Sexually explicit language - Words or phrases referring to sexual acts, sexual content, and body parts.

Aggressive language - Hostility towards other people, often associated with bullying.

Profanity - Expletives, curse words, and vulgarity. This filter especially helps those who wish to keep their community family-friendly.

What AutoMod catches at each level:

> Level 0: Only commonly blocked terms.
>
> Level 1: Only remove hate speech.
>
> Level 2: Also remove sexually explicit language and abusive language.
>
> Level 3: Remove even more hate speech and sex words.
>
> Level 4: All of the above, plus profanity and mild trash talk.

Appendix B: AFINN word-score examples

Neutral Affect	Negative Affect
combat -1	betraying -3
apologizes -1	agonises -3
exposing -1	destroying -3
oxymoron -1	swindle -3
provoked -1	abhors -3
limited -1	humiliation -3
escape -1	chastises -3
unconfirmed -1	victimizing -3
passively -1	bribe -3
blocks -1	lunatic -3
poverty -1	scandal -3
attacked -1	outrage -3
gun -1	betrayed -3
feeling 1	terror -3
intrigues 1	abuse -3
alive 1	greenwash -3
protected 1	falsified -3
unified 1	douche -3
relieves 1	agonized -3
fit 1	criminals -3
restore 1	defects -3
relieve 1	idiotic -3
greeting 1	woeful -3
yeah 1	acrimonious -3

Notes: Raw scores shown. Standardized scores used in analysis. Full list includes 2,477 total word-score mappings and can be obtained here: http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6010