Spring 5-19-2023

Tempers Rising: The Effect of Heat on Spite

Jake C. Cosgrove
University of San Francisco, cosgrovejake2@gmail.com

Tempers Rising: The Effect of Heat on Spite

Jake Cosgrove

Department of Economics
University of San Francisco
2130 Fulton St.
San Francisco, CA 94117

Thesis Submission for the Masters of Science Degree
in Applied Economics

email: *jcosgrove@dons.usfca.edu*

5 May, 2023

Abstract: The relationship between heat and harmful outcomes is well documented, with research connecting various adverse economic outcomes to the climate. In the presence of increasing global warming and climate change, understanding why the climate leads to negative economic outcomes is essential for forming peaceful institutions of the future. We study how behavioral economic outcomes change in the presence of heat through a lab experiment involving 1,110 observations conducted in five different countries. This paper specifically focuses on the social preference outcome of spite. We find that increased time exposure to the treatment effect of heat is required to elicit an individual's spiteful behavior. Our results also suggest heterogeneity in this effect with a particular difference along gender and income consistency. We deploy novel methods to analyze heterogeneity using a machine-learning causal forest and Sorted Group Average Treatment Effect (GATES).

Acknowledgements: Thank you to Professor Wydick, Professor Anttila-Hughes, Professor Hobbs Bruce, Professor Cassar! Thanks Nikita for making this thesis template, you can find the link here.

Table of Contents

1. Introduction

Climate and economic outcomes have been at the forefront of research and policy concerns in recent decades as global warming predictions materialize (Bathiany et al. 2018). Compounding current-day climate volatility with scientists' predictions that temperatures will continue to rise in decades to come makes understanding climate and its effect on human behavior a crucial concern for policymakers when designing future institutions. Although climate concerns have recently elevated their importance in modern science, the role that climate plays in shaping societal outcomes has had a long history of sparking researchers' interest (Almås et al. 2019a).

The large body of research connecting climate with behavioral outcomes overwhelmingly shows a link between increased temperatures and detrimental socioeconomic outcomes (Hsiang, Burke, and Miguel 2013a). Research has frequently shown evidence of the relationship between hot climates and increased group-level and individual-level conflict (Burke, Hsiang, and Miguel 2015a). Heat's linkage to increased conflict and aggression is supported through substantial research mapping heat as a causal force driving harmful societal outcomes. Recent studies have mapped heat to increased crime rates, hostility towards others, civil conflict, political unrest, and more (Hsiang, Burke, and Miguel 2013a). Temperatures' connection to harmful outcomes is well established, yet the mechanisms behind how warmer climates are causing detrimental outcomes are still unknown.

Climate can affect societal outcomes in three ways (Falk et al. 2018). The first effect the literature defines is known as the direct effect. The direct effect describes the process humans directly undergo when the temperature rises; people may get uncomfortable, more irritable, or lethargic (Bushman and Anderson 2020). The direct effect is often difficult to pin down because detrimental outcomes correlated with hot climates are endogenous with many other variables that the climate affects. For example, hot temperatures are also responsible for droughts, volatile crop yields, and extreme weather events (Arnell et al. 2019). These outside effects of heat can then cause outcomes of conflict which are what the literature defines as indirect effects. Research frequently shows indirect effects being at least partially responsible for poverty, instability, and migration outcomes. This paper takes advantage of a lab experiment's ability to block out the indirect effects of hot temperatures on behavioral outcomes. Our experiment will exogenous vary room temperatures to look at different behavioral outcomes. We will also introduce a competition within the experiment to examine the heterogeneous treatment effects between winners and losers.

Research suggests that the causal mechanism behind heat's relationship to harmful outcomes may be two-fold. First, rising temperatures cause people to become irritable, uncomfortable, or upset, and when combined with a provoking event, an individual is more likely to react anti-socially. Studies have found evidence of this interaction in sporting events (Larrick et al. 2011a), parking lots (Kenrick and MacFarlane), and social media (Baylis et al., 2018). This experiment pulls inspiration from a similar lab experiment from (Almås et al. 2019a), where the temperature was controlled in a lab setting. They found little evidence of heats direct effect on social preferences, except for a significant treatment effect for a sub population of individuals from Kenya that identified as belonging to an ethnic group that had been politically marginalized in a recent national election. The heterogeneity found in this subpopulation in Kenya supports the theory that heat requires a provoking interaction to produce harmful outcomes. This paper will add to the literature in three ways:

1. We conducted a randomized control experiment across five countries, collecting over 1,100 observations and measuring various behavioral economic outcomes.

2. We will analyze the treatment effect on the anti-social outcome of spitefulness.

3. We will test out novel machine learning methods to compare there results wtih traditional methods for examining heterogeneous treatment effects.

Spitefulness will be the central behavioral outcome that this paper examines. Spite comes from the root word despite and is defined by many behavioral economists as any action that causes harm to others without having any benefit to the actor themselves (Fehr, Glätzle-Rützler, and Sutter 2013). Our experiment will measure spitefulness through four rounds of a single shot, anonymous dictator games, which are commonly used in economic literature to measure individuals' social preferences. We find that 7% of the sample act in a way categorized as "Strong Spite" and 24% of the sample categorized as "Weak Spite" based on their dictator game answers. We look at both categories as separate outcome variables with our primary analysis on the Strong Spite outcome.

We find that the treatment effect of heat has a negligible effect on individuals' probability of acting spitefully for both outcomes, with a coefficient less than 0.05 and an insignificant p-value, however we do find significant heterogenaity within the treatment effect with specific subpopulations displaying a statistically significant treatment effect. We find a significant positive treatment effect for individuals who played version B of the economic experiment. Version B differed from version A in two ways. First that individuals played a competition round immediately before answering the dictator games, where spiteful behavior was measured. The second difference between the two versions is that version B exposed individuals to the temperature of the room for 15 minutes before they answered the dictator games compared to 5 minutes in version A. Our results suggest that this increased exposure to high temperatures may be creating a significant treatment effect of temperature on spite. We find that for individuals playing version B and in room over 24 wet bulb Celsius, they are 9% more likely to respond spitefully with a significance at the below the 5% level.

Furthermore we find that there is heterogeneity in this later treatment effect of individuals that playued version B, among gender and income consistency. We uncover our findings through numorus methods including traditional OLS and have these findings tested through novel methods of a machine learning methods of a causal forest (Wager and Athey 2018) and generic machine learning (Chernozhukov et al. 2018). The techniques of a causal forest and generic machine learning have been leading the way in the recent research in estimating heterogeneous treatment effects. Our findings can contribute to the literature by provide insight into for whom does having increased exposure to high temperatures cause anti-social outcomes.

It is important to consider our results' external validity in the context of the more prominent topic of climate change's impact on human behavior. Two limitations to keep in mind from our lab experiment are one, the lack of variation in the age and occupation of our participants due to the fact that all experiments where conducted on university campuses. Secondly, our experimental environment was all indoors, where temperature variation was easy to manipulate however the effects of climate change will predominantly be experienced outdoors. Our findings most closely generalize to situations with hot indoor environments; however, these results can still provide evidence to the broader concern of how climate change will change our behaviors.

2. Literature Review

2.1. Global Warming

In 1748 Montesquieu argued in The Spirit of Laws that an “excess of heat” made men “slothful and dispirited”. However, because of the global temperature increases due to global warming, climates affect on humans and what this means for the economy is a high importance (Arnell et al. 2019). It’s projected that the frequency of extreme wet bulb temperature events could increase by a factor of 100 - 250 (Coffel, Horton, and Sherbinin 2018). It is also projected that by the mid to late 21st century, those exposed to deadly heat waves will substantially increase (Coffel, Horton, and Sherbinin 2018). Climate change is not just something that is projected but has already negatively impacted the lives of many. The 2003 heat wave in Europe caused tens of thousands of deaths, while a 2010 Russian heat wave has been attributed to increased global food prices (Dell, Jones, and Olken 2014). Recent heat waves of wet bulb temperatures between 29C and 31C have caused tens of thousands of deaths (Stott, Stone, and Allen 2004).

Increasing global temperatures and humidity is a real problem that the globe will have to face and is predicted to accelerate in the decades to come, even if we are able to slow down global warming (Coffel, Horton, and Sherbinin 2018). Extreme heat is one of the most noticeable impacts that climate change will have in the coming decades (Coffel, Horton, and Sherbinin 2018). The change of our climate will have impacts in numerous aspects of society, and a more subtle uncertain effect that climate change may affect is how human decision-making will be impacted due to these increased temperatures. By 2070 –2080, it is projected that global multi-GCM mean increases in annual maximum wet bulb temperature across the tropics and mid-latitudes of 2 - 3 Celsius(Coffel, Horton, and Sherbinin 2018). Of all the negative impacts that climate can have on human lives, research has shown that rising temperatures has the potential to have the most significant impact on human behavior (Burke, Hsiang, and Miguel 2015b).

2.2. Climate & Conflict

There is an established relationship between a positive correlation between ambient temperature and aggressive behaviors (Baron and Bell, n.d.; Craig et al. 2016; Lange, Rinderu, and Bushman 2017). Although the curve relating temperature and aggression may be unclear, whether it is linear or non-parametric, the evidence shows that as temperature increases, so does aggressive behavior. Aggression has been measured by increases in crime rates (Bushman, Wang, and Anderson 2005) and aggression during in athletic games like baseball and football (Craig et al. 2016; Larrick et al. 2011b). A 2015 (Burke, Hsiang, and Miguel 2015b) meta-analysis looked at over 50 studies relating temperatures' relationship to conflict and found that one standard deviation increases in temperature leads to increase in interpersonal conflict by 2.4% and inter-group conflict by 11.3% (Burke, Hsiang, and Miguel 2015b). More concerningly is that some research suggests that the negative effects of temperature on aggression affect certain groups more than others. Research looking at 20 years of monthly climate and crime data found that disadvantaged neighborhoods experienced substantially higher amounts of violence due to higher temperatures (Mares 2013). This relationship has led to many theories attempting to describe the link between temperature and aggression, with two of the leading theories being the General Aggression Model (GAM) and the Routine

Activity Theory (Lange, Rinderu, and Bushman 2017).

The two models differ greatly in the fact that the General Aggression Model says that temperature acts as a trigger that increases aggression, suggesting that there is an internal mechanism that is at play when humans' environmental temperature increases (Lange, Rinderu, and Bushman 2017). On the other hand, the Routine Activity Theory suggests that the temperature increases the distribution of social interactions in terms of creating a more probable chance of conflict or aggression (Lange, Rinderu, and Bushman 2017). These by no means are the only two theories relating to climate and aggression, as no theory is yet to have overwhelming empirical evidence to support them (Lange, Rinderu, and Bushman 2017). There is also plenty of mechanisms that may be at play in the reason for temperature's effect on aggression. There is also evidence to suggest that temperature may alter one's reaction to a stressful situation or "triggering" event. Craig Anderson's research on professional baseball players shows evidence that the interaction between temperature and a "triggering" event, in this case, the presence of an aggressive act from the opposition, creates an aggressive act of retaliation (Larrick et al. 2011b). There is also supporting evidence from research done on NFL football games finding that temperature required an interation with indiviudals also playing a home game for temperatures to increase aggression (Craig et al. 2016). Such effects are especially pronounced in correctional facilities as high temperatures increase daily violent interactions by 20% and the probability of any violence by 18%, according to a study in Mississippi (Hsiang, Burke, and Miguel 2013b).

2.3. Spite

Spite is one of the four pro-social behaviors but is one of the least understood of the four. Spite has historically been defined in a few different ways in the economic literature. One popular way it is seen is that spite is at the intersection of causing harm to ones self as well as to the other individual. Other definitions of spite have been that spite is the action of reducing another material payoff for the very purpose of increasing one's relative payoff (Fehr, Hoff, and Kshetramade 2008). Fehr has extensive literature on measuring anit-social behavior and uses this definition of spite in able to measure it through the use of dictator games, public good experiments, and ultimatum games (Fehr, Hoff, and Kshetramade 2008; Falk, Fehr, and Fischbacher 2005). Falk even finds that spiteful actions disappear when there is no longer a way for an individual to increase their relative payment due to their opponent (Falk, Fehr, and Fischbacher 2005). Another way of being defined is that spite puts a negative value on the other person's well-being (Fehr, Glätzle-Rützler, and Sutter 2013). In 2012 Fehr ran experiment that categorized 717 subjects ages 8 - 17 as either egalitarian, altruistic, or spiteful and found a strong decrease in spite in age. Often, spite is measured in three-person ultimatum, prisoner dilemma games (Falk, Fehr, and Fischbacher 2005) or in as in the case of this paper, dictator games.

Theories around why spiteful outcomes exist are difficult to explain, with little theory being empirically validated in the field. Levine is one of the views who does attempt to put a theoretical framework around spitefulness by defining spite as being a negative weight one has on their indiviudal utility function with respect to anothers income (Levine 1998). Making measuring spite is as simple as looking at the coefficient that one places on the utility they gain from the income of another individual. A spiteful actor will have a negative coefficient. Staying with Levine's theoretical model, spite can also be described as an individual valuing the payoff of another individual negatively. Spitefulness poses a problem to cooperation because cooperation would usually mean increasing the payoff of the other group members at the expense of one's own payoff (Falk, Fehr, and Fischbacher 2005). Spitefulness is surprisingly prevalent in many behavioral economic experiments. In the perspective of the climate and behavior literature, spite is a less common and subtler outcome variable to look at that is surprisingly robust in societal outcomes (Fehr, Hoff, and Kshetramade 2008).

2.4. Mechanisms

There are several mechanisms that have been theorized to be at play when describing the effect of temperature on aggression and, more broadly, the temperature on overall human behavior (Miles-Novelo and Anderson 2019). There is a theory that the mechanism may be physiological and that increase in temperature activates the part of the brain that is responsible for thermoregulation and emotional regulation (Miles-Novelo and Anderson 2019). Another physiological mechanism that could be at play is the additional adrenaline that is produced during heat increase, which may lead to increased aggressive behavior. On the psychological side, there are theories that the stress of the environment influences how we think (Miles-Novelo and Anderson 2019). Research shows that higher temperatures can cause discomfort, which increases irritability and hostility, which are pre-courses to aggression (Anderson 2001). It is likely that both physiological and psychological mechanisms for describing the effect of temperature on human behavior are at play. The mechanism of the direct effect of temperature on human behavior has been difficult to pin down because there are many indirect factors at play when measuring anti-social outcomes that are caused by the climate.

There have been three major theories when describing temperature and human behavior. One early theory is the General Aggression Model or GAM (Bushman and Anderson 2020). The General Aggression Model in the context of heat's impact on behavior, claims the heat itself changes one's propensity for violence. This would be more consistent with a physiological mechanism at play when describing that heat makes one more irritable and hence more likely to be aggressive (Bushman and Anderson 2020). Cohen and Marcus Felson's Routine Activity Theory is more generally used to model the occurrence of crime, which includes many other factors outside of temperature. Routine Activity Theory (RAT) in the context of the temperature and behavior discussion, explains that the presence of aggression and violence is due to the increase in social activity and aggressive opportunities that come with higher temperatures. When temperatures are lower, people have less of an opportunity to go outside and be more social, and thus less aggression is the outcome. The third and most recent theory is the CLASH Theory, standing for climate aggression and self-control in humans (Lange, Rinderu, and Bushman 2017). The CLASH theory describes temperature and behavior at the city level and describes regions of lower average temperatures as having slower life history, more of a focus on the future, and more self-control which is why they exhibit more self-control (Lange, Rinderu, and Bushman 2017). In other words, CLASH predicts that locations with hotter climates have a faster lifestyle, care more about the present day, and have less self-control which leads to the relationship between heat and aggression that has been observed so often in experiments. These are the three leading theories to describe increasing temperature's influence on human behavior.

3. Research Design

3.1. Sample, Timeline, & Sites

The experiment occurred in five sites: Delhi, India; Mexico City, Mexico; Davis, California; Nairobi, Kenya; and Bogota, Columbia. At the time of this paper, Columbia's data still needed to be processed, so the data used in this analysis is from the remaining four locations. The overall timeline for data collection in the field was between June 2022 - March 2023. Each location spent two to three weeks experimenting on a college campus in their respective locations1. Because the experiment was exclusively conducted on college campuses, the data set is predominantly college students, with participants average age being 21 years old. The literature suggests that developing nations with growing populations with limited access to cooling resources and a heavy reliance on agricultural jobs will likely be the most affected by climate change. Thus, it was important for our study to include locations from developing nations. Of the four locations used in this paper, we conducted 105 sessions with an average session size of approximately 11 individuals, giving us a final data set of 1,131 observations.

Each session was randomly assigned treatment ($>$ 30C) or control ($<$ 30C), with treatment and control sessions varying distribution throughout the different times of the day. Other than the varying temperature of the room, we also varied which of the two experimental packets each individual received. The two versions, Version A and Version B, only varied in which order the dictator games were played. Since the dictator games are where we measure the behavioral outcomes of interest, it is essential to understand the order in which they are played. In Version A, the dictator games are played first. In contrast, in

Version B, the dictator games were played second, allowing individuals to win or lose the competition in the previous round. In the final data set, Version A was given out to 51% of the sample, and 49% received Version B. The individuals who played Version B allow us to research whether the provoking event of losing a competition creates a difference in observed treatment effects.

The experiment was randomized on the session level as we could not randomly place the individual in either treatment or not at the location as only one experiment was being run at a time. Because of this, we cluster our errors at the session level to account for any confounding characteristics within sessions. Figure 6.1 shows a balance check between treatment and control, looking at individual-level characteristics.

3.2. Temperature Manipulation

The experiment involved manipulating the temperature in a room on a continuum of varied temperatures. The temperature was measured using digital thermometers placed in the center of the room, and both temperature and humidity were recorded at five-minute intervals. The treatment sessions were assigned to temperatures above 30 Celsius, while the control sessions were set to temperatures below 30 Celsius. The mean temperature for the treatment sessions was 31.79 Celsius, and the mean temperature for the control sessions was 26.54 Celsius. The target temperature for each session varied; the treatment temperatures ranged from 30 Celsius to 33.8 Celsius, while the control temperatures ranged from 19 Celsius to 29.95 Celsius. Each session's mean length was 1 hour and 17 minutes, and each observation's recorded temperature was the mean temperature during the entire session.

Humidity impacted our treatment measure because wet bulb Celsius is the primary treatment variable we use in our specifications which takes into account humidity. Each location had minimal variations in setup and ability to control temperatures. Each location had an air conditioning and heating unit to control room temperatures as best as possible, except for Delhi, which did not have a heating unit. Temperatures above 30 Celsius in Delhi were achieved by closing all windows and heating the room naturally. The experiment in Delhi took place in July, during the summer season, with a median temperature of 31.67 Celsius and a maximum outside temperature exceeding 34 Celsius. The Davis, California location was treated similarly to Delhi, with observations taken during the summer season and a median outside temperature of 31.11 Celsius. Locations like Mexico City, Mexico, and Nairobi, Kenya, had more moderate temperatures during the experimentation period, with median outside temperatures of 20 Celsius and 23.89 Celsius, respectively. These two locations required additional heating units to bring the temperatures up to the required threshold of 30 Celsius for the treatment sessions.

3.3. Measuring Spite Through Dictator Games

Dictator games are frequently used in behavioral economics literature to measure pro-social and anti-social behaviors (Cason and Mui 1998). Our experiment will use dictator games to measure the individuals' social preferences. This paper is concerned with the social preference for spitefulness. Other contributors to the project will research the remaining outcomes and will be presented in their research.

The type of dictator game that our subjects played was a two-person dictator game, where each individual was always in the position of the dictator, and their partner remained anonymous. They were aware that their partner would be undisclosed in the current experiment session. In each of the four rounds, the individual was the position of the dictator, and had the decision-making power. In a single round of the dictator game, an individual would be shown two options, option A and option B. Option A was always the egalitarian option of eight tokens for me, and eight tokens given to the other. Option B would be the option that had variation from each round. For example, option B had eight tokens for me and four for the other in round one of the dictator games. The tokens would have a conversion to the local currency in the upper right corner of each experimental page so that the individual knew the monetary value of their decisions.

We measure spite through the use of our three rounds of dictator games. Dictator games were played in four rounds; however, round 3 did not have a spiteful option, so we do not use it in creating our primary spiteful outcome variable. The primary outcome variable, Strong Spite, will be an indicator variable that takes a value of one if the three dictator games that provide an option to act spitefully are all chosen.

For example, round one presents an opportunity for the individual to choose an egalitarian choice of eight tokens to each themselves and another individual. Alternatively, they can choose the option that gives themselves the eight tokens and the other individual four tokens. Option B is the spiteful choice, as the individual who gave their opponent four tokens instead of eight gains utility from having the other individual receive less than them. Importantly, this individual who chooses the spiteful option in round one can not be confused with being egalitarian as spiteful options in rounds two and three can. Round one is the only round where option B is a purely spiteful choice and can not get confused with other social preferences. For this reason, we use the individuals who answered spitefully on only round one as a secondary outcome variable. These individuals answered spitefully much more in this round than in all three rounds. Out of the sample of 1,131, 24% answered spitefully for round one (Weak Spite), and only 7% answered spitefully for all three rounds that had a spiteful opportunity (Strong Spite).

3.4. Raven Matrices Competition Losers

Raven Matrices have been used frequently in behavioral economics to measure the cognitive ability of individuals (Almås et al. 2019a). The Raven Matrices that individuals had to complete were questions that showed eight independent shapes with the ninth shape missing. The individual would have to recognize the pattern and select the correct one missing out of eight multiple-choice options. A measure of cognitive ability was then created based on the sum of the total raven matrices the individual answered correctly out of the three rounds1. There were three rounds of raven matrices played, with round 2, the tournament round, being the round of interest for this paper. Round 2 of the raven matrices is a tournament game where individuals compete against an undisclosed partner in the room. Each individual has two minutes to answer as many raven matrices correctly as possible. Once the time is complete, the individual's total score was calculated by the total correct answer plus the amount from the role of a six-sided dice. The dice roll adds a bit of "luck" to the individuals' final score, allowing for an individual who answered fewer raven matrices correctly than their partner to have still a chance to win. The outcome of this competition creates one loser and one winner, and losing this competition is how we introduce a provoking event into our experiment. A crucial variable in our analysis will be the individuals who lost the competition. The individuals that qualify for this condition will be by a one in the binary "Loss" variable. This Loss variable interacted with individuals who played version B will show us the individuals who lost the competition before they answered the dictator games to see if this "triggering" event effects their treatment effect.

3.5. Survey Data

The last task individuals completed during the experimental session was an 81 questions survey to gather information about each subject's characteristics such as age, gender, occupation, socioeconomic status, and household information. We also had multiple questions to measure subjective characteristics such as social trust, stress exposure, and life satisfaction. The survey's groupings of questions created an index for three subjective measures of interest, social trust, stress, and life satisfaction. Principal component analysis reduced the groupings of questions to a single index that could be used during estimation. The survey is where we get two variables of baseline characteristics that are part of crucial findings during our heterogeneous treatment effect analysis, gender and income consistency.

4. Estimation & Methods

4.1. Wet Bulb Temperature Measure

Although treatment and control were determined based on the 30 Celsius room temperature threshold, our estimation models use wet bulb temperature as the treatment variable. Wet bulb is defined as the temperature that an air parcel would reach through evaporative cooling once fully saturated (Coffel, Horton, and Sherbinin 2018). Wet Bulb temperature gives a full measure of the amount of heat-induced stress that the climate has on an individual, as it also takes into account the humidity of the climate. wet bulb temperatures are lower than the standard Celsius temperature, which can make it difficult for individuals to comprehend what a specific wet bulb temperature feels like. Although Delhi may have maximum temperatures of over 35 Celsius, wet bulb temperatures of over 35 C seldom occur and would be extremely dangerous heat to be exposed to (Coffel, Horton, and Sherbinin 2018). Recent heat waves have been between 29C and 31C, resulting in tens of thousands of fatalities (Horton et al. 2016). Our wet bulb range spans from 12.702 to 30.47 Celsius with a standard deviation of 3.87 and a mean of 21.81. The primary treatment variable in our specifications uses wet bulb Celsius standardized around the mean to give it a mean zero and a standard deviation of one. Standardizing the continous treatment variable aids in interpretability for models with multiple interactions.

4.2. Treatment Effect Specification

The main specifications, as registered in the pre-analysis plan before the experiment, will test two different treatment variations on the binary outcome variable of spite. The y_i is the spiteful outcome for each individual observation, either 1 or 0, as measured through our Strong Spite and Weak Spite indicators. The primary outcome of interest will be the Strong Spite indicator. The two specified estimations, estimation 1 and estimation 2, differ among the form of treatment effect they are testing. In estimation 1 we check for the treatment effect, τ_1, on the continuous treatment variable of wet bulb Celsius standardized, $WetBulbTemp$, will then be interpreted as the change in the probability that an individual behaves spitefully given a one degree Celsius increase in wet bulb temperature. We use wet bulb as a continuous treatment variable because we were able to have a wide distribution of wet bulb temperatures throughout our experiment. A wet bulb as a dummy variable is used as a robustness check and in estimating heterogeneous treatment effects for the methods that require a binary treatment variable. Due to the benefits of analyzing data from a randomized control experiment, we do not need to worry much about confounding variables in our estimation. We will, however control for country-fixed effects with the term θ_c. This will allow the model to account for the correlations among observations within the same country. The X_i' is a vector of covariates that control for baseline characteristics of the sample. We will most common control for age and gender when running different variations of our specified estimations. Lastly, our errors, ϵ_i, will be clustered by the session level to account for any correlation within observations in the same session.

4.2.0.0.1 Treatment Effect Specification

$$y_i = \alpha + \tau_1 \text{Wet Bulb Temp}_i + \theta_c + X_i'\beta + \epsilon_i$$

The second estimation differs from our first observation by introducing an interaction term with the treatment, to create a new treatment effect τ_2 . The interaction is created by adding in two new terms, $Loss$ and $VersionB$. Both terms are dummy variables, and individuals who both lost the competition and played version B will be capture in the coefficent of this interaction, γ_2. We can then interact this interaction with the treatment variable, $WetBulbTemp$, and see if individuals who lost the competition before answering the dictator games were more effected by hotter temperatures in terms of there likelihood to act spitefully. The τ_2 can then be interpreted as the change in probability that an individual will act spitefully conditional on losing the tournament before playing the dictator games. The estimation will also add $Loss$ and $VersionB$ as individual terms to control for there non-interacted effect as well. This specification allowed us to look at if losing the competition before answering the dictator games made individuals more spiteful as well as if these same individuals had a more spiteful response to heat. $WetBulbTemp$ is the main treatment variable of interest however we will also use a dummy treatment variable of temperatures of 24 Celsius wet bulb as well. Just looking at Figure 6.6 we see that after 24 Celsius wet bulb, the probability of spiteful outcomes begins to be linearly and positively correlated with temperature. For this reason we explore a treatment threshold of 24 Celsius wet bulb.

4.2.0.0.2 Treatment Interaction Specification

$$
\begin{aligned}
y_i = & \alpha + \tau_1 \text{Wet Bulb Temp}_i + \gamma_1 \text{Loss} + \gamma_2 \text{Version B}_i + \gamma_2 \left(\text{Wet Bulb Temp}_i \times \text{Loss}_i\right) + \gamma_3 (\text{Wet Bulb Tem} \\
& \gamma_4 \left(\text{Loss}_i \times \text{Version B}_i\right) + \tau_2 \left(\text{Wet Bulb Temp}_i \times \text{Loss}_i \times \text{Version B}_i\right) + \theta_c + X_i' \beta + \epsilon_i
\end{aligned}
$$

4.3. Machine Learning Methods for Heterogeneity

A central purpose of this paper is to check if there is heterogeneity in our treatment of wet bulb temperature on spiteful outcomes. We will initially look at heterogeneous effects using classical OLS and interaction terms. The covariates of interest were already specified in our pre-analysis plan in order to do our best to avoid finding false positives in our analysis. The covariates of interest that I will be looking in our classical OLS interactions are; gender, age, cognitive ability, social trust, acquaintances, income consistency, and Socioeconomic status. In section 4.2 I explain how each of these covariates are measured in our data set. In this paper I focus on the two covariates that showed signgicance, gender and income consistency. Traditional economics has used interaction terms within OLS models to look at conditional treatment effects on different covariates, however this method runs into many limitations, in particular, its lack of interpretability with a large number of covariates.

Estimating heterogeneous treatment effects is a question that is a challenging and complex coefficient to estimate but one that can provide meaningful insight into experimental results and external validity. For this reason, statistical research on the topic of heterogeneous treatment effects has exploded in recent years with the advent of a new tool that economists are quickly finding ways to take advantage of, machine learning. Machine learning provides superior predictive power when compared to classical econometric methods such as OLS but it has always lacked interpretability, possing a significant problem for causal inference. However, in recent years there have been much research and several novel methods that attempt to solve the difficulty of estimating statistically valid heterogenous treatment effects for many covariates. Two of these methods, which I will be implementing in my analysis, are a Causal Forest (Athey, Imbens, and Wager 2018) and Generic Machine Learning (Chernozhukov et al. 2018). Both methods combine the benefits of machine learning's ability to handle data in high dimensional space while maintaining the ability to calculate standard errors for statistical inference. Our analysis explores these novel methods and discuss their results on our data set, benefits, shortcomings, and comparison to other methods.

4.3.1. Causal Forest

Causal Forests are a machine learning algorithm that estimates treatment effects conditional on covariates at the individual level. This method seeks to estimate heterogeneous treatment effects by differentiating observations by their covariates that show the largest treatment effect. Causal forests work by splitting the data into a training and testing subset in order to avoid overfitting. The final output from a causal forest is a decision tree with estimations of a treatment effect for each subgroup. They sometimes refer to these as the leaves of the tree.

This approach allows for a better look at sub-populations' relationship between treatment and outcome than traditional methods that estimate average treatment effects. Causal forests have several advantages over traditional linear models for estimating treatment effects. They are more flexible and can capture nonlinear relationships between covariates and treatment effects. They are less susceptible to biases caused by confounding variables since the method accounts for interactions between covariates and treatment. Additionally, causal forests can handle high-dimensional data, which is a crucial advantage of the method when compared to classical heterogeneous treatment effect methods. Despite causal forests being a relatively novel method, they have already been used in many research papers.

4.3.2. Sorted Average Treatment Effect & Classification Analysis

Inspired by the recent emergence of generic Machine Learning by (Chernozhukov et al. 2018), we will look at the sorted group average treatment effects (GATES) and classification analysis (CLAN) to see if there is evidence that heterogeneity exists. Sorted average treatment effect is the concept of using a machine learning predictor to predict treatment effects for each individual observation, also know as conditional average treatment effects. These linear predictor makes the prediction based on all the covariates to give each indiviudal a unique treatment effect. Once you have obtained the treatment effect predictions for each observation, you can sort them in ascending order. This order of treatment effects allows one to look at if there is a difference between the individuals that have the highest predicted treatment effect and the lowest predicted treatment effect. GATES analysis is the comparing the lowest 20% quantile verse the highest 20% quantile in terms of predicted treatment effect.

After calculating our sorted average treatment effects (GATES) from our two machine learning models, we preform a classification analysis (CLAN) on the specific characteristics that these groups of treatment effects are made of. We will do this by looking at the average value of a covariate in both the lowest (G1) and highest (G5) quantile. We then run a t-test between the two values to see if they are significantly different. By doing classification analysis, we can look at more comparatives than traditional OLS interactions allow us to do. We are also able to utilize different models, such as a causal forest, that perform better than traditional OLS in higher dimensions. The results of our classification analysis are shown in Figure 6.16. These models were run on the strong spite outcome and the binary treatment of Wet Bulb 24 Celsius. The "Diff" column are not coefficients, but they are the difference between the averages of the covariate of interest in each quantile. The values in difference correspond to the unit that the variable is measured at.

5. Results

Our results show the treatment effects of wet bulb temperature on the primary outcome, Strong Spite, and the secondary outcome, Weak Spite. Primarily we use wet bulb Celsius as a continuous treatment variable and standardize it to help with interpretability. We also use a binary treatment variable where treatment is temperatures of anything over 24 degrees wet bulb Celsius. A binary treatment variable is necessary for our machine learning methods to analyze treatment heterogeneity in described in Section 4.3. Twenty-four degrees wet bulb is used as the cutoff for treatment because it was the cutoff that maximized the coefficient on the interaction between treatment and loss while minimizing the statistical significance compared to the other cutoff options. Also when graphing non-parametric graphs of wet bulb temperature and spiteful outcomes, temperatures above 24 Celsius wet bulb have a linear and postive correlation with spiteful outcomes (See Figure 6.6).

Our results show a positive and significant effect between the interaction between our continuous treatment variable and those individuals that answered version B. However we find no significant effect on our τ_2 , which is the individuals that lost the competition before answering the dictator games and were exposed to hot temperatures. This finding contrasts our original hypothesis we had when creating the research design. It seems that individuals playing version B are having a more significant treatment effect, however the outcome of the competition is not the driving force behind this difference. One theory could be that individuals playing version B are having a more significant treatment effect than those playing version A may be that the individuals playing version B are being exposed to the hot environment for more than three times the amount of time when compared to version A. This increased amount of time exposed to increase temperatures could be what is driving the significance that we see in our models, however our results here can not for certain prove that theory correct. Looking at heterogeneity in this treatment effect for individuals who played version B, we see significant differences in individual characteristic across gender and income inconsistency. Unfortunately the novel machine learning methods show inconsistent results when compared to the heterogeneity found through traditional OLS. The data and treatment variable may be to blame for some of the shortcomings of our machine learning methods, however they do provide insight and hopefully knowledge for future researches applications.

5.1. The Effect of Temperature

We start our analysis by running the treatment estimation one on the entire data set (n = 1,131). We run the treatment effect estimation one specified in Section 4.2 with the continuous treatment variable of wet bulb Celsius standardized to have a mean zero and standard deviation of one. The range of wet bulb temperatures spans from a minimum of 12.70 wet bulb Celsius to a maximum of 30.47 wet bulb Celsius. We run the model on both Strong Spite and Weak Spite outcomes, including covariates for age and gender[1]. Our coefficient on Wet Bulb Temp, τ_1, for model one with no covariates shows a value of 0.004 with a standard error of 0.014. This insignificant and small magnitude coefficient holds among all four models ran in Figure 6.3. Based on these results, we can not reject the null that temperature has no treatment effect on spiteful behavior. The null results held when we ran the model with a binary treatment variable indicating treatment as anything over Wet Bulb 24. The coefficients on Age and Male are positive, suggesting a positive relationship between increasing age or being male and the likelihood of acting spitefully. However, the coefficients are also not significant at any level, making the estimation's results inclusive on all levels. This estimation does not show any treatment effect on spiteful outcomes, so the following section looks at a variation of the treatment effect to see if it can explain the subset of the sample that is acting spitefully.

5.2. Main Results

The main results table, Figure 6.4, includes the three term interaction with the treatment variable, $WetBulbTemp$, the individuals that lost the competition, $Loss$, and individuals

[1]Footnote: All models are run with country-fixed effects and standard errors clustered at the session level

who answered the dictator games last in version B, $VersionB$. You can think of this interaction as a form of heterogeneity where as we are now looking at the effect of temperature conditional on an individual losing the competition before they answered the dictator games. The main results table, Figure 6.4, builds our OLS model up from left to right introducing the interactions one by one to see how they effect the coefficients. The fifth column of the table shows the full specification as described in section 4.2. The results show null effects in the treatment effect as well as in the treatment effect with the three way interaction. Both of these effects were hypothesized to be positive and significant. However not hypothesized in our research design was the significance that the model finds in those individuals who played version B and were exposed to hotter temperatures. When the interaction between version B and the treatment, Wet Bulb Temp, is introduced to the model on its own it shows a coefficient of 0.040 with a significance at the 5% level. This significance is interpreted as for the individuals that played version B, when the temperature of the room increases one standard deviation, there likelihood of answering spitefully increases by 4%. This is a substantial amount when we compare it to the original amount of Strong Spiteful outcomes in the sample of 7%. This coefficient maintains and even increases its significance and magnitude as we introduce the other interaction terms that make up our main specification. In column five, the main specification, we see that the coefficient increased to a 0.058 and is significant past the 1% level (t-stat = 2.9). Although there is no significance on the individuals who lost the competition and played version B, the direction of there coefficients are negative, opposite of what we hypothesized. In the main specification, column five, the coefficient for the interaction of loss and version B is a -0.020 and when this interaction is then interacted with treatment in the three way interaction, it has a value of -0.049. Again although these coefficients are not significant, the direction of these estimates are suggesting that when individuals loss the competition, they are acting less spitefully. In other words, individuals are acting more spitefully after they have won the competition.

The same main estimation with the outcome of weak spite instead of our primary outcome of strong spite produces consistent results with our primary outcome, strengthening our the validation in our findings. The coefficient for the interaction of $WetBulbTemp$ and $VersionB$ is again positive, however the significance and magnitude is less. This is expected as individuals who are weak spiteful are displaying inconsistent preferences of acting out spitefully and is not the best measure of an individuals spiteful intentions. The coefficients on the interaction of the main model is 0.047 and only significant at the 5% level this is a decline of magnitude from strong spite of 0.011 and a decline in significance from 1% to 5% level. There is however the Loss coefficient in the weak spite outcome model that comes up significant that previously in the strong spite model did not. The estimation is consistently positive and significant at the 5% level with a main specification value of 0.069. Unfortunately this estimation does not tell us much about the losers of the competition because half of the observations who are included in this dummy variable, $Loss$, played version A which means they lost the competition after they revealed there spiteful preferences in the dictator game. In other words it is a noisy estimate and the proper estimation to look at is the interaction between $Loss$ and $VersionB$ which in this model is has a small in magnitude but positive coefficient and is by very insignificant.

The main specification used wet bulb Celsius as a continuous standardized variable. This means that the treatment coefficient's magnitude capture the change of a single standard deviation change from the mean has on spiteful probability. The mean wet bulb temperature of our sample is 21.81 with a standard deviation of 3.87. For this reason we also look at the base specification with a dummy treatment variable where the cutoff is 24 wet bulb Celsius temperature. By looking at Figure 6.6, we can see that just by looking at the unconditional relationship between wet bulb temperature and strong spiteful outcomes, wet bulb temperatures past wet bulb 24 Celsius appear to have a linear and positive relationship with strong spiteful outcomes. In our pre-analysis plan, we specified running secondary models with a treatment dummy variable indicating any temperatures over 25 wet bulb Celsius, however our in our sample, only India obtained temperatures over 25 Celsius wet bulb. When we bring the dummy threshold to 24 Celsius wet bulb, we are able to include observations from both India and Mexico. Unfortunately one of the limitations of our data set at the time of this paper is the concentration of hotter temperatures being in India and not even distributed across other countries.

Our previous findings are confirmed when we run the main specification with 24 wet bulb Celsius dummy. Figure 6.7 shows how the same significance holds true as from the continuous treatment model. We again see significance on interaction between 24 wet bulb Celsius and version B at the 5% level for the simpler models and at the 1% level for the main specification model in column five. The magnitude this coefficient when the interaction is first introduced in column two is 0.090. To interpret this coefficient, for individuals who played version B in a room that was hotter than 24 wet bulb Celsius, they are 9% more likely to act spitefully than compared to individuals who played version B in a room under 24 wet bulb Celsius. This coefficient is over two times the magnitude that we saw in the continuous treatment model, where the coefficient on the interaction term was 0.040. This is consistent with what we see on the non parametric graph in Figure 6.6, that after 24 wet bulb Celsius strong spiteful outcomes is increasing, especially for individuals playing version B.

Our main results suggest that there is a treatment effect of heat on spiteful outcomes, however this effect is only seen in individuals who were exposed to these temperatures for over 15 minutes before showing there anti-social prefrence. Individuals in version A were exposed to heat for approximately 5 minutes before giving there answers to social preferences while individuals in version B were exposed for approximately 15 minutes. Version B also had individuals play a competition before giving answers of there social preferences, however due to the null significance of all coefficients with the exception of the treatment effect on version B it is likely that the excess time exposed to heat is driving this effect. Our findings do not show evidence that previous findings from (Larrick et al. 2011a), (Craig et al. 2016), and (Almås et al. 2019b) that a provoking event is necessary for heat to have a significant treatment effect on anti-social outcomes. In contrary the individuals who lost the competition, which was are purposely designed "provoking event", actually ended up answering dictator games less spitefully than those that won the competition in our sample. However in our models these effects were not significant so there are no substantial conclusions that we can draw from the treatment effect between individuals who won and lost the competition at the time of this paper.

5.3. Heterogeneous Treatment Effects

In this Section, we explore heterogeneity in treatment effects and test two separate forms of treatment[2]. We use the treatment dummy variable indicating temperatures greater than 24

[2] All treatment values are binary in the heterogeneous treatment effects because causal forests provide the best results with a binary treatment

wet bulb Celsius, as used in the OLS models previously. We use this treatment variable to predict individual treatment effects for each observation using linear regression and causal forest separately. For more information on the methods used here refer to Section 4.5.

Predicting individual treatment effect estimations allowed us to look at both, linear regression and causal forest, models' sorted average treatment effects (GATES). See sections 4.4 and 4.5 for more information on GATES method. The Figure 6.14 shows each model's predicted treatment effect for each observation in ascending order of predicted treatment effect. Both linear regression and Causal Forest show differences in predictions for individuals with the lowest treatment effect (G1) and individuals with the highest treatment effect (G5). Linear regression shows a more extreme difference in predicted treatment effect most likely due to over fitting. The linear regression model was trained on the same data that it was tested on while the causal forest takes advantage of sample splitting to ovoid over fitting. The Figure 6.14 shows this visually as the linear regression prediction line has a greater slope than the causal forest prediction lines. When running a t-test between the differences in means of the lowest quantile (G1) and highest quantile (G5) the values are statistically significant at past the 0.1% level, meaning that there is heterogeneity in the conditional predicted treatment effects. GATES analysis also allows for classification analysis (CLAN), as described in Section 4.6. Through CLAN analysis, we find conflicting results between linear regression and causal forest predictions when looking at treatment effects for the covariates;$VersionB$, $VersionB$ interacted with $Loss$, $Male$, and $LowIncomeConsistency$.

Our CLAN analysis found conflicting results between the linear regression predictor and the casual forest predictor. The linear regression predictor was most consistent with the heterogeneity that we found with our traditional OLS interaction terms. For example, the linear predictor showed the most heterogeneity in treatment effects within observations that took version B compared to version A. The difference in means between the lowest and highest treatment effect quantiles (G5 - G1) was 0.875. In other words, there were 87% more individuals who played version B in the highest predicted treatment effect group from linear regression. This is a large difference and is consistent with our more traditional OLS coefficients findings. The casual forest predictor however disagreed with the findings from the linear regression. The causal forest found 7.7% less individuals that played version B in the highest treatment effect group. When preforming a t-test on this prediction, it does not come up significantly different from zero and therefore we can not reject the null that there is not heterogeneity within the subcategory of individuals who played version B. The rest of the covariates of interest, as shown in Figure 6.15, follow the same pattern with linear regression and causal forest disagreeing on the direction of the differences between high and low treatment quantiles. Some reasons for the differences may be due to the differences in how both models are trained, with the casual forest taking advantage of sample splitting while linear regression does not. When applied to our sample, linear regression seems to be over fitting which leads to upward bias, however the sign of the results still give us important insight into the heterogeneity. The causal forest on the other uses sample splitting, but with only 1,131 observations, the causal forest was unable to have the power necessary to find statistically significant heterogeneity.

5.3.1. Gender

Our main results show heterogeneity within gender, with females being the largest drives of the treatment effect that our findings shows within individuals who played version B. The non-parametric graphs, Figure 6.9a and Figure 6.9b, show the unconditional differences of the two genders differences in spiteful responses in comparison with wet bulb temperature. Figure 6.9b shows females having a large treatment effect when temperature get to the high end of the scale but this effect is only apparent in version B. The regression Figure 6.12, confirms this effect by splitting the sample by gender and running a model with the interaction between treatment and version B. These results show that the significance and positive magnitude of the coefficient is largely driven by the females. In the strong spite column for females, we find a 0.067 coefficient that is significant at the 5% level. This is with a continuous treatment variable of wet bulb Celsius and just like in the main results when we run the regression with the dummy treatment variable, the coefficient increase in magnitude. The machine learning methods conflict on this effect, with linear regression finding a greater treatment effect in males and a casual forest finding a greater treatment effect in females. Based on how the methods were implemented, more weight should be placed in the casual forest findings, as this method creates unbiased predictions while the linear regression had an upward bias on all of its predictions. Our results suggest that there is heterogeneity within gender interacted with those playing version B. Again version B had an extra 15 minutes of heat exposure which may be telling us that genders are reacting differently when exposed to longer periods of heat in relation to there anti-social behavior.

5.3.2. Income Consistency

Income consistency was measured through our end-of-the-experiment survey. The question asked to rank how consistently the received income from any source on a scale from one to four. Four meant that the individual received no income in the last month, while one meant the individual received income weekly. Our OLS results show a positive and significant effect for the treatment effect of individuals who have low income consistency and played version B. As seen in Figure 6.11, the effect on both strong and weak spite outcomes on the interaction term is significant at the 5% level. This model with the continuous treatment variable shows a coefficient for the strong spite outcome of 0.054 while the coefficient for the same model but for high income consistent individuals finds a coefficient of -0.013. These results suggest that low income consistent individuals are having a more spiteful response when temperatures are rising during the longer heat exposure of version B. These findings are confirmed when using the machine learning predictor of linear regression however are conflicted with the casual forest prediction method. The linear regression finds a higher concentration of low income consistent individuals in the highest treatment group while the causal forest finds a lower concentration of low income individuals. It is important to note however that for the causal forest this difference is not different from zero and so the model may just not have enough statistical power to find the appropriate direction of the heterogeneity. Our results suggest that the consistency at which one receives income is creating differences in individuals treatment effect of heat and their spiteful outcomes. One limitation of this income consistency is the fact that our sample was predominantly college students and so we are unable to look at characteristics like annual income as most of the individuals are students.

Although we are limited by the distribution of age by our sample, the income consistency still gives insight into the behavioral of individual who have more verse less income.

6. Conclusion

Our findings provide insight into a previously unexplored hypothesis of our research design, that increased exposure to high temperatures may be an significant factor in climates relationship to anti-social behaviors. The interaction between high temperatures and individuals who were exposed to temperatures for three times longer than version A, in version B, is where we find the strongest treatment effect of our results. We recognize that individuals who played version B also were effected by the competition round played directly before they revealed there social preferences but suspect that the treatment effect is not being driven by this compeition and instead by the prolonged heat exposrue. We also find heterogeneous treatment effects in females and individuals with low income consistency. Futures work should explore closer the sub populations that are most effected by increased temperatures as our results show evidence of substantial heterogeneity in those effected. Climate change is set to increase temperatures and those individuals who are in this heat for excessive amounts of time may be at the highest risk of experiencing behavioral changes.

References

Almås, Ingvild, Maximilian Auffhammer, Tessa Bold, Ian Bolliger, Aluma Dembo, Solomon Hsiang, Shuhei Kitamura, Edward Miguel, and Robert Pickmans. 2019b. "Destructive Behavior, Judgment, and Economic Decision-Making Under Thermal Stress." w25785. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w25785.

———. 2019a. "Destructive Behavior, Judgment, and Economic Decision-Making Under Thermal Stress." Cambridge, MA. https://doi.org/10.3386/w25785.

Anderson, Craig A. 2001. "Human Aggression." *HUMAN AGGRESSION*.

Arnell, N. W., J. A. Lowe, A. J. Challinor, and T. J. Osborn. 2019. "Global and Regional Impacts of Climate Change at Different Levels of Global Temperature Increase." *Climatic Change* 155 (3): 377–91. https://doi.org/10.1007/s10584-019-02464-z.

Athey, Susan, Guido W. Imbens, and Stefan Wager. 2018. "Approximate Residual Balancing: Debiased Inference of Average Treatment Effects in High Dimensions." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 80 (4): 597–623. https://doi.org/10.1111/rssb.12268.

Baron, Robert A, and Paul A Bell. n.d. "Aggression and Heat: The Influence of Ambient Temperature, Negative Affect, and a Cooling Drink on Physical Aggression."

Bathiany, Sebastian, Vasilis Dakos, Marten Scheffer, and Timothy M. Lenton. 2018. "Climate Models Predict Increasing Temperature Variability in Poor Countries." *Science Advances* 4 (5): eaar5809. https://doi.org/10.1126/sciadv.aar5809.

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. 2015b. "Climate and Conflict." *Annual Review of Economics* 7 (1): 577–617. https://doi.org/10.1146/annurev-economics-080614-115430.

———. 2015a. "Climate and Conflict." *Annual Review of Economics* 7 (1): 577–617. https://doi.org/10.1146/annurev-economics-080614-115430.

Bushman, Brad J., and Craig A. Anderson. 2020. "General Aggression Model." In, edited by Jan Bulck, 1st ed., 1–9. Wiley. https://doi.org/10.1002/9781119011071.iemp0154.

Bushman, Brad J., Morgan C. Wang, and Craig A. Anderson. 2005. "Is the Curve Relating Temperature to Aggression Linear or Curvilinear? Assaults and Temperature in Minneapolis Reexamined." *Journal of Personality and Social Psychology* 89: 62–66. https://doi.org/10.1037/0022-3514.89.1.62.

Cason, Timothy N., and Vai-Lam Mui. 1998. "Social Influence in the Sequential Dictator Game." *Journal of Mathematical Psychology* 42 (2-3): 248–65. https://doi.org/10.1006/jmps.1998.1213.

Chernozhukov, Victor, Mert Demirer, Esther Duflo, and Iván Fernández-Val. 2018. "Generic Machine Learning Inference on Heterogeneous Treatment Effects in Randomized Experiments, with an Application to Immunization in India." Cambridge, MA. https://doi.org/10.3386/w24678.

Coffel, Ethan D, Radley M Horton, and Alex de Sherbinin. 2018. "Temperature and Humidity Based Projections of a Rapid Rise in Global Heat Stress Exposure During the 21st Century." *Environmental Research Letters* 13 (1): 014001. https://doi.org/10.1088/1748-9326/aaa00e.

Craig, Curtis, Randy W. Overbeek, Miles V. Condon, and Shannon B. Rinaldo. 2016. "A Relationship Between Temperature and Aggression in NFL Football Penalties." *Journal of Sport and Health Science* 5 (2): 205–10. https://doi.org/10.1016/j.jshs.2015.01.001.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3): 740–98. https://doi.org/10.1257/jel.52.3.740.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde. 2018. "Global Evidence on Economic Preferences*." *The Quarterly Journal of*

Economics 133 (4): 1645–92. https://doi.org/10.1093/qje/qjy013.

Falk, Armin, Ernst Fehr, and Urs Fischbacher. 2005. "Driving Forces Behind Informal Sanctions." *Econometrica* 73 (6): 2017–30. https://doi.org/10.1111/j.1468-0262.2005.00644.x.

Fehr, Ernst, Daniela Glätzle-Rützler, and Matthias Sutter. 2013. "The Development of Egalitarianism, Altruism, Spite and Parochialism in Childhood and Adolescence." *European Economic Review* 64 (November): 369–83. https://doi.org/10.1016/j.euroecorev.2013.09.006.

Fehr, Ernst, Karla Hoff, and Mayuresh Kshetramade. 2008. "Spite and Development." *American Economic Review* 98 (2): 494–99. https://doi.org/10.1257/aer.98.2.494.

Horton, Radley M., Justin S. Mankin, Corey Lesk, Ethan Coffel, and Colin Raymond. 2016. "A Review of Recent Advances in Research on Extreme Heat Events." *Current Climate Change Reports* 2 (4): 242–59. https://doi.org/10.1007/s40641-016-0042-x.

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. 2013b. "Quantifying the Influence of Climate on Human Conflict." *Science* 341 (6151): 1235367. https://doi.org/10.1126/science.1235367.

———. 2013a. "Quantifying the Influence of Climate on Human Conflict." *Science* 341 (6151): 1235367. https://doi.org/10.1126/science.1235367.

Lange, Paul A. M. Van, Maria I. Rinderu, and Brad J. Bushman. 2017. "Aggression and Violence Around the World: A Model of CLimate, Aggression, and Self-Control in Humans (CLASH)." *Behavioral and Brain Sciences* 40: e75. https://doi.org/10.1017/S0140525X16000406.

Larrick, Richard P., Thomas A. Timmerman, Andrew M. Carton, and Jason Abrevaya.

2011b. “Temper, Temperature, and Temptation: Heat-Related Retaliation in Baseball.” *Psychological Science* 22 (4): 423–28. `https://doi.org/10.1177/0956797611399292`.

———. 2011a. “Temper, Temperature, and Temptation: Heat-Related Retaliation in Baseball.” *Psychological Science* 22 (4): 423–28. `https://doi.org/10.1177/0956797611399292`.

Levine, David K. 1998. “Modeling Altruism and Spitefulness in Experiments.” *Review of Economic Dynamics* 1 (3): 593–622. `https://doi.org/10.1006/redy.1998.0023`.

Mares, Dennis. 2013. “Climate Change and Levels of Violence in Socially Disadvantaged Neighborhood Groups.” *Journal of Urban Health* 90 (4): 768–83. `https://doi.org/10.1007/s11524-013-9791-1`.

Miles-Novelo, Andreas, and Craig A. Anderson. 2019. “Climate Change and Psychology: Effects of Rapid Global Warming on Violence and Aggression.” *Current Climate Change Reports* 5 (1): 36–46. `https://doi.org/10.1007/s40641-019-00121-2`.

Stott, Peter A., D. A. Stone, and M. R. Allen. 2004. “Human Contribution to the European Heatwave of 2003.” *Nature* 432 (7017): 610–14. `https://doi.org/10.1038/nature03089`.

Wager, Stefan, and Susan Athey. 2018. “Estimation and Inference of Heterogeneous Treatment Effects Using Random Forests.” *Journal of the American Statistical Association* 113 (523): 1228–42. `https://doi.org/10.1080/01621459.2017.1319839`.

Appendix

Summary Stats (5.17.2023) Figure 6.1

Characteristic	Mean	Std. Dev	Min	Max
Age	20.84	2.21	16	35
Male	54%			
Income Inconsistency	2.9	1.1	1	4
Country				
Mexico	23%			
India	34%			
Kenya	25%			
USA	19%			

Session Information	Mean	Std. Dev	Min	Max
Session Size	10.8	3.4	4	17
Temperature				
Wet Bulb Celsius	21.82	3.88	12.70	30.48
Standard Celsius	29.09	3.25	19.30	33.90
Standard Fahrenheit	84.36	5.85	66.74	93.02

Figure 6.1: Summary-Stats

Wet Bulb 24 Dummy Variable Indicator Summary Statistics Figure 6.2

	Wet Bulb 24 Indicator	
	Control	Treatment
Observations	851	280
Mean Age	21.01	20.3
Males	54%	51%

	Version A	Version B
Observations	579	552
Mean Age	20.7	20.9
Males	51%	56%

Figure 6.2: wb24-summary-stats

Treatment Effect Results - (5.17.2023) Figure 6.3

Main Results

	Strong Spite		Weak Spite	
	(1)	(2)	(3)	(4)
Wet Bulb Temp[1]	0.004	-0.001	-0.006	-0.009
	(0.014)	(0.013)	(0.018)	(0.019)
Age		0.005		0.007
		(0.004)		(0.005)
Male		0.026		0.021
		(0.018)		(0.026)
Num.Obs.	1131	1125	1131	1125
R2	0.024	0.028	0.061	0.062
Std.Errors	by: Session	by: Session	by: Session	by: Session
FE: country	X	X	X	X

Conrtol for Outside Wet Bulb Temperature Scaled

[1] Wet Bulb Temp is a continuous variable of wet bulb celsius standardized

* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.3: treatment-effect

Main Results - Strong Spite (5.17.2023) Figure 6.4

Main Results

	Strong Spite				
	(1)	(2)	(3)	(4)	(5)
Wet Bulb Temp[1]	0.004	-0.017	-0.009	-0.019	-0.019
	(0.014)	(0.020)	(0.019)	(0.017)	(0.017)
Version B	0.007	0.007	0.011	0.014	0.020
	(0.016)	(0.015)	(0.015)	(0.018)	(0.019)
Loss	0.019		0.020	0.021	0.025
	(0.015)		(0.015)	(0.020)	(0.019)
Wet Bulb Temp x Version B		0.040**	0.037*	0.061***	0.058***
		(0.019)	(0.019)	(0.019)	(0.020)
Wet Bulb Temp x Version B x Loss				-0.050	-0.049
				(0.035)	(0.035)
Version B x Loss				-0.015	-0.020
				(0.030)	(0.030)
Wet Bulb Temp x Loss			-0.021	0.003	0.002
			(0.018)	(0.023)	(0.023)
Male			0.025		0.024
			(0.018)		(0.017)
Age			0.006		0.006
			(0.004)		(0.004)
Num.Obs.	1131	1131	1125	1131	1125

Controls: Outside Wet Bulb Temperature

Fixed Effects: Country

Std. Errors Clustered: Session

[1] Wet Bulb Temp is a continuous variable of wet bulb celsius standardized

* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.4: main-results-strong

Main Results - Weak Spite (5.17.2023) Figure 6.5

Main Results

	Weak Spite				
	(1)	(2)	(3)	(4)	(5)
Wet Bulb Temp[1]	-0.010	-0.027	-0.009	-0.023	-0.026
	(0.019)	(0.028)	(0.019)	(0.023)	(0.024)
Wet Bulb Temp x Version B		0.031		0.050**	0.047**
		(0.029)		(0.022)	(0.023)
Wet Bulb Temp x Loss				-0.002	-0.003
				(0.043)	(0.043)
Wet Bulb Temp x Version B x Loss				-0.040	-0.040
				(0.059)	(0.059)
Version B x Loss			-0.043	-0.052	-0.052
			(0.044)	(0.046)	(0.045)
Version B	0.002	0.003	0.020	0.025	0.026
	(0.023)	(0.023)	(0.024)	(0.023)	(0.024)
Loss	0.044**		0.065**	0.065**	0.069**
	(0.022)		(0.031)	(0.033)	(0.032)
Male		0.019			0.019
		(0.027)			(0.026)
Age		0.007			0.007
		(0.005)			(0.005)
Num.Obs.	1131	1125	1131	1131	1125

Controls: Outside Wet Bulb Temperature

Fixed Effects: Country

Std. Errors Clustered: Session

[1] Wet Bulb Temp is a continuous variable of wet bulb celsius standardized

* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.5: main-results-weak

Main Non-Parametric Graph By Version(5.17.23) Figure 6.6

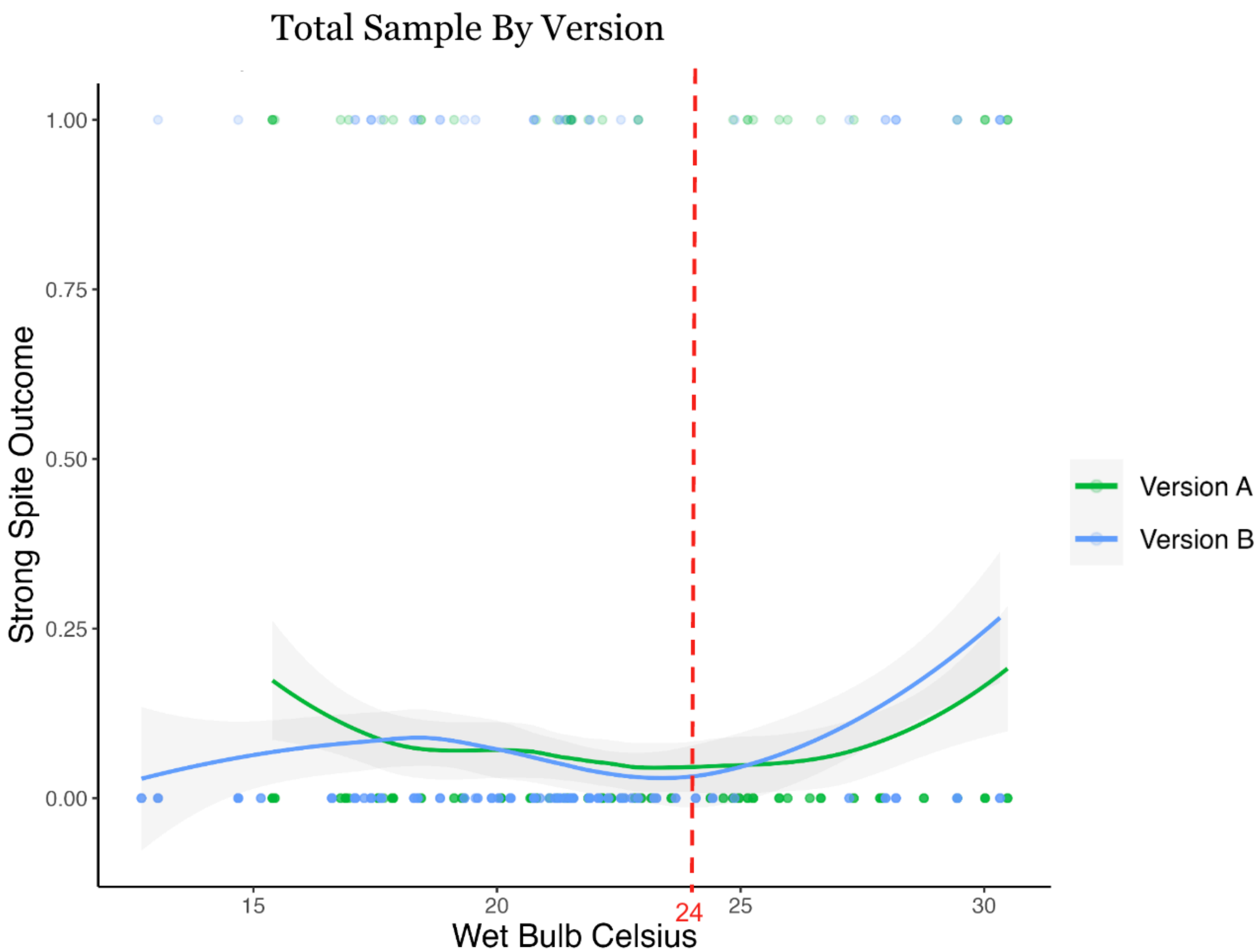


Figure 6.6: Non-Parametric

Strong Spite - Dummy 24 Celsius Wet Bulb Treatment (5.17.2023) Figure 6.7

Main Results

	Strong Spite				
	(1)	(2)	(3)	(4)	(5)
Wet Bulb 24 C	0.004	-0.029	-0.011	-0.036	-0.031
	(0.029)	(0.036)	(0.038)	(0.036)	(0.036)
Version B	0.007	-0.014	-0.008	-0.022	-0.014
	(0.016)	(0.018)	(0.019)	(0.020)	(0.021)
Loss	0.019		0.029*	0.016	0.023
	(0.015)		(0.016)	(0.023)	(0.023)
Wet Bulb 24 C x Version B		0.090**	0.080**	0.149***	0.138***
		(0.038)	(0.039)	(0.050)	(0.052)
Wet Bulb 24 C x Version B x Loss				-0.132	-0.129
				(0.084)	(0.084)
Version B x Loss				0.019	0.012
				(0.033)	(0.032)
Wet Bulb 24 C x Loss			-0.036	0.018	0.011
			(0.038)	(0.042)	(0.041)
Male			0.024		0.024
			(0.018)		(0.018)
Age			0.006		0.006
			(0.004)		(0.004)
Num.Obs.	1131	1131	1125	1131	1125

Controls: Outside Wet Bulb Temperature
Fixed Effects: Country
Std. Errors Clustered: Session
* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.7: main-results-wb24-strong

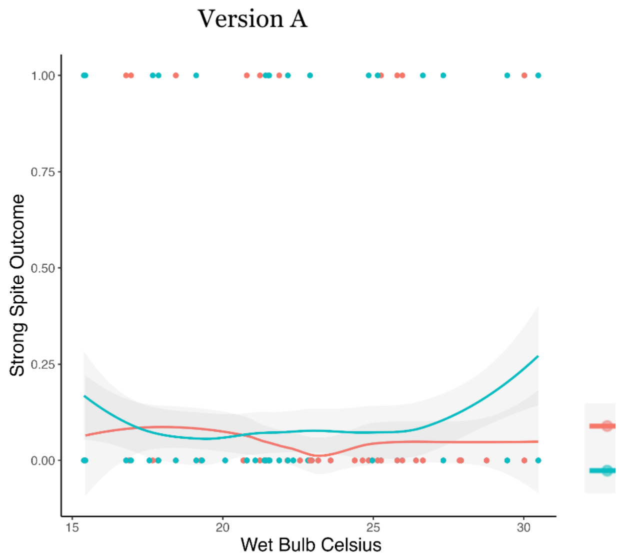
Weak Spite - Dummy 24 Celsius Wet Bulb Treatment (5.17.2023) Figure 6.8

Main Results

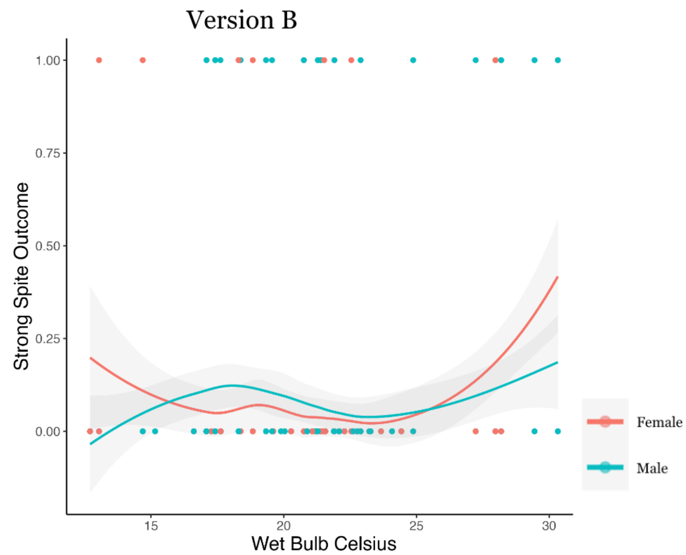
	Weak Spite				
	(1)	(2)	(3)	(4)	(5)
Wet Bulb 24 C	-0.027	-0.064	-0.049	-0.050	-0.047
	(0.035)	(0.048)	(0.049)	(0.047)	(0.047)
Version B	0.001	-0.023	-0.019	-0.002	0.001
	(0.023)	(0.025)	(0.026)	(0.026)	(0.027)
Loss	0.044**		0.055**	0.075**	0.080**
	(0.022)		(0.023)	(0.036)	(0.035)
Wet Bulb 24 C x Version B		0.101*	0.093*	0.106*	0.101*
		(0.055)	(0.056)	(0.054)	(0.055)
Wet Bulb 24 C x Version B x Loss				-0.013	-0.016
				(0.125)	(0.125)
Version B x Loss				-0.047	-0.047
				(0.047)	(0.046)
Wet Bulb 24 C x Loss			-0.032	-0.030	-0.035
			(0.058)	(0.071)	(0.070)
Male			0.018		0.018
			(0.026)		(0.026)
Age			0.007		0.007
			(0.005)		(0.005)
Num.Obs.	1131	1131	1125	1131	1125

Controls: Outside Wet Bulb Temperature
Fixed Effects: Country
Std. Errors Clustered: Session
* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.8: main-results-wb24-weak

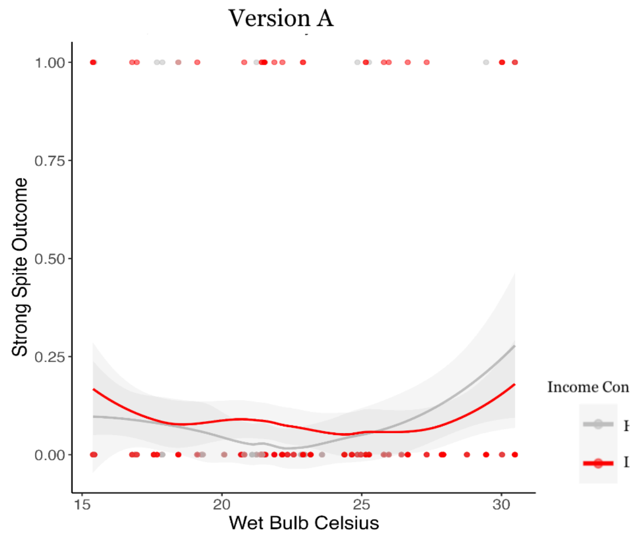


(a) non-parametric-gender-vA

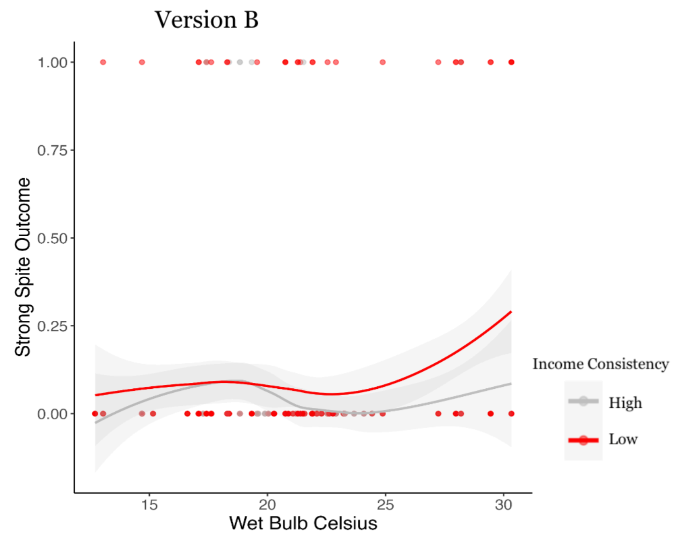


(b) non-parametric-gender-vB

Figure 6.9: Non-Parametric Graphs By Gender



(a) non-parametric-income-vA



(b) non-parametric-income-vB

Figure 6.10: Non-Parametric Graphs By Income Consistency

Income Consistency Heterogeneity Figure 6.11

	High Income Consistency		**Low Income Consistency**	
	Strong Spite	Weak Spite	Strong Spite	Weak Spite
Wet Bulb Temp[1]	0.018	0.060	-0.028	-0.056
	(0.026)	(0.053)	(0.026)	(0.034)
Version B	-0.022	-0.049	0.023	0.019
	(0.020)	(0.038)	(0.019)	(0.028)
Wet Bulb Temp x Version B	-0.013	-0.057	0.054**	0.064**
	(0.031)	(0.063)	(0.023)	(0.031)
Num.Obs.	377	377	721	721

Controls: Outside Wet Bulb Temperature
Fixed Effects: Country
Std. Errors Clustered: Session
[1] Wet Bulb Temp is a continuous variable of wet bulb celsius standardized
* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.11: results-income

Gender Heterogeneity Figure 6.12

	Male		Female	
	Strong Spite	Weak Spite	Strong Spite	Weak Spite
Wet Bulb Temp[1]	-0.019	-0.022	-0.018	-0.033
	(0.029)	(0.035)	(0.016)	(0.030)
Version B	-0.004	-0.022	0.016	0.021
	(0.024)	(0.030)	(0.023)	(0.037)
Wet Bulb Temp x Version B	0.021	0.009	0.067*	0.064
	(0.027)	(0.036)	(0.036)	(0.042)
Num.Obs.	611	611	520	520

Controls: Outside Wet Bulb Temperature

Fixed Effects: Country

Std. Errors Clustered: Session

[1] Wet Bulb Temp is a continuous variable of wet bulb celsius standardized

* p < 0.1, ** p < 0.05, *** p < 0.01

Figure 6.12: results-gender

GATES Comparison Figure 6.13

Method	Treatment	Outcome	Lowest 20%	Highest20%	Diff(G5-G1)	p-value
OLS	Wet Bulb 24	Strong Spite	-0.0964632	0.0921373	0.1886005	0.00000
Causal Forest	Wet Bulb 24	Strong Spite	-0.0055274	0.0061733	0.0117007	0.00007

Figure 6.13: gates-table

GATES line graph Figure 6.14

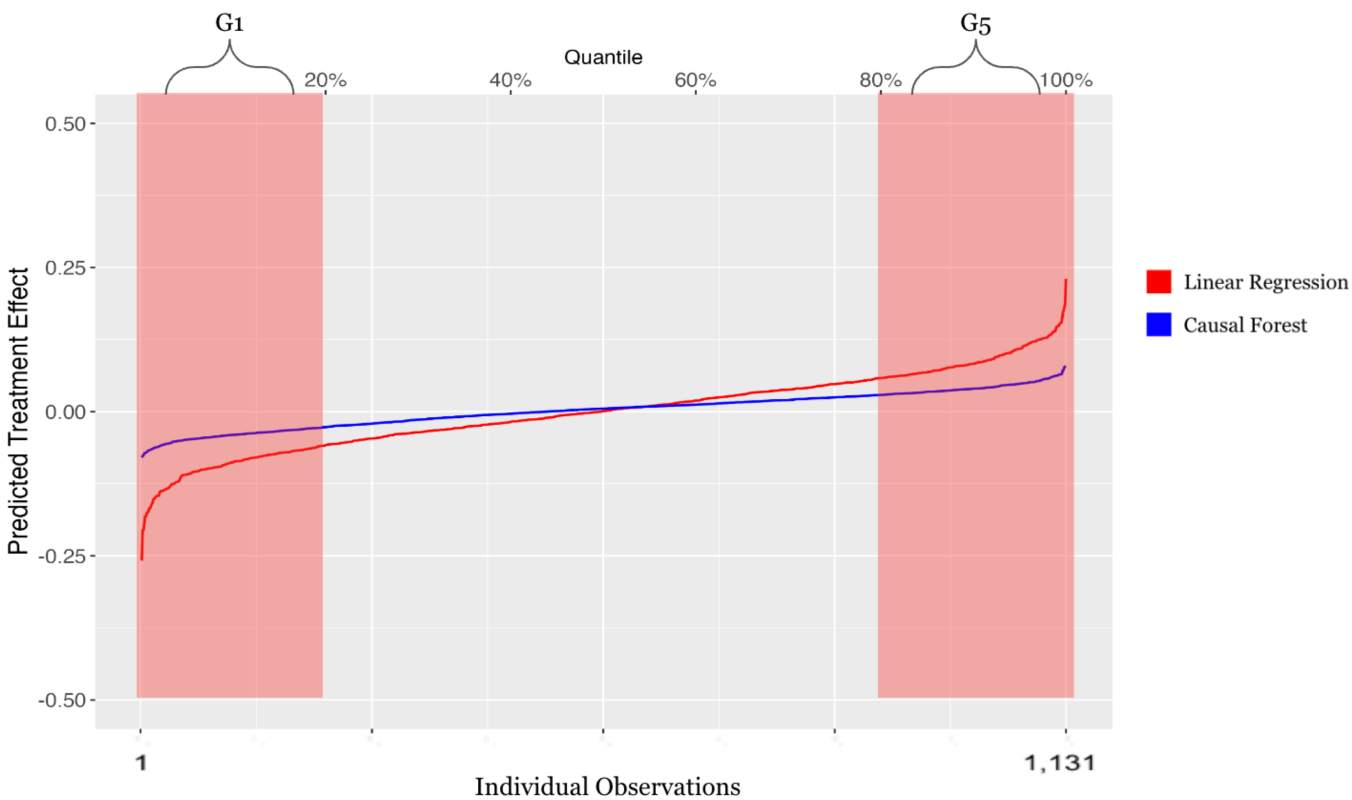


Figure 6.14: gates-line-graph

CLAN Analysis Bar Graph Figure 6.15

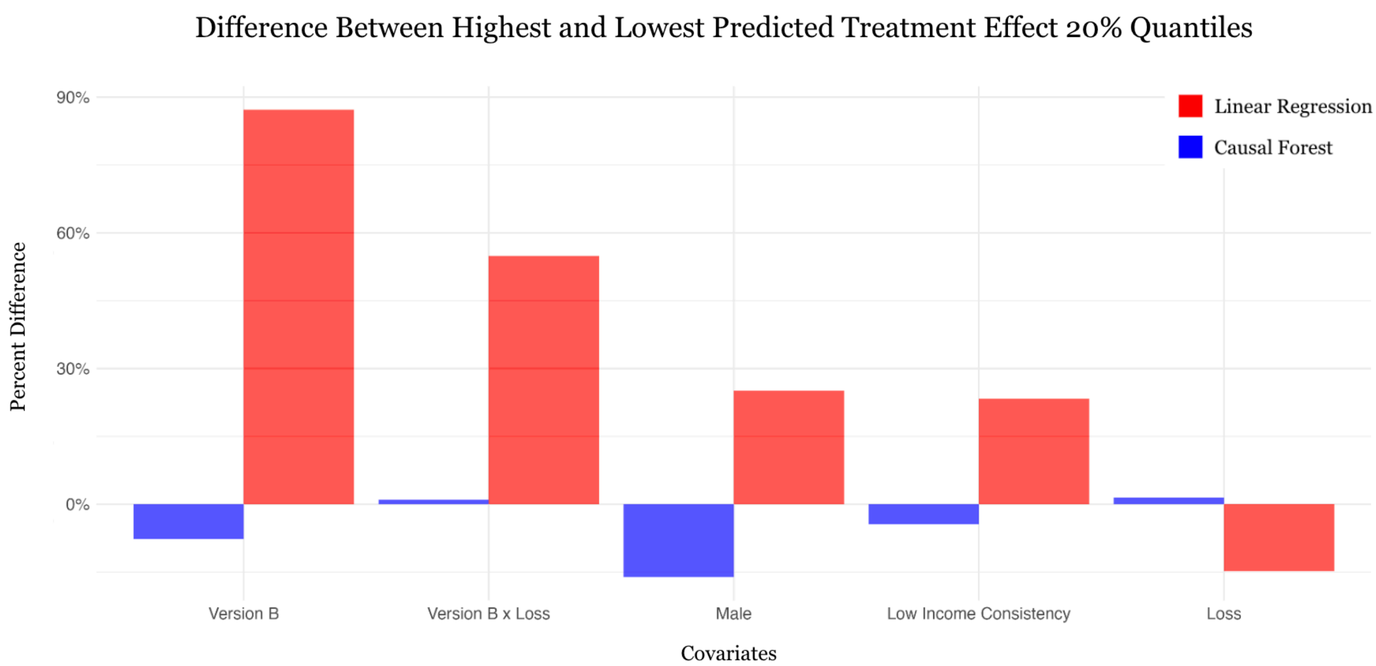


Figure 6.15: clan-bar-graph

Classification Analysis Table Figure 6.16

Classification Analysis (CLAN)				
Treatment Variable: Wet Bulb 24 Celsius				
Variable	**Predictor**	**Diff (G5-G1)**	**T stat (G5-G1)**	**P value (G5-G1)**
Version B	Linear Regression	0.87256	33.15113	0.00000
	Causal Forest	-0.07723	-1.64520	0.10063
Loss	Linear Regression	-0.14861	-2.89271	0.00406
	Casual Forest	0.01577	0.33843	0.73519
Loss x Version B	Linear Regression	0.54907	14.14272	0.00000
	Casual Forest	0.00795	0.21165	0.83247
Age	Linear Regression	-1.73918	-6.74116	0.00000
	Casual Forest	-1.93252	-9.62262	0.00000
Male	Linear Regression	0.25192	4.84192	0.00000
	Casual Forest	-0.16151	-3.52563	0.00047
USA	Linear Regression	0.09148	2.05649	0.04049
	Causal Forest	-0.04499	-1.22009	0.22307
India	Linear Regression	-0.28633	-5.68279	0.00000
	Casual Forest	0.13970	3.12836	0.00187
Mexico	Linear Regression	0.11504	2.96916	0.00320
	Casual Forest	0.11849	3.46747	0.00058
Kenya	Linear Regression	0.07982	1.75916	0.07944
	Casual Forest	-0.21321	-5.12522	0.00000
Low Income Consistency	Linear Regression	0.23394	4.67306	0.00000
	Casual Forest	-0.04450	-1.01130	0.31242
Satisfaction PCA	Linear Regression	-1.42846	-10.43674	0.00000
	Casual Forest	-2.07529	-20.64889	0.00000
Stress Factor	Linear Regression	-0.25669	-0.38966	0.69703
	Casual Forest	-0.43226	-0.76419	0.44519
Cognition	Linear Regression	-1.68400	-2.94308	0.00347
	Casual Forest	1.79722	3.53270	0.00045
Aquantiances	Linear Regression	-0.11577	-0.71275	0.47648
	Casual Forest	0.09417	0.66275	0.50783
Hungry	Linear Regression	-0.07067	-1.67065	0.09570
	Casual Forest	-0.03612	-0.99720	0.31920
Trust PCA	Linear Regression	0.93909	5.40770	0.00000
	Casual Forest	0.64318	4.04399	0.00006

Figure 6.16: clan-table