Weather and Maternal Mortality

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Abstract

This paper produces the first econometric estimates of the relationship in the U.S. between temperature and maternal mortality. Exploiting the year-to-year variation in temperature within states, I use a semiparametic estimation strategy to capture non-linear effects in mortality risks at extreme temperatures. I use wet bulb temperatures, a metric which accounts for both temperature and humidity, this analysis shows that an additional day with an average wet bulb temperature above of 80°F is associated with roughly 2.2 additional maternal deaths per 100,000 births. These estimates suggest that excess maternal mortality associated with very hot days due to climate change may be as high as 3,859 deaths per year by 2090.

Keywords: Climate Change, Health, Maternal Mortality

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1 Introduction

There is a growing consensus that man-made emissions of greenhouse gases will permanently alter the earth's climate, both by increasing temperatures and increasing variability in weather extremes (IPCC, 2013). While there are many costs associated with climate change, estimates of the harm resulting from climate change need to incorporate the costs in terms of lives lost , and much of the analysis of mortality effects has focused on infants and elderly. However, pregnant women may differ from the average prime-age adult in terms of mortality risk due to temperature extremes. This paper explores the mortality cost of temperature extremes for pregnant women and new mothers.

It is well known in the medical literature that extremes in ambient temperature may worsen health outcomes during pregnancy, and research has found adverse outcomes for both mother (Bodnar et al., 2007) and baby (Strand et al., 2011). Bodnar et al. (2007) finds that rates of preeclampsia, a hypertensive disorder related to pregnancy, has seasonal patterns with rates that are highest in the winter, but are also high in the summer for black women. Bodnar et al. (2007) shows there is a correlation between extreme temperatures and outcomes which increase the risk of maternal mortality, but the study uses monthly variation as a proxy for temperature, and ignores other plausible reasons for monthly variations in health outcomes. We cannot be sure if additional maternal morbidity was due to the climate of winter and summer months or due to other seasonal factors such as additional vacation time taken over winter and summer holidays which may delay doctors visits and reduce the likelihood a mother receives preventative care before developing preeclampsia. The issue of maternal mortality and its possible relationship with extreme temperature deserves additional scrutiny because maternal mortality rates have increased in the United States in the past 15 years (Creanga and Callaghan, 2017), a trend which I show climate change threatens to make worse. To my knowledge, there have not been any population-wide explorations of the temperature-mortality relationship for pregnant adult women.

I exploit unexpected variations in temperature between years for a given month in a given region to demonstrate the relationship between temperature, humidity, and maternal mortality with a particular focus on the effect of unusually hot days in the years 1963-1998. For example, though August in Houston is always hot, I test the effect of an August in Houston which is unusually hot relative to a typical August in Houston. Because mortality risk due to temperature variation is non-linear, I will use a semi-parametric functional form with non-parametric temperature bins to model mortality risk both with and without effects of humidity.

I use a regression structure common to econometric research on the effects of extreme temperatures (Deschênes et al., 2009; Deschênes and Greenstone, 2011), which features non-parametric temperature bins, to estimate the effect of temperature on maternal mortality. Dry bulb (thermometer) temperatures show small and statistically insignificant effects of temperature on mortality. However, wet bulb temperatures, which better incorporate the effects of both temperature and relative humidity, show statistically significant increases in maternal mortality on very hot days. This analysis suggests single additional day with a wet bulb temperature above 80°F is associated with roughly 2.2 additional maternal deaths per 100,000 births.

There also have been papers which have studied all-cause mortality in the population. Typically, studies create an age group for infants (under 1 year) and elderly (over 65), while people between ages 1-65 are put into bins with very little scrutiny of prime age adults. It is common to use a specification with non-parametric temperature bins, and fixed effects to control for the typical outcomes of a population. For example, Deschênes and Greenstone (2011) finds a significant increase in the annual mortality rate for both extremely hot and cold days in the population weighted average. Though they find an increase in all-cause mortality for prime-age groups (ages 1-44 and 45-64, respectively) on hot days, they find these groups have smaller mortality effects than other age groups due to the relative health of the prime-age population. While they provide excellent analysis of all-cause mortality, their estimate of an additional 0.224 deaths per 100,000 people for each additional day above

90°F for those aged 1-44 cannot be used to predict maternal mortality due to the inclusion of women who are not of child-bearing age, men, and lack of controls for fertility level within the population. Furthermore, the difference between the Deschenes and Greenstone estimate of all-cause mortality and an estimate for maternal mortality cannot be signed, since their measure of mortality includes people who do not have the underlying risk factor of a pregnancy, but may include people with more underlying health risks than the average mother (e.g. those with a chronic illness). However, as I lay out in this paper, it is reasonable to suspect that pregnant women are a population vulnerable to extreme temperatures, and policy implications of maternal deaths may be different from prescriptions to mitigate all-cause mortality, where infants and elderly are the more susceptible populations.

Deschênes et al. (2009) found that warm temperatures reduce birth weights, and Barreca (2018) provides evidence that warm temperatures may reduce gestational length. While both papers find that extreme temperatures effect pregnancy, they focus on outcomes which affect the health of infants. To my knowledge, there are no papers which conduct a population-wide statistical analysis to address the health effects of temperature on mothers during pregnancy.

My paper makes the following contributions. Firstly, while the previous literature likely captures maternal mortality in the all-cause mortality estimates, policy prescriptions typically focus on infants and elderly as at-risk groups in the analysis. If pregnant women in particular are more affected than the general population, prescriptive public policy initiatives need to give particular focus to this group.

Secondly, my analysis is the first to document the joint effect of humidity and mortality in the United States. Following the work of Geruso and Spears (2017) my primary specification will use wet bulb temperature, a metric which tests the joint effect of temperature and relative humidity. Existing papers have tested the prediction power of moisture in the air and found that while temperature continues to predict mortality, humidity information adds predictive power. My main results will be presented using both traditional dry bulb temperatures and wet bulb temperatures to demonstrate the differences in results achieved using each method.

2 Conceptual Framework

2.1 The Temperature-Maternal Mortality Relationship

Pregnant women may be particularly susceptible to temperature extremes, as health production during pregnancy may leave women more susceptible to dangers of temperature extremes.

The human body is designed to function within a narrow range of body temperatures. Humans cope with exposure to temperature extremes via thermoregulatory functions. On cold days, the body keeps warm by reducing blood flow to extremities where heat is quickly lost. In contrast, when the human body begins to overheat, it triggers vasodilation, moving blood into capillaries which are closer to the skin surface to allow excess heat to exit the body. Extremely hot temperatures cause an increase in the heart rate to more quickly move blood from the body's core to the capillaries close to the skin. If the outside temperature is too hot to allow the human body to release the excess temperature through convection, humans begin to sweat, which creates evaporative cooling. Thus, the human body is able to cool itself through the surface of the skin. These responses allow individuals to pursue physical and mental activities even in uncomfortable temperatures.

However, even with our thermoregulatory abilities, exposure to temperature extremes for prolonged periods of time endangers human health and can result in mortality. Heat stroke can occur if the body is physically unable to adequately cool itself. Because of the prominent role of the cardiovascular system in thermoregulation, cardiac activity increases in hot environments as the body attempts to cool itself. Extreme temperatures are also a risk factor for cardiovascular events, and previous literature has found an increase in cardiac events in hot temperatures (Basu and Ostro, 2008). Previous literature of temperature and mortality found cardiovascular disease explains roughly 40% of the observed increase in mortality (Deschênes et al., 2009).

There are physiological reasons to suppose temperature extremes may affect pregnant women more than other similar women, conditional on observables. In the course of performing standard metabolic functions, heat is produced as a function of body mass, and, as discussed above, excess heat is discharged by temperature exchange on the skin surface. Thus, the ability to lose thermal energy is improved by a high ratio of surface area to body mass. Because women gain mass during pregnancy with a smaller relative increase in surface area, the body is less able to remove thermal energy (Wells, 2002). Pregnancy also places a strain on the cardiovascular system, and by the end of pregnancy, women's blood volume increases by roughly 50%. Coupled with high temperatures, pregnant women may thus be at an elevated risk for cardiovascular events. This limited thermoregulatory ability and increased cardiac strain may warrant inclusion of pregnant women as an at-risk class in the face of heat exposure (Kuehn and McCormick, 2017).

2.2 Wet Bulb Temperature

Sweating and evaporative cooling are important methods of thermoregulation in hot temperatures, but evaporation is less efficient in high relative humidity. Thus, it is reasonable to believe humidity plays a role in temperature and health. While I will show specifications which use dry bulb temperature (the temperature displayed by a typical thermometer) and specifications which interact temperature and relative humidity, wet bulb temperature has the advantage of providing easily interpretable results regarding the effects of high relative humidity.

In scientific terms, wet bulb temperature is the temperature a volume of air would have if cooled to saturation by evaporation of water into it, with all latent heat being supplied by the volume of air. In practical terms, wet bulb temperature is the lowest temperature which may be achieved by a water-wetted surface in a well-ventilated area, thus approximating how well evaporative cooling works for a given temperature and relative humidity. By definition wet bulb temperature will always be lower than dry bulb temperature, and is equivalent only when relative humidity reaches 100% and no evaporative cooling can occur.

To give a sense of the difference between wet and dry bulb temperatures, in Figure 1 I present a grid of dry bulb temperatures above 0°F in each state-year-month-day with the corresponding wet bulb temperature. As the figure shows, wet and dry bulb temperatures converge in very cold temperatures because cold air can hold less water vapor. On warm days, the wet and dry bulb temperatures can be very different in areas with different relative humidity. For example, a day with a dry bulb temperature between 80°F and 90°F may have a wet bulb temperature as low as 50°F to 60°F or as high as 80°F and 90°F. When the dry bulb temperature is above 90°F very few observations have relative humidity close to 100%, thus we see very few wet bulb temperatures above 80°F.

3 Data and Summary Statistics

3.1 Data Sources

Vital Statistics data. Maternal mortality rates are constructed using Vital Statistics Mortality Multiple Cause Files and Birth data files.

Following the standard practice of demographers, maternal mortality is calculated as a rate, normalized by the number of births within a population. This normalization corrects for changes in the number maternal deaths due to changes in population size, and also corrects for changes in the fertility rate across time and geography.

For the numerator of this variable, Mortality Multiple Cause Files were used to identify maternal deaths in each state-year-month. In the 1963-1978 time period, cause of death was coded using the International Classification of Diseases Revision 8 (ICD-8) and between 1979-1998 the 9th Revision was used. I counted as a maternal death any death with included one of the obstetric death codes (defined by the ICD) as a primary or contributing cause of death. These codes identify any women who died while pregnant or within 42 days of a pregnancy due to any condition caused by or exacerbated by the pregnancy, but excludes women who died of accidental or incidental causes while pregnant. To construct the denominator of this number Vital Statistics Birth Data files were used to construct the number of births in each state-year-month cell.

Weather data. The temperature data comes from weather stations and observations are collected from the NOAA Global Historical Climatology Network-Daily (GHCN-Daily), a database of daily weather summaries from land surface stations that are subjected to a common set of quality assurance checks. The key variables for the analysis are the daily maximum and minimum temperatures. To construct monthly measures of weather from the daily records, I use only weather stations that have no missing records in any given year. The station-level data are then aggregated to the county level by taking an inverse-distance-squared weighted average of the temperature measurements from the selected stations that are located within a 200-kilometer radius of each countys centroid. Thus, measurements from a single weather station are weighted such that it is inversely proportional to the squared distance to the county centroid, so that the closer stations are given more weight. Finally, since the mortality data are at the state-year-month level, the county-level temperature variables are aggregated to the state-year-month level by taking a population-weighted average over all counties in a state, where the weight is the county-year population.

To add relative humidity data and wet bulb temperature to the analysis, pressure and humidity data were collected from the Princeton Meteorological Forcing Dataset (Sheffield et al., 2006). This dataset uses meteorological variables taken from multiple sources, including satellites and weather balloons, and uses NCAR-NCAP reanalysis to create a gridded dataset of weather observations every 3 hours at 0.25 degrees latitude-by-0.25 degrees longitude. A distance-weighted average of the four grid-points nearest to each weather station are used to construct an average water vapor and air pressure measurement for each station.

See the data appendix for a more detailed explanation of how the weather data sources were combined.

Predictions of climate change from this model is available for several emission scenarios, which describe the way the world (population, economies, etc.) may develop over the next

100 years. I focus on the A2 scenario which assumes continuous population growth. This model assumes trade between nations remains imperfect, and fuel mix by region is determined primarily by local resource availability and economic development is regionally oriented.

I use the Hadley 3 model's daily temperature predictions for the period 2050-2090, which has grid points spaced at 2.5°(latitude) x 3.75°(longitude). I use a weighted average of the four nearest gridpoints to each state centroid to construct the daily average for each state-day-month-year.

3.2 Summary Statistics

Figure 2 shows the average annual distribution of wet bulb and dry bulb daily mean temperatures which occur in this period. The daily mean temperature shown here is the average of the daily maximum and daily minimum temperature in degrees Fahrenheit. The probability density function of dry bulb temperatures is overlaid on the same graph to give a sense of the difference between the two distributions. Though it follows a similar distributional form, notice the function is shifted to the right because dry bulb temperatures are higher than wet bulb by construction.

Table 1 Panel A gives some demographic information about mothers in this time period, representing over 98 million observed births. I classify women as white (including Hispanic whites), black, and all other races (primarily Asian and Native American women.) 14% of births in this time period are to mothers under the age of 20, and 1.74% are to mothers over the age of 40. Demographic characteristics of mothers in each state-year-month cell are used as control variables in my regression.

4 Econometric Strategy

4.1 Equation

Mortality Rates To estimate mortality rates, I use the following equation:

$$MMR_{sym} = \beta_0 + \sum_j \theta_j^{TEMP} TEMP_{sym} + \beta_1 X_{sym} + \alpha_{sm} + \gamma_{ym} + \epsilon_{sym} \quad (1)$$

Standard errors are clustered at the state $\times$ month level. The dependent variable, MMR_{sym}, is the maternal mortality rate for women in state s in year y and month m, where the maternal mortality rate is defined as the number of maternal deaths per 100,000 births in a given state-year-month.

The variables of interest are the measures of temperature $\theta_j^{TEMP} TEMP_{sym}$. Following the functional form used by Deschênes and Greenstone (2011) and Barreca et al. (2016), I construct 10 temperature bins in which the variable $TEMP_{sym}$ represents the number of days in when the mean of the daily maximum and daily minimum temperature falls into temperature bin j in state s, year y, and month m. Thus, θ_j^{TEMP} represents the mortality risk from a single additional day in temperature bin j relative to a day in the excluded category. For my dry-bulb analysis, I follow the literature and use 60-69°F as the excluded category, because this is a comfortable and safe temperature bin for human health. Referring back to Figure 1, this temperature bin frequently corresponds to a wet-bulb temperature between 40-69°F. I will use 40-59°F as the excluded category for my wet bulb analysis, because this bin typically has the lowest mortality rates. This semi-parametric functional form imposes the restriction that the impact of a day of mean temperature j is consistent within 10°F intervals, but allows the data to flexibly determine the impact of each bin without imposing restrictions on the effect of temperature across bins.

The equation includes a full set of year-by-month fixed effects which flexibly controls for U.S.-wide changes in the maternal mortality rate over time, due to factors such as changes in technology. Additionally, this specification includes a state-by-month fixed effect to absorb differences by state in seasonal mortality. This fixed effect adjusts for time-invariant unobserved state-level determinants of the mortality rate, such as differences in hospital quality. Importantly, the use of a state $\times$ month fixed effect also controls for seasonal variation in weather outcomes. Although women make a choice about where and when to become pregnant, they cannot have prior knowledge about the variations in temperature within a month in their state. When fertility decisions are made women cannot know the temperature outcomes in the months which they carry the pregnancy to term after conditioning on typical seasonal weather. Thus, though people may become acclimated to the place they choose to live, this specification examines the mortality outcomes within a state $\times$ month using random, unexpected fluctuations in temperature between years to predict the effect of temperature on mortality outcomes.

4.2 Excess Zeros

Econometric modeling of maternal mortality is challenging for two reasons. First, maternal mortality is defined as the number of deaths per 100,000 births, thus the dependent variable is bounded between zero and one. Second, due to the rarity of maternal deaths, the outcome is zero for several state-year-month cells, and model choice must account for this excess mass at the boundary.

These zero outcomes represent a corner solution where the underlying distribution of observable and unobservable characteristics of an area (including, but not limited to, the temperature outcomes) produced some positive *probability* of a death, but the realized outcome in this time period is zero. An increase in risk factors such as temperature increase the probability of an adverse outcome, but the realization may remain at zero. Thus, these outcomes represent important information regarding realized outcomes for a given temperature and should not be discarded, as they might be in a log transformation.

Papke and Wooldridge (1996) demonstrates that OLS is only an appropriate model for a proportion when most values lie near the middle of the distribution, and there are very few zero or one outcomes. A better prediction will be formed using a Poisson model with a control for exposure, in this case the number of births in a given state-month-year. The Poisson model with an exposure variable works similarly to a model with log maternal mortality rate as the outcome variable.

$$E(ln(\frac{NumDeaths}{NumBirths})|X) = X\beta \tag{2}$$

This model can be transformed by exponentiating both sides:

$$\frac{NumDeaths_{sym}}{NumBirths_{sym}} = e^{(\beta_0+\sum_j \theta_j^{TEMP} TEMP_{sym}+\beta X_{sym}+\alpha_{sm}+\gamma_{ym}+\epsilon_{sym})}$$
$$NumDeaths_{sym} = NumBirths_{sym} \times e^{(\beta_0+\sum_j \theta_j^{TEMP} TEMP_{sym}+\beta X_{sym}+\alpha_{sm}+\gamma_{ym}+\epsilon_{sym})}$$
$$NumDeaths_{sym} = e^{(ln(NumBirths_{sym})+\beta_0+\sum_j \theta_j^{TEMP} TEMP_{sym}+\beta X_{sym}+\alpha_{sm}+\gamma_{ym}+\epsilon_{sym})}$$

The effect of $ln(NumBirths_{sym}$ is constrained to equal 1. Thus, the model predicts that if the number of births doubles, there will be a 100% increase in $NumDeaths_{sym}$. Tables will present the results of the Poisson model, which is roughly equivalent to the effect of a one unit change of the regressor on the outcome variable $\frac{ln(NumBirths_{sym}}{NumDeaths_{sym}}$. For figures, I will instead present the marginal effect $\frac{\partial MMR}{\partial \theta_j^{TEMP}}$ per 100,000 births. The exponential form has an advantage over taking the log of the dependent variable, in that it allows state-month-year cells with zero maternal deaths to remain estimable.

5 Results

Although the discussion above suggests OLS may be misspecified, I begin with OLS regressions as a baseline test of the relationship between temperature and mortality. However, using a basic least squares specification in this instance may give incorrect inference for the reasons discussed in the strategy section. Figure 3a shows the results of such an analysis using the dry bulb temperatures typically used in temperature and mortality studies. We do not see a u-shaped pattern of increasing mortality risk at temperature extremes as we would expect from previous analysis of temperature risk and all-cause mortality. In fact, we see a sharp decrease in mortality at the lowest temperatures, and all other temperature bins are not significantly different from zero. Figure 3b shows the analogous results for wet bulb temperatures. Here we see a similar pattern emerge. There appears to be a stronger relationship between high temperatures and increasing mortality, though the estimate is not statistically significant.

The main results using the Poisson model described in Section 4 are presented graphically in Figures 4a and 4b, with the point estimates showing the estimated change in the maternal mortality rate (that is, the number of deaths per 100,000 births.) For dry bulb temperatures we see there are no statistically significant results. Most of the point estimates remain close to zero, and though the point estimate for days above 90°F suggests an increased risk of maternal mortality, a very large confidence interval means we cannot reject that the effect of a very hot day is actually zero.

However, effect of wet-bulb temperatures on maternal mortality does take on the characteristic u-shape we might expect in the relationship between temperature and mortality. An additional day above 80°F wet bulb, relative to a day between 40-50°F wet bulb is associated with significantly more maternal mortality, on the order of an additional 2.2 deaths per 100,000 births. In 1990, the U.S. had an average annual maternal mortality rate of 12 deaths per 100,000 live births (Kassebaum et al., 2016), thus, this represents a 18.3% increase in maternal mortality on very-hot days.

Tables 2 and 3 allow us to look more carefully at the point estimates of these models, along with the joint effect of temperature and high humidity. The point estimates in these tables represent the estimated number of predicted additional deaths in a month from a single additional day of temperature in bin j. In Table 2 column 1, the OLS estimates for dry bulb temperature show very hot dry-bulb days have a large negative effect on maternal mortality rate, but this estimate is insignificant. In fact, we cannot reject that temperature has no effect on maternal mortality. In column 2, I present the joint effect of temperature and a relative humidity above 40%. In the hottest temperature bins there seems to be a positive and significant effect of high temperature with high humidity. Although the AIC scores for goodness of fit are similar, this does lend credence to the idea that testing for only high temperatures ignores an important risk factor for mortality. When using wet-bulb temperatures we once again find no significant results for the hottest days.

Table 3 presents the analogous results of the Poisson regression. Column 1 shows the results of our dry bulb analysis. We see there is no significant change in maternal mortality rates due to an additional day in any temperature bin relative to a day between 60-69°F. Column 2 presents the effect of a day within a given temperature bin and the interaction effect of a day in the temperature bin which is above 40% relative humidity. The effect of days which have a dry bulb temperature above 90°F and high humidity is significant and positive. Like with the OLS results, it seems reasonable to believe that dry bulb temperature alone does not fully explain the relationship between temperature and maternal mortality. Column 3 shops the results for wet bulb temperature, and an additional day above 80°F wet bulb is associated with 0.102 additional deaths in the month the temperature shock occurs.

5.1 Heterogeneity

The effects of temperature are not equally felt by all women. Technology such as air conditioning and heating may be instrumental in preventing mortality in extreme temperatures (Barreca et al., 2016; Heutel et al., 2017). In addition, access to quality medical care in the event of an obstetric emergency could determine the severity of outcomes. Thus, richer women are more less likely to suffer mortality consequences of extreme temperatures. Vital Statistics data does not include information on the wealth of each woman. However, race of the mother is recorded, and because race is highly correlated with wealth, a comparison of outcomes between women of different races can lend insight into the effect of wealth on maternal mortality outcomes.

Figure 5 shows the mortality effects of wet bulb temperature per 100,000 births for non-white women and white women . In Figure 5a we see the result for non-white women has the characteristic u-shape of temperature mortality, with positive and statistically significant results for both hot and cold temperatures. For an additional day above 80°F, there will be approximately 6.42 additional maternal deaths per 100,000 births. By comparison, Figure 5b shows the relationship between temperature and maternal death is never statistically significant for white women.

5.2 Robustness Checks

Based on the biological background laid out in section 2, we may expect some types of maternal mortality to be related to extreme temperature. The World Health Organization divides maternal mortality deaths into seven different categories, including obstetric hemorrhage, pregnancy related infection, general complications of management, and hypertensive disorders of pregnancy. Hypertensive disorders of pregnancy should be the category which includes cardiovascular mortality and should be the most sensitive to temperature changes. For this analysis I divide the year into annual quarters [1] and the analysis is done with state-by-quarter and year-by-quarter fixed effects. Figure 6 and Table 4 shows the results when I estimate the relationship between the maternal mortality rate and temperature for each cause of death separately. While maternal mortality due to cardiovascular causes never rises to statistical significance at the 5% level, the point estimate is increasing in each temperature bin above the excluded category and the top two bins are significant at the 10% level. The other causes of death, which we would believe are less likely to be related to temperature based on the biological description of temperature related health risk, do not show a

[1] January-March, April-June, July-September, October-December

consistent relationship between extreme temperature and mortality.

One possible concern is that the effect of birth timing shifts due to extreme temperatures. Emerging evidence shows that very hot days can reduce gestational lengths (Barreca, 2018). The day in which a woman gives birth a particularity risky part of the pregnancy, if an additional hot day in a given month can shift birth timings from a later month into a month with very hot days, then the stated results may be due to harvesting, by changing birth timings to occur on very hot days, even if the mortality effects would occur regardless of temperature. If this is the case, a monthly estimator may overstate the risk of maternal mortality because more births, including risky births, occur in the month with additional hot days. However, additional hot days are unlikely to shift birth timing between years, since extremely hot days occur mid-year in the U.S. context. Figure 7 replicates the main analysis, aggregating the data to an annual level. The outcome of interest in this specification is the annual maternal mortality rate, and the point estimates represent the expected change in the annual maternal mortality rate given a single additional day of a given temperature within the year, relative to a day between 40-49°F wet bulb. The results show no statistical relationship between temperature and mortality in cool temperatures. However, for each additional very-hot day per year, we expect roughly 2.81 additional maternal deaths per 100,000 which is consistent with our monthly predictions.

Another concern might be that the results are sensitive to the functional form I use. To test this, I try a number of other functional forms, presented in the appendix. Figure B.1 and Table 6, column 3 show the results when I use a negative binomial function, and the results are very similar to the exponential model. We still see a significant increase in maternal mortality in hot temperatures, with the standard U-shaped curve with excess deaths occurring in very hot and very cold temperatures. Neither temperature extreme rises to significance at the 5 percent level, but we do see a sharp increase in mortality outcomes on very hot days.

As another check, I consider maternal mortality outcomes as having two discrete margins, both an extensive margin where covariates and weather outcomes may affect the probability of a death, and an extensive margin wherein the same variables may effect the number of maternal deaths which occur. To estimate the effect of temperature on the extensive margin, I fit equation (1) as a logistic function, with the outcome variable Y_{smy} presented as a binary outcome of any mortality event. For the intensive margin, I estimate equation (1) using the OLS model with the outcome variable $Y_{smy} = (MMR_{smy}|MMR_{smy} > 0)$. Appendix Figure B.2 and Table 6, column 1 presents the extensive and intensive margin for wet bulb temperatures. The logistic odds ratio presented in Figure B.2a shows a sharp increase in the probability of a death occurring on the coldest days, but there is no similar increase on the hottest days. The OLS regression in Figure B.2b and Table 6, column 2 similarly seems to show no effect on hot days, but some effect on cold days, though none of the point estimates are significant.

The total marginal effect of temperature θ_j^{TEMP} is constructed by multiplying the predictions from each part of the model

$$(MM\hat{R}_{smy}|\theta_j^{TEMP}) = (\hat{p_i}|\theta_j^{TEMP}) \times (MM\hat{R}_{smy}|MMR_{smy} > 0, \theta_j^{TEMP})$$

where $\hat{p_i}$ is the probability the maternal mortality rate is greater than 0. Standard errors are calculated using the delta method [2]. Figure B.3 presents the total marginal effect of temperature on maternal mortality, where $\frac{\partial MMR}{\partial \theta_j^{TEMP}}$ represents the additional mortality correlated with one additional day in temperature bin j is shown in . The effect of cold weather on maternal mortality is positive and significant, but there is no indication that hot temperatures effect mortality.

[2]Further information on the calculation of the total marginal effect and its standard errors can be found in Belotti et al. (2015)

6 Mortality Implications of Climate Change

Using state of the art global climate models, I predict the mortality that might be caused by a shift in temperatures due to climate change. The Hadley Centres 3rd Coupled Ocean-Atmosphere General Circulation Model, which I refer to as Hadley 3 (Johns et al., 1997; Pope et al., 2000), is the most complex and recent model in use by the Hadley Centre. It is a coupled atmospheric ocean general circulation model, so it considers the interplay of several earth systems and is therefore considered the most appropriate for climate predictions. We also use predictions from the National Center for Atmospheric Researchs Community Climate System Model (CCSM) 3, which is another coupled atmospheric-ocean general circulation model (NCAR, 2007). The results from both models were used in the 4th IPCC report (IPCC, 2007).

When considering the costs of climate change, it is clear one needs to consider the effect on maternal mortality. However, the economic costs of maternal mortality are hard to fully quantify. While it is standard in the economics literature to quantify the value of a statistical life, there are likely additional hidden costs to maternal mortality. For example, while there are no studies to my knowledge in the modern U.S. context regarding the impact of maternal loss on child development, studies of maternal orphans in foreign contexts find that a mother's death can reduce a child's education (Case and Ardington, 2006) and have adverse effects on health outcomes (Gertler, 2018). [3]

An additional "hot" day between 1964-1998 can be treated as a proxy for a "typical" day after climate change. Figure 8 shows Hadley3 model estimates for additional days with a dry bulb temperature above 90°F. Some regions of the United States such as the Pacific Northwest are predicted to have very few additional hot days, while areas such as the Southeast are likely to have between 30 and 40 more days of dangerously hot temperatures

[3]While I do not have adequate data to perform a back of the envelope calculation, some maternal mortality may result in the loss of the child's life which imposes an additional cost in terms of foregone life-years. However, the cost of additional loss of life-years for the mother due to increasing temperatures can serve as a lower bound for the cost of climate change due to maternal deaths.

by 2050.

Because I have estimated the likely mortality associated with a day of each temperature, I can predict how many additional maternal deaths we might see due to climate change. Panel A of Table 5 shows the total predicted additional mortality for the US due to a change in the distribution of number of days with each wet bulb temperature. Column 1 shows that a decrease in very cold days will have protective effects, which will result in a small and insignificant decrease mortality rates. However, an increase in the number of days above a wet-bulb temperature of 70°F will increase the number of maternal deaths, causing an additional 4,230 deaths due to very hot days. When we consider all temperature changes, we see there is a predicted increase in total deaths, and we might expect an additional 3,860 deaths in the year 2090.

Figure 9 shows how these additional deaths will be distributed geographically. The southeastern United States, which already experiences a warm and humid climate will experience the most additional maternal deaths, while the Western United states will be the least affected by the change in climate.

Panel B of Table 5 analyzes the cumulative change in the number of days in each bin for the years 2050 to 2090, and creates a measure of the additive effects of additional very hot days over this 40 year time period. Over this time period, the model predicts and additional 133,005 deaths due on very hot days. The aggregate results, with accounts for the protective effect of fewer cold days still predicts a marginally significant increase in overall deaths, with 114,749 total additional maternal deaths due to climate change.

Based on the EPA's calculation of the value of a statistical life (VSL) of $2million, it may be worthwhile to spend at least $7.7 billion each year by 2090 on efforts to provide pregnant women with technological interventions such as air conditioning on very hot days. However, maternal mortality affects a population different from the typical population affected by climate change in that women give birth while they are prime-age adults. Prime age adults may have a different value of a statistical life than these traditional populations (Aldy and

Viscusi, 2008) (AV), so it may be more appropriate to study the cost of maternal mortality in terms of value of a statistical life-year (VSLY). According to AV, the VSL of this population, calculated as the cumulative effect of lost life-years, should more accurately be calculated as between \$3.24 million and \$9.66 million. Using the most conservative estimate of \$3.24 million, the value of directing protective resources to pregnant women on very hot days could total \$12.5 billion.

7 Conclusion

Using a semiparametic estimation strategy to capture non-linear effects in mortality risks at extreme temperatures, I estimate the effect of temperature on maternal mortality. Though I find no statistically significant effect of additional very hot dry bulb days, my analysis suggests that an additional day with an average wet bulb temperature above of 80°F is associated with roughly 0.245 additional maternal deaths per 100,000 births, which is statistically significant. These estimates suggest that, the cost of additional maternal deaths associated with very hot days due to climate change may be as high as \$842 million per year by 2050.

There are several implications of this research. First, the mortality predictions related to maternal deaths reflect the current level of infrastructure, medical technology, and adaptation technologies. If climate change progresses, it is likely we will choose to invest in ways which mitigate climate outcomes. My results suggest the value of directing protective investments towards pregnant women could total \$842 million per year by 2050.

Finally, the impacts of climate change will be felt throughout the planet. This paper can be used to better estimate a world-wide risk of climate change by better incorporating the risk of heat-related death associated with fertility. Ultimately, the development of rational climate policy and calculating a social cost of carbon requires knowledge of the health and other costs of climate change from around the world (Burgess et al., 2011).

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Tables

Summary Statistics	
Panel A. Annual Maternal Mortality Rate (per 100,000 births)	
All Women	16.52
Women Under 21	14.68
Women 21 to 30	9.49
Women 31 to 40	25.88
Women Over 40	68.54
Black Women	41.06
White Women	12.69
Panel B. Days of Extreme Temperature	
Dry Bulb Below 30*F	34.59236
Dry Bulb Above 80*F	17.44687
Wet Bulb Above 70*F	30.20694

Table 1: Demgraphic Characteristics of Mothers

Effect of Temperature and Humidity on Average Maternal Deaths per State-Month-Year Cell

	OLS		
	Dry Bulb Temperature	Dry Bulb Temperature Interacted with Relative Humidity	Wet Bulb Temperature
$\leq$ 10F	-2.37832+	-4.03918*	-2.60139+
	(1.24862)	(1.63704)	(1.37924)
10F-20F	0.69905	-1.04743	0.47433
	(0.90870)	(1.10733)	(1.05583)
20F-30F	-0.15770	2.30703+	-0.95362
	(0.75419)	(1.26921)	(0.73879)
30F-40F	-0.12010	-0.37239	-0.34343
	(0.88234)	(1.65315)	(0.61742)
40F-50F	-0.11360	-0.94024	-0.59944
	(0.55103)	(1.44004)	(0.59217)
50F-60F	-0.19409	0.20161	-
	(0.47833)	(1.10956)	
60F-70F	-	-	-0.41688
			(0.48755)
70F-80F	0.02197	-0.50641	-0.00128
	(0.36072)	(0.59165)	(0.66234)
$\geq$ 80F			1.38820
			(1.94229)
80F-90F	0.15171	-1.01462	
	(1.00730)	(0.83991)	
$\geq$ 90F	0.81184	-0.10603	
	(0.80232)	(0.90893)	
$\leq$ 20F High Humidity		2.11534	
		(1.38921)	
20F-30F High Humidity		-2.24655	
		(1.38170)	
30F-40F High Humidity		0.56406	
		(1.46427)	
40F-50F High Humidity		1.12286	
		(1.59235)	
50F-60F High Humidity		-0.12685	
		(1.20698)	
70F-80F High Humidity		1.04499	
		(0.79145)	
80F-90F High Humidity		1.76336	
		(2.01736)	
$\geq$ 90F High Humidity		1.88902	
		(3.57605)	
AIC	289,469.40	289,455.40	289,858.30

Results Clustered at the state level. Standard Errors in Parenthesis. + p$\leq$ 0.10, * p$\leq$ 0.05, ** p$\leq$ .01.
High Humidity is relative humidity above 40%

Table 2: Effect of Temperature on Mortality OLS Results

Effect of Temperature and Humidity on Average Maternal Deaths per State-Month-Year Cell

	Poisson		
	Dry Bulb Temperature	Dry Bulb Temperature Interacted with Relative Humidity	Wet Bulb Temperature
$\leq$ 10F	-0.044 (0.075)		0.020 (0.070)
10F-20F	0.015 (0.051)	-0.353+ (0.207)	0.030 (0.064)
20F-30F	-0.007 (0.040)	0.284+ (0.160)	0.032 (0.039)
30F-40F	-0.023 (0.032)	-0.051 (0.161)	0.028 (0.027)
40F-50F	-0.044* (0.022)	0.096 (0.144)	0.043+ (0.024)
50F-60F	-0.031* (0.015)	-0.205* (0.092)	-
60F-70F	-	-	0.04346* (0.020)
70F-80F	-0.034+ (0.020)	-0.112+ (0.062)	0.044+ (0.025)
$\geq$ 80F			0.10209* (0.04786)
80F-90F	-0.020 (0.025)	-0.161** (0.053)	
$\geq$ 90F	0.058 (0.227)	-0.122 (0.213)	
$\leq$ 20F High Humidity		0.349+ (0.197)	
20F-30F High Humidity		-0.286+ (0.160)	
30F-40F High Humidity		0.033 (0.163)	
40F-50F High Humidity		-0.138 (0.150)	
50F-60F High Humidity		0.182+ (0.150)	
70F-80F High Humidity		0.096 (0.066)	
80F-90F High Humidity		0.162** (0.055)	
$\geq$ 90F High Humidity		0.874+ (0.529)	
AIC	58,208.44	58,211.05	58,196.01

Results Clustered at the state level. Standard Errors in Parenthesis. + p$\leq$0.10, * p$\leq$0.05, ** p$\leq$.01.
High Humidity is relative humidity above 40%

Table 3: Effect of Temperature on Mortality Main Result

Effect of Wet Bulb Temperature and Humidity on Maternal Mortality by Cause of Death				
	Cardiac	Infection	Hemorrhage	Other Complications
Wet Bulb Temperature				
$\leq$ 10F	0.05087	-0.16684+	-0.01109	-0.02606
	(0.05684)	(0.09656)	(0.04659)	(0.13730)
10F-20F	-0.03631	0.07532	-0.02619	0.20168+
	(0.04233)	(0.05315)	(0.02492)	(0.11185)
20F-30F	0.02616	0.02253	-0.02259+	0.02740
	(0.02545)	(0.03585)	(0.01300)	(0.10524)
30F-40F	-0.01235	-0.01608	-0.01503	0.06226
	(0.01449)	(0.02689)	(0.00941)	(0.06776)
50F-60F	-0.00570	-0.01832	-0.00122	0.04091
	(0.01248)	(0.01477)	(0.00931)	(0.03777)
60F-70F	-0.00235	-0.01485	-0.00713	0.08240*
	(0.01417)	(0.01565)	(0.01011)	(0.03963)
70F-80F	0.00981	0.00476	-0.00429	0.02916
	(0.01398)	(0.01718)	(0.01508)	(0.05423)
$\geq$ 80F	0.05808	-0.01473	0.01884	-0.01550
	(0.03922)	(0.04038)	(0.02192)	(0.07443)

Clustered at the state level. Regression includes state by annual quarter and year by annual quarter fixed effects as well as state level controls fully interacted with annual quarter.

Table 4: Effect of Temperature on Mortality By Cause

Estimated Impact of Climate Change on Annual Maternal Mortality Incidence

	Days ≤ 20 F	**Days ≥ 70 F**	**Overall**
Panel A - Deaths in the Year 2090, United States			
U.S. Overall	-131.406	4,230.202**	3,859.688**
	(213.099)	(1913.736)	(1894.608)
Panel B - Cumulative Deaths 2050-2090, United States			
U.S. Overall	-4,957.046	133,005.2**	114,748.9**
	(8105.941)	(58670.1)	(56954.59)

The results from fitting the annual main Poisson estimating equation in combination with Hadley 3 A2B scenario predictions of additional temperature-days in 2050 and 2050 to 2090. Standard errors are clustered at the state level and take the error-corrected Hadley 3 A2B climate change predictions as constants.
+ p≤0.10, * p≤0.05, ** p≤.01

Table 5: Maternal Deaths Expected Due to Additional Days in Each Bin

Figures

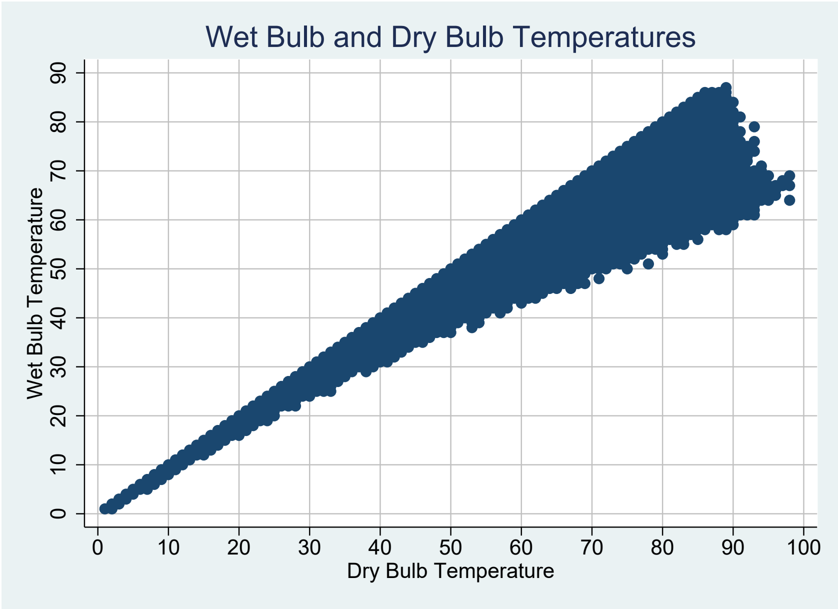


Figure 1: Wet to Dry Temperature Conversion

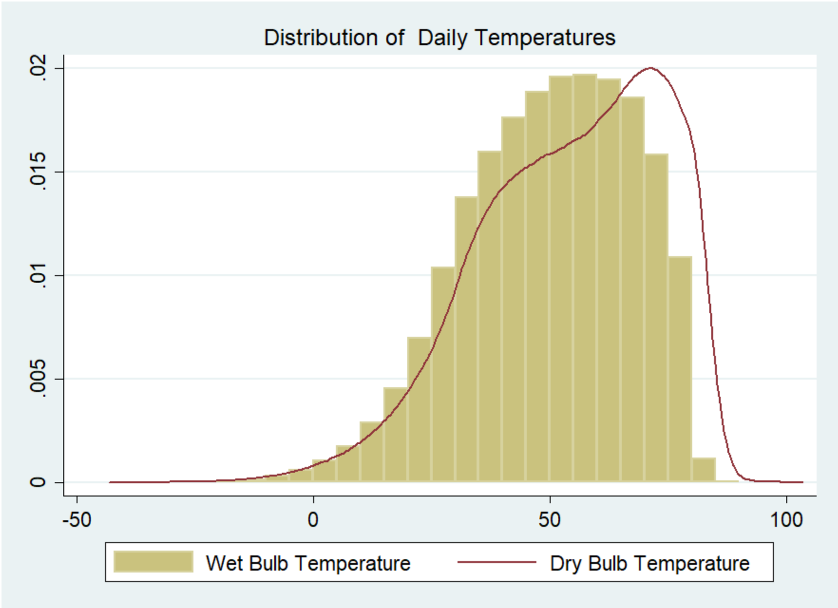
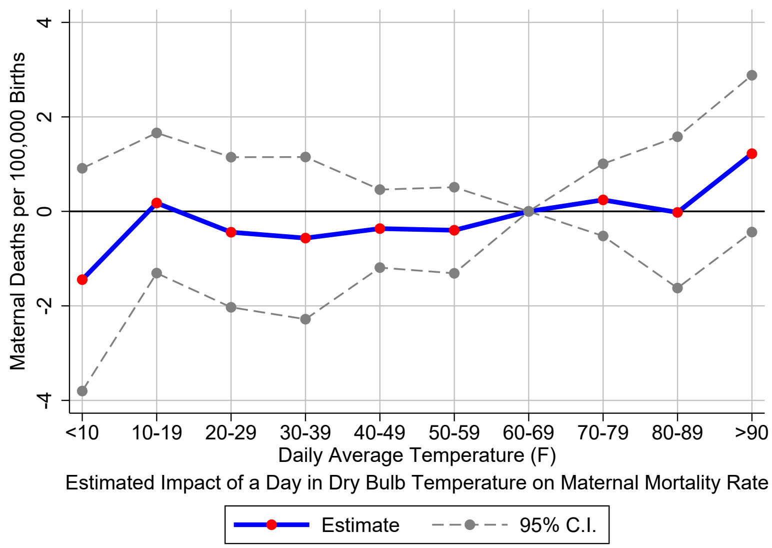
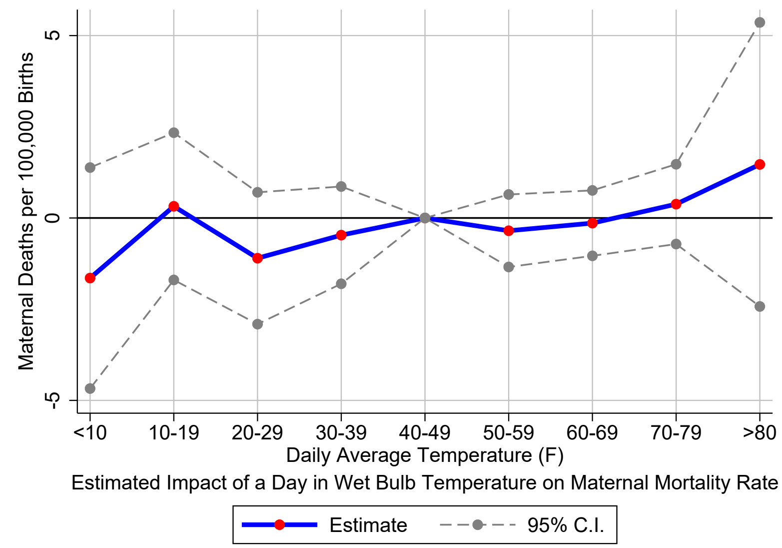


Figure 2: Distribution of Temperatures

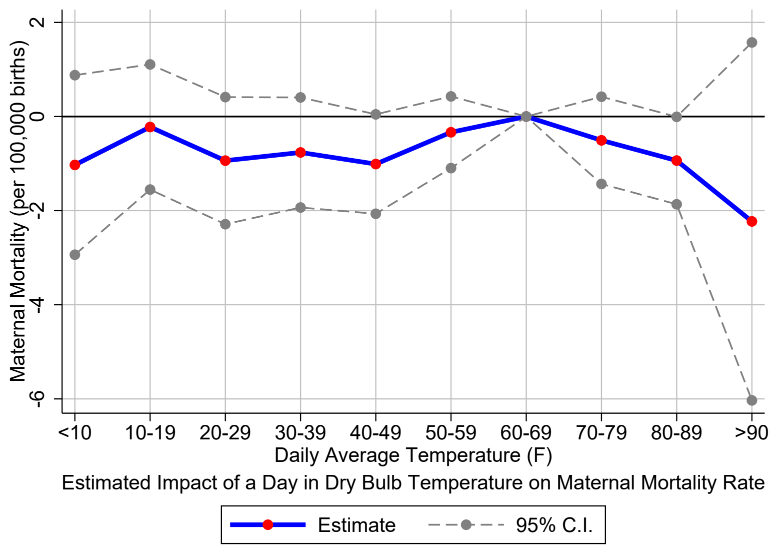


(a) Using Dry Bulb Temperatures

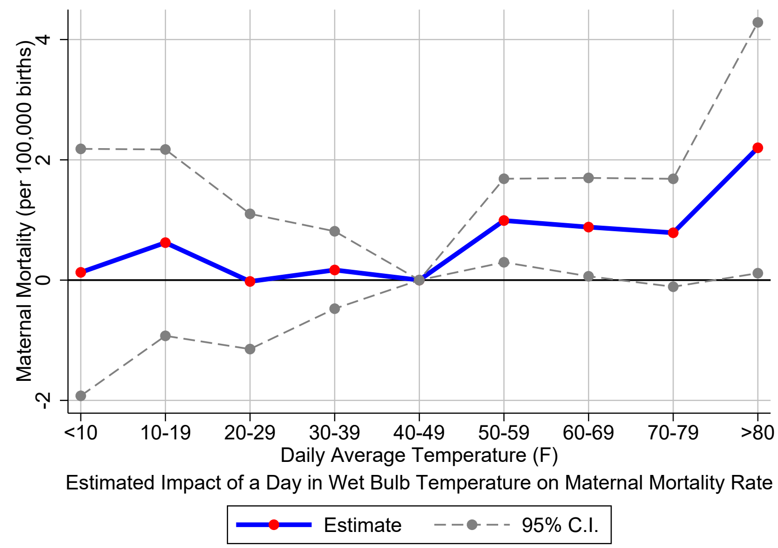


(b) Using Wet Bulb Temperatures

Figure 3: Naive OLS Results

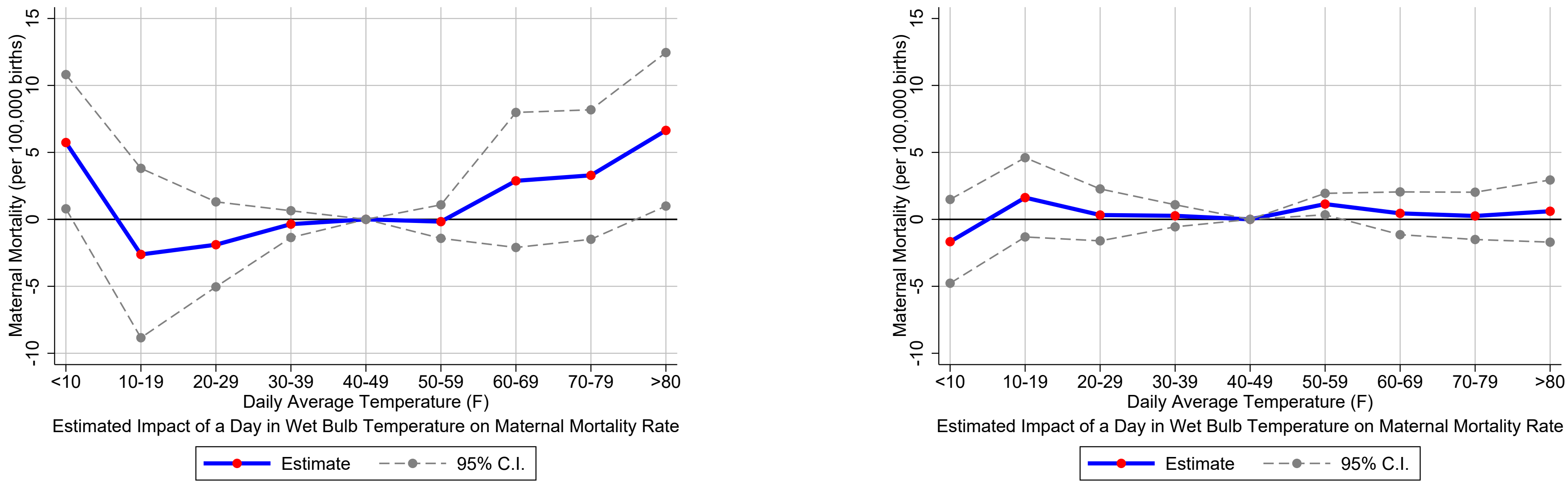


(a) Using Dry Bulb Temperatures



(b) Using Wet Bulb Temperatures

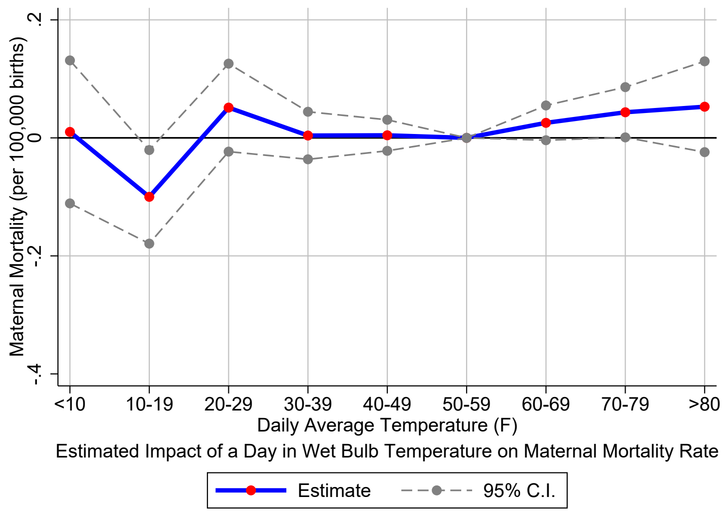
Figure 4: Poisson Results



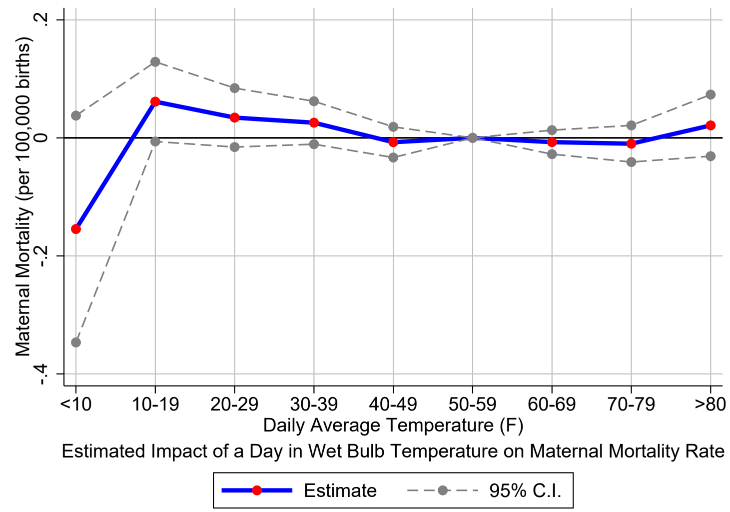
(a) Non-White Women

(b) White Women

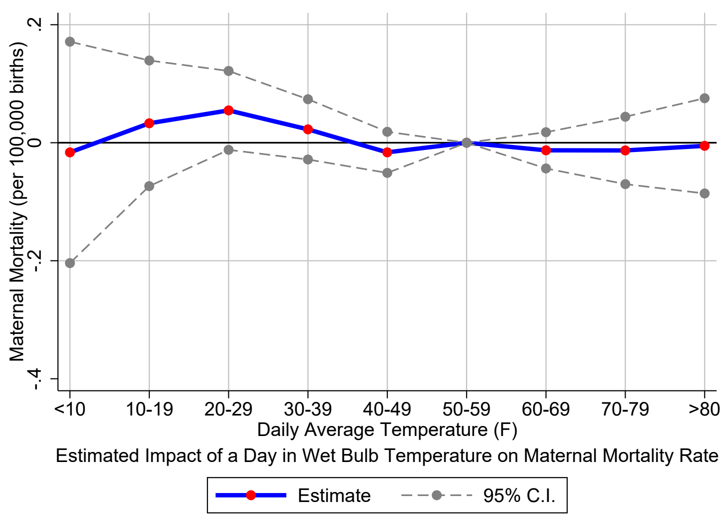
Figure 5: Heterogenous Results by Race



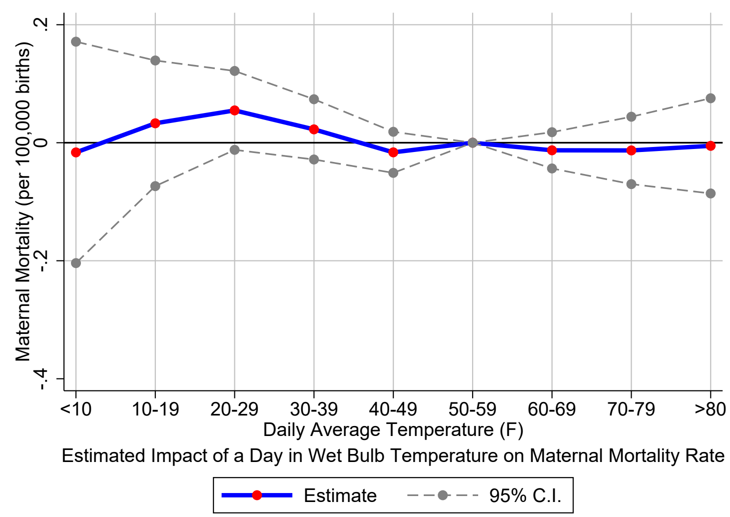
(a) Maternal Mortality Due to Cardiac Complications



(b) Maternal Mortality Due to Infection



(c) Maternal Mortality Due to Hemorrhage



(d) Maternal Mortality Due to General Complications

Figure 6: Results by Cause of Death

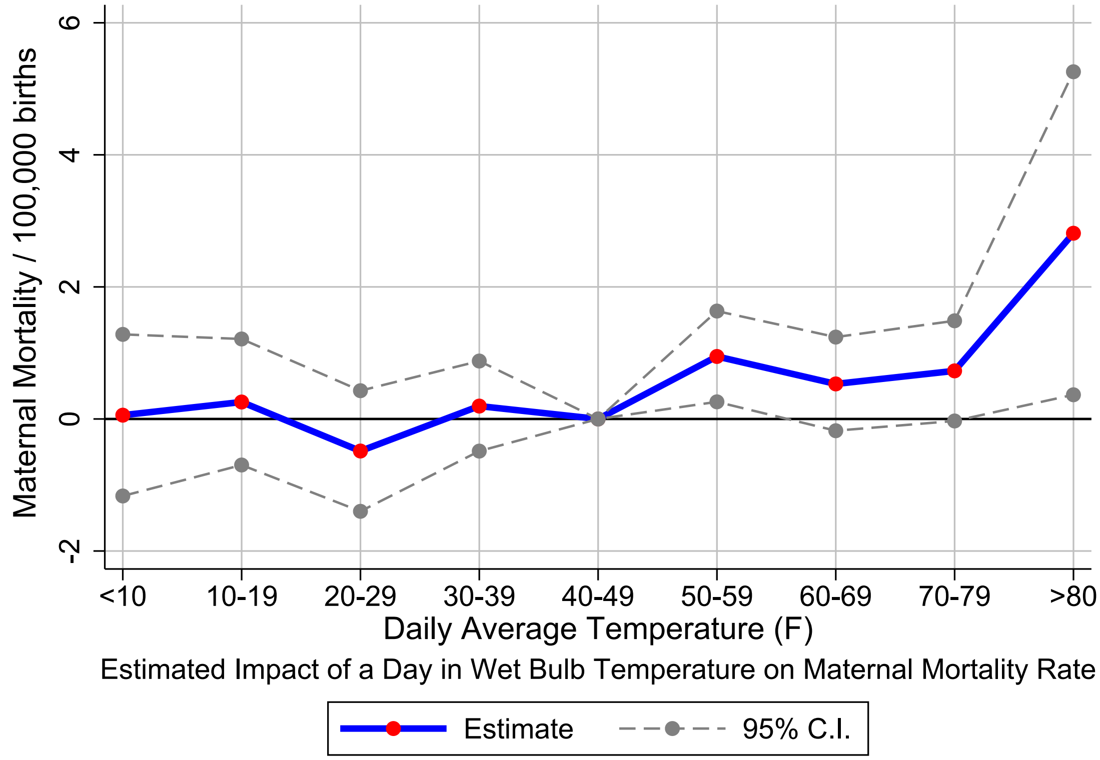


Figure 7: Robustness Check: Annual Maternal Mortality Rates

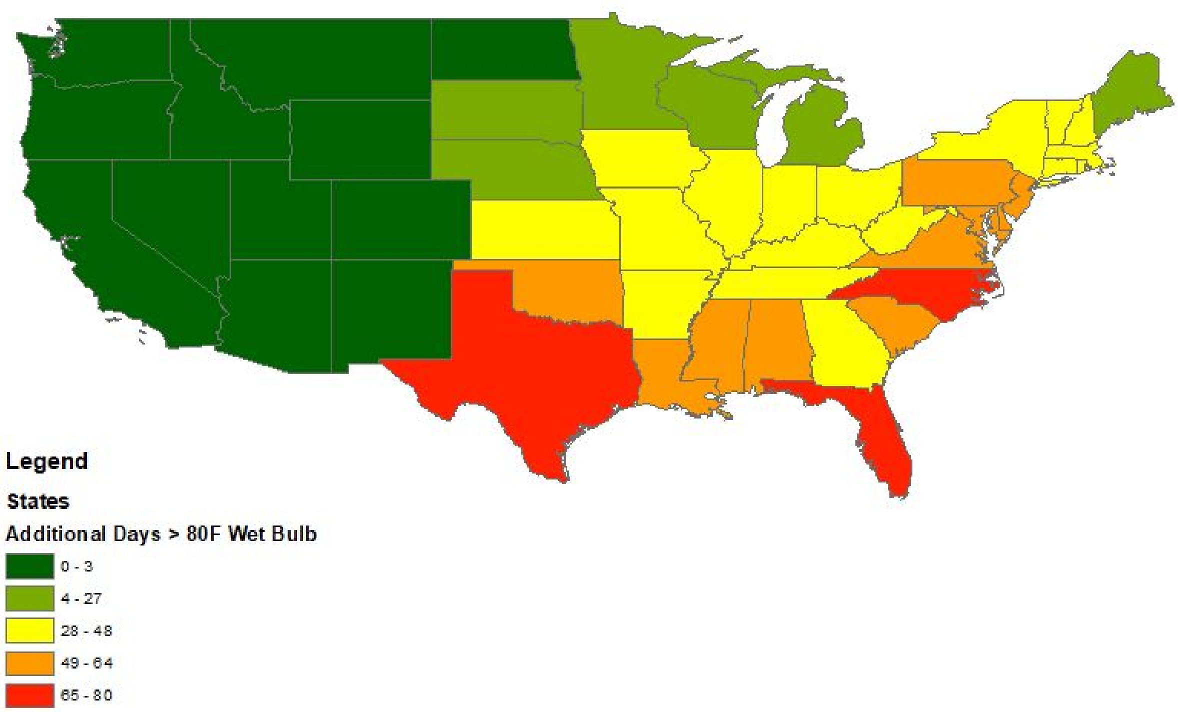


Figure 8: Change in Very Hot Days by 2090

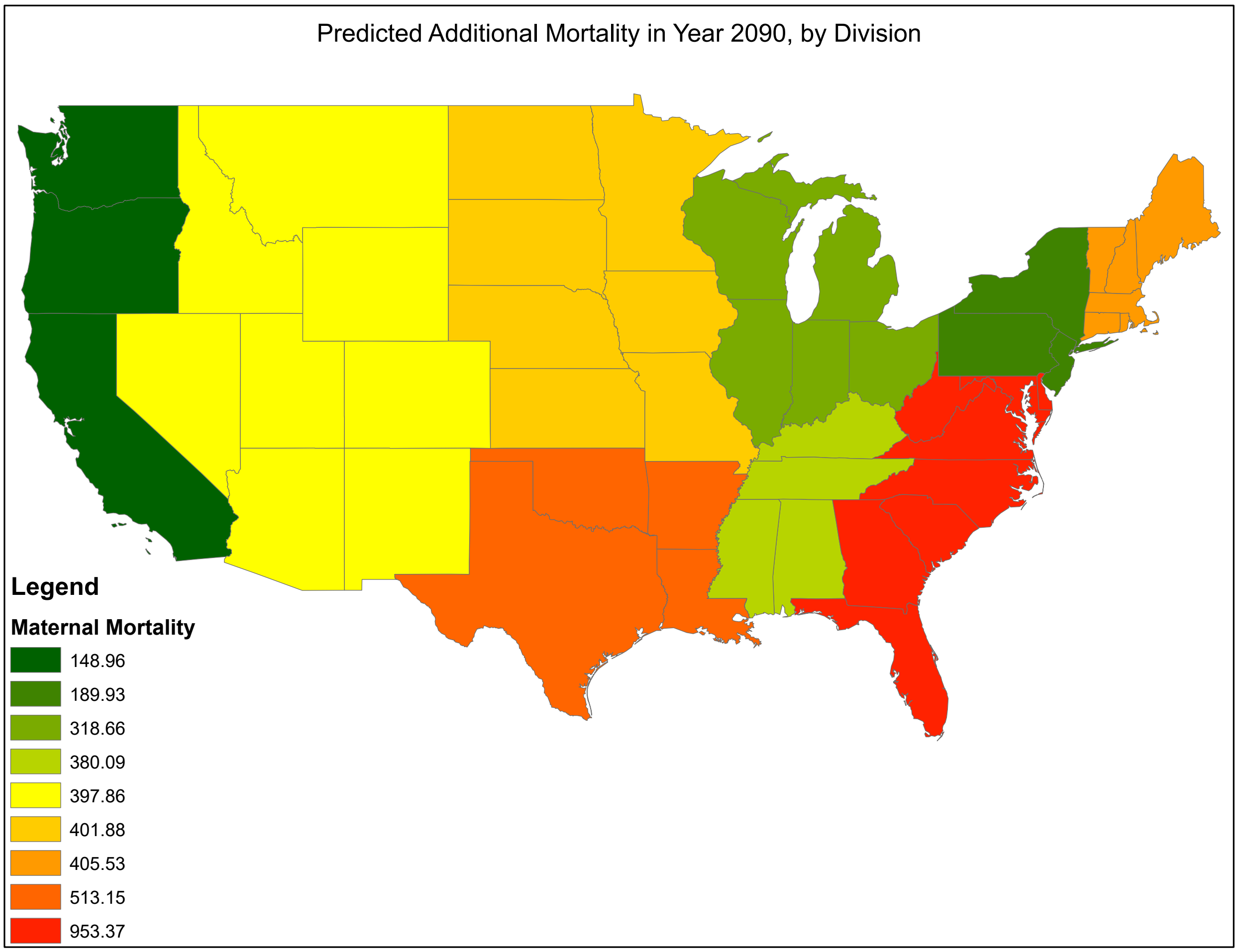


Figure 9: Change in Very Hot Days by 2090

Alternative Specifications

A Tables

Effect of Wet Bulb Temperature and Humidity on Maternal Mortality			
	Two Part Model	Two Part Model	Negative Binomial
Wet Bulb Temperature	Logit (Extensive)	OLS (Intensive)	
≤ 10F	0.02297	-3.91792	0.12627
	(0.024)	(4.596)	(0.09244)
10F-20F	0.00982	1.98636	0.15964*
	(0.014)	(3.263)	(0.06695)
20F-30F	0.006	-2.5924	0.14662+
	(0.012)	(2.465)	(0.08060)
30F-40F	0.0005	-0.97869	0.06163
	(0.009)	(1.328)	(0.04807)
50F-60F	0.00844	-0.86299	0.16775**
	(0.008)	(0.901)	(0.05254)
60F-70F	0.01709	-0.22836	0.25610**
	(0.013)	(0.929)	(0.08642)
70F-80F	0.01416	1.19286	0.27831**
	(0.016)	(1.084)	(0.07868)
≥ 80F	0.03656	3.66063	0.56715**
	(0.028)	(2.942)	(0.19079)

Clustered at the state level. Regression includes state by month and year by month fixed effects as well as state level controls fully interacted with month.

Table 6: Robustness Checks

B Figures

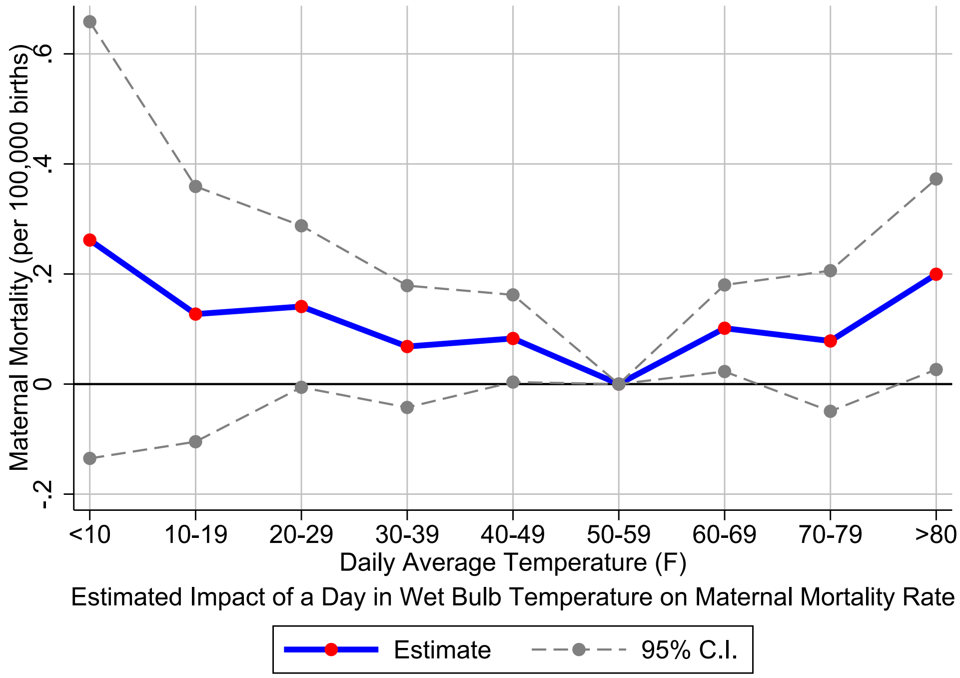
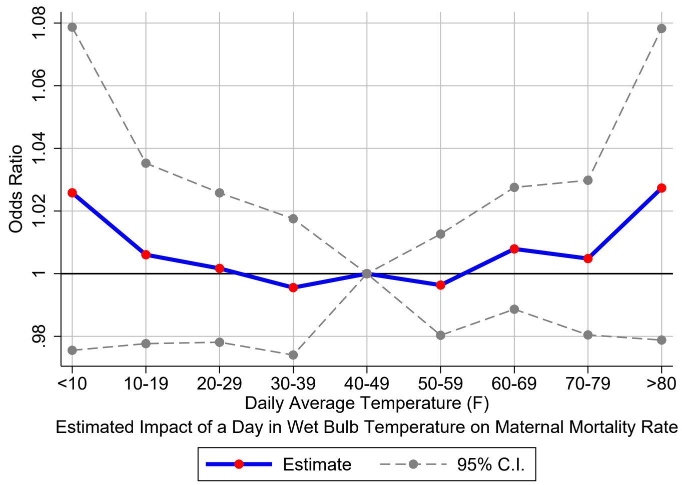
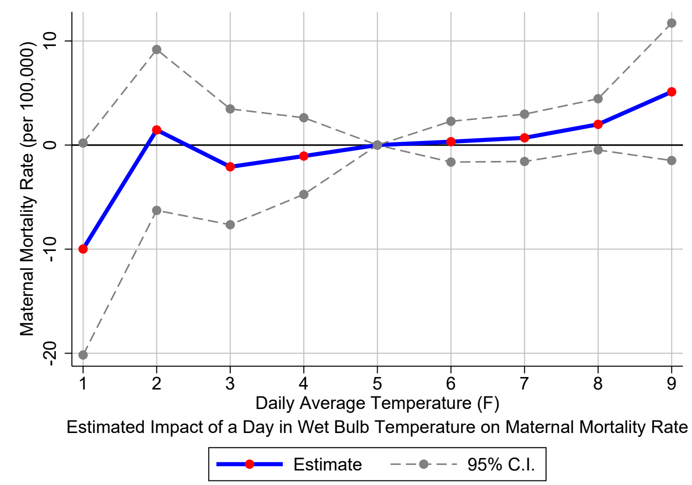


Figure B.1: Negative Binomial with Number of Maternal Deaths Outcome (Wet Bulb)



(a) Logistic Odds Ratio



(b) Conditional Regression

Figure B.2: Wet Bulb Temperature and Maternal Mortality

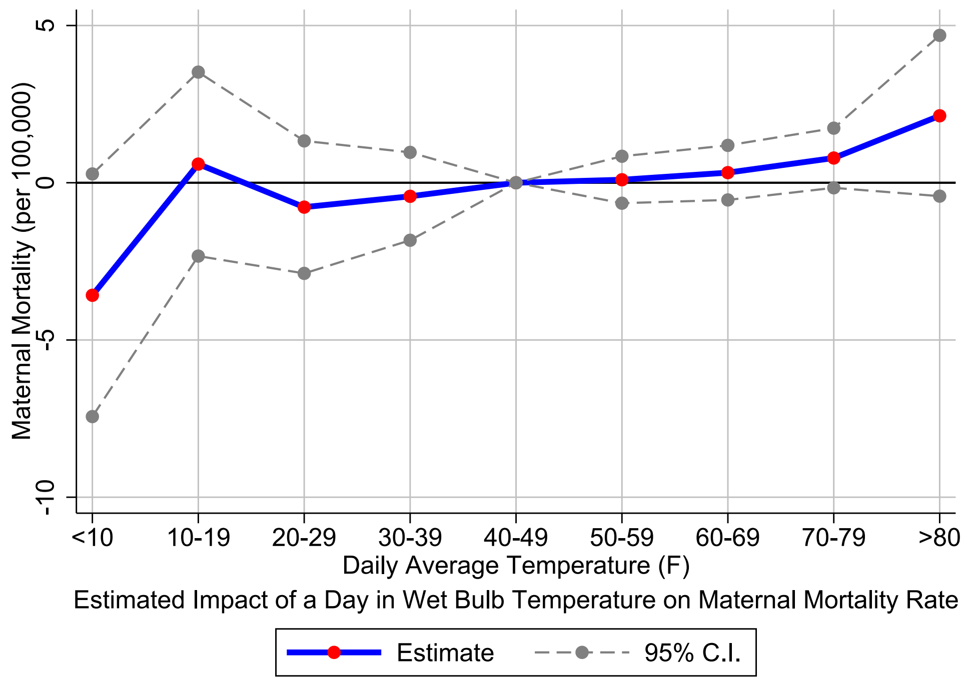


Figure B.3: Total Marginal Effect

Data Appendix

This analysis combines daily temperature data from National Oceanic and Atmospheric Association's (NOAA) Global Historical Climatology Network with specific humidity and air pressure readings from the Princeton Meteorological Forcing Dataset.

The Princeton dataset combines observational data from the Climactic Research Unit's (CRU) historical dataset using weather station observations and Global Precipitation Climatology Project's (GPCP) microwave and infrared measurements as well as outgoing long wave radiation retrievals from multiple satellite instruments in addition to rain gauge observations. These are combined with reanalysis data from the National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR).

Like all reanalysis datasets, the Princeton dataset combines observational data with physics-based models to improve the data in observationally sparse regions. The NCEP-NCAR reanalysis uses balloon data from the NCEO-Global Telecommunications System data as the main observational data source, but includes observations from aircraft data, satellite sounder data sources, and marine data. Biases in the reanalysis precipitation and near-surface meteorology are corrected in the Princeton data using observational data on precipitation, temperature, and radiation. I use the Princeton data for specific humidity and air pressure at a 0.25 x 0.25 degree, 3-hourly resolution from 1963-1998. To produce the final weather variables, I take the following steps:

- From the GHCN dataset I retrieve daily maximum and minimum temperatures from each weather station operating in the United States.

- I keep only observations for weather stations which operated contiguously for a full year.

- Using the Princeton dataset, I assign the highest (lowest) specific humidity recorded each day to correspond to the maximum (minimum) daily temperature and match it with the pressure occurring at the same time of day.

- I match each weather station to the four nearest grid points of Princeton humidity and pressure data.

- I calculate relative humidity for the daily maximum temperature and daily minimum temperature using the following equation:

$$RH = 0.263 * P * SH * [exp(\frac{17.67(T - 273.16)}{T - 29.65})]^{-}1$$

where P is pressure (Pa), SH is specific humidity, and t is temperature (K).

- From the daily maximum (minimum) temperature and the corresponding relative humidity, I calculate wet bulb temperature suing the Stull Calculation, which is standard for sea level pressure:

$$\begin{aligned} wb =& T_c * [atan(0.151977) * (RH + 8.313658)^(1/2)] + atan(T + RH) - \\ & atan(RH - 1.676331) + 0.00391838(RH)^(3/2) * atan(0.023101RH) - 4.686035 \end{aligned}$$

  Where T_c is temperature in degrees Celsius.

- I create a daily mean variable for both wet and dry bulb temperature, with is an average the the daily maximum and minimum.

- From the daily means, I create a 10 temperature bins and classify each daily observation into the bin corresponding the to temperature bin in which the daily average falls.

- I collapse to the monthly level, such that each bin contains a count of number of observations which occur in each bin.