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Weather and Death in India: Mechanisms and Implications for Climate Change*

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ABSTRACT

This paper estimates the impact of inter-annual variation in weather on mortality and well being in India with data from 1957-2000. The main results indicate a highly nonlinear relationship between daily temperatures and annual mortality rates. For example, 1 additional day with a mean temperature above 32° C, relative to a day with a mean temperature in the 22° - 24° C range, increases the annual mortality rate by roughly 0.8%. This effect is almost entirely concentrated in the rural regions of India where even now more than two thirds of the population lives. We then set out to understand the mechanisms behind this result. We analyze the impact of temperature shocks on agricultural outcomes and find evidence that supports the finding of excess rural mortality: Exposure to extreme temperatures causes stark declines in the agricultural wage rate and has no effect on labor supply, causing large declines in rural workers real income. In addition, we analyze the response of the formal banking sector to the temperature shocks. We estimate models that relate credit disbursements per capita to our measure of exposure to extreme temperatures. We find that credit disbursements are negatively impacted in rural areas in periods of unexpected exposure to high temperatures. Based on this evidence it appears that the availability of smoothing mechanisms in response to temperature shocks in the formal sector varies across rural and urban areas and this may explain part of the differential mortality response. Finally, the paper takes the estimated response functions between temperatures, precipitations, and mortality to provide some predictions on the impacts of climate change on mortality in India. It is important to bear in mind that this paper relies on inter-annual variation in temperature and thus will produce an overestimate of the costs of climate change, because individuals can engage in a limited set of adaptation in response to inter-annual variation. With this caveat in mind, our predictions based on 'business as usual' scenarios suggest an increase in the overall Indian annual mortality rate of approximately 8% - 56% by the end of the century. The estimated increase in rural areas ranges between 16% and 71%. As a reference point, a similar exercise suggests that climate change will lead to a roughly 2% increase in the US by the end of the century (Deschenes and Greenstone 2008). These mortality impacts are large. This is true regardless of whether one views them as the current impact of weather shocks on mortality in India or as informative about the costs of climate change.

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Introduction

The climate is a key ingredient in the earth's complex system that sustains human life and wellbeing. This is especially so in poor countries located in hot regions of the Earth. In these places, human wellbeing rests on a thin reed because most economic activity is agricultural and so weather shocks have a direct impact on output. Additionally, extreme temperatures place great stress on the body and can have a direct impact on human health (see e.g., Basu and Samet 2002 for a review). Further, the low levels of income can limit opportunities for adaptation in response to weather shocks. The urgency of the challenges posed by climate in these countries is further underscored by the growing consensus that emissions of greenhouse gases due to human activity are altering the earth's climate, most notably by causing temperatures, precipitation levels, and weather variability to increase (IPCC 2007).

This paper estimates the impact of inter-annual variation in weather on well being in India with data from 1957-2000. It is the first such large-scale study for a developing country that we are aware of. Our primary outcome variable is the mortality rate as this is the ultimate measure of individuals' abilities to smooth consumption and more generally withstand income shocks. This is a break from much of the previous literature in development economics that measures smoothing with expenditures or savings data (see e.g., Morduch 1995 for a survey).

The main results are striking and indicate a highly nonlinear relationship between daily temperatures and annual mortality rates. For example, 1 additional day with a mean temperature above 32° C, relative to a day with a mean temperature in the 22° - 24° C range, increases the annual mortality rate by roughly 0.8%. This effect is almost entirely concentrated in the rural regions of India where even now more than two thirds of the population lives; 1 additional day with a mean temperature above 32° C, relative to a day with a mean temperature in the 22° - 24° C range, increases the annual mortality rate by roughly 1% in rural areas. It is evident that individuals in rural areas are unable to fully smooth consumption across periods or don't have access to technologies to protect them against high temperatures.

We then set out to understand the source of this result. The analysis indicates that an extra day with a mean temperature exceeding 32°C, again relative to a day with a mean temperature in the 22° - 24° C range, leads to a roughly 0.5% decline in the annual wage rate of agricultural workers. Further, we fail to find any evidence that workers adjusted their labor supply either to seek out new types of work or in a dynamic labor supply context. The result is that their annual incomes appear to have declined substantially. This decline is due to a marked reduction in agricultural production associated with these same hot days; put another way, the hot days cause a substantial decline in the marginal product of labor.

In addition, we also analyze the response of the formal banking sector to the temperature shocks. We estimate models that relate deposits per capita and credit disbursements per capita to our measure of exposure to daily temperature fluctuations. The analysis reveals a strikingly different response of the formal banking sector across rural and urban areas. In rural areas, a day with a mean temperature exceeding 32° C, relative to a day with a mean temperature in the 22° - 24° C range, leads to a roughly 0.5% decline in credit disbursements per capita. In urban areas the corresponding figure is a 0.2% increase in credit disbursements per capita. Thus it appears the availability of smoothing mechanisms in response to temperature shocks in the formal sector varies across rural and urban areas may explain part of the differential mortality response.

Finally, the paper takes the estimated response functions between temperatures, precipitations, and mortality to provide some predictions on the impacts of climate change on mortality in India. It is important to bear in mind that this paper relies on inter-annual variation in temperature. This will produce an overestimate of the costs of climate change, because individuals can engage in a limited set of adaptation in response to inter-annual variation.

With this caveat in mind, we combine the estimated impacts of temperature on mortality with predicted changes in climate from 'business as usual' scenarios to develop estimates of the mortality impacts of climate change in India. The preferred mortality estimates suggest an increase in the overall Indian annual mortality rate of approximately 8% - 56% by the end of the century. The estimated increase in rural areas ranges between 16% and 71%. As a reference point, a similar exercise suggests that climate change will lead to a roughly 2% increase in the US by the end of the century (Deschenes and

Greenstone 2008).

These mortality impacts are large. This is true regardless of whether one views them as the current impact of weather shocks on mortality in India or as informative about the costs of climate change.

The analysis is conducted with a new data file that we put together for this paper. It includes the most detailed and comprehensive data available on weather, mortality, agricultural workers' wages and labor supply, crop output and prices, and climate change predictions. These data are available for a panel of more than 600 Indian geographic units from 1957-2000.

Finally, the paper's statistical model has several appealing features. First, the estimation of annual mortality equations, rather than daily ones, mitigates concerns about failing to capture the full mortality impacts of temperature shocks due to harvesting or delayed impacts. Second, the rich data allow us to include separate fixed effects for each geographic unit (i.e., district by rural-urban) so the resulting estimates are adjusted for any differences in unobserved health across locations due to sorting. Third, we model daily temperature semi-parametrically by using fifteen separate variables, so we do not rely on functional form assumptions to infer the impacts of the hottest and coldest days. Fourth, we estimate separate mortality models for infants and those older than 1 year of age, which allows for heterogeneity in the impacts of temperature.

I. Conceptual Framework

The cornerstone of any model of intertemporal consumption choice is the Euler equation of intertemporal optimization that governs consumption decisions:

$$(1)\quad \lambda_t\left(c_t\right)=E_t\left[\left(1+r_{t+1}\right)\lambda_{t+1}\left(c_{t+1}\right)\right].$$

Here $\lambda_t(c_t)$ is the marginal utility of consumption, r_{t+1} is the real interest rate between periods t and t+1, and c_t and c_{t+1} are consumption in periods t and t+1, respectively. The insight is that up to a discount factor, individuals value money at the margin equally in all periods. Indeed in the case where the discount factor equals the interest rate and the marginal utility function is linear in consumption, then current consumption is equal to expected consumption in all periods. These assumptions may be unreasonable in practice, especially in poor countries, however the important insight is that individuals prefer smooth consumptions paths, rather than large fluctuations in consumption from year to year.

The critical assumption that leads to this result is that there is unrestricted borrowing across periods. The availability of unlimited credit means that individuals can move consumption from periods where income is high to periods where it is low. There is a substantial empirical literature that assesses the impact of household-specific shocks on household income (see Morduch 1995 for a review). This literature has found that even in places where formal credit markets are not plentiful, households can smooth away many income shocks through sharing resources with other households, often those of family members (Paxson 1992).

In many respects, this paper is a departure from the consumption smoothing literature because we focus on mortality as a measure of smoothing, rather than consumption. Mortality is certainly a blunt measure of smoothing, indeed it may be the bluntest since $\lambda_t(c_t)$ is likely equal to infinity when death is on the line. Nevertheless, evidence that temperature-induced income shocks increase mortality rates is consistent with a failure to smooth consumption.

It is important to underscore that the temperature-mortality relationship could be due to different channels and not simply provide a test of consumption smoothing. For example, high temperatures place a stress on the body that can lead to mortality (Klinenberg 2002; Huynen et al. 2001; Rooney et al. 1998). Additionally, it may simply be that the rural parts of India where the excess mortality is concentrated lack the infrastructure necessary for individuals to protect themselves from high temperatures, no matter their income level. For example, the absence of reliable electricity service may make the use of electric fans or the production of ice nearly impossible. Finally, the individuals in these areas may be so poor that even with moving consumption across periods they cannot afford life preserving technologies.

III. Data Sources and Summary Statistics

To implement the analysis, we collected the most detailed and comprehensive district-level data available from India on population, births, mortality, wages, agricultural productivity and infrastructures. The latter variables are intend to capture the mechanisms through which extreme temperatures may affect mortality, as well as measures of variables that may help to reduce the impact of climate change on human health. We combine these data with high-frequency daily data on historical weather and predicted future climates. This section briefly describes these data and reports summary statistics. More details on the data sources are provided in the Data Appendix.

A. Data Sources

Mortality and Population Data. The annual mortality and population data are taken from the Vital Statistics of India (VSI) for 1957-2001 which were digitized for this project. These data represent the universe of reported births and deaths in each year. The raw data in VSI are collected via the civil registration system in India and registration was compulsory throughout our sample period, but it is well know that these data suffer from under-reporting.[1] The units of observation are districts, with separate tallies for urban and rural areas.[2] From these we construct 'adult' mortality rates per 1000 population, where adult pertain to population aged 1 or above. We can also derive infant mortality rates per 1000 births, defined as the number of registered deaths before the age of 1 normalized by the number of births in the year. While registration of births and deaths was compulsory throughout our sample period, numerous commentators have argued that some areas of the country suffer from significant under-reporting. As a result, since 1965, a parallel registration system, known as the Sample Registration System, has sought to obtain more accurate vital statistics through the use of randomized sample surveys. We are currently collecting these data and will incorporate them in the analysis as they become available. More details are presented in the data appendix.

In addition to under-reporting, vital statistics are also missing for certain districts in certain years. That is especially true in lower population states. In other to reduce the missing data problem, our main estimation sample is based on vital statistics data from 15 of the largest states: Andhra Pradesh, Bihar, Gujarat, Himachal Pradesh, Jammu and Kashmir, Kerala, Madhya Pradesh, Madras, Maharashtra, Mysore, Orissa, Punjab, Rajasthan, Uttar Pradesh, and West Bengal. These states account for about 85% of India's population and the results in the paper are mostly unaffected by the inclusion or exclusion of the states with the higher rate of missing data.

Agricultural Sector Data. The data on agricultural outputs, price, and labor market outcomes come from the 'India Agriculture and Climate Data Set', which was prepared by the World Bank.[3] The file contains detailed district-level data from the Indian Ministry of Agriculture and other official sources for 271 districts over the period 1956-1987. The major agricultural states are included in the database, with the exceptions of Kerala and Assam. We are currently working on expending some of these series to 2000.

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[1] According to the National Commission on Population of India, only 55% of the births and 46% of the deaths are being registered.

[2] The rural/urban assignment is based on the following criteria: "(a) all places with a Municipality, Corporation or Cantonment or Notified Town Area; and (b) all other places which satisfied the following criteria: (i) a minimum population of 5,000, (ii) at least 75% of the male working population was non-agricultural, and (iii) a density of population of at least 400 per sq. Km. (i.e. 1000 per sq. Mile)."

[3] Lead authors are Apurva Sanghi, K.S. Kavi Kumar, and James W. McKinsey, Jr.

Weather Data. A key finding from Deschenes and Greenstone (2008) is that a careful analysis of the relationship between mortality and weather requires daily weather data. This is because the relationship between mortality and temperature is highly nonlinear and the nonlinearities would be missed with annual or even monthly temperature averages. Although India has a system of weather stations with daily readings dating back to the 19th century, the geographic coverage is poor (interestingly there are more stations prior to 1970). Further, there are many missing values so the application of a selection rule that requires observations from 365 days out of the year would yield a database with very few observations.

As a solution, we follow Guiteras (2008) and use data from a gridded daily dataset that use non-public data and sophisticated climate models to construct daily temperature and precipitation records for 1° (latitude) × 1° (longitude) grid points (excluding ocean sites). This data set, called NCC (NCEP/NCAR Corrected by CRU), is produced by the Climactic Research Unit, the National Center for Environmental Prediction / National Center for Atmospheric Research and the Laboratoire de Météorologie Dynamique, CNRS. These data provide a complete record for daily average temperatures and total precipitation for the period 1950-2000. To capture the distribution of daily temperature variation within a year, we assign each gridpoint's daily mean temperature realization to one of fifteen temperature categories. These categories are defined to include daily mean temperature less than 10° C (50° F), greater than 36° C (96.8° F), and the thirteen 2° C wide bins in between. The 365 daily weather realizations within a year are distributed over these fifteen bins. This binning of the data preserves the daily variation in temperatures, which is an improvement over the previous research on the mortality impacts of climate change that obscures much of the variation in temperature.

We model the impact of precipitations by using monthly averages. This provides enough flexibility to capture the differential effects of precipitation during the monsoon season and other periods of the year. Given the nature of the precipitation distribution in India, where 60% of the yearly precipitation falls between June and September, more flexible models are too demanding on the data.

To create daily district-level weather records from the grid points, we take weighted averages of the binned daily mean temperature variables and binned annual precipitation variables for all grid points within 100 KM of each district's geographic center. The weights are the inverse of the squared distance from the district center. On average, there are 1.9 grid points within the 100 KM radii circles. The subsequent results are insensitive to taking weighted averages across grid points across distances longer than 100 KM and using alternative weights (e.g., the distance, rather than the squared distance). This method preserves a great deal of the variation and allows us to semi-parametrically model daily temperature and precipitation in the subsequent analysis. After the inverse distance weighting procedure, 339 out of a possible 342 districts have a complete weather data record.[4]

B. Summary Statistics

Vital Statistics Data. Table 1 summarizes the available vital statistics data from the 1957-2000 period. The data are reported separately by state, and throughout this paper we focus on the 1961 geographical classification, and have adjusted the district-level data for post-1961 splits. The first column reports the total number of districts, the second reports the number of districts for which we have non-missing vital statistics data for at least one year, and the third column details the fraction of district by year observations with non-missing data over the entire sample.

In our main sample, the mean annual population is about 547 million, with 408 million living in rural areas. The five states with populations exceeding 50 million are Andhra Pradesh, Bihar, Madhya Pradesh, Maharashtra, and West Bengal.

The table reveals that measured mortality rates are high throughout this period. For example, the infant mortality rate is 40.5 per 1,000. Geographically, infant mortality rate ranges from 17.7 per 1,000 in Kerala to 71.3 per 1,000 in Orissa, revealing the substantial heterogeneity. As a basis of comparison, the mean US infant mortality rate over these years was roughly 12 per 1,000. The Indian overall mortality rate was 6.6 per 1,000. It is important to recall that these mortality rates are likely to be understated and we explore that below.

Figure 1 provides an opportunity to understand the time variation in the age 1+ mortality rate (Panel A) and the infant mortality rate (Panel B). These time series are plotted separately for rural and urban areas. There is a remarkable decline in both mortality rates in rural and urban regions. For example, the overall mortality rate declines from roughly 12 in 1957 to about 4 in rural areas and 6 in urban areas by 2000. The decline in the infant mortality rate is also impressive, going from about 100 per 1,000 in 1957 to roughly 13.5 per 1,000 in 2000. In the econometrics section, we describe our strategy to avoid confounding these trends in mortality rates with any time trends in temperatures.

Weather Statistics. Table 2 reports on national and state-level measures of observed temperatures and precipitation from 1957-2000. This is calculated across all district by year observations with non-missing vital statistics data, where the weight is the total district population in the year.

Column (1) in Table 2 reports that for India as a whole, the average daily mean temperature is 25.7° C. This reflects the variation across all years and district, as well as the within-year variation. The

[4] These districts are Alleppey (Kerala), Laccadive, Minicoy, and Amindivi Islands, and the Nicobar and Andaman Islands.

entries for the 15 states reveal the substantial geographical variation in this average, which ranges from 11.9°C (Jammu and Kashmir) to 27.5°C (Andhra Pradesh). Column (2) reports the average number of days per year exceeding 32° C (89.6° F). Across India, the average exposure is 33.1 days per year or roughly 1 month. There is substantial variation across states, to a major larger extent than the variation in average daily temperatures. Residents of Rajasthan are exposed to 61 days above 32C per year while residents of Kerala are exposed to none on average. These statistics are relevant, because the subsequent analysis reveals that the largest mortality impacts occur on days when the temperature exceeds 32° C. In fact, some of our analysis will be based on models where the number of days in excess of 32° C of average daily temperature is used as a "single-index" measure risk factor due to exposure to extreme temperature.

Columns (3)-(5) report statistics on precipitations. Column (3) shows the average total annual precipitation (in centimeters). The national average is roughly 1 meter, and it ranges from 60.1 centimeters per year on average in Rajasthan to 171.5 centimeters in West Bengal. A well-known feature on the precipitation distribution in India is that most days are without any significant rainfall. This is shown in column (4) which reports the number of days per year with less than 0.2 cm of rainfall. The national average is 257 such days per year, and every of the fifteen states in Table 2 faces at least 195 days per year with practically no precipitation. The last column considers the other extreme, that is, days with 3 cm or more in precipitation. Across states, the average is about 3 such days per year, with a geographical range of 2-6 days.

Figure 2 depicts the average variation in the measures of temperature across the fifteen temperature categories or bins, again during the 1957-2000 period. The height of each bar corresponds to the mean number of days that the average person in the vital statistics data experiences in each bin; this is calculated as the weighted average across district-by-year realizations, where the district-by-year's total population is the weight. The average number of days in the modal bin of 26° - 28° C is 72.9. The mean number of days at the endpoints is 3.7 for the less than 10° C bin and 3.4 for the greater than 36° C bin.

Figure 3 shows the average monthly precipitation, over the period 1957-2000. This is calculated as the weighted average across district-by-year realizations, where the district-by-year's total population is the weight. It is well known that precipitations are not uniformly distributed over the course of the year in India, and the figure shows that. July is the wettest month, with an average of 25.5 cm of rain per district, while January is the driest, with just about 1 cm of average precipitation.

Agricultural Data. Table 3 reports on a series of agricultural variables constructed for this analysis over the 1957-87 period. These variables are all recorded at the district level and pertain to rural India. Over the course of the sample, average daily wage is 6.88 Rs. (1980 Rs). This mean wage is calculated as a weighted means across districts where the weights are the district's rural population in the most recent Census. Wages are the highest in Punjab (12.67) and the lowest in Madhya Pradesh (5.34). We also report averages of our labor supply measures, which are reported in million man-days. Column 2 reveals that in an average year, Indians work 20.8 billion man-days per year in the agricultural sector. There is substantial across variation in man-days, reflecting population differences, and differences in agricultural sector intensity. The last two columns break down the total agricultural labor supply into agricultural laborers (landless, work for wage) and cultivators (cultivate land that they either own or sharecrop). The majority of the agricultural labor supply (in man-days) comes from cultivators.[5]

Rural Public Goods and District-Level Banking Data. Our analysis will also investigate a large host of potential mechanisms and mitigating factors. A first mechanism considered is the availability (or lack thereof) of formal sector consumption smoothing mechanisms. To this end, we will utilize data from the banking sector for 1972-2000.[6] The data set contains the number of functioning bank branches, number of accounts amount of deposits and credit disbursements (in lakhs), among all types of banks (public or private), in rural and urban areas. The deposits and credits totals are collected for one or more months over the course of the year. After 1990, the deposit/credit totals are collected in March. In prior years the data is available for more months, which we averaged to get March equivalent totals.[7]

We will also investigate the role of local public health infrastructures as potential mitigators of temperature shocks and study the extent of differential mitigation across rural and urban areas. In particular, we will estimate models with interactions between the temperature effects with measures of per capita availability of local hospitals and dispensaries. These data were we obtained from the 1991 Census of India and contain information on the stock of public goods available in each town and village of each district.[8]

IV. Econometric Strategy

This section describes the econometric models used to predict the impact of climate change on mortality

[5] The Census defines an agricultural laborer as a person who worked in another person's land for wages in cash, kind or share. Such a person had no risk in cultivation and had no right of lease or contract on the land on which he worked. A cultivator is defined as one engaged either as employer, single worker or family worker in cultivation of land owned or held from government, private institutions or persons for payment in money, kind or share of crop. Cultivation included supervision or direction of cultivation, and included ploughing, sowing, harvesting and production of cereals and millet crops, but not fruits or vegetables (definitions taken from Maryland Indian District Database).

[6] We thank Shawn Cole for providing these data.

[7] To have only month per year for each district, from December 1972-June 1989, we averaged over December year 'x' and June year 'x+1' to get the equivalent of March year 'x+1'.

[8] Jammu and Kashmir was not surveyed in 1991 due to political instability. In addition, a number of districts do not have areas satisfying the definition of either urban or rural.

and other outcomes in India. The basic estimating equation is:

$$(2)\ Y_{dt} = \sum_j \theta_j TMEAN_{dtj} + \sum_{m=1}^{12} \delta_m TOTPREC_{dtm} + \alpha_d + \gamma_t + \lambda_S t^3 + \varepsilon_{dt},$$

where Y_{dt} is the log mortality rate (or an alternative outcome) in district d in year t. The s subscript refers to a state. The last term in the equation is the stochastic error term, ε_{dt}.

The variables of interest are the measures of temperature and precipitation. The variables $TMEAN_{dtj}$ denote the number of days in district d and year t where the daily mean temperature is in the j^{th} of the fifteen bins used in Figures 2. Thus, the only functional form restriction is that the impact of the daily mean temperature on the annual mortality rate is constant within 2°C degree intervals. The choice of fifteen temperature bins represents an effort to allow the data, rather than parametric assumptions, to determine the mortality-temperature relationship, while also obtaining estimates that are precise enough that they have empirical content. This degree of flexibility and freedom from parametric assumptions is only feasible because we are using district-level data from 44 years.

The variables in $TOTPREC_{dtm}$ denote the total precipitation in month m, in district d and year t. The average of these variables is displayed in Figure 3. The equation includes a full set of district fixed effects, α_d, which absorb all unobserved district-specific time invariant determinants of the mortality rate. So, for example, permanent differences in the supply of medical facilities will not confound the weather variables. The equation also includes unrestricted year effects, γ_t. These fixed effects control for time-varying differences in the dependent variable that are common across districts (e.g., changes in health related to the 1991 economic reforms). The assumption that shocks or time-varying factors that affect health are common across districts is unlikely to be valid. Consequently, equation (2) includes separate cubic time trends for each of the five regions of India. Since the underlying weather data only varies for 1° (latitude) × 1° (longitude) squares, it isn't possible to control for time-varying local determinants of health as flexibly as would be ideal. In the below, we demonstrate that the results are robust to a series of methods to control for these shocks.

The validity of this paper's empirical exercise rests crucially on the assumption that the estimation of equation (2) will produce unbiased estimates of the θ_j and δ_m vectors. By conditioning on the district, year fixed effects, and cubic state time trends, these parameters are identified from district-specific deviations in weather about the district averages after controlling for the portion of shocks that remains after adjustment for the year effects and cubic state-specific trends. Due to the unpredictability of weather fluctuations, it seems reasonable to presume that this variation is orthogonal to unobserved determinants of mortality rates.

There are two further issues about equation (2) that bear noting. First, it is likely that the error terms are correlated within districts over time. Consequently, the paper reports standard errors that allow for heteroskedasticity of an unspecified form and that are clustered at the district level. Second, we fit weighted versions of equation (2), where the weight is the square root of the population in the district (i.e., the denominator) for two complementary reasons. The estimates of mortality rates from large population counties are more precise, so it corrects for heteroskedasticity associated with these differences in precision. Further, the results reveal the impact on the average person, rather than on the average district, which we believe is more meaningful.

V. Results

This section is divided into several subsections. The first provides estimates of the impact of annual shocks to the temperature distribution on annual mortality rates. This analysis is stratified by age group and by rural/urban sectors. The second examines the relationship between temperature and precipitation shocks on the agricultural outcomes such as wages and employment. The last section uses these relationships to infer the predicted impact of climate change on the mortality rates in the overall population.

A. Relationship Between Daily Temperature and Precipitation Exposure and Mortality

Figure 4 plots the regression coefficients (i.e., $\hat{\theta}_j$) from the estimation of the pooled regression for our two age groups and across urban and rural areas. Since the number of days per year is always 365 (we dropped the 366 days in leaping years), we must normalize the coefficient for one of the bins. The bin associated with 22°-24° C was normalized to zero, so each θ_j measures the estimated impact of an additional day in bin j on the log annual mortality rate, relative to the impact of a day in the 22° - 24° C range. The figure also plots the estimated θ_j 's plus and minus two standard errors, so their precision is evident.

It is evident that mortality risk is highest at the hottest temperatures. Indeed, the response function shows a significant and increasing relationship between log mortality rates and temperature beginning with days that exceed 30°C. The largest coefficient is for the highest temperature bin (>36C). The magnitude is nearly 0.01, so exchanging a single day in this range for one in the 22°-24° C range would lead to a reduction in annual mortality rates of 1%. It is noteworthy that the null of equality with the base category can be rejected at the conventional significance levels for all bins above the reference category, with the exception of the 28°-30° C bin. Finally, the coefficients associated with the temperatures bins below the reference category are all smaller in magnitude and are estimated with lesser precision.[9]

Figure 5 reports the coefficients associated with the 12 variables corresponding to monthly precipitation, measured in cm. The results indicate that the impact of rainfall on mortality is not uniform over the course of the year. For example, an extra cm of rainfall in the month of June leads to a 0.3% increase in annual mortality, while an extra cm of rainfall in December leads to a 0.8% decline in annual mortality. It is important to note that only the effect of rainfall in January, February, June, July, November, and December are individually statistically significant at the 5% level. The null hypothesis of joint equality to zero of the precipitation effects is easily rejected at the 5% level.

B. Differential Impacts Across Rural and Urban Sectors

Figure 6 presents estimated response functions between log annual mortality rate and temperature exposure, estimated separately for rural and urban sectors. Again, these models pool across age groups and pertain to the total population of a sector.

Panel A shows the rural response function. The response function shows a significant and increasing relationship between log mortality rates and temperature beginning with days that exceed 24°C. The largest coefficient is for the highest temperature bin (>36C), and the magnitude is 0.013, so exchanging a single day in this range for one in the 22°-24° C range would lead to a reduction in annual mortality rates of 1.3% in the rural sector. The statistical precision of the coefficients above the reference category is evidence as shown by the 95% confidence interval that is bounded away from 0. However, the coefficients associated with the temperatures bins below the reference category are all smaller in magnitude and not statistically different from 0.

[9] The p-value on a joint test of equality of the temperature effects to zero is less than 0.0001.

Panel B shows the response function estimated from the urban population. The results are remarkably different than in the rural sector. The largest coefficient is for the highest temperature bin (>36C), and the magnitude is roughly 0.003, so exchanging a single day in this range for one in the 22°-24° C range would lead to a significant reduction in annual mortality rates of 0.3% in the urban sector. It is notable to none of the other temperature effects are statistically significant, and all are relatively small in magnitude. As such the estimates of the response function in urban areas suggest either a better availability of adaptation mechanisms to temperature shocks, or perhaps the lesser connection between extreme temperatures and well-being in these areas.

C. Specification Analysis and Further Results

Table 4 report estimates of the relationship between temperature and mortality across sub-samples and for various specifications, while controlling for monthly precipitations, and the usual set of fixed effects and trends. For brevity, we report these as point estimates rather than figures. Specifically, we estimate variants of equation (2) were we replace the 15 temperature bins by the average daily temperature in a district over the course of the year. This provides a parsimonious specification that captures the salient temperature effects reported in the previous figures.

The first column in Table 4 shows the 'baseline' estimates that pool all age groups. The stark rural/urban difference in the effect of high temperatures on mortality documented earlier is also evident using this more parsimonious specification. The estimates indicate that a 1°C increase in average daily temperature leads to a 12% increase in mortality in rural areas and essentially no effect on mortality in urban areas. The hypothesis of equality of the temperature effects across urban and rural areas is rejected with a p-value of 0.002.

Rows 2 and 3 pertain to models that are estimated separately for the 2 ages groups available in the VSI (infants and ages 1+). The basic results are also maintained here, with the added information that the impacts on infants are slightly larger in magnitude than those for the individuals aged 1+. For both age groups, there is excess rural mortality associated with higher daily temperatures, and the rural/urban equality is rejected at the conventional level.

Row 4 is based on a model pooling the two age groups, but that allows for interactions between the temperature and the monthly precipitation effects. The estimates reported correspond to the marginal effects evaluated at the sample mean of the relevant variables. The point estimates are essentially the same as those reported in the first column. Finally, row 5 adds the controls for the previous years's temperature and precipitation to allow for the possibility that equation (2) inadequately accounts for the dynamics of the mortality-weather relationship. The marginal effects reported are the sum of the current and previous years's temperature effects. The similarity of the estimates in columns 1 and 5 suggest that the dynamics are well-captured with a single year of exposure period.

Taken as a whole, the evidence provided so far demonstrates an important and pervasive rural/urban difference in the impact of exposure to extreme temperatures on annual mortality. In the next section we build on the predictions of our consumption smoothing model and set out to empirically understand why the response functions vary so dramatically across urban and rural areas.

D. Impacts of Weather Fluctuations on Agricultural Labor Market and Output

In this section we focus on the rural sector of India and examine the rela
tionship between inter-annual temperature fluctuations and outcomes in the agricultural labor market (wages and labor supply) as well as agricultural output. Since all agricultural activities take place in the rural sector, we use the words interchangeably.

Figure 7 shows the response function liking agricultural daily wage and the fifteen temperature bins used in all the models so far. The wage measure corresponds to the average daily agricultural wage in a state-district-year, expressed in Rupees. In addition to the 12 controls for monthly precipitation, the regression model also controls for controls for year effects, cubic region*year trends, and district effects. The dependent variable is the log agricultural wages and the model is weighted by census population.

The salient feature of Figure 7 is the negative impact of exposure to hot temperatures on agricultural wages. Each of the point estimates above the reference category (22°-24° C) are statistically significant at the conventional level and range from -0.2% to -0.5%. For example, the coefficient for the highest temperature bin (>36°C) is -0.5%, and so exchanging a single day in this range for one in the 22°-24° C range would lead to a increase in agricultural wages of 0.4%. There also appears to be a significant relationship between agricultural wages and low temperatures, although the relationship is not as precisely estimated. The key point is that agricultural productivity as measured by the daily wage is reduced in period of exposure to too high or too low temperatures, a finding that is confirmed below when we examine other measure of agricultural productivity.

Figure 8 displays the estimated relationship between labor supply and temperature shocks. In this model, the dependent variable is the log total man-days worked in the agricultural sector.[10] It is clearly evident that the labor supply response to the wage effects documented in Figure 7 is negligible. The point estimates are very close to zero, and the confidence intervals includes zero in all temperature bins. One interpretation of the findings in Figures 7 and 8 is that the labor supply curve in the agricultural sector is essentially vertical and so a change in labor demand induced by temperature shocks leads to an

[10] This includes labor supply (in man-days) by agricultural laborers and cultivators.

adjustment only on the wage margin and not on the labor supply. As such increased exposure to extreme temperatures is likely to cause agricultural income to decline substantially.

E. Impacts of Weather Fluctuations on Credit Disbursements

In this section we analyze another potential explanation for the rural/urban differential in the effect of extreme temperature on mortality. One possible explanation for the excess rural mortality is a rural/urban difference in the direct effect of temperature on mortality (i.e. the heat stress effect). Any other explanation involves differences in the adaptation mechanisms that varies by rural and urban sector.

One such potential explanation is the differential ability by households to smooth consumption in the rural and urban sectors. The literature on consumption smoothing has focused on access to credit in the formal and informal sectors as one the chief instruments available to household to smooth consumption. Here we investigate this possibility and examine how rural/urban differences in availability of credit may have contributed to the large rural excess mortality following exposure to extreme temperatures.

To this end, we estimate models that relate log bank credits disbursements per capita to the same measures of exposure to daily temperatures and precipitation that we considered before. A full description of the data is presented in Section III. As before, the models also control for unrestricted year effects, cubic region*year trends and unrestricted district effects. Figure 9 presents the results of this analysis. It shows the estimated response function between log credit disbursements and the 15 temperature variables, separately by rural and urban areas (Panels A and B, respectively). There are clear differences in the profiles that support the hypothesis of differential access to credit in rural and urbans areas following episodes of extreme temperatures. In rural areas, days above 32C cause log credit disbursements to decline by a significant 0.3-0.6%. The corresponding figure for urban areas suggest that exposure to days above 32C *increases* credit payments by 0.1-0.2%, although the effects are not statistically significant. Nevertheless, a test of equality of the temperature response functions across rural and urban rejects the null hypothesis of equality at the 0.001 level. So clearly there is differential availability of smoothing mechanisms, and it may have contributed to the observed mortality differential.

Taken as a whole, the evidence presented so far suggest a dramatic increase in mortality in response to exposure to hot temperatures. One explanation for this is the direct channel that links mortality to exposure, because of thermal stress on the human body (Basu and Samet 2002). However, it is unlikely that heat stress hypothesis can reconcile the large rural/urban mortality differentials. Therefore, we have also investigated the source of this differential.

First, the evidence suggests that agricultural workers in rural India have limited capacity to adjust to the temperature shocks and smooth consumption across periods. Real wages strongly decline in years with more extreme temperatures. Labor supply adjustment to these shocks appears small and therefore the total agricultural wage bill must decline substantially in these years. Combined with the evidence of higher crop prices and lower crop revenues per hectare it is clear that exposure to extreme temperatures causes significant declines in agricultural real income. Finally, there is clear evidence of differential rural/urban access to credit following exposure to extreme temperatures. We are currently investigating the role of local public health infrastructure in mitigating the impact of the temperature shocks.

VI. Implications for Climate Change

Climate Change Prediction Data. Climate predictions are based on two state of the art global climate models. The first is the Hadley Centre's 3rd Coupled Ocean-Atmosphere General Circulation Model, which we refer to as Hadley 3. This is the most complex and recent model in use by the Hadley Centre. We also use predictions from the National Center for Atmospheric Research's 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).

Predictions of climate change from both of these models are available for several emission scenarios, corresponding to 'storylines' describing the way the world (population, economies, etc.) may develop over the next 100 years. We focus on the A1FI and A2 scenarios. These are "business-as-usual" scenarios, which are the proper scenarios to consider when judging policies to restrict greenhouse gas emissions. See the Data Appendix for more details on these scenarios.

We obtained <u>daily</u> temperature and precipitation predictions for grid points throughout India from the application of A1FI scenario to the Hadley 3 model for the years 1990-2099 and the A2 scenario to the CCSM 3 for the years 2000-2099. The Hadley model gives daily minimum and maximum temperatures, while the CCSM model reports the average of the minimum and maximum. Each set of predictions is based on a single run of the relevant model and available for an equidistant set of grid points over land in India.

We calculate future temperature and precipitation realizations by assigning each district a daily weather realization directly from the Hadley and CCSM predictions. Specifically, this is calculated as the inverse-distance weighted average among all grid points within a given distance from the county's centroid. These daily predicted temperature realizations are used to develop estimates of predicted end of century climate.[11] The Hadley 3 model has predictions for the years 1990 through 2099. We utilize the

[11] We follow an analogous procedure to obtain precipitation predictions.

historical predictions to account for the possibility of model error.[12] In particular, we undertake the following multiple step process:

1. For each Hadley 3 grid point, we calculate the daily mean temperature for each of the year's 365 days during the periods 1990-2000 and 2070-2099. These are denoted as $T^{H}_{gt2070-2099}$ and $T^{H}_{gt1990-2000}$, respectively, where the H superscript refers to Hadley 3, g indicates grid point and t references one of the 365 days in a year (e.g., January 15).

2. We calculate the grid point-specific predicted change in temperature for each of the 365 days in a year as the difference in the mean from the 2070-2099 and 1990-2000 periods. This is represented as $\Delta T^{H}_{gt} = (T^{H}_{gt2070-2099} - T^{H}_{gt1990-2000})$.

3. We then take these grid-point specific predicted changes for all 365 days and assign district-specific predicted changes by taking weighted averages within 250 KM of the district centers. Again, the weight is the inverse of the square of distance. This procedure yields a predicted change in the daily mean temperature for all 365 days for each district or ΔT^{H}_{dt}, where d denotes district.

4. Using the NCC weather data, we calculate the grid-point specific daily mean temperature for each of the 365 days over the 1957-2000 period. We then take weighted averages of these daily mean temperatures for all grid points within 100 KM of each district's geographic center, with the same weights as above. This yields $T^{NCC}_{dt1957-2000}$.

5. The predicted end of century climate for each day of the year is equal to $T^{NCC}_{dt1957-2000}$ + ΔT^{H}_{dt}. To preserve the daily variation in temperature, we apply the fifteen temperature bins from above to these 365 daily means. The resulting distribution of temperatures is the Hadley 3 predicted end of century distribution of temperatures that is utilized in the subsequent analysis.

In the case of the CCSM 3 predictions, we are unable to account for model error because these predictions are only available for the years 2000 through 2099, so there aren't historical years available to remove model error.

Before proceeding, it is important to underscore that the validity of the paper's estimates of the impacts of climate change depend on the validity of the climate change predictions. The state of climate modeling has advanced dramatically over the last several years, but there is still much to learn, especially about the role of greenhouse gases on climate (Karl and Trenberth 2003). Thus, the Hadley 3 A1FI and CCSM 3 A2 predictions should be conceived of as two realizations from a superpopulation of models and scenarios. The sources of uncertainty in these models and scenarios are unclear, so it cannot readily be

[12] At least in the case of the Hadley model, there is evidence of model error. See, for example, Deschenes and Greenstone (2008) for some evidence of model error in the Hadley 3 A1FI predicted temperature in the US.

incorporated into the below estimates of the impacts of climate change. Nevertheless, the use of two sets of daily business as usual climate change predictions provides some sense of the variation.

Figure 10 provides a fuller opportunity to understand how climate change is expected to change the full distributions of daily mean temperatures. The figure reveals that there will be large reductions in the number of days in the 14° to 28° C range. These reductions are predicted to be offset by increases in days with temperatures exceeding 28° C. Thus, the mortality impacts of climate change rest on the impact of the days in the 14° to 28° C ranger, relative to days at higher temperatures. Due to India's already warm climate, it is unlikely to get much benefit from reductions in the number of days in its left tail of the temperature distribution, which stands in stark contrast to Russia and other relatively cold countries.

Finally, Figure 11 reports the predicted change in the monthly precipitations according to our two climate models. Both models suggest an increase in total annual precipitations of about 30 cm (38 cm in CCSM and 25 cm in Hadley), but this increase is not distributed uniformly across the year. The largest predicted increases in the CCSM model are in the months of April and May (a combined increase of about 20cm), while the largest increases in the Hadley predictions are in June and July (a combined increase of about 11 cm). These model differences in predicted change in precipitation will in turn explain some of the model differences in the predicted impacts of climate change on mortality.

Climate Change Impacts on Mortality in India. The revealed mortality-weather relationship can be combined with any predictions about climate change to develop estimates of mortality impacts. As noted before, this approach will produce an overestimate of the costs of climate change, because individuals can engage in a limited set of adaptation in response to inter-annual variation.

Figure 10 demonstrated that the state of the art climate models predict dramatic increases in the number of days in the two highest temperature bins, especially the > 32°c bins. Further, these increases are largely predicted to be offset by decreases in the number of days in the middle of the temperature distribution where mortality rates are the lowest. Under these scenarios, India will exchange relatively low mortality days for high mortality ones.

We now turn to a more precise calculation of the predicted mortality impacts of climate change on India. Table 6 presents estimates based on the estimation of equation (2) for the various subsamples. The predictions are based on the Hadley 3 A1FI and CCSM 3 A2 models, and pertain to the years 2070-2099. The impacts reported are based on district-level predictions calculated as the population weighted average of:

$$(3)\ \sum_j (\hat{\theta}_j \bullet \Delta TMEAN_{dj}) + \sum_{m=1}^{12} (\hat{\delta}_m \bullet \Delta PREC_{dm})$$

That is, the predicted change in the number of days in each temperature cell in a district ($\Delta TMEAN_{dj}$) is multiplied by the corresponding impact on log mortality rate ($\hat{\theta}_j$). A similar calculation is done for the number of days in each precipitation bin. The final estimate corresponds to the weighted average of (3) across all districts in India, where the weight is the population. The standard errors of the predictions are calculated accordingly.

Columns (1a) – (1c) summarize this calculation for the three daily mean temperature categories (i.e., < 16° C, 16° - 32° C, and > 36° C). Column (2) reports the total temperature impact and column (3) adds in the impact of the change in monthly precipitation. Column (4) reports the total effect of climate change by summing the temperature and precipitation impacts. Finally the rows correspond to different statistical models and different climate change models.

For each climate change model, we calculate the predicted % change in annual mortality for rural areas, urban areas, and India as a whole. All models are based on the pooled age specification. The top panel reports the Hadley 3 A1FI results and suggests that climate change would lead to a 56.4% increase in the annual mortality rate in India. These estimates are precise and importantly the null hypothesis of a zero effect is rejected at conventional significance levels. Examination of column (1c) shows that the increased mortality is entirely attributable to the increase in the number of very hot days (where the mean temperature exceeds 32°C).

The next columns break down the analysis by rural/urban area. As before, the results are sharply different for urban and rural areas. For rural areas, annual mortality rates are predicted to increase by 71% and this estimate is precise, with robust t-statistics in excess of 3. Again, the increased mortality is almost entirely attributable to the increase in the number of very hot days (where the mean temperature exceeds 32°C). Column 3, which focuses on urban areas tells a completely different story. The predicted change in annual mortality is 11.8%, and is not statistically distinguishable from zero at the conventional level.

The lower panel shows the results derived from the CCSM 3 A2 model. The predicted change in annual mortality are smaller than in Panel A, but still large and concentrated in the rural areas, ranging from -3% to 15.5%. The discrepancy between the Hadley and CCSM predictions reflects in part the fact that the A1FI scenario is associated with larger increases in temperature than the A2 scenario. In addition, the increase in precipitation in the CCSM model is associated with significant predicted declines in mortality.

The overall CCSM impacts are insignificant, but like in Panel A, it is clear that the increase in annual mortality is caused by the predicted increase in exposure to extreme temperatures. It is noteworthy that the segment of the temperature distribution that is predicted to increase the most (days above 32°C) is associated with large and significant increase in annual mortality rates.

VI. Conclusions

This study has produced the first such large-scale study of the impact of weather shocks on mortality and adaptations for a developing country that we are aware of. It is based on the finest geographical data available on mortality for India over the period 1957-2000, augmented with rich high-frequency data on historical daily weather realizations and predicted future climates.

The results are striking and indicate a highly nonlinear relationship between daily temperatures and annual mortality rates. For example, we find that a <u>single</u> additional day with a mean temperature above 32° C, relative to a day with a mean temperature in the 22° - 24° C range, increases the annual mortality rate by roughly 0.8%. This effect is even larger in the rural regions of India where even now more than two thirds of the population lives.

We then empirically examine possible explanations for this large impact in the rural areas of India. One key finding is that an extra day with a mean temperature exceeding 32° C, again relative to a day with a mean temperature in the 22° - 24° C range, leads to a roughly 0.5% decline in the annual wage rate of agricultural workers. Further, we fail to find any evidence that workers adjusted their labor supply either to seek out new types of work or in a dynamic labor supply context. The result is that their annual incomes appear to have declined substantially. The key point is that in addition to any direct effect of heat exposure on mortality because of thermal stress on the body, part of the large mortality effect in rural areas is caused by limited capacity of the rural Indians engage in sufficient consumption smoothing to preserve life in response to temperature shocks.

Finally, the paper takes the estimated response functions between temperature and mortality to provide some predictions on the impacts of climate change on mortality in India. It is important to bear in mind that this paper relies on inter-annual variation in temperature. This will produce an overestimate of the costs of climate change, because individuals can engage in a limited set of adaptation in response to inter-annual variation.

With this caveat in mind, we combine the estimated impacts of temperature on mortality with predicted changes in climate from 'business as usual' scenarios to develop estimates of the mortality impacts of climate change in India. The preferred mortality estimates suggest an increase in the overall Indian annual mortality rate of approximately 8% - 56% by the end of the century. The estimated increase in rural areas ranges between 16% and 71%.

These mortality impacts are large. This is true regardless of whether one views them as the current impact of weather shocks on mortality in India or as informative about the costs of climate change.

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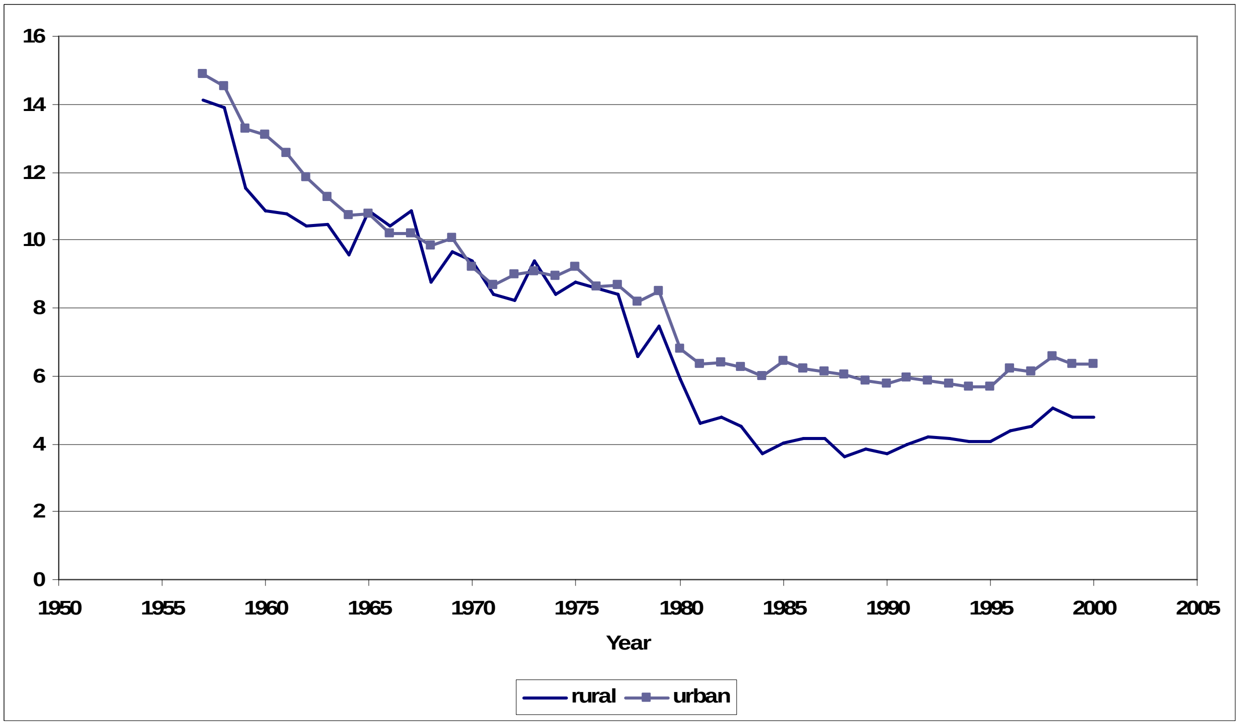
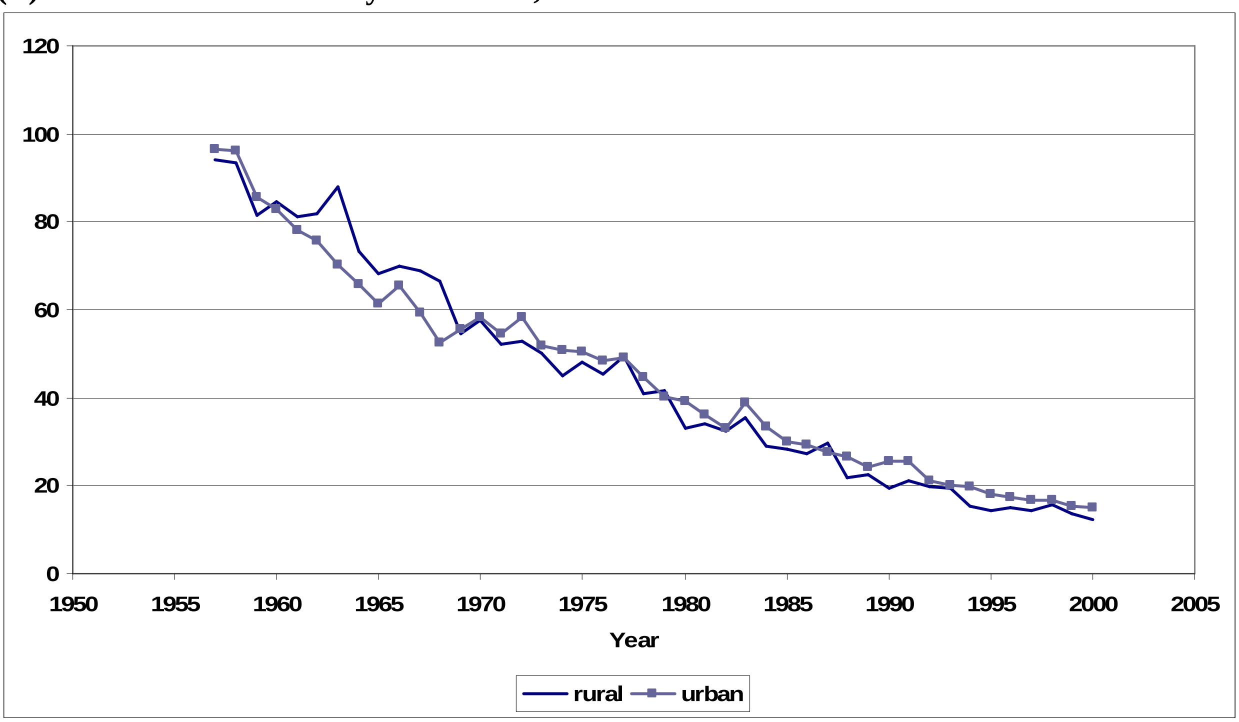
Figure 1: Trends in Mortality Rates by Rural/Urban Designation, 1957-2000

(A) Annual Mortality Rate Per 1,000 Population (excluding infants)



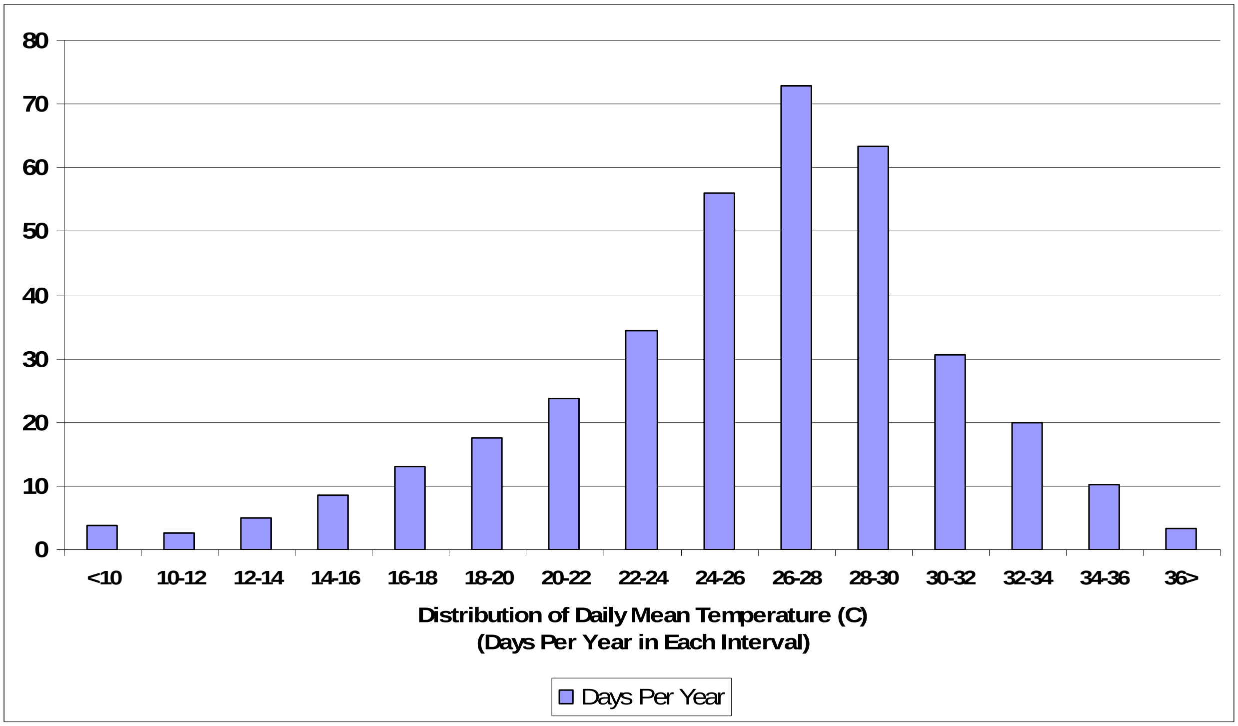
Notes: Means weighted by census population

(B) Annual Infant Mortality Rate Per 1,000 Live Births



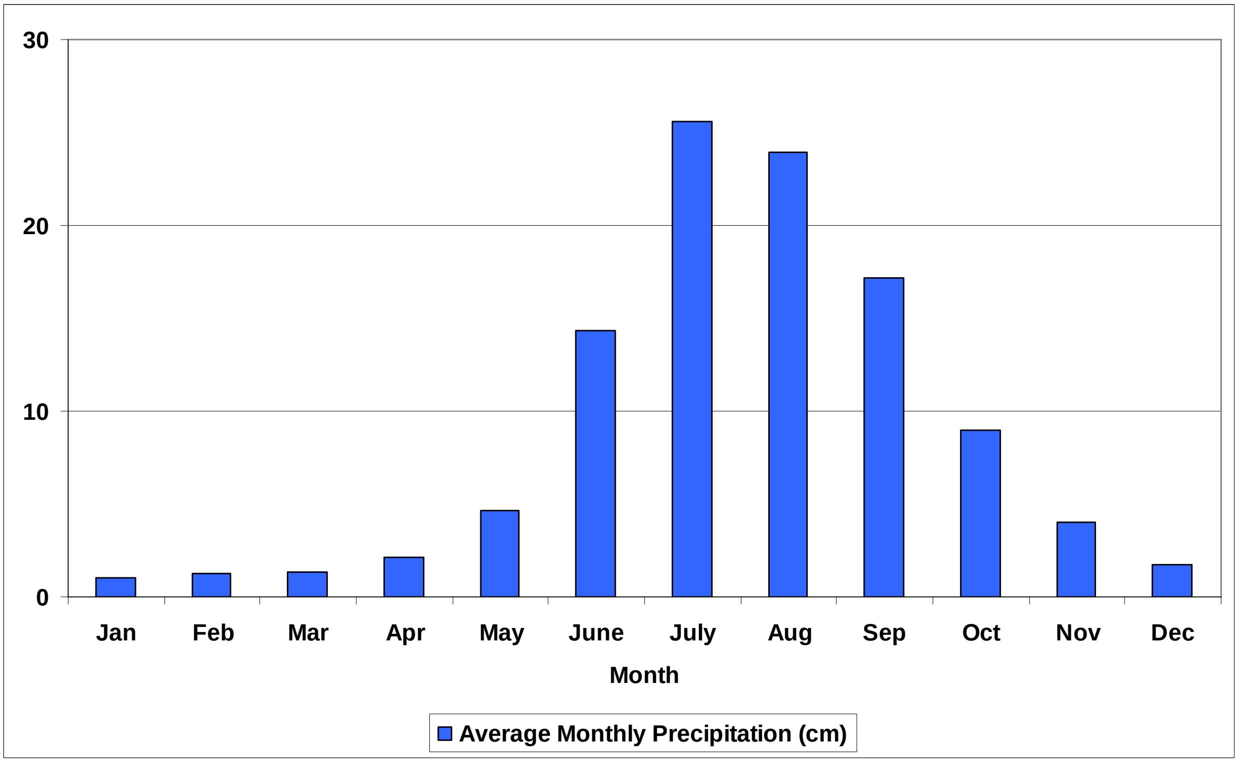
Notes: Means weighted by number of births

Figure 2: Annual Distribution of Daily Mean Temperature, 1957-2000



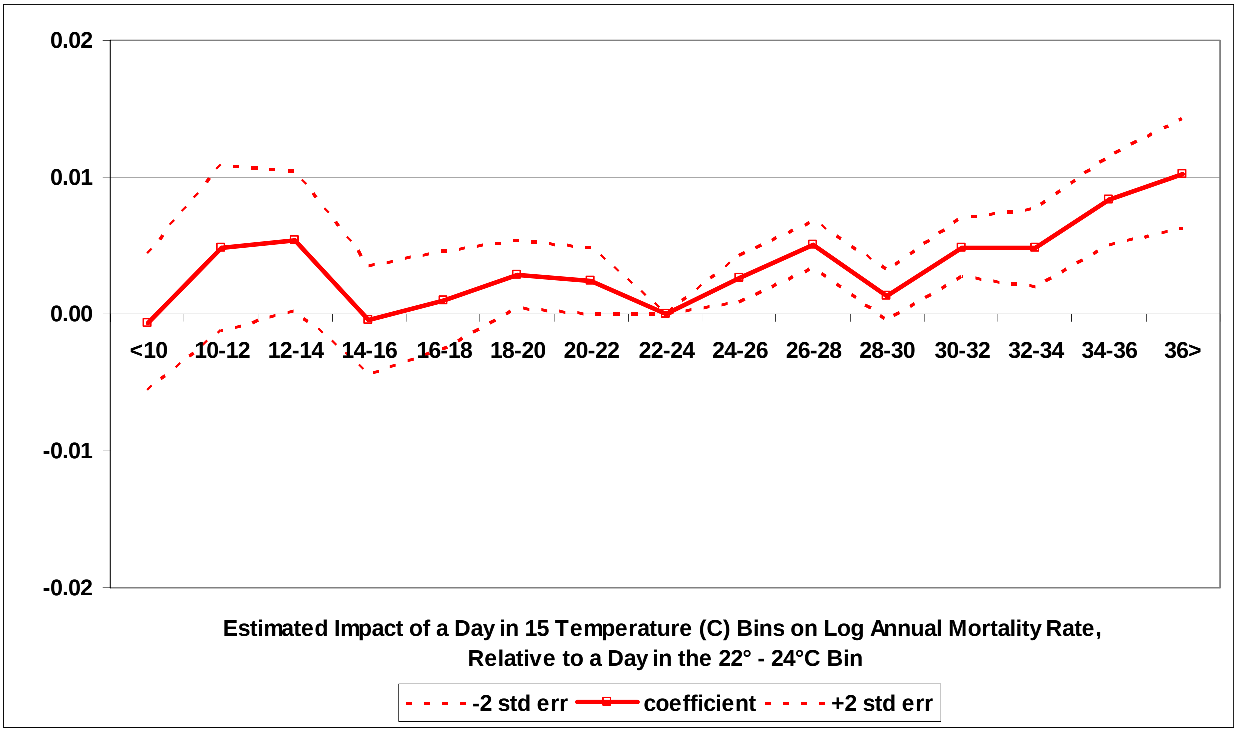
Notes: Means weighted by census population

Figure 3: Average Monthly Precipitations, 1957-2000 (cm)



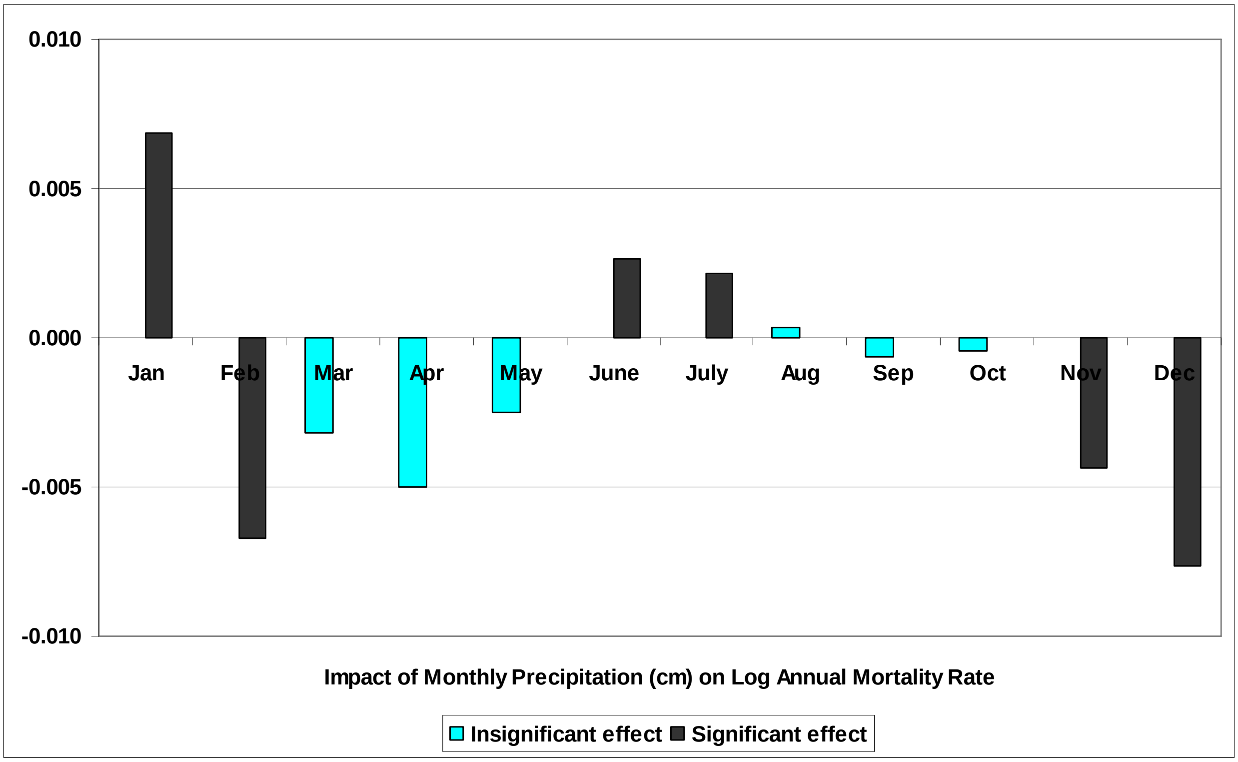
Notes: Means weighted by census population

Figure 4: Estimated Response Function Between Daily Temperature Exposure and Log Annual Mortality Rate (All Ages)



Notes: The dependent variable is the log annual all-age mortality rate. The model also includes controls for monthly total precipitation and controls for unrestricted year effects, cubic region*year trends and unrestricted district effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

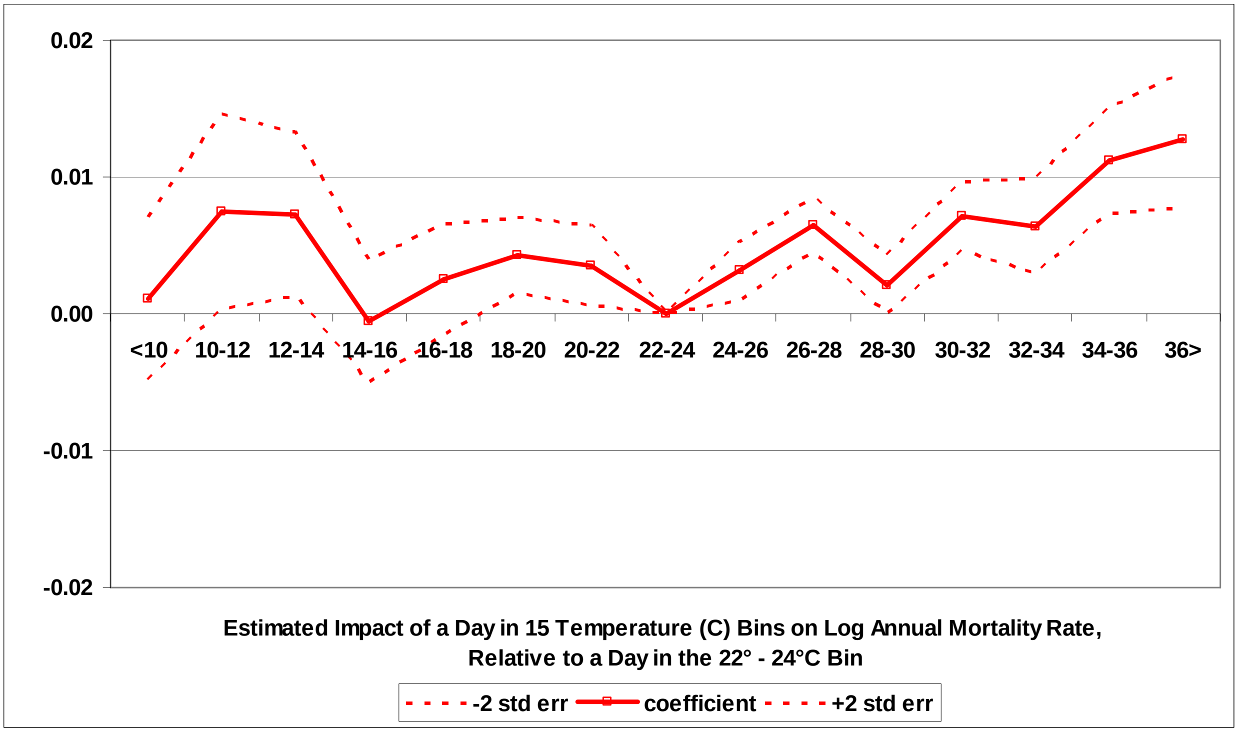
Figure 5: Estimated Impact of Monthly Precipitation on Log Annual Mortality Rate (All Ages)



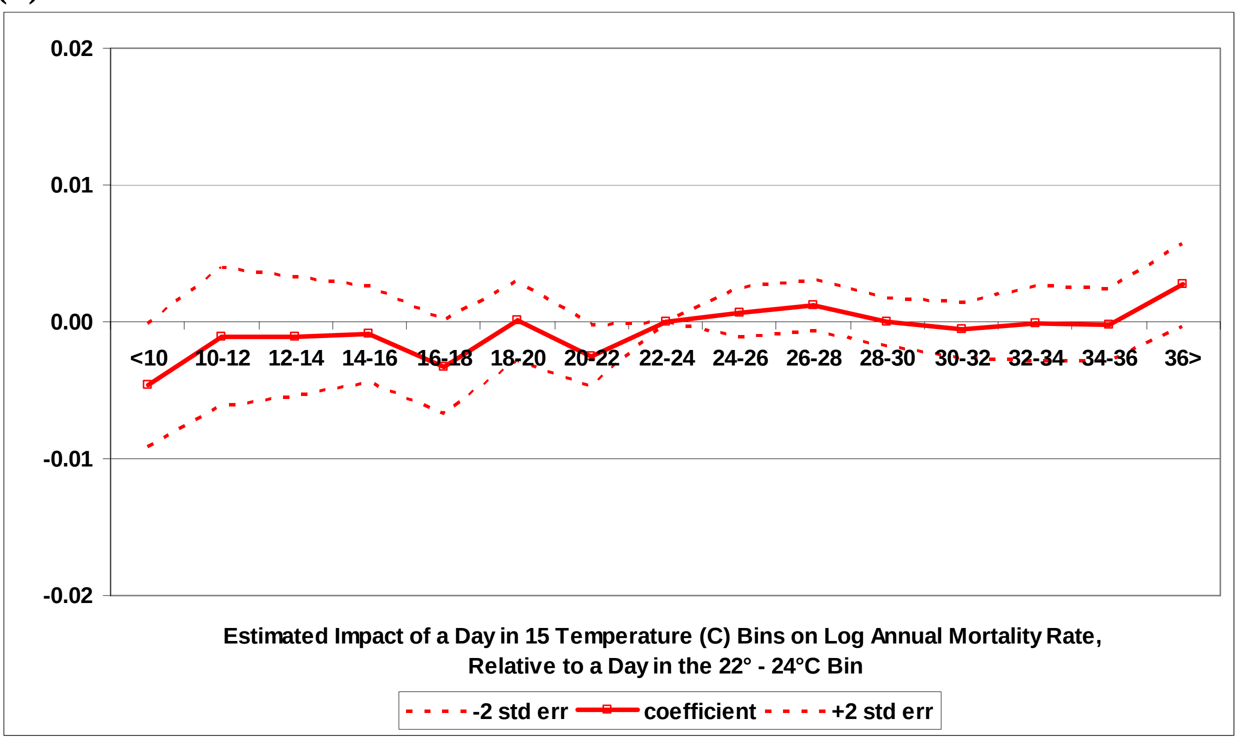
Notes: The dependent variable is the log annual all-age mortality rate. The model also includes controls for 15 temperature bins and controls for unrestricted year effects, cubic region*year trends and unrestricted district effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

Figure 6: Estimated Response Function Between Daily Temperature Exposure and Log Annual Mortality Rate (All Ages), by Rural/Urban Designation

(A) Rural Areas

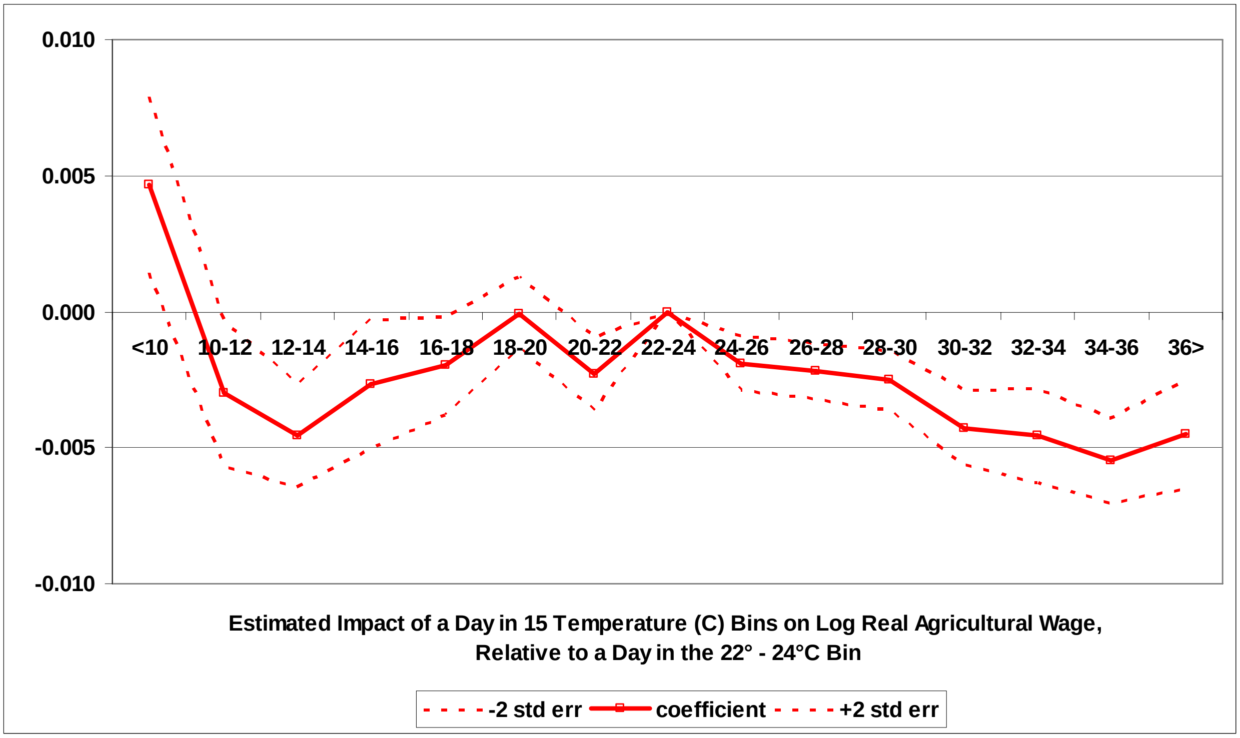


(B) Urban Areas



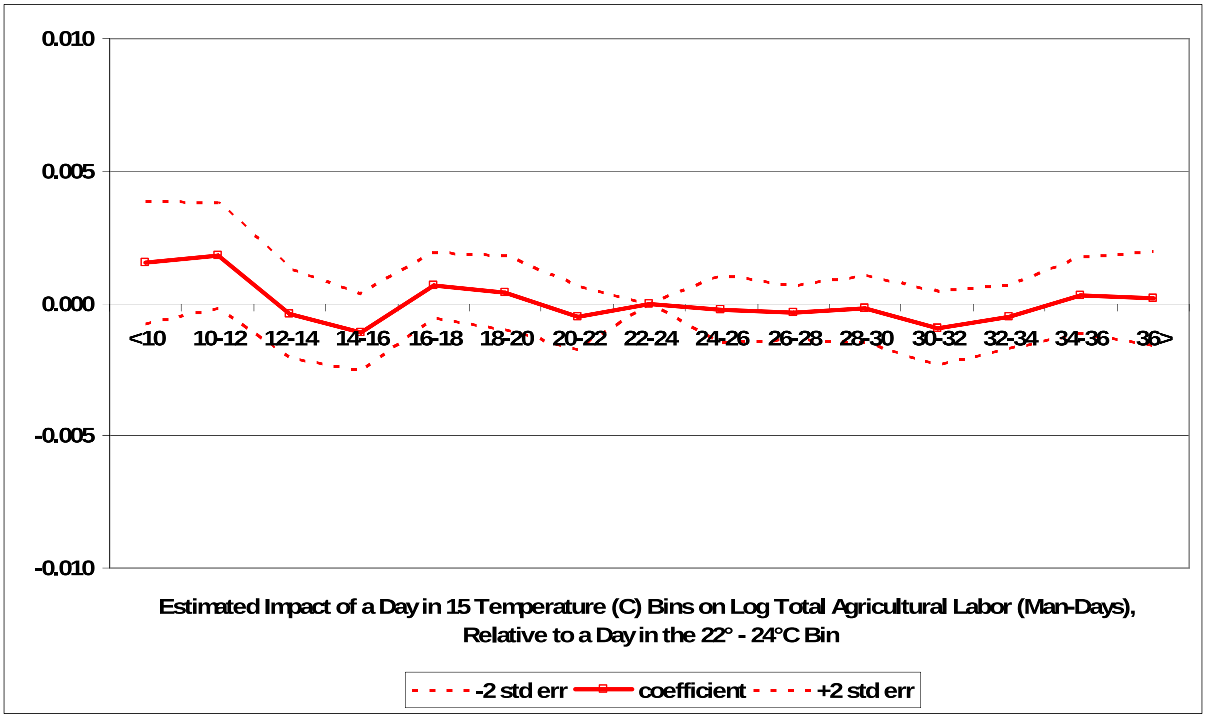
Notes: The dependent variable is the log annual all-age mortality rate. The model also includes controls for monthly total precipitation and controls for unrestricted year effects, cubic region*year trends and unrestricted district effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

Figure 7: Estimated Response Function Between Daily Temperature Exposure and Log Real Agricultural Wages



Notes: The dependent variable is the log daily real agricultural wage. The model also includes controls for monthly total precipitation and controls for unrestricted year effects, cubic region*year trends and unrestricted district effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

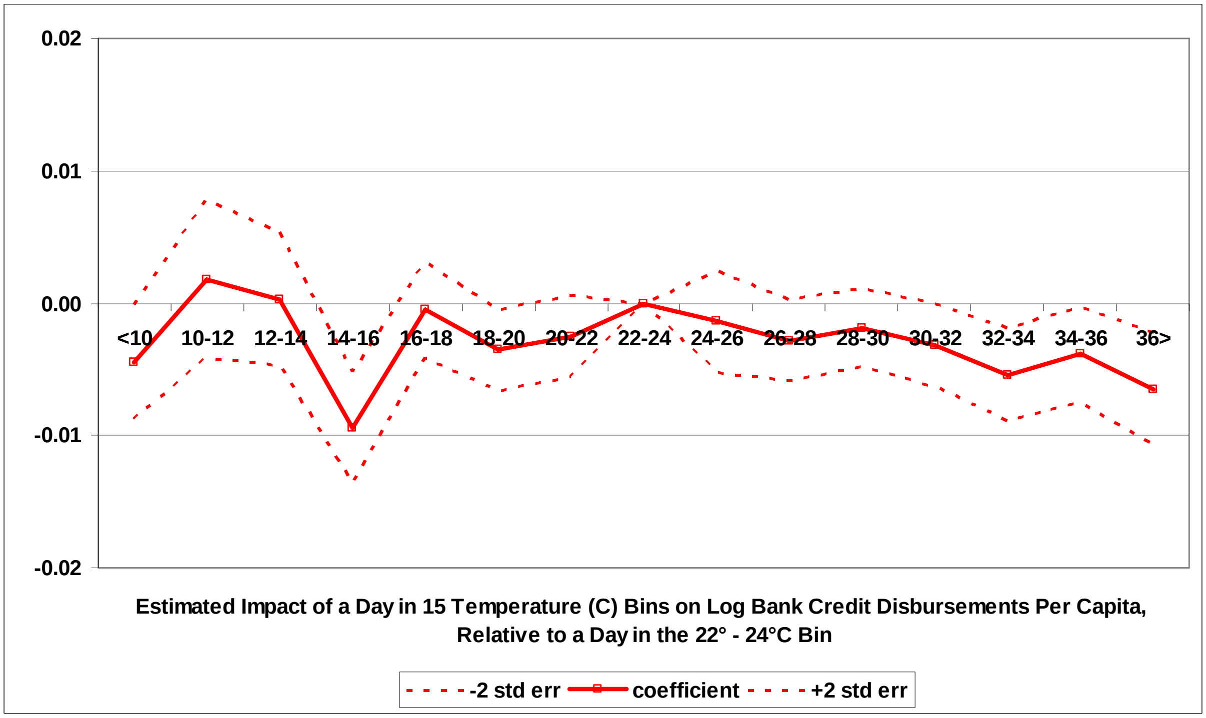
Figure 8: Estimated Response Function Between Daily Temperature Exposure and Log Agricultural Total Labor (Man-Days)



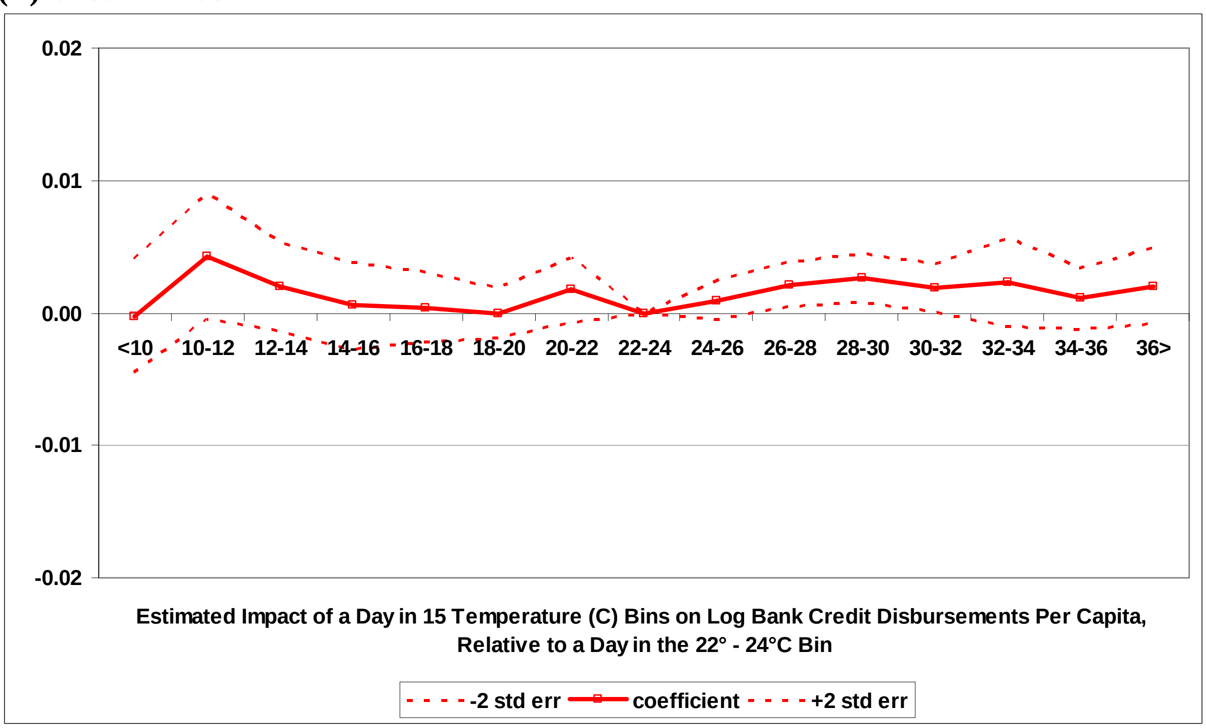
Notes: The dependent variable is the log total agricultural labor (man-days). The model also includes controls for monthly total precipitation and controls for unrestricted year effects, cubic region*year trends and unrestricted district effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

Figure 9: Estimated Response Function Between Daily Temperature Exposure and Log Bank Credit Disbursements Per Capita, by Rural/Urban Designation

(A) Rural Areas

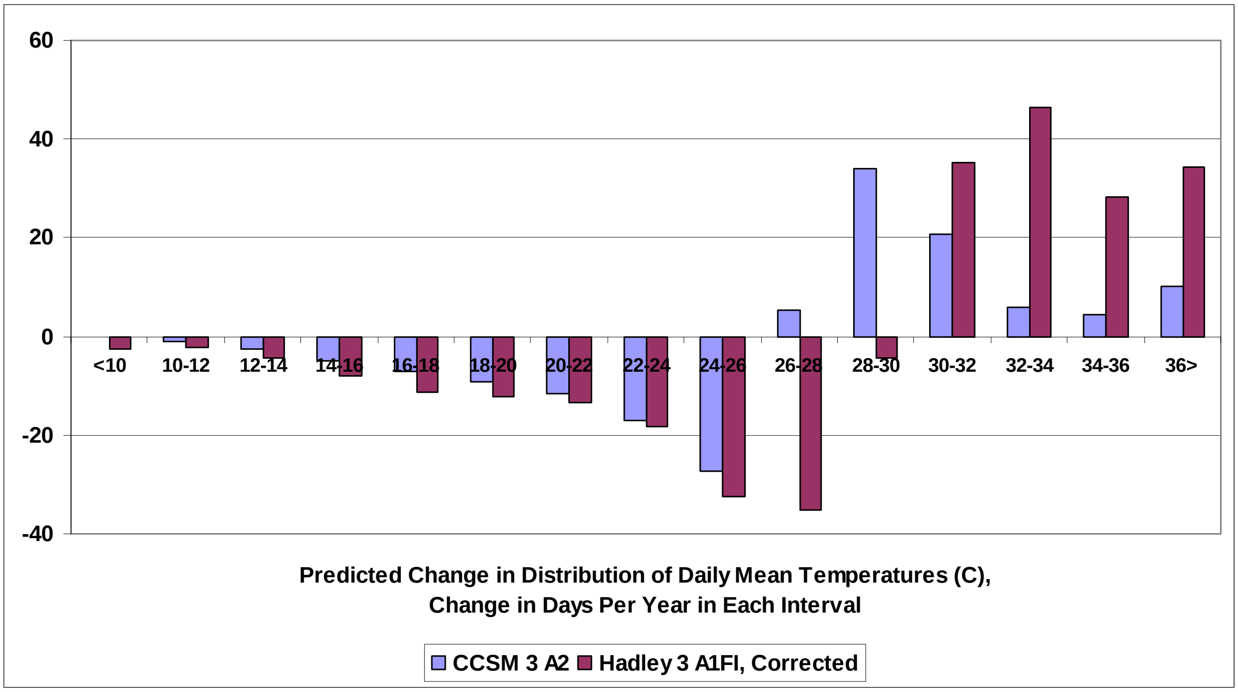


(B) Urban Areas



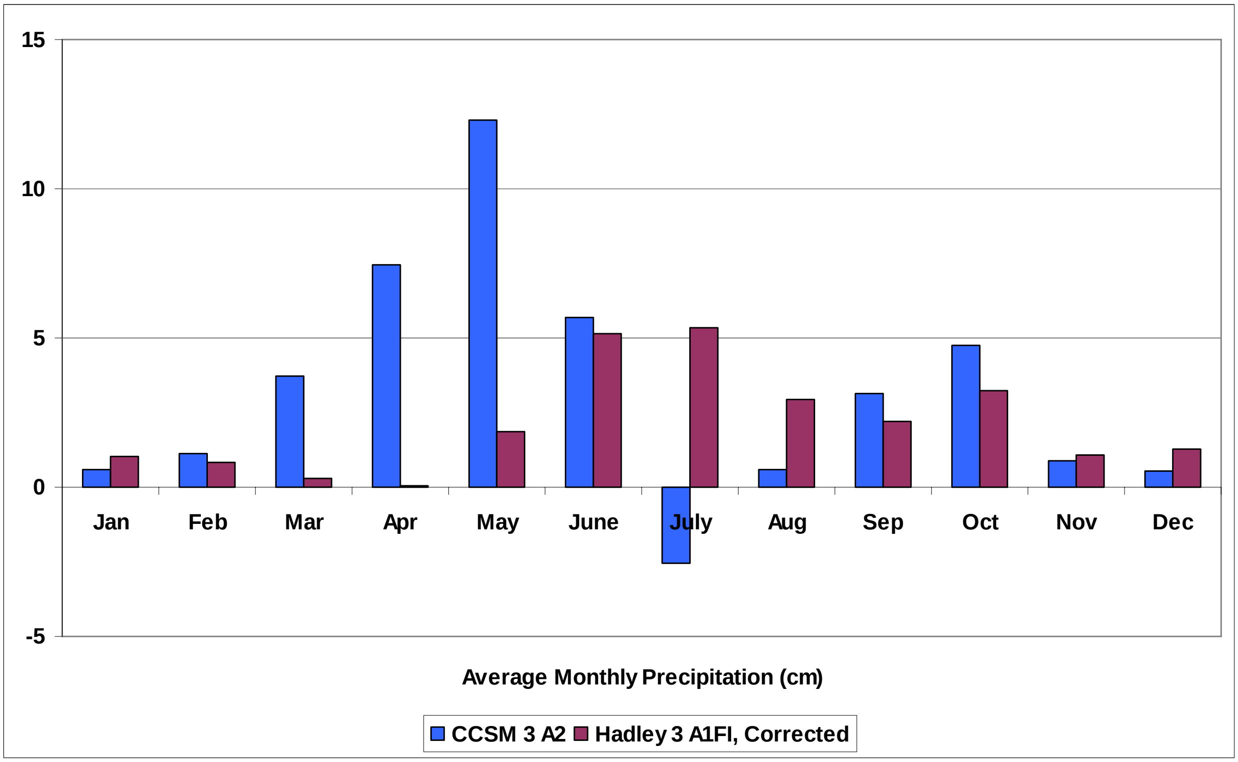
Notes: The dependent variable is the log bank credits per capita. The model also includes controls for monthly total precipitation control for unrestricted year effects, cubic region*year trends and unrestricted district*area effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

Figure 10: Predicted Change in Distribution of Daily Mean Temperature



Notes: Means weighted by average district population, 1957-2000.

Figure 11: Predicted Change in Monthly Average Precipitation



Notes: Means weighted by average district population, 1957-2000.

Table 1: Summary of Vital Statistic Data, By State, 1957-2000

State (1961 designation)	**Annual Averages:** Population	Births	Deaths	Infant Deaths	Death Rate (per 1000)	Infant Death Rate (per 1000)
All States	546,738,680	9,543,675	3,578,092	439,014	6.6	40.5
All States, Rural Areas	408,165,500	6,119,540	2,397,919	287,890	6.5	47.1
All States, Urban Areas	128,351,100	3,230,657	847,244	115,478	7.5	35.8
Andhra Pradesh	50,202,710	680,926	247,150	24,549	5.4	36.1
Bihar	65,722,030	846,359	386,398	33,869	6.3	40.3
Gujarat	33,389,420	817,606	220,084	29,255	7.5	35.8
Himachal Pradesh	1,479,823	26,902	7,326	809	5.5	30.1
Jammu and Kashmir	6,571,914	110,641	30,353	2,214	4.9	20.1
Kerala	22,330,980	461,318	115,527	8,138	5.5	17.7
Madhya Pradesh	51,849,850	948,526	381,024	56,213	8.4	59.3
Madras	47,324,520	1,007,699	375,627	45,913	8.9	45.6
Maharashtra	62,041,520	1,412,751	476,264	71,261	8.8	50.4
Mysore	35,835,590	717,996	260,517	23,107	7.9	32.2
Orissa	750,293	11,350	167,063	28,729	8.4	71.3
Punjab	23,130,620	403,321	221,499	32,954	8.0	43.0
Rajasthan	31,560,240	766,886	94,594	8,207	3.4	34.1
Uttar Pradesh	30,441,050	242,035	391,547	50,638	5.2	46.6
West Bengal	84,108,120	1,089,360	203,117	23,157	4.3	32.1

Table 2: Average Historical Weather Exposure, By State, 1957-2000

	Temperature:		Precipitation:		
	Daily Average (C)	Annual Days Above 32C	Annual Average (cm)	Annual Days Less Than 0.2 cm	Annual Days More Than 3 cm
	(1)	(2)	(3)	(4)	(5)
All States	25.7	33.5	106.1	257.0	3.0
Andhra Pradesh	27.5	42	89.9	255	2
Bihar	25.0	26	122.2	242	2
Gujarat	26.8	42	82.9	292	4
Himachal Pradesh	15.5	1	86.1	275	3
Jammu and Kashmir	11.9	4	76.8	275	2
Kerala	25.8	0	165.0	195	6
Madhya Pradesh	25.6	50	107.0	268	3
Madras	27.2	13	101.3	235	2
Maharashtra	26.3	31	99.0	255	2
Mysore	25.6	11	101.2	234	2
Orissa	26.1	23	128.2	237	3
Punjab	23.5	49	66.3	306	4
Rajasthan	25.5	61	60.1	310	3
Uttar Pradesh	24.7	49	96.0	279	4
West Bengal	26.0	22	171.5	220	5

Notes: Means weighted by census population.

Table 3: Averages of Agricultural Outcomes, By State, 1957-1987

	Real Ag. Wage (Rs / Day)	Total Labor (Mil. Man-Days)	Agricultural Laborers (Mil. Man-Days)	Cultivators (Mil. Man-Days)
All States	6.88	20,839*	5,826*	14,501*
Andhra Pradesh	6.33	1,545	589	956
Bihar	6.45	2,197	806	1,391
Gujurat	7.82	820	212	608
Madhya Pradesh	5.34	2,057	486	1,571
Madras	5.80	1,721	633	1,088
Maharashtra	6.00	2,142	739	1,403
Mysore	6.35	1,100	301	799
Orissa	5.46	1,061	302	760
Punjab	12.67	981	269	712
Rajasthan	9.58	1,122	94	1,029
Uttar Pradesh	6.55	3,990	788	3,202
West Bengal	7.94	1,590	608	982

Notes: Weighted by census population. Entries with * represent average totals.

Table 4: Alternative Estimates of the Impact of Exposure to Extreme Temperature on Annual Mortality Rates

	Marginal Effect of Average Daily Temperature		
	(1) Rural areas	(2) Urban Areas	(3) Test of equality (p-value)
Baseline (All Age)	0.120	-0.009	0.002
	(0.035)	(0.033)	
Infants	0.144	0.009	0.041
	(0.037)	(0.047)	
Age +1	0.106	-0.020	0.008
	(0.042)	(0.032)	
Interacted with precipitations	0.129	-0.005	0.002
	(0.037)	(0.033)	
Including lags	0.127	0.007	0.038
	(0.048)	(0.047)	

Notes: The dependent variable is the log annual all-age mortality rate. The model also includes controls for monthly total precipitation and controls for unrestricted year effects, cubic region*year trends and unrestricted district effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details.

Table 5: Predicted Impacts of Climate Change on Log Annual Mortality Rates, 2070-2099

	Impact of Change in Days with Temperature:			Total Temperature Impact	Total Precipitation Impact	Temperature and Precipitation Impact
	<16C	16C-32C	>32C			
	(1a)	(1b)	(1c)	(2)	(3)	(4)
A. Based on Hadley 3, A1FI						
Pooled	-0.011	-0.144	0.671	0.516	-0.108	0.408
	(0.032)	(0.047)	(0.126)	(0.127)	(0.022)	(0.132)
Rural Areas	-0.029	-0.168	0.846	0.648	-0.130	0.519
	(0.039)	(0.056)	(0.151)	(0.154)	(0.027)	(0.160)
Urban Areas	0.046	0.006	0.143	0.195	-0.017	0.179
	(0.032)	(0.058)	(0.111)	(0.097)	(0.019)	(0.103)
B. Based on CCSM3, A2						
Pooled	-0.008	0.033	0.155	0.180	-0.057	0.123
	(0.014)	(0.043)	(0.029)	(0.062)	(0.019)	(0.066)
Rural Areas	-0.014	0.064	0.195	0.245	-0.068	0.177
	(0.017)	(0.050)	(0.035)	(0.073)	(0.023)	(0.079)
Urban Areas	0.012	0.036	0.041	0.089	-0.015	0.073
	(0.014)	(0.039)	(0.023)	(0.050)	(0.018)	(0.056)

Notes: Based on models that include 15 temperature bins, controls for monthly total precipitation, and controls for unrestricted year effects, cubic region*year trends and unrestricted district*area effects. Standard errors are clustered by district. Regressions weighted by census population. See the text for more details. Standard errors are clustered by district. Regressions weighted by census population. Projections compares historical period (average over 1957-2000) with end of century (average over 2070-2099). Hadley model predictions are adjusted for model error. See the text for more details.