Weather and Death in India

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April 2011

Abstract

Weather fluctuations have shaped the economic activities of humans for centuries. And in poor, developing countries, where large swathes of the population continue to depend on basic agriculture, the weather continues to be a key determinant of production and employment. This raises the possibility that weather shocks may translate into increases in mortality. To investigate this possibility we examine the relationship between weather and death across Indian districts between 1957 and 2000. Our estimates imply that hot days (and deficient rainfall) cause large and statistically significant increases in mortality within a year of their occurrence. The effects are only observed for rural populations and not for urban populations, and it is only hot days that occur during the period when crops are growing in the fields that account for these effects. We also show that hot and dry weather depresses agricultural output and wages, and raises agricultural prices, in rural areas—but that similar effects are absent in urban areas. Using the coefficients from our analysis of Indian districts combined with two leading models of climate change we demonstrate that the mortality increasing impacts of global warming are likely to be far more strongly felt by rural Indians relative to their counterparts in urban India or the US.

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1 Introduction

Understanding the links between the weather, economic production and mortality has been the focus of academic enquiry and policy debate for centuries. A large and distinguished literature has focused on the role of adverse weather and production shortfalls in triggering famines (Sen 1981). In developed countries and the majority of developing countries these mass starvation events have been consigned to history. Structural change and industrialization in the developed nations means that citizens depend very little on weather contingent production activities and can also marshall considerable resources to protect themselves against the direct effects of adverse weather conditions. In these countries the power of weather to result in excess mortality is extremely limited as has been confirmed by recent analysis in countries like the US (Deschenes and Greenstone 2008).

The situation in developing and, in particular, poor developing countries is very different. Here large swathes of the population continue to depend on weather-contingent agricultural incomes. Households and communities in these settings have developed a range of mechanisms to smooth consumption across income downturns (Townsend 1994). But these localized forms of informal insurance may not offer much protection in the case of weather shocks which affect the majority of citizens across a range of rural communities. Protection afforded by the state is also often limited. In these settings weather shocks which interrupt production and dent incomes may still have the power to increase mortality.[1]

The purpose of this paper is to find out whether this is the case or not by conducting the first large-scale investigation into this phenomenon. To do this we take a large, developing country – India. We assemble over forty years of daily temperature and rainfall records at the district level and relate these to annual observations of mortality. Our main finding is illustrated in Figure 1. The two lines show, for the USA and India respectively, the impact of having an extra day whose *daily mean* temperature lies in each of fifteen temperature bins relative to a day in the 'reference' bin of 22°-24° C (∼ 72°-75° F).[2] As can be seen in the figure, interannual variation in temperature in the US shows only a very weak comovement with the mortality rate. By strict contrast, hot days in India appear to lead to significantly more death. Mortality increases steeply when there are more days at or above the 30°-32°C (∼ 86°-90° F) range, relative to the 22°-24°C range. And these effects are large—for example, one *single* additional day with a mean temperature above 36°C, relative to a day with a mean temperature in the 22°-24°C range, increases the annual mortality rate by roughly 0.75 %. Accross the subcontinent, relatively hot years have many more of these

[1] The extensive literature which finds that levels of undernutrition and ill-health are extremely high in rural populations that depend on agriculture also points in this direction.

[2] The blue line comes from analysis using US counties (Deschenes and Greenstone 2008).

lethal days, as we detail below.

Put simply, hot weather is a major source of excess mortality in India but not in the US. To better understand why this is the case we first split out mortality observations into those observed for rural and urban populations of Indian districts. This allows us to understand whether or not the weather-death relationship is different for populations that are more or less dependent on weather contingent forms of economic production. The high frequency of our weather data also allows us to examine if weather during the growing season affects mortality differently from weather in the non-growing season. We also gather data on output, wages and prices for both urban and rural parts of districts in order to dig into the channels via which weather might affect death.

The results we uncover suggest weather in India kills by denting agricultural incomes via the interruptions it imposes on agricultural production and employment. We observe no effect of weather on death in urban areas of India. This is true even for infants. All the effects we observe in Figure 1 are coming through effects in rural areas. And it is only the weather in the growing season that leads to higher death rates despite the fact that the non-growing season in India is the hottest period of the year. Finally hot weather is associated with low agricultural yields, lower agricultural wages and higher agricultural prices. Yields and wages exhibit a pattern which is the inverse of that shown in Figure 1 where having more days at or above the 30°-32° C range (relative to 22°-24°C) is associated with significantly lower wages and yields. These results suggest that weather variation plays an important role in the economic lives and health status of India's rural citizens.

An important finding from the paper is that the structure of production and employment mediates the impact of weather on death. This is the motivation for looking seperately at effects on rural and urban populations in the same Indian district and at the effects of weather during the growing and non-growing seasons in rural areas. In our analysis rural and urban populations experience the same weather. However, it is only in the former that we see downturns in output, incomes, wages and increases in prices. And moreover, these effects are only the result of weather during the growing season. And it is inclement weather precisely during this period that is driving up mortality in rural but not urban populations within districts. Weather during the non-growing season which is the hottest, driest part of the year does not affect mortality in either rural or urban areas. Thus though much of the literature in developed countries has focussed on heat stress leading to excess mortality our results suggest that agricultural incomes represent a key channel via which hot weather (and deficient rainfall) affects death in poor, developing countries like India.

Our results match well with an extensive development literature on lean or hungry seasons (Khandker 2009). This literature documents that malnutrition and morbidity are highest in the run-up to the post-monsoon harvest when food stocks are depleted, demand for labor and agricultural wages are low, and food prices are high. Abnormally hot weather during this period (particularly days above the 32°-34° C) limit the formation of grains in key crops such as rice and therefore negatively affects the sizes of harvest and accentuate income downturns for those dependent on agriculture. These effects are magnfied if rainfall is also scant. Therefore hot weather (and deficient rainfall) can be particularly damaging for agricultural incomes, wages and prices during the post-monsoon growing season which is precisely what we find in our data. A variety of behaviours have evolved to deal with weather shocks during the lean season – running down food stocks and other assets (e.g. savings, livestock), borrowing money, forward selling labor and migrating have all been documented in the literature. But our results suggest that the poorest, rural residents (e.g. landless laborers) may be unable to fully withstand these income shocks and and as a result excess mortalty results. And morevoer the mortality effects of growing season weather shocks appear to persistent in the sense that abnormally hot weather in previous years' growing seasons adversely affects mortality in the current year though this effect dies out over time.

Famines may have indeed come to an end in India. However, our results suggest that citizens or rural India still live in a world where inclement weather can significantly elevate mortality. The fact that the weather may become more inclement via global warming is then likely to pose particular challenges in these poor, rural settings. In a final section of this paper we use our estimated coefficients of the within-sample (1957-2000) temperature-death relationship in India to investigate the mortality predictions implied by two leading climatological models of climate change. Our within-sample mortality estimates suggest an increase in the overall Indian annual mortality rate of approximately 12% to 46% by the end of the century. The estimated increase in rural areas ranges between 21% and 62%. As a reference point, a similar exercise performed on the United States suggests that climate change will lead to a roughly 2% increase in the mortality rate there by the end of the century. We fully expect rural Indians to adapt to an anticipated and slowly warming climate in various ways and so these should be viewed as upper bound estimates. But the direction of travel is nonetheless worrying and the fact that rural Indian citizens are already not fully protected from the effects of weather implies that much more careful thinking has to be applied to understanding how such protection might be afforded. And our results suggest that calls for workable solutions are likely to need to become more urgent and strident as global warming proceeds.

The remainder of this paper proceeds as follows. The next section outlines a theoretical framework that describes the mechanisms through which weather might be expected to lead to death. Section 3 describes the background features of India in our sample period from 1957-2000, as well as the data on weather, death and economic variables that we have collected in order to conduct our analysis. Section 4 outlines our empirical method. Section 5 presents results of the weather-death and weather-income relationships. Section 6 discusses what these estimates imply for predicted climate change scenarios in India, and finally Section 7 concludes.

2 Conceptual Framework

In this section we discuss the potential mechanisms through which weather extremes could lead to excess mortality in developing countries. The goal is to elucidate two potential mechanisms: a 'direct' channel, in which human health suffers because of extreme weather conditions that put human physiology under stress or exacerbate the disease environment, and an 'income-based' channel, in which human health suffers because of the stress placed on physiology, on which agents' real incomes may depend. To capture both of these potential channels relating weather to death, we develop a theoretical framework in which households face both 'direct' health shocks due to temperature extremes as well as lower income due to temperature extremes. In this model, an extension of Becker (2007), households can choose to spend a share of their scarce income on health-improving goods that enhance the probability of survival in the face of extreme temperatures.

Consider a representative agent who is potentially infinitely-lived. However, the agent faces some probability of death in any period—the probability of the agent being alive in period t having survived up to period $t-1$ is given by the conditional probability of survival, $s_t \leq 1$. The agent derives utility in period t from consumption c_t according to the intra-temporal utility (or felicity) function, $u(c_t)$. Finally, we asume that the agent discounts each future period with a constant discount factor $\beta < 1$. Given all of this, the agent obtains an expected value of lifetime utility given by

$$V = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \left(\prod_{t'=0}^{t} s_{t'}\right) u(c_t)\right]. \tag{1}$$

Note that here, the term $\prod_{t'=0}^{t} s_{t'}$ is equal to the probability of the agent being alive in period t.

We now endogenize the conditional probability of survival, s_t. Let $s_t = s(h_t, T_t)$, where h_t is the amount of health-improving inputs that are consumed by the agent and T_t is a variable (possibly multivariate) that captures the weather in period t. We assume that the function $s(h_t, T_t)$ is increasing and concave in h_t, and we define T_t such that s_t is decreasing in T_t .

Crucial to this framework is the assumption that h_t is a choice variable that is under the agent's control (subject to a budget constraint). Note that, in this formulation, there are two types of goods. Consumption goods (denoted by c_t) are goods that the agent values directly—they enhance the agent's quality of life and are the sole argument in the utility function, $u(c_t)$. Health input goods (denoted by h_t) are valued only because they improve the likelihood of survival in the current period and in future periods. We provide some examples of health input goods, especially those that are important in our context, below.

The fact that the weather T_t affects that conditional probability of survival directly (ie $s_t = s(h_t, T_t)$) allows for the *direct effect* relating weather to mortality. The weather T_t is assumed to be out of the agent's control. Holding health inputs h_t constant, high temperatures can cause death (decrease survival chances s_t) directly. An extensive public health literature discusses the potential direct effects of high temperatures on human health (see, for example, Basu and Samet (2002) for a comprehensive review).[3] Periods of excess temperature place additional stress on cardiovascular and respiratory systems due to the demands of body temperature regulation. This stress is known to impact on the elderly and the very young with particular severity, and can, in extreme cases, lead to death (Klineberg 2002, Huynen, Martents, Schram, Weijenberg, and Kunst 2001). An alternative 'direct' effect of extreme weathers on death in India could include the possibility that disease pathogens (for example, diarrhoeal diseases) thrive in hot and wet conditions, or that some vectors of disease transmission (such as mosquitoes in the case of malaria) thrive in hot and wet environments. We collapse all of these potential 'direct' channels into the possibility that some index of temperature T_t enters the function $s(h_t, T_t)$ directly (and negatively).

To allow for an 'income-based channel' through which weather extremes can cause death, we include the possibility that the agent's income is a function of the weather: $y_t = y(T_t)$. This is extremely likely in rural areas where incomes depend on agriculture directly or indirectly. For simplicity, we assume that the weather variable T_t potentially affects both income and survival in the same direction, such that y is decreasing in T. Because incomes are observable the weather-to-income relationship is one that we are able to estimate. Naturally, we expect this relationship to be minimal or even absent in urban areas. In contrast, following well-known effects in the agronomic literature, as well as the literature on expected effects of hotter climates on Indian agriculture (eg Kumar, Kumar, Ashrit, Deshpande, and Hansen (2004) and Guiteras (2008)), we expect a strong negative relationship between

[3] Extremely cold temperatures can also affect human health adversely through cardiovascular stress due to vasoconstriction and increased blood viscosity. Deschnes and Moretti (2009) find evidence for a moderate effect of extreme cold days on mortality (especially among the elderly) in the United States, though this effect is concentrated among days below 10° F (ie −12° C). Days in this temperature range are extremely rare in India.

incomes in rural areas (ie agricultural incomes) and temperatures.

An income shortage caused by weather extremes could lead to death if this shortage forces the agent to cut back on health input goods, h_t. We take a broad view of these health input goods, which the poor may struggle to afford even at the best of times, nevermind those periods when weather extremes have caused income shortages. These could include traditional health goods such as medicine or visits to a health center. Equally, they could include the subsistence component of food consumption (that which increases the likelihood of survival but is not valued in $u(c)$ directly). Or given our focus on temperature an important 'health good' might be the use of air conditioning. More broadly, this 'health good' could also encompass any leisure or rest (ie foregone labor, or income-earning opportunities) that the agent might decide to 'purchase' so as to improve his health. This could include the decision to work indoors rather than outdoors when it is hot, or to accept an inferior paying job so as to avoid working outside on a hot day.

Finally, we specify the timing through which the uncertainty is resolved through time. At the beginning of a period (for example, period $t = 0$), the temperature in the current period (eg T_0) is drawn. The agent then makes his choices in the current period (ie c_0 and h_0) as a function of the current temperature (ie $c_0 = c_0(T_0)$ and $h_0 = h_0(T_0)$). After the agent's decision has been made, the agent's death shock arrives (ie, having survived up to date 0, the agent survives with probability $s_0 = s(h_0, T_0)$.) Finally, if the agent survives this death shock he enjoys intra-period utility $u(c_0)$ and the next period begins. If the agent dies in period 0 then he enjoys no utility from this period (though the assumption of zero utility in death is merely a normalization).

We specify the agent's budget constraint as follows. We assume that the price of the consumption good c_t is p^c and that of the health input good h_t is p^h; this relative price governs intra-temporal decisions. For simplicity we assume these prices are constant over time. We also assume, for simplicity, that agents are able to borrow or save across periods at the interest rate r (which is assumed to be constant, for simplicity) and that the agent has access to a complete and fair annuity market (the only role of which is to simplify the presentation of the lifetime budget constraint by ruling out the possibility that the agent lives longer than expected and runs out of resources, or that the agent dies early when in debt).

Under the above assumptions the agent's inter-temporal budget constraint, starting from period 0, can be written as:

$$s_0[y(T_0) - p^c c_0 - p^h h_0] = \mathbb{E}\left[\sum_{t=1}^{\infty} R^{-t}\left(\prod_{t'=0}^{t} s_{t'}\right)(p^c c_t + p^h h_t - y(T_t))\right], \tag{2}$$

where $R = (1+r)$. That is, if total expenditure in period 0 (ie $p^c c_0 + p^h h_0$) exceeds income in period 0, $y(T_0)$, then this must be funded by future surpluses.

An agent who maximizes lifetime utility, equation (1), subject to his lifetime budget constraint, equation (2), from the perspective of period 0 after T_0 is known will make choices that satisfy the following necessary first-order conditions for optimization. First, his allocation of consumption across time will satisfy a standard Euler equation:

$$u'(c_0) = \frac{\beta R \mathbb{E}\left[s_1 u'(c_1)\right]}{\mathbb{E}[s_1]}.$$

This result states that the marginal utility of consumption in period 0 will be equal to the expected marginal utility of consumption in the next period, times the opportunity cost of consumption in the next period. This is the standard Euler equation adjusted for the fact that the marginal utility of consumption in period 1 (ie $u'(c_1)$) will only bring utility if the agent survives (ie $s_1 = 1$), and adjusted also for the fact that opportunity cost of consumption in period 0 is also reduced by the possibility of non-survial (ie $s_1 <= 1$).

Second, the choice of the health input good in period 0, h_0, will satisfy the following first-order equation

$$\frac{\partial s_0}{\partial h}\left[u(c_0) + \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^t \left(\prod_{t'=1}^{t} s_{t'}\right) u(c_t)\right]\right] = \lambda p^h s_0,$$

where λ is the marginal utility of lifetime income (in terms of the numeraire, the health input good). In what follows we will find it useful to define $\mathbb{E}[V_0] = u(c_0) + \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^t \left(\prod_{t'=1}^{t} s_{t'}\right) u(c_t)\right]$ as the expected utility of surviving the death shock (that is, of being alive) in period 0. If the agent is alive in period 0 then he enjoys both consumption this period (ie $u(c_0)$) and the possibility of being alive in the future to enjoy utility from consumption then. This first-order equation for the choice of h_0 can therefore be written as

$$\frac{\partial s_0}{\partial h} \frac{\mathbb{E}[V_0]}{\lambda s_0} = p^h.$$

In this formulation, the term $\frac{\mathbb{E}[V_0]}{\lambda s_0}$ is the agent's 'value of a statistical life' (VSL). This is the value (in monetary units) of being alive at the start of date 0. The first-order condition therefore states that, at the optimal choice, the marginal benefit of spending more money on the health input (which is given by the product of the effect that the health input has on survival, $\frac{\partial s_0}{\partial h}$, and the value of survival, the VSL) equals the marginal cost of spending money on the health input (given simply by the price of the health input, p^h).

Finally, by studying the agent's expected choice of the health input in period 1, h_1, one can derive an equation for the change in health spending across periods 0 and 1 which is analogous to the consumption Euler equation presented above. This health input Euler equation is:

$$\mathbb{E}\left[\frac{\partial s_0}{\partial h}\frac{V_0}{\lambda s_0}\right] = \beta R \mathbb{E}\left[\frac{\frac{\partial s_1}{\partial h}\frac{V_1}{s_1\lambda}}{1+\frac{\partial s_1}{\partial h}\frac{W_1}{s_1}}\right]. \tag{3}$$

Here, V_1 is the value of being alive at the start of period 1, and W_1 is the agent's net asset position at the start of period 1. To gain intuition for this equation, imagine that the agent's net asset position at the start of period 1 is zero (ie $W_1 = 0$), just as it was (by normalization) at the start of period 0. In such a setting, this health input Euler equation is entirely analogous to the consumption Euler equation introduced earlier: up to the dynamic adjustment factor βR (which trades off the agent's taste for impatience β with the returns to saving R), the agent tries to equalize the expected marginal value of health spending across periods. Since the maginal value of health spending is given by the product of the marginal effect of health saving on survival ($\frac{\partial s}{\partial h}$) and the value of survival (the VSL, $\frac{V}{s\lambda}$), the result in equation (3) follows. More generally, W_1 may not equal zero. But this simply adjusts the above intuition for the fact that the agent does not want to risk dying with assets unspent.

This last result, the health spending Euler equation in equation (3), suggests that we should expect a great deal of smoothing, not only in health expenditure but also in the probability of survival itself. For a potentially long lived agent, the value of life at date 0 should be close to that at date 1, as long as the probability of death is being smoothed over time. And since (by assumption) the marginal effect of health expenditure on survival ($\frac{\partial s}{\partial h}$) is strictly decreasing in h, equation (3) suggests that we should expect the agent to be trying to smooth (again, up to the adjustment factor βR) expected health expenditures h as well as the expected value of life.

A final implication of the above first-order conditions is that they can be used to characterize the agent's willingness to pay (WTP) to avoid a worsening in the weather ($\Delta T_0 > 0$) in period 0. One way to derive the WTP is to imagine a transfer that varies as a function of the observed weather T_0 in period 0 and is designed to hold expected lifetime income V constant for any value of T_0. Denote this transfer $y^*(T_0)$. It is then straightforward to show that this transfer scheme will vary with T_0 in the following manner:

$$\frac{dy^*(T_0)}{dT_0} = -\frac{dy(T_0)}{dT_0} + \frac{\partial h_0}{\partial T_0} - \frac{ds(h_0, T_0)}{dT_0}\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]. \tag{4}$$

This expression, which characterizes the agent's willingness to pay to avoid a small worsening in the weather dT_0, is intuitive. WTP is the sum of three terms in this model. First, since weather increases may adversely affect incomes directly (the 'income-based channel') the WTP first requires compensation for any loss of income caused by worse weather (ie a payment of $-\frac{dy(T_0)}{dT_0}$, which we expect to be positive if bad weather leads to lower incomes). Second, since inclement weather causes the agent to spend resources on health inputs that have no direct utility benefits, the WTP requires the agent to be compensated for any change in expenditures on health inputs caused by the worsening in the weather (ie a payment of $\frac{\partial h_0}{\partial T_0}$, which we expect to be positive if there is a direct effect of weather extremes on survival chances that the agent is attempting to offset through the purchase of the heath good). The final term in this WTP expression compensates the agent for the heightened risk of death caused by inclement weather. Such a compensation requires a payment of $-\frac{ds(h_0,T_0)}{dT_0}\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$, which is the product of the *total* effect of weather extremes on survival chances (ie $\frac{ds(h_0,T_0)}{dT_0}$) and the dollar value of survival in period 0, $\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$, often referred to as the 'value of a statistical life'. The fact that this expression depends on the total deriviative of survival with respect to weather, $\frac{ds(h_0,T_0)}{dT_0}$, rather than the partial deriviative holding the health input constant, is attractive from an empirical perspective.

It is important to note that all of the terms in the WTP expression in equation (4) are potentially observable. Our empirical analysis below will aim to estimate both the the *reduced-form* (or 'total') effect of weather extremes on death, ie $\frac{ds(h_0,T_0)}{dT_0}$, and the effect of weather extremes on income, ie $\frac{dy(T_0)}{dT_0}$. Armed with these two essential ingredients and an estimate of the value of a statistical life in our setting (ie $\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$) we will therefore be able to estimate a lower bound on the agent's willingness to pay to avoid a small worsening of the weather, dT_0. This estimate will be a lower bound on the WTP because of our inability to observe the full vector of health inputs that households are purchasing, and hence our inability to estimate $\frac{\partial h_0}{\partial T_0}$.

An important lesson from the WTP expression in equation (4) is that, in this model, because money is fungible, it is irrelevant whether the agent suffers a heightened risk of death due to weather extremes because of a 'direct' effect of bad weather on death or an 'income-based' effect. In either case, the agent has a well-defined willingness to pay to avoid a inclement weather that is given by our WTP expression. This fact informs our empirical approach which is centered on estimating two important ingredients that are required to obtain bounds on the agent's WTP, the reduced-form effect of weather on death (ie $\frac{ds(h_0,T_0)}{dT_0}$) and the effect of weather on incomes (ie $\frac{dy(T_0)}{dT_0}$).

We conclude with a final word about policy in this environment. There are no market failures in the above model—though it is clearly easy to imagine extensions to the model that would involve plausible market failures, most notably constraints on the ability of agents to borrow across periods without any restraint other than the inter-temporal budget constraint. The absence of market failures implies no role for a self-funded policy here—a policy-maker facing the same constraints as the agent could do no better than the agent is doing himself. But the WTP expression above does characterize the value that households place on avoiding temperature extremes, which an external funder, such as a foreign donor, might wish to use to compare the merits of competing policy proposals.

3 Background and Data

To implement the analysis in this paper, we have collected the most detailed and comprehensive district-level data available from India on the variables that the above conceptual framework in Section 2 suggests are important. These variables include demographic variables (population, mortality and births), and variables that capture key features of India's urban and rural economies (output, prices and wages). We then study the relationship between these data and high-frequency daily data on historical weather that we have assembled. In this section we describe these data, their summary statistics, and the essential features of the background economy they describe.

Throughout this paper we draw heavily on the implications of the differential weather-death relationship in urban and rural areas. We therefore begin with a short discussion of the essential differences between these regions. Despite the dramatic extent to which the world has urbanized in the last sixty years, the extent of urbanization in India has been relatively slow: even in 2001, 72.2 percent of Indians lived in rural areas. The overriding distinction between economic life in rural and urban India is the source of residents' incomes. 76 % of rural citizens belong to households that draw their primary incomes from employment in the agricultural sector, while only 7 % of those in urban areas do so. Another distinction between rural and urban areas lies in their consumption of food—that is, in their exposure to fluctuations in the prices of foodstuffs. Deaton and Dreze (2009) draw on consumption surveys to report that in 2001, 58 % of the average rural residents' budget was spent on food, while only 45 % of the average urban budget was devoted to food. Naturally, these consumption differences may represent differences in the level of household per capita incomes between rural and urban areas. Urban households are, on average, richer than rural households: in 2001 urban residents were 69 % richer on average than rural residents, according to Deaton and Dreze (2009).

3.1 Data on Mortality and Population

The cornerstone of the analysis in this paper is district mortality data taken from the *Vital Statistics of India* (VSI) publications for 1957-2000, which were digitized for this project.

The VSI data represent the universe of registered deaths in each year and registration was compulsory in India throughout our sample period. This source contains the most detailed possible panel of district-level mortality for all Indian citizens.

Death tallies in the VSI are presented for infants (deaths under the age of one) and for all others (deaths over the age of one), by rural and urban areas separately.[4] From this information we construct two measures of mortality: an infant mortality rate, defined as the number of deaths under the age of one per 1000 live births; and an 'all ages' mortality rate, defined as the total number of deaths over the age of one normalized by the population in 1000s.

Table 1 (which contains all of the summary statistics for data used in this paper) summarizes the VSI data from the 1957-2000 period that we use in this paper, which comprise 315 districts spanning 15 of India's largest states (and account for over 85 % of India's population).[5] The table reveals that measured mortality rates are high throughout this period. For example, the average infant mortality rate is 40.5 per 1,000 live births. Geographically, average infant mortality rates range 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 stress that these mortality rates are almost surely underestimates of the extent of mortality in India. Despite compulsory registration of births and deaths, many areas of the country suffer from significant under-reporting.[6]

Table 1 also documents the time variation in the two mortality rates. There is a remarkable decline in both mortality rates in both 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 Section 4 below, we describe our strategy to avoid confounding these trends in mortality rates with any time trends in

[4]The rural/urban assignment is based on the following criteria, used throughout official Indian statistics: urban areas comprise "(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)."

[5]These states are (in 1961 borders and names): Andhra Pradesh, Bihar, Gujarat, Himachal Pradesh, Jammu and Kashmir, Kerala, Madhya Pradesh, Madras, Maharashtra, Mysore, Orissa, Punjab, Rajasthan, Uttar Pradesh, and West Bengal. These are the states with a consistent time series of observations in the VSI data. The results in this paper are largely insensitive to the inclusion of all observations in the VSI data.

[6]According to the National Commission on Population of India, only 55 % of the births and 46 % of the deaths were being registered in 2000. These estimates were obtained from India's Sample Registration System, which administers an annual survey of vital events to a nationally representative sample of households. The data published by the SRS, however, are only available at the state level.

temperatures.

3.2 Data on Weather

A key finding from Deschenes and Greenstone (2008) is that a careful analysis of the relationship between mortality and temperature requires *daily* temperature 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. This message is echoed in the agronomic and agricultural economics literatures (as emphasized, for example, by Deschenes and Greenstone (2007) and Schlenker and Roberts (2008)).

Although India has a system of thousands of weather stations with daily readings dating back to the 19th century, the geographic coverage of stations that report publicly available temperature readings is poor (and surprisingly the public availability of data from these stations drops precipitously after 1970). Further, there are many missing values in the publicly available series 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 uses 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. We match these gridpoints to each of the districts in our sample by taking weighted averages of the daily mean temperature and total 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.[7]

To capture the distribution of daily temperature variation within a year, we use two different variables. The first of these temperature variables assigns each district's daily mean temperature realization to one of fifteen temperature categories—as already seen in Figure 1. 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

[7] On average, there are 1.9 grid points within a 100 km radius 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). After the inverse distance weighting procedure, 339 out of a possible 342 districts have a complete weather data record. The three districts that are dropped in this procedure are Alleppey (Kerala), Laccadive, Minicoy, and Amindivi Islands, and the Nicobar and Andaman Islands.

daily weather realizations within a year are then distributed over these fifteen bins. This binning of the data preserves the daily variation in temperatures, which is an improvement over previous research on the relationship between weather and death that obscures much of the variation in temperature.

Figure 2 illustrates the average variation in daily temperature readings across the fifteen temperature categories or bins over 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 (described below) 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.

As a second approach to capturing the influence of temperature, we draw on a stark non-linearity in the relationship between daily temperatures and both human and plant physiology that is well known in the public health and agronomy literatures: temperatures above (approximately) 32° C are particularly severe. We therefore construct a measure of the cumulative number of degrees-times-days that exceed 32° C in a district and year. This 'degree-days' measure has the advantage of collapsing a year's 365 daily temperature readings down to one single index, while still doing some justice to what is known about the non-linear effects of temperature. Table 1 reports on summary statistics of this measure. The national average is approximately 65 degree-days per year over 32° C, which implies an average of just over two months during the year in which the daily mean temperature is at 34° C.

While the primary focus of our study is the effect of high temperatures on mortality, we use data on rainfall to control for this potential confounding variable (to the extent that temperature and rainfall are correlated). Table 1 reports annual precipitation totals. However, the striking feature of rainfall in India is its intra-annual distribution: in an average location, over 95 percent of annual rainfall arrives after the arrival of the southwest (summer) monsoon, a stark arrival of rain on the southern tip of the subcontinent around June 1^{st} which then moves slowly northwards such that the northern-most region of India experiences the arrival of the monsoon by the start of July—see, for example, Wang (2006). Naturally this stark arrival of rainfall after a period of dryness triggers the start of the agricultural season in India. We exploit this feature of the timing in our analysis below.

3.3 Data on Economic Outcomes in Rural India

3.3.1 Agricultural Yields

It is natural to expect that the weather plays an important role in the agricultural economy in India. In turn, the agricultural economy may play an important role in the health of rural citizens who draw their incomes from agriculture. To shed light on these relationships we draw on the best available district-level agricultural data in India. The data on agricultural outputs, prices, wages, and employment come from the 'India Agriculture and Climate Data Set', which was prepared by the World Bank.[8] This file contains detailed district-level data from the Indian Ministry of Agriculture and other official sources from 1956 to 1986. From this source we utilize three distinct variables on the agricultural economy: yields, prices, and wages.

We construct a measure of annual, district-level yields by aggregating over the output of each of the 27 crops covered in the World Bank dataset (these crops accounted for over 95 percent of agricultural output in 1986). To do this we first create a measure of real agricultural output for each year (using the price index discussed below) and then divide this by the total amount of cultivated area in the district-year. Table 1 reports on the resulting yield measure for the 271 districts contained in the World Bank dataset, over the period from 1956 to 1987. All of the major agricultural states are included in the database, with the exceptions of Kerala and Assam.

3.3.2 Agricultural Prices

Because rural households spend so much of their budgets on food, food prices are an important determinant of rural welfare in India. We construct an agricultural price index for each district and year which attempts to provide a simple proxy for the real cost of purchasing food in each district-year relative to a base year. Our simple price index weights each crop's price (across the 27 crops in the World Bank sample) by the average value of district output of that crop over the period.[9] Table 1 reports on the level of this price index in rural India. (The price data used in the World Bank source are 'farm harvest prices', so we prefer to interpret these as rural prices rather than urban prices.) These figures and their accompanying standard deviations show that prices are not as variable over space and time as the yield figures in Table 1, potentially reflecting a degree of market integration across India's districts (so that a market's price is determined by supply conditions both locally

[8] The lead authors are Apurva Sanghi, K.S. Kavi Kumar, and James W. McKinsey, Jr.

[9] Annual, district-level consumption data, which would be required to construct a more appropriate *consumption*-based price index, are not available in India.

and further afield).

3.3.3 Real Agricultural Wages

A second important metric of rural incomes (in addition to agricultural productivity, discussed above) is the daily wage rate earned by agricultural laborers. The World Bank dataset contains information on daily wages, as collected by government surveys of randomly chosen villages in each district and year. All figures are given in nominal wages per day, and are then converted into equivalent daily rate to reflect the (low) degree of variation in the number of hours worked per day across the sample villages. We divide the reported, nominal wage rate by the agricultural price index described above to construct an estimate of the real rural agricultural wage in each district-year.[10] As can be seen in Table 1, the level of real wages is low throughout the period—never rising above 33.96 Rupees (base year 2000), or approximately 2 US dollars (base year 2000) per day in PPP terms.

3.4 Data on Economic Outcomes in Urban India

As emphasized in Section 2, an important channel through which weather variation can reduce welfare and lead to death is through household's incomes. While it is natural to expect strong effects of temperature extremes on rural, agricultural incomes, we also investigate the extent to which economic conditions in urban areas react to temperature fluctuations. To this end we have collected the best available data on urban economic conditions, and describe the sources of that data here. It is important to stress at the outset that, perhaps because of the over-riding current and historical importance of agriculture for economic welfare in India, the statistics on India's urban economy are not as detailed as those on India's rural, agricultural economy. All of the sources listed below report data on urban outcomes at the *state* level, whereas all of the rural equivalents introduced above were available at the *district* level.

3.4.1 Manufacturing Productivity

India's manufacturing sector (especially its 'registered' or formal manufacturing sector) is almost entirely located in urban areas. For this reason we use a measure of state-level registered manufacturing productivity (real output per worker) as one measure of the productivity of the urban area of each state in each year. We draw this data from Besley and

[10] A better real wage measure would of course also incorporate price information on non-agricultural items in the rural consumption basket. Unfortunately, the price and quantity information that would be required to do this are unavailable annually at the district level in India.

Burgess (2004), who collected the data from publications produced by India's Annual Survey of Industries.

3.4.2 Urban Consumer Price Index

Every year India's statistical agencies produce two official consumer price indices, one intended to be relevant for agricultural workers and one intended to be relevant for manufacturing workers. These are published by the Labour Bureau. The latter index is collected (by the NSSO) from urban locations, and is based on weights drawn from NSS surveys of manufacturing workers. We therefore follow standard practice and use on the manufacturing workers' CPI as a CPI that reflects urban prices. Data on this index is taken from Besley and Burgess (2004), who collected the data from the annual *Indian Labour Yearbook* publication.

3.4.3 Real Manufacturing Wages

The final measure of incomes in urban areas that we exploit comes from manufacturing wage data. To construct this variable we first use data on nominal (registered) manufacturing wages, as surveyed by the Annual Survey of Industries and published in the annual *Indian Labour Yearbook*, which was collected by Besley and Burgess (2004). We then divide nominal manufacturing wages by the urban CPI variable introduced above to create a measure of real manufacturing wages.

4 Methodology

In this section we describe the econometric method that we use to analyze the weather-death relationship and accompanying relationships in this paper.

We pursue two different approaches to modeling the temperature-death relationship, but our approach to the precipitation-death relationship is held constant throughout. Our *first approach* to estimating the temperature-death relationship was introduced briefly in the Introduction, and results based on it were presented in Figure 1, but we provide details here. Our estimating equation uses a flexible specification to model the relationship between daily temperature variation and annual mortality rates as follows:

$$\begin{aligned} Y_{dt} &= \sum_j \theta_{j=1}^{15} \mathrm{TMEAN}_{dtj} + \sum_k \delta_k \mathbf{1}\left\{\mathrm{RAIN}_{dt} \text{in tercile } k\right\} \\ &+ \alpha_d + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{dt}, \end{aligned} \tag{5}$$

where Y_{dt} is the log mortality rate (or an alternative outcome variable such as an income measure) in district d in year t. We use the log of the death rate (or of alternative outcome variables) in order to draw straightforward comparisons across different outcome variables, but our results are largely unchanged if we instead use the level of the death rate (or alternative outcome) rather than its log as our dependent variable. The r subscript refers to a 'climatic region' (explained below). The last term in the equation is a stochastic error term, ε_{dt}.

The key variables of interest here are those that capture the variation in daily temperatures in district d within year t. The variable $TMEAN_{dtj}$ denotes the number of days in district d and year t on which the daily mean temperature fell in the jth of the fifteen bins used in Figure 2. We estimate separate coefficients θ_j for each of these temperature bins. However, because the number of days in a standardized year always sums to 365 one of these fifteen coefficients cannot be identified; we use the middle bin, that for temperatures between 22° C and 24° C, as a reference category whose coefficient is therefore normalized to zero.

This approach makes three assumptions about the effect of a day's mortality impact on the outcome variable. First, this approach assumes that the impact is governed by the daily mean alone; since daily data on the intra-day ('diurnal') variation of temperatures in India over this time period is unavailable to us, this assumption is unavoidable. Second, our approach assumes that the impact of a day's mean temperature on the annual mortality rate is constant within 2° C degree intervals; our decision to estimate separate coefficients θ_j on each of fifteen temperature bin coefficients 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 of the use of district-level data from 44 years. Finally, by using as a regressor the number of days in each bin we are assuming that the sequence of relatively hot and cold days is irrelevant for how hot days affect the annual outcome variable. This is a testable assumption, for which we find support. Specifically, including regressors that capture the presence of two or more 'hot' days (eg over 32° C) does not change our main results.

The second set of variables on the right-hand side of equation (5) aims to capture variation in precipitation (essentially rainfall, given our sample restriction to non-Himalayan India). Given that our primary focus is on the effects of temperature on death, the coefficients on rainfall regressors are of secondary importance. However, because it is possible that temperature variation is correlated with rainfall variation, the inclusion of these rainfall variables is important. We model rainfall in a manner that is fundamentally different from our approach to modeling temperature because of one key difference between temperature and rainfall: rainfall is far more able to be stored (in the soil, in tanks and irrigation systems, and in stagnant water that might breed disease) than is temperature. Given this distinction, while we have modeled the effect of temperature as the sum over daily impacts, we model the effect of rainfall as the impact of sums over daily accumulations. The specific approach pursued in equation (5) above uses regressors that aim to flexibly capture how a given year's total annual rainfall affects the outcome variable. To do this as simply as possible we calculate whether the total amount of rainfall in year t in district d was in the upper, middle or lower tercile of annual rainfall amounts in district d over all years in our sample; these are the regressors $\mathbf{1}\left\{\text{RAIN}_{dt}\text{in tercile } k\right\}$. We estimate a separate coefficient on each of the three tercile regressors (though of course one of these regressors is omitted as a reference category, which we take to be the middle tercile regressor).

The specification in equation (5) also includes a full set of district fixed effects, α_d, which absorb all unobserved district-specific time invariant determinants of the log 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 (for example, 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 (5) includes separate quadratic time trends for each of the five climatic regions r of India (groupings of states with similar climates according to India's Meteorological Department.)

Our *second approach* to modeling the temperature-death relationship estimates fewer parameters while still doing some justice to the non-linear nature of this relationship. This second approach, which we refer to as the 'single-index' approach, estimates the parameters in:

$$Y_{dt} = \beta \text{CDD32}_{dt} + \sum_{k=1}^{3} \delta_k \mathbf{1}\left\{\text{RAIN}_{dt}\text{in tercile } k\right\} + \alpha_d + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{dt}, \qquad (6)$$

where the variable $CDD32_{dt}$ is the number of cumulative degree-days in district d and year t that exceeded 32° C.[11] This is a particular restriction on the flexible approach in equation (5)—where the 13 temperature bin coefficients θ_j below 32° C are restricted to be zero and the three coefficients above 32° C are restricted to be linearly increasing in their average temperatures—for which we find some support below.

Our assumptions in pursuing this simplification are that: (i) on days during which the mean temperature is below 32° C, temperature is irrelevant for determining the outcome

[11]For example, if a given district-year had only two days over 32° C, one at 34° C and the other at 36° C, its value of $CDD32_{dt}$ would be 6.

variable (eg mortality) Y_{dt}; and (ii), the effect of days whose mean temperatures exceed 32° C is linearly increasing (at the rate β) in the mean daily temperature. This is broadly in line with a large public health and agronomy literature that uses the cumulative degree-day approach. The advantage of this single-index approach is that by estimating one coefficient rather than 15 we have more statistical power for teasing out the heterogeneous effects of temperature in order to learn more about the weather-death relationship.

The validity of this paper's empirical exercise rests crucially on the assumption that the estimation of equations (5) and (6) will produce unbiased estimates of the θ_j, β and δ_k parameters. By conditioning on district fixed effects, year fixed effects, and quadratic polynomial time trends specific to each climatic region, 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 time polynomials. Due to the randomness and unpredictability of weather fluctuations, it seems reasonable to presume that this variation is orthogonal to unobserved determinants of mortality rates.

There are two further points about estimating equations (5) and (6) 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 equations (5) and (6), where the weight is the square root of the population in the district for two complementary reasons.[12] First, the estimates of mortality rates from large population counties are more precise, so this weighting corrects for heteroskedasticity associated with these differences in precision. Second, the results reveal the impact on the average person, rather than on the average district, which we believe to be more meaningful.

5 Results

5.1 Weather and Death

Figure 1 in the Introduction of this paper displayed the result of running a regression of weather on death for India and the US. The two lines in Figure 1 show the impact of having an extra day in fifteen temperature bins relative to a day in the 22°-24° C bin for the US and India respectively. That is, the fifteen coefficient estimates $\widehat{\theta}_j$ for each of fifteen temperature bins j from estimating equation (5) are presented graphically, under the normalization that coefficient on the middle bin, the 22°-24° C bin, is zero. Further, as

[12]When estimating relationships in which the outcome variable concerns agricultural income we weight by the cultivated area of the district-year since the fundamental sampling unit in the data used to construct these outcome variables is a parcel of land.

discussed in Section 4, while only the coefficients on these fifteen temperature regressors are plotted, these coefficients were estimated while controlling for rainfall variation, district and year fixed effects, and quadratic polynomial trends for each climatological region. This is also true for all further graphical presentations of estimates of equation (5) shown below, in Figures 3 to 5.

As can be seen in Figure 1, interannual variation in temperature in the US shows no clear relationship with mortality. In strict contrast having more hot days in India is associated with significantly more death. Mortality increases steeply when there are more days at or above the 30°-32° C range (relative to 22°-24° C). And the effects are large, for example, one additional day with a mean temperature above 36° C, relative to a day with a mean temperature in the 22°-24° C range, increases the annual mortality rate by roughly 0.75 %. Put simply, hot weather kills in India but not—at least on nowhere near the same scale—in the US.

To better understand why this is the case we first split out mortality observations into those observed separately for the rural and urban populations of each Indian district. This allows us to understand whether or not the weather-death relationship is different for populations that are more or less dependent on weather contigent forms of economic production. The high frequency of our weather data also allows us to examine if weather during the growing season affects mortality differently from weather in the non-growing season.

5.1.1 Urban versus Rural

In terms of economic structure, urban and rural India look very different. In employment terms the rural areas of India are dominated by agriculture whilst urban areas are dominated by services and manufacturing. As we have seperate observations of mortality for rural and urban populations within the same district we can test whether the weather-death relationship differs for these two populations.

The results from doing this are shown in Figures 3 and 4. These figures plot estimated response functions between log annual mortality rate and temperature exposure, estimated separately for urban and rural populations. These models pool across age groups and pertain to the total population of a particular area within each district (i.e. the urban or rural segment of a district).

Figure 3 shows the response function estimated from the urban population. For both the urban Indian population and the US population there is, in effect, no significant relationship between weather and death. The results are remarkably different from those in the rural areas. The largest urban India coefficient is for the highest temperature bin ($> 36°$ C), and the magnitude is only 0.003—half the magnitude of the all-India coefficient (of 0.075) in

Figure 1. Further, it is notable that none of the other temperature effects is statistically significant, and all are relatively small in magnitude. Figure 4 shows the rural response function. This plot shows a significant and increasing relationship between log mortality rates and temperature. The largest coefficient is for the highest temperature bin ($> 36°$ C), and the magnitude is 0.010, so exchanging a single day in the 22°-24° C range for one in the $> 36°$ C range would lead to an increase in annual mortality rates of 1.0% in the rural sector. Looking only at the rural population thus significantly increases the size of the response function. The statistical precision of the coefficients above the reference category is evident, as shown by the 95% confidence interval that is bounded away from zero. However, the coefficients associated with the temperatures bins below the reference category are all smaller in magnitude and not statistically different from zero.

Figures 5 repeats the analysis of the temperature-death relationship in urban and rural India but this time for infants, rather than for the entire population. The urban-rural pattern we observe in Figures 3 and 4 persists—and interestingly the point estimate for the rural infant population is similar to that for the rural all-ages population, so both groups of the rural population appear equally vulnerable. The most important finding in Figure 5 is that weather extremes appear to cause death among rural but not urban infants. It is remarkable that even India's urban infants, a group that is widely though to be a fragile population and that is the concern of an enormous public health literature, are seemingly immune to temperature extremes. As such, the estimates of the response function in urban areas, both for adults and infants, suggest either that urban citizens are better positioned to adapt to temperature shocks, or perhaps, more plausibly, that there exists a weaker connection between extreme temperatures, incomes and death owing to the lower dependence on weather contingent forms of production.

As a final look at the simple, baseline relationship between weather and death in rural and urban India, Table 2 presents estimates of equation (6) in various forms, and for urban and rural sub-populations separately. Column (1) estimates the coefficient on 'CDD32', the number of cumulative degrees-times-days above 32° C, for the rural population. The estimated coefficient is statistically significant and equal to 0.013 for every 10 degree-days over 32° C. This implies that, among the rural population, a one standard deviation increase in the number of degree-days over 32° C (approximately 60, as seen in Table 1) would cause an increase in the mortality rate of approximately 8 percent (ie $0.013 \times 60 \div 10 = 0.078$ log points, or roughly 8 percent). To put this change in context, recall (from Table 1) that, in our data, all of the public health improvements in rural India, and the Green Revolution in agricultural practice, over the period from 1957-2000 reduced the death rate by only a factor of approximately 2.5.

Column (2) of Table 2 includes coefficients capturing variation in rainfall as well as those capturing variation in temperature. Two interesting patterns emerge. First, it is important to note that the coefficient on temperature (CDD32) changes only slightly after controlling for rainfall in this manner. This suggests that the rainfall tercile variables used in equation (6) are largely uncorrelated with (the residual variation in) our temperature regressor—and this turns out to be true for every different specification of rainfall that we have estimated. Second, the coefficients on rainfall themselves suggest a pattern that is sensible but statistically imprecise. That is, the coefficient on the 'rainfall in lowest tercile' regressor is positive and statistically significant, but only at the 10 percent level; the coefficient on the 'rainfall in highest tercile' regressor, on the other hand, is much closer to zero. This lines up with expectations—as well as with our results below—that particularly devastating scenarios concerning rainfall for Indian agriculture involve a surfeit rather than a surplus of rainfall. It also fails to square with a mechanism through which excess rainfall leads to a rise in water-borne disease that leads to excess mortality.

The final two columns of Table 2 estimate similar relationships to those in columns (1) and (2), but for urban rather than rural areas. These estimates demonstrate that the weather-death nexus in urban areas is much weaker than in urban areas, a pattern that was clear from Figures 3 and 4. As expected from the coefficient estimates for urban areas plotted in Figure 3, since the coefficient on the highest temperature bin (the extreme bin of $> 36°$ C) was statistically significant at the 5 percent level, the coefficient on the urban 'CDD32' variable is also statistically significant. However, this estimate is three times smaller than that in urban areas (and as we shall see below, is not robust to variants in the estimated specification in the way that the rural counterpart in column (1) is).

Table 3 continues to explore the relationship between temperature and death in rural and urban India, but in various different ways that intend to explore the robustness of our baseline results in Table 2. Column (2) considers whether there is an important interaction effect between the temperature and rainfall regressors in equation (6). Because the coefficient on temperature is highly invariant (changing from 0.0128 in column (1), the baseline, to 0.0133 in column (2)) to the inclusion of such interaction terms we conclude that these interaction terms are unimportant. This is an important finding because it fails to line up with the simple hypothesis that hot years kill people because they create ideal (ie hot and wet) conditions for the growth of (for example, diarrhoeal) disease.

Column (3) of Table 3 reports the estimate of the temperature coefficient in equation (6), but where the temperature regressor involves the number of degree-days over 30° C rather than 32° C as in column (1). The coefficient falls, as one should expect (since the mean value of the regressor rises) but is still large and statistically significant. Column (4) investigates the possibility that, in addition to hot days killing people, cold days kill people in rural India. The coefficient on the 'cold days' regressor is small and statistically insignificant, while the coefficient on 'CDD32' has hardly changed. We conclude that, as was reasonably apparent from the estimates in Figure 4, hot days are the serious killer in rural India.

Finally, the remaining four columns of Table 3 repeat the above analysis on urban areas. A similar pattern prevails, except that we see in column (7) that measurement of the temperature-death relationship in urban India is not robust to the manner in which temperature is included. This suggests that the underlying relationship is considerably weaker than in rural areas.

To summarize, the results in this sub-section demonstrate that those in the previous subsection—which referred to all-India averages—masked a striking heterogeneity between rural and urban India. In rural areas, ambient temperatures play an important role in determining the starkest aspect of health, the probability of dying. But in urban areas of India, this effect is largely absent, even among presumably vulnerable children under the age of one. That is, even though rural and urban residents experience the same weather extremes, these extremes have a dramatically different effect on these two populations.

5.1.2 Growing versus Non-Growing Seasons

Our analysis so far has documented a strong effect of a given year's weather on a given year's death rate. But it is natural to expect the effect of weather on mortality to differ according to the seasons. In particular, as considered in Section 2, if the weather causes mortality in rural areas because it harms rural residents' agricultural incomes, then it is weather during the agricultural growing seasons that should matter for death in rural areas while weather during non-growing seasons should be irrelevant for determining rural mortality.

To evaluate this hypothesis we take a parsimonious approach to determining the 'growing' and 'non-growing' seasons of Indian agriculture. As discussed in Section 3.2 above, the agricultural calendar in India is driven by the arrival of the southwest monsoon rains, after which time the vast majority of an average district's annual rainfall arrives. The southwest monsoon begins to arrive on the subcontinent at its southern tip (roughly the state of Kerala) on approximately June 1^{st} of every year. After this first arrival the onset of the monsoon moves slowly northwards throughout India, reaching its northern limits by, on average, the start of July. Because of this slow onset, the arrival of the monsoon, and therefore the start of the main agricultural season, varies throughout the country.

In order to partition a given year's weather data in any given district into that in the growing and non-growing season, we have obtained data on each district's 'typical' date of monsoon arrival from the Indian Meteorological Department. Within a calendar year, we define all dates after a given district's typical date of monsoon arrival as the growing season. To define the non-growing season we take all dates that are within the three-month (that is, 91-day) window prior to each district's typical date of monsoon arrival.[13]

Using this district-specific definition between growing and non-growing seasons, Figure 6 presents results that demonstrate the differential effects of weather on death at these two distinct times of the year. Because this split of the data entails a loss of precision, we use to the single-index specification introduced in equation (6); as discussed above, this has the advantage of estimating only one temperature coefficient rather than 15 coefficients while still capturing the essential features of non-linearity evident from the 15 coefficient estimates in Figure 1.

Figure 6 reports the coefficient on 'CDD32', the number of degree-days over 32° C, estimated separately when counting degrees-times-days within the growing and non-growing seasons separately. In the same specification we also estimate six separate lagged coefficients for both the growing and non-growing CDD32 coefficients. As a further cut of the data in Figure 6, we present these fourteen separate CDD32 coefficients for rural and urban areas separately. A number of striking patterns emerge. First, the rural CDD32 coefficients in the non-growing seasons, be they contemporaneous or lagged, are always close to zero and never statistically different from zero. Second, the rural CDD32 coefficients in the growing seasons are large and statistically significant in the contemporaneous year and, while they fall with longer and longer lags, growing season weather appears to kill people in rural India even three years after the fact. Finally, in urban areas, where one would presumably not expect to see an agricultural cycle having any bearing on people's lives, our estimates do not find one; all urban point estimates in Figure 6 are close to zero and statistically insignificant. This is of course reassuring.

A final important implication of the results in Figure 6 is that the point estimate of the mortality impact of a given day above 32° C is even larger than our earlier estimates in Table 2 suggested. Just as the move from all-India results (Figure 1) to rural-only results (Figure 4) increased our point estimates of the extent to which hot days kill members of a given population, we see that the coefficient on 'CDD32' (divided by 10) has risen from 0.0128 in column (2) of Table 2 to almost 0.035 in the contemporaneous growing season ('GS(t)') results in Figure 6. Further, an increase of 10 degrees-times-day above 32° C in the growing season appears, according to Figure 6, to raise the death rate by roughly 3.5 percent (0.035 log points) in the current year, and then another 3.3 percent in the next year, another 3.0

[13]The use of three months rather than the entire year matters little because there are so few hot days in the first months of the year. But we pursue this approach because in many regions the entire growing season, typically two harvests, the *kharif* and then the *rabi*, can be as long as nine months, so the first few months of a calendar year are typically the tail months of the previous year's agricultural season.

percent in the year after that, and another 2.5 percent in the year after that. That is, a single 34° C day (ie 2 degree-days), if and only if it occurs in the growing season will, according to our estimates, lead to an approximately 2.5 ($(3.5 + 3.3 + 3.0 + 2.5) \times 2 \div 10 = 2.46$) percent rise in the death rate over the course of the next four years. Clearly these hot growing season days are lethal.

It should be stressed that the hottest time of the year in virtually every part of India occurs in the non-growing season, in the build up to the arrival of the southwest monsoon. The absence of any effect of temperatures on death in urban India in Figure 6 suggests that there is probably no time of the year during which temperature extremes matter for the urban death rate. And the absence of any effect of hot days on death in rural India when these hot days occur before crops have been planted seems difficult to understand in the context of 'heat stress', or a direct physiological connection between hot days and the suffering of cardiovascular systems.

The results in this sub-section therefore paint a compelling picture. The weather-death connection in India is a rural phenonmenon, and it is a phenomenon that is strikingly (as seen in Figure 6) concentrated around the agricultural cycle. Put simply, temperature extremes kill people when crops are in the soil, in parts of the country where people's livelihoods are tied to these same crops. In the next section we explore the plausibility of an agricultural explanation for the fact that hot days kill so many people in rural India by examining agricultural incomes directly. Before doing so we first briefly discuss results on how the weather-death relationship in India has changed throughout our sample.

5.1.3 Has the Effect of Weather on Death Changed Over Time?

The sample period used in the analysis throughout this paper has been from 1957 to 2000. (This choice of years is entirely driven by data availability.) These 44 years have seen a great deal of change in India–important improvements in rural health practice, significant background reductions in rural mortality rates, and significant increases in rural incomes (due, among other causal factors, to the Green Revolution in agricultural technologies). A natural reaction to the results we have presented so far might be that, given all of these improvements, it is possible that our estimates are being driven in large part by the earliest years in our sample. Put another way, it is possible that the lethal effects of inclement weather in rural India are a thing of the past.

We investigate this possibility by estimating separate coefficients on our 'cumulative degree-days over 32° C' regressor for four separate 11-year periods (1957-1967, 1968-1978, 1979-1989 and 1900-2000). That is, we estimate equation (6) above but with the 'CDD32' variable interacted with categorical variables representing each of these four periods.

The results of this analysis are presented in Figure 7. The findings here suggest that, while the effect of weather on death in rural India has indeed been falling over the past 44 years, our CDD32 coefficient appears to be remarkably stable since the 1968-1978 period. That is, weather and death in rural India is by no means a thing of the past.

5.2 Weather and Incomes

Given the findings in the previous section—that inclement weather kills in large magnitudes in India, but that this is only true in rural areas and when inclement weather occurs in the growing season—we now investigate the possibility that these weather and death effects are being driven by the effects of inclement weather on income levels. We begin this section by assessing whether the the same hot days and rainfall shortages that kill people are also harming rural, agricultural incomes. We then go on to look at the effect of these same weather variables in urban areas. A striking finding is that all agricultural income variables to which we have access—yields, prices and wages—respond to inclement weather in exactly the same manner as the rural mortality rate was seen to in the previous section. Likewise, we find virtually no response of urban incomes to weather variation, which again parallels the results for the mortality rate in urban areas.

5.2.1 Agricultural Incomes (Yields, Wages and Prices)

An agricultural income channel relating weather to death in rural India would begin with an effect of weather shocks on agricultural productivity. Using the data on agricultural yields introduced in Section 3, we therefore estimate this weather-yields relationship in this section. We model temperature and precipitation in precisely the same manner as when estimating the weather-death relationship, as laid out in equations (5) and (6); that is, temperature is modeled using either 15 temperature bins or the single-index approach (ie based on the number of cumulative degree-days over 32° C), and precipitation is modeled using separate coefficients for two terciles of district-specific annual rainfall amounts.[14]

[14] One small difference here, when compared to the death regressions, is our adjustment of the timing of the weather data when relating it to agricultural outcomes (that is, to yields in this section as well as to prices and wages in following sections). The agricultural yield data used here are based on measures of the total amount of output produced during the agricultural year (defined as running from June 1st to May 31st). If the weather in 'year t' is to matter for agricultural output in 'year t', it is important to define 'year t' in the same way across both the weather and agricultural output data. In the agricultural regressions in this and following sections, we therefore re-label the years in the weather data so that weather on dates from January 1st to May 31st are lagged by a year. Put another way, when estimating equations (5) and (6) on agricultural outcomes here, the year t is defined as the 365 days beginning on June 1st of any given calendar year.

Figure 8 plots the 15 temperature bin coefficients when agricultural yields are regressed on the 15 temperature bin regressors (as well our rainfall controls, fixed effects and quadratic region-specific polynomials in time). The pattern of coefficients that emerges is strikingly similar to that between temperature and death in rural India presented in Figure 4, only it is inverted because high temperatures damage plants and therefore reduce yields. High temperature days reduce agricultural yields significantly—for example, the coefficient estimate for days with mean temperatures exceeding 36° C implies that every *single* day in this category (relative to a day in the 22° - 24° C reference category) reduces agricultural yields by 0.04 %. And the point estimates on each of these temperature bin coefficients are individually statistically different from zero above the 28° C mark.

Figure 9 repeats this same exercise for our measure of nominal agricultural wages (wages of agricultural day laborers, as described in Section 3. It would would be natural to expect that when agricultural productivity falls in years with hot days, as seen in Figure 8, so too do wages in the agricultural sector. We indeed see a similar pattern, at least as concerns the range of effects that is of interest to us, those above 22° - 24° C.[15]

As with the results in the previous section on weather and death, we now estimate the relationship between weather and income in a more parsimonious manner, following the estimating approach in equation (6). These results are presented in Table 5. Column (1) reports the 'CDD32' coefficient (that capturing the effect of cumulative degrees-times-days above 32° C) for agricultural yields, as well as the two rainfall tercile coefficients. As expected (based on Figure 8), the effect of hot days as captured by CDD32 is strongly negative, and the coefficient on rainfall in the lowest tercile is also negative (abnormally dry years lead to lower yields). The effect of abnormally wet years is slightly positive, but not statistically significant. All of these temperature and rainfall coefficients line up, but with signs reversed, with their counterparts in an equivalent weather-and-rural death regression in column (2) of Table 2.

Column (2) of Table 4 then reports results from the same regression as column (1) but for nominal agricultural wages as the outcome variable instead of agricultural yields. Consistent with the results in Figure 9, there is a strong effect of hot days (as captured by 'CDD32') on agricultural wages. Further, there is a strong and statistically significant effect of abnormally low rainfall amounts on reducing agricultural wages (that is, years with in which the amount

[15]A similar, but reversed because adverse production raises prices, pattern obtains for our third measure of rural economic activity, the agricultural price index. Notably the coefficients on the highest temperature bin regressors are smaller in absolute value than those in Figure 8 for agricultural yields. (These coefficients are still statistically significant, however, at the 5 percent level.) One interpretation of this finding is that (albeit incomplete) markets integration across Indian districts prevents local production shocks from strongly affecting local prices. We omit these results for brevity but they are available upon request.

of annual rainfall is in the lowest district-specific tercile experience significantly lower wages). Finally, in line with the yield results in column (1), and the rural weather and death results in Table 2, the effect of bountiful rainfall is small and imprecisely estimated.

A natural implication of reduced agricultural yields in a locality—in any type of trading regime shy of the small open economy limit—is a rise in that locality's agricultural prices. We therefore turn to estimates that involve agricultural price data. The results from estimating equation (6) in which agricultural prices are the outcome variable are contained in column (3) of Table 4. A now familiar pattern emerges: hot days and low rainfall amounts raise agricultural prices, and abnormally high amounts of rainfall do not. Interestingly the 'CDD32' coefficient in the agricultural price regression in column (3) is approximately one-tenth the size (in absolute value) of the coefficient for agricultural yields in column (1). This is consistent with a strong extent of market integration across Indian districts—that is, with the notion that, in a very open economy, a change in local production does little to move the effective aggregate supply curve in a location. An alternative explanation, of course, is that price- and/or income-elasticities for the demand of these agricultural goods are very low.

The results in this section paint a coherent picture. When measured in every way that we are able, markers of agricultural incomes respond to weather shocks in a consistent manner, and this response is similar (but inverted) to the response of the rural death rate to weather shocks. This is entirely consistent with our findings that the rural weather-death relationship is entirely confined to the growing, rather than the non-growing, periods within a year and suggests that it is plausible that weather-induced income shortfalls are large enough, and that opportunities for consumption smoothing are poor enough, in rural areas that weather fluctuations can cause death through an income-based channel.

5.2.2 Urban Incomes (Productivity, Wages and Prices)

In this section we report results that suggest that, in contrast to the rural income responses to inclement weather documented above, there is no similar response of incomes to the weather in urban India. Naturally, evidence in the previous section on how agricultural productivity, wages and prices respond strongly to weather variation was not unexpected. A large body of agronomic work documents how plants suffer at temperatures above approximately 32 C, and that scanty rainfall is detrimental to yields in largely unirrigated environments like India. By contrast, the enquiry into the weather-urban income relationship in this section is more speculative because it cannot draw on a rich theoretical and experimental literature (like the body of research assembled by agronomists) about what direction we should expect, say, manufacturing productivity to turn when temperatures are hot or rainfall is scanty. We therefore see the results here largely as a check that, in our data, the relationship between weather fluctuations and urban living standards is not strong.

Our results are contained in columns (4) through (6) of Table 4. An important caveat regarding the results in this table is that, as explained in Section 3, we have been unable to obtain information on India's urban economy at the district-level; instead, all of the data used in columns (4) through (6) is available only at the state-level. This means that all of these estimates will be considerably less precise, given the smaller sample size.[16]

Columns (4) through (6) of Table 4 report estimates of equation (6) when using urban productivity (measured as the amount of output per worker in the registered manufacturing sector), urban nominal wages (measured as nominal earnings per worker in the registered manufacturing sectors), and urban prices (measured using the standard urban CPI, the 'agricultural workers' CPI'), as outcome variables, respectively. While in many ways these are not perfect analogues of the rural, agricultural income variables in columns (1) through (3), as we describe in Section 3 we believe that they are reasonable proxies for urban incomes and prices.

The relationship between weather (temperature and rainfall) extremes and these three outcome variables in columns (4) through (6) is never estimated with enough precision to have standard levels of confidence in the sign of these relationships—that is, the standard errors in these regressions are very large relative to the point estimates. And most importantly, the three regressions fail to portray a simple and consistent picture with respect to one another (for example, the effect of hot days on productivity is very trivially negative, and it is positive on prices, but it is also positive on wages). We conclude—albeit tentatively, given the caveats above—that there is no strong weather-income relationship in urban India.

6 Implications of Climate Change

The results in Section 5 above suggest that weather extremes, in the form of hot or dry years, have strong effects on mortality in rural areas. Likewise, the results in Section 5.2 above suggest that these same weather extremes leave a remarkably similar pattern of results on markers of economic welfare among the rural population—such as agricultural yields, real agricultural wages, and agricultural food prices—but not on similar markers among the urban population. Both of these sets of results are important in their own right as they suggest that weather fluctuations may matter a great deal for the welfare of poor citizens in developing countries. However, in an era when climatologists are increasingly confident that the world's climate is changing and will continue to change, our estimates of the weather-

[16]For the purposes of the results in Table 4, we aggregate our district-level weather data to the state-level by using weights proportional to size of each district's urban population.

death relationship obtained above can also be used to provide—with considerable caution, as we stress below—upper-bound estimates of some of the health costs of this predicted climate change.

To shed light on this we have obtained data on the predicted change in India's climate that emerges from two leading global circulation models (GCMs), the models that climatologists use to make predictions about how greenhouse gas emissions will lead to likely climate change scenarios. We refer to these models as 'Hadley 3' (the preferred model in use by the Hadley Centre, which provided climate change predictions for the influential Stern Review), and 'CCSM 3' (the preferred model in use by the National Center for Atmospheric Research). These models were used in the most recent Intergovernmental Panel on Climate Change (IPCC) report. In the Data Appendix we describe the construction of these models in more detail.

These climatological models make predictions about the evolution of daily weather at finely spaced gridpoints all over the world, on every day for the next 100 years. We use these predictions (averaged over hundreds of simulations of the models) to construct a set of temperature predictions, one for each of the two GCM models, for each of India's districts using a procedure detailed in the Data Appendix. In particular, in order to align the predicted climatic variation with the inter-annual climatic variation we used in Section 5 to estimate the within-sample weather-death relationship, we use the GCM models to predict the average number of days in which the mean temperature will fall into each of the 15 temperature bins between the years 2070 and 2099. (We choose to average over 30 years of predicted values in order to smooth out prediction error in these climate models). This generates a variable that we denote $TMEAN_{dj}^{2070-2099}$, the climate change model's prediction for the number of days on which the mean temperature in district d will fall into temperature bin j on average over the 2070-2099 period.

These models also make predictions about changes to the distribution of rainfall in India and we treat these predictions similarly. However, it should be noted that there is considerably less agreement in the climatological literature about how climate change will affect precipitation patterns (particularly in India, where the complex dynamics of the monsoon are not well understood). For this reason we separate our results below into those that are due to the predicted change in temperatures and those that are due to the predicted change in rainfall.

Before proceeding, it is important to underscore that the validity of this 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 gas emissions on climatic behavior (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 uncertainty cannot readily be incorporated into the below estimates of the impacts of climate change. Nevertheless, the use of two sets of (prominent) daily climate change predictions provides some sense of the variation.

Figure 10 provides an opportunity to understand how climate change is expected to change the full distributions of daily mean temperatures in India. In this figure we compare the predicted distribution of daily mean temperatures across the 15 temperature bins (ie $TMEAN_{dj}^{2070-2099}$ averaged over districts d, for each temperature bin j) with the actual historical average equivalent over the observed period used in this paper (ie 1957-2000). We denote the historical average number of days in which the mean temperature in district d fell into temperature bin j between 1957 and 2000 by $TMEAN_{dj}^{1957-2000}$.

Figure 2, discussed in Setion 3, plotted the distribution of daily temperatures into 15 temperature bins $TMEAN_{dj}^{1957-2000}$ averaged over all districts d. In Figure 17 we therefore plot the predicted *change* in the average daily temperature distribution going out to 2070-2099, ie $\Delta TMEAN_{dj} \equiv TMEAN_{dj}^{2070-2099} - TMEAN_{dj}^{1957-2000}$, averaged over districts d.[17] Since the two GCMs make different predictions about this distributional change we plot both of their predictions in Figure 10. The resulting plot 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 differential mortality impact of the days in the 14° to 28° C range, 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. That is, under both predicted climate change scenarios, India will exchange days that we have estimated (in Figure 1) to be relatively low mortality days for days that we have estimated (again in Figure 1) to be high mortality ones.

We now turn to a more precise calculation of the predicted mortality impacts of climate change on India. Table 5 presents estimates based on the estimation of equation (5) 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 predicted impact in district d is based on

[17] When computing all such averages we weight by district population.

district-level predictions calculated as:

$$\Delta \widehat{Y_{dt}} = \sum_j \widehat{\theta}_j \Delta TMEAN_{dj}, \tag{7}$$

where $\Delta \widehat{Y_{dt}}$ is the predicted change in the log mortality rate, $\widehat{\theta}_j$ is the estimated coefficient on temperature bin j obtained in Section 5, and $\Delta TMEAN_{dj}$ is the predicted (according to the Hadley 3 or CCSM 3 A2 model) change in the number of days on which the mean temperature will fall into temperature bin j by 2070-2099. This is the predicted impact of climate change, according to these models and an extrapolation of our estimated weather-death relationship, in district d. In order to construct a meaningful total impact for all of India, we report the population-weighted average of each district d's predicted impact. The standard error of this prediction is calculated accordingly.

Columns (1)-(3) of Table 5 summarize this calculation for three daily mean temperature categories, those for $< 16^\circ$ C, $16^\circ - 32^\circ$ C, and $> 32^\circ$ C respectively. Column (4) then reports the total temperature impact obtained by summing the impacts in columns (1)-(3), and column (5) includes the predicted precipitation impact. Finally, the rows of Table 5 correspond to different statistical models (covering different regions of India) and different climate change models. For each climate change model, we calculate the predicted percentage 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 46.2% 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 3 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 rows break down the analysis by rural/urban area. As expected, given the estimates in Figures 3 and 4, the results are sharply different for urban and rural areas. For rural areas, annual mortality rates are predicted to increase by 61.7% 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). The third row, which focuses on urban areas tells a completely different story. The predicted change in annual mortality is 11.6%, and is not statistically distinguishable from zero at conventional levels.

The lower panel shows the results derived from the CCSM 3 A2 model as opposed to the Hadley model. The predicted increases in annual mortality are smaller than those from the Hadley model in Panel A, but still large and concentrated in the rural areas; the predicted effect in rural areas according to this model is 20.7%. The discrepancy between the Hadley and CCSM predictions reflects in part the fact that the Hadley scenario is associated with larger increases in temperature than the CCSM scenario. The overall CCSM impacts are marginally significant, 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.

The results reported in this section suggest that the health costs of predicted climate change in India could be severe—when standard models of climate change are used in combination with our estimates of the weather-death relationship, these models predict large increases in the death rate in India by 2080. Because our focus has been on mortality rather than on morbidity, the effects of weather on wider health indicators in India are likely to be understated by our estimates. And as stressed in Section 2, the full welfare impact of weather fluctuations should involve computations of lost income and of resources spent on health input goods, in addition to those involving heightened mortality.

However, it is important to bear a number of caveats in mind when interpreting these findings. First, we have estimated the effect of weather on death using inter-annual variation, so our estimates are best thought of as short-run impacts to unexpected shocks. As such they are likely to provide only an upper-bound to the impact of long-run, predictable climate change of the sort forecasted by standard climatological models. This is because individuals are likely to be better able to adapt to long-run, predictable change, for example through migration (for example, from rural to urban areas), technology adoption, or occupational change away from climate-exposed industries such as agriculture. Second, our estimates of the weather-death relationship have been based on exploiting cross-regional differences in exposure to weather extremes in any given year. Climate change scenarios, by contrast, involve all regions seeing higher temperatures. If there is any scope for cross-regional insurance against differential regional-level shocks then our estimates are being estimated in settings in which that insurance is potentially mitigating the effects of a region's shock on its own fortunes. In this sense our estimates could be seen as underestimates of the effects of hotter days in future scenarios in which all of India becomes hotter. Finally, the climatological models whose climate change predictions we have used here do not incorporate any possibility of catastrophic change in India's climate as a result of a rise in greenhouse gas emissions. That is, while some climatological models predict that modest rises in temperatures may have catastrophic knock-on effects (eg rises in ocean temperature, widespread melting of Himalayan glaciers, reversal of trade winds, or cessation of the Southwest monsoon), we have deliberately obtained our climate predictions from climatological models in which these catastrophic, but highly uncertain and controversial, effects are not in operation.

7 Conclusion

As weather sweeps across the Indian sub-continent it exerts a profound effect on the economic activities of Indian citizens. Hence the fascination in the Indian media with the rise and ebb of temperature and with the arrival (or late arrival) of the southwest monsoon. And nowhere is this influence more keenly felt than amongst rural citizens who depend on basic agriculture (either as cultivators or laborers) for their livelihoods. It is in these rural parts of India, where structural change towards less weather-reliant forms of production has been limited, that people feel the brunt of weather shocks. And these effects are particularly acute when inclement weather coincides with periods of agricultural production.

That inclement weather affects incomes and employment in these settings is undisputed. What is less well understood is whether weather shocks still have the power to cause excess mortality in post-Independence India. Much has been made of the dissapearance of famines during this period (Sen 1981) but the high levels of ill-health and malnutrition observed amongst agricultural laborers and small-scale cultivators in India suggests that their survival may be threatened by extremes of weather. Hence the obsession with seasonality and with hungry or lean seasons in discussions of rural welfare (Khandker 2009). Thus though mass starvation events like famines may have been eliminated there is always the suspicion that below the media radar hunger and malnutrition, caused by weather related income shortfalls, may be grinding away at the survival chances of India's poorest citizens (Dreze and Sen 1989). The objective of this paper has been to find out whether this is the case or not.

In this paper we find that weather and death remain closely related in post-Independence India. Quasi-random weather fluctuations introduce a lottery in the survival chances of Indian citizens. But this lottery only affects people living in the rural parts of India where agricultural yields, wages and prices are adversely affected by hot and dry weather.

In contrast, the citizens of urban India are largely immune to these mortality increasing effects of inclement weather as are citizens in the US. The effects of weather on death, in short, are highly unequal even within a single country. This in turn suggests that the effects of climate change will be highly unequal. Using the coefficients from our analysis of Indian districts combined with two leading models of climate change we confirm this by demonstrating that the mortality increasing impacts of global warming will be far more keenly felt by rural Indians relative to their counterparts in urban India or the US.

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A Data Appendix

A.1 Climate Change Prediction Data

To obtain predictions on the manner in which India's climate is predicted to change by the end of the century we use the output of two leading general circulation 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 appropriate scenarios to consider when judging policies to restrict greenhouse gas emissions.

We obtain daily temperature 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 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 the climate that is predicted in India at the end of this century. The Hadley 3 model has predictions for the years 1990 through 2099. We utilize the historical predictions to account for the possibility of model error. 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 $T^H_{gt,2070-2099}$ and $T^H_{gt,1990-2000}$, respectively, where the 'H' superscript refers to Hadley 3, g indicates grid point and t references one of the 365 days in a year.

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 $\Delta T^H_{gt} = (T^H_{gt,2070-2099} - T^H_{gt,1990-2000})$.

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 that has been used throughout this paper, 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 $T^{NCC}_{dt,1957-2000}$.

5. The predicted end of century climate for each day of the year is equal to $T^{NCC}_{dt,1957-2000} + \Delta T^H_{dt}$. 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 are no historical years available with which to remove model error.

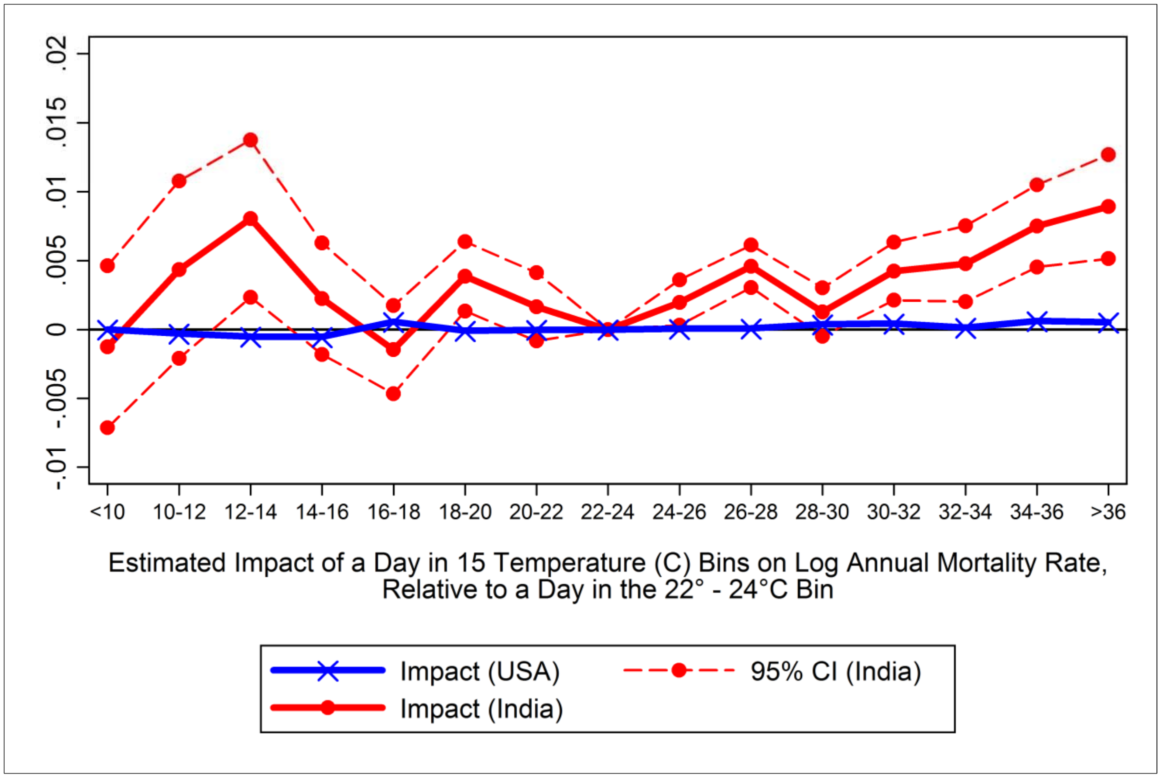

Figure 1: Mortality Impact of Temperature in India and United States. Note: The two solid 'impact' lines report 14 coefficient estimates, representing the effect on annual (all ages) mortality of a single day in each of the corresponding 14 temperature bins, relative to the effect of a day in the 22-24 C bin. Dashed lines represent the 95% confidence interval of the Indian estimates. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

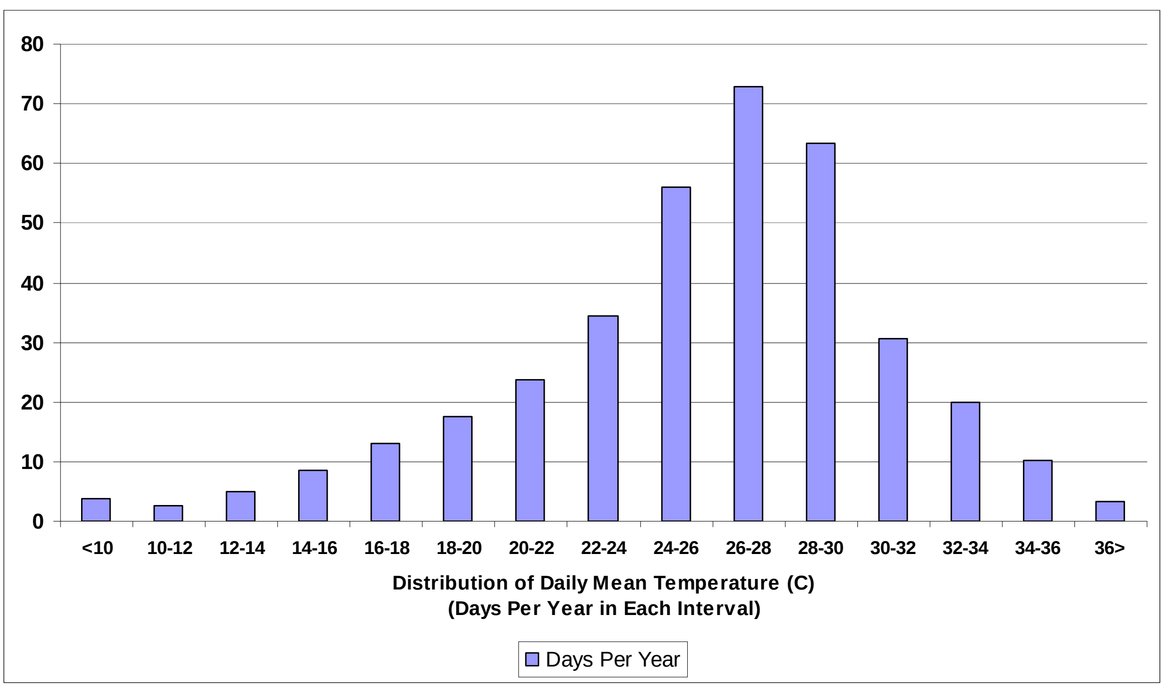

Figure 2: Distribution of Daily Temperatures. Note: Mean daily temperature for each district and year, averaged while weighting by district population. Each of the 365 daily realizations of the mean temperature in a year are placed into one of 15 bins, the same 15 bins as used in the regression estimated in Figure 1.

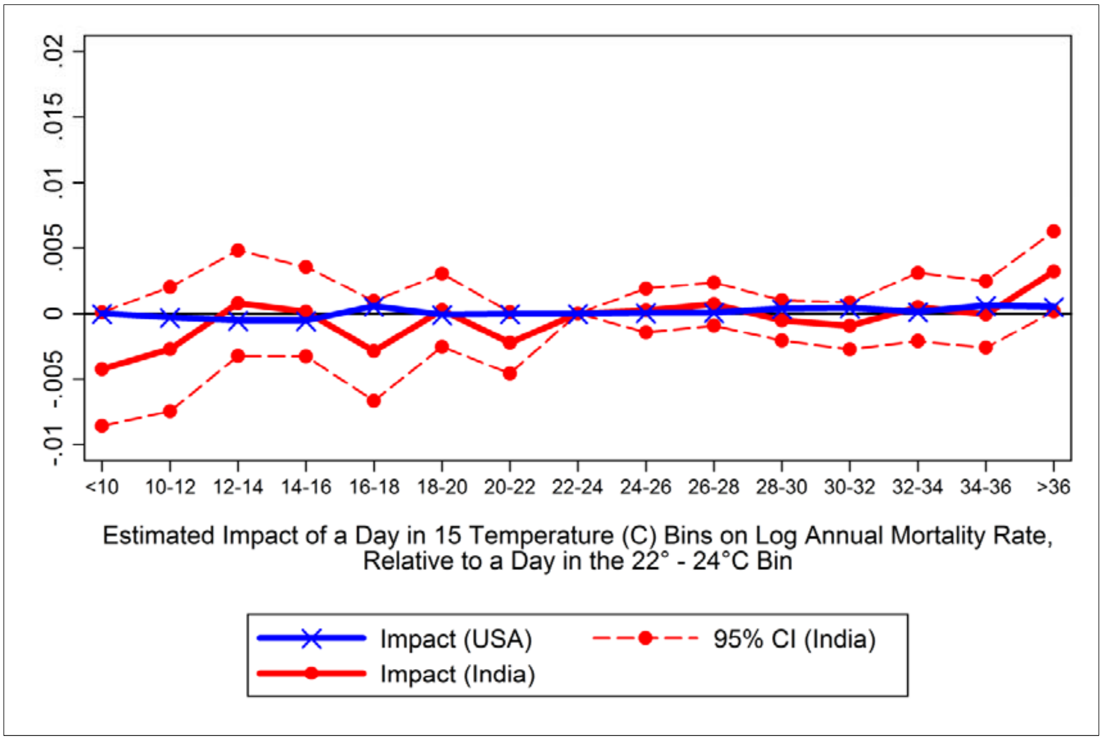

Figure 3: Mortality Impact of Temperature in Urban India and United States. Note: The two solid 'impact' lines report 14 coefficient estimates, representing the effect on annual (all ages) mortality of a single day in each of the corresponding 14 temperature bins, relative to the effect of a day in the 22-24 C bin. The dashed lines represent the 95% confidence interval of the urban India estimate. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

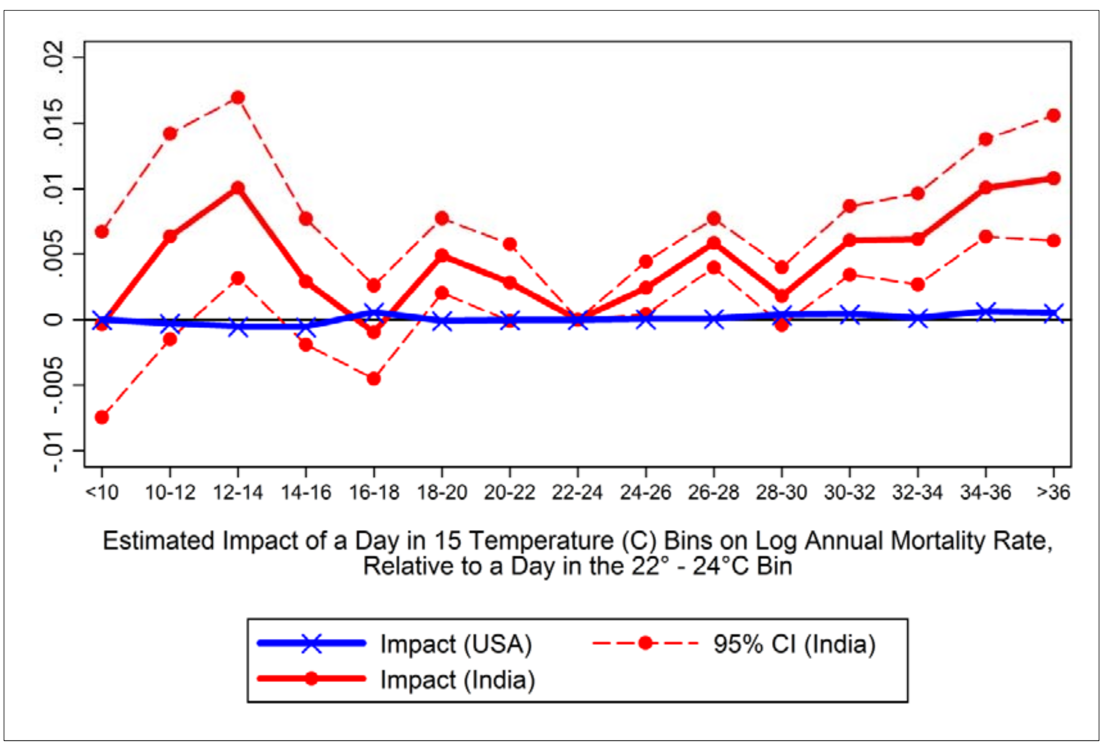

Figure 4: Mortality Impact of Temperature in Rural India and United States. Note: The two solid 'impact' lines report 14 coefficient estimates, representing the effect on annual (all ages) mortality of a single day in each of the corresponding 14 temperature bins, relative to the effect of a day in the 22-24 C bin. The dashed lines represent the 95% confidence interval of the rural India estimate. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

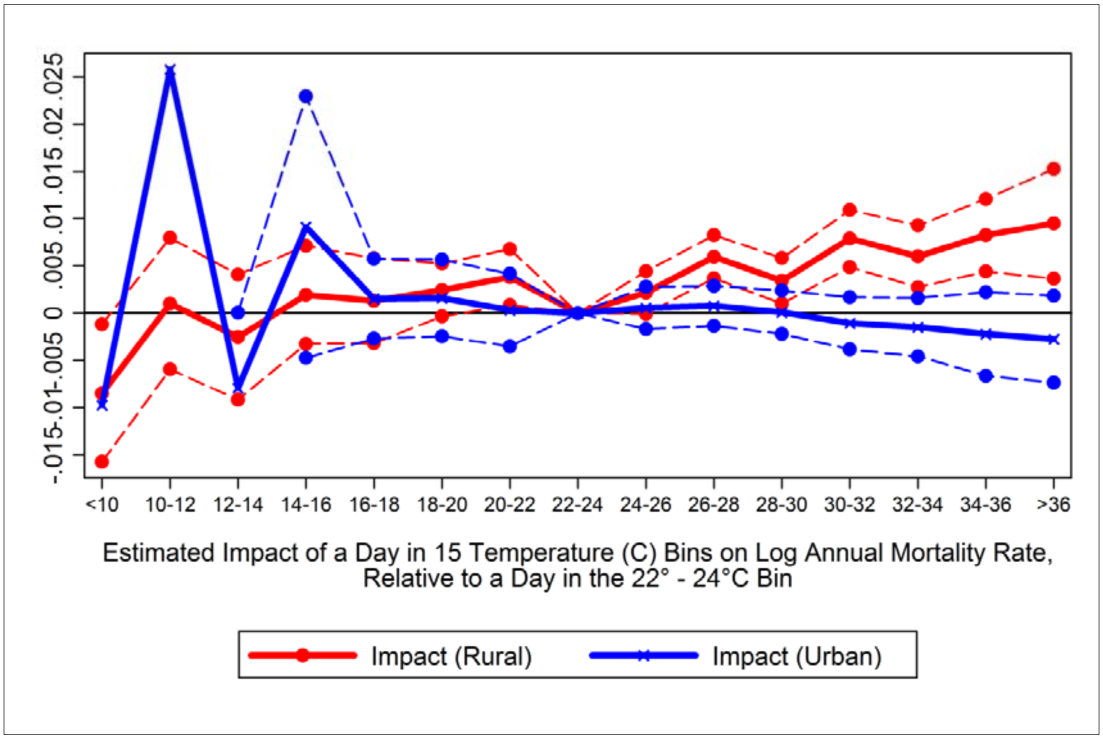

Figure 5: Infant Mortality Impact of Temperature in Urban and Rural India. Note: The two solid 'impact' lines report 14 coefficient estimates, representing the effect on annual infant (under age one) mortality of a single day in each of the corresponding 14 temperature bins, relative to the effect of a day in the 22-24 C bin. The dashed lines represent 95% confidence intervals. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

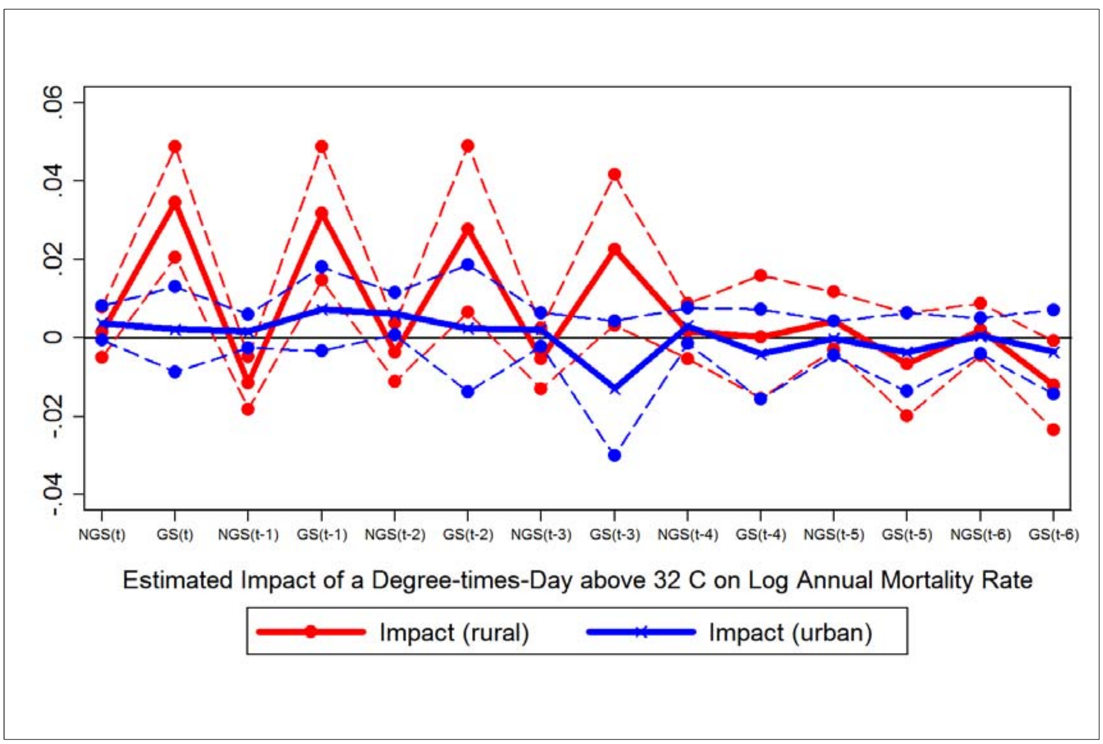

Figure 6: Mortality Impact of Temperature in Urban and Rural India, Along Agricultural Cycle. Note: The two solid lines report the coefficient estimate of a cumulative degree-day over 32C when those degree-days occur at different points in the agricultural cycle. 'NGS(t)' refers to the non-growing season in year t, 'GS(t)' refers to the growing season in year t; other values of the x-axis are lags (of up to 6 years) of these growing and non-growing season effects.

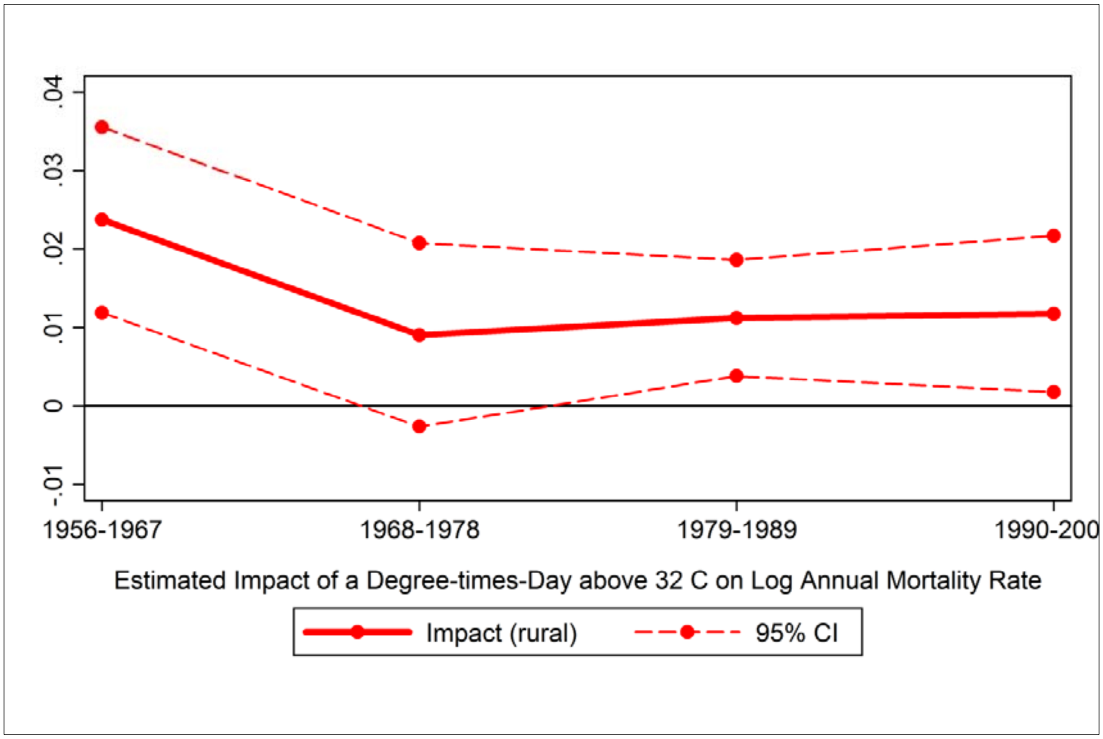

Figure 7: Mortality Impact of Temperature in Rural India, by Historical Period. Note: The solid line reports the impact of a cumulative degree day over 32C on the mortality rate in rural India, separately for each of four historical periods. The dashed lines report the 95% confidence interval of these estimates. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

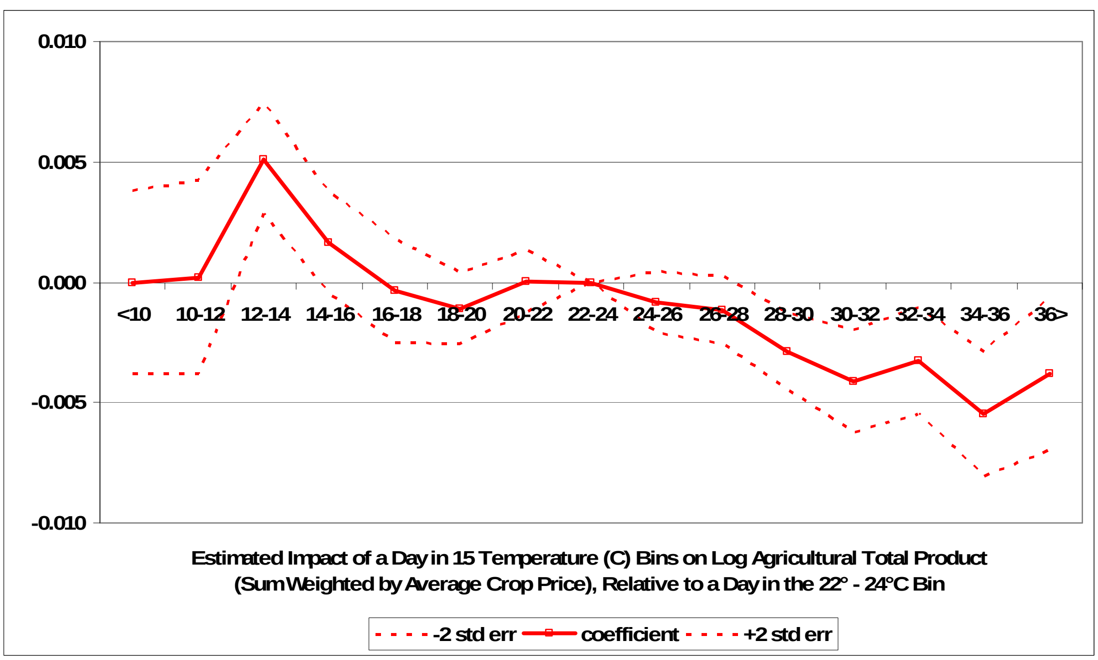

Figure 8: The Effect of Daily Temperatures on Agricultural Yields. Note: The solid 'coefficient' line reports 14 coefficient estimates, representing the effect on annual agricultural yields of a single day in each of the corresponding 14 temperature bins, relative to the effect of a day in the 22-24 C bin. The dashed lines represent the coefficient plus/minus two standard errors. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

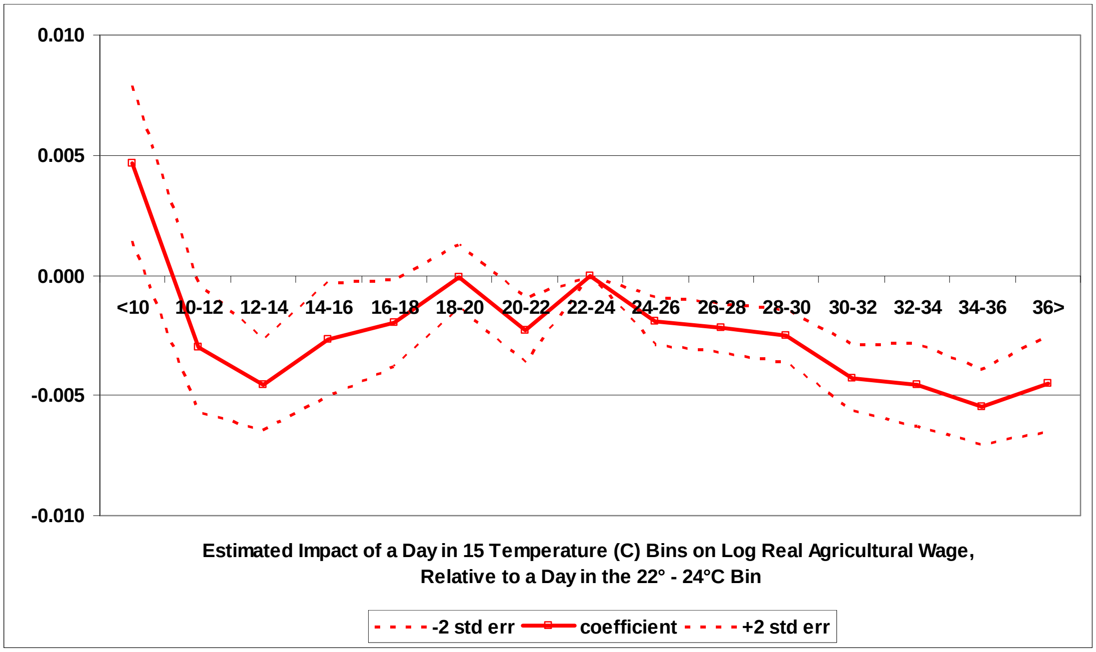

Figure 9: The Effect of Daily Temperatures on Agricultural Wages. Note: The solid 'coefficient' line reports 14 coefficient estimates, representing the effect on annual agricultural wages (wages of agricultural laborers) of a single day in each of the corresponding 14 temperature bins, relative to the effect of a day in the 22-24 C bin. The dashed lines represent the coefficient plus/minus two standard errors. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

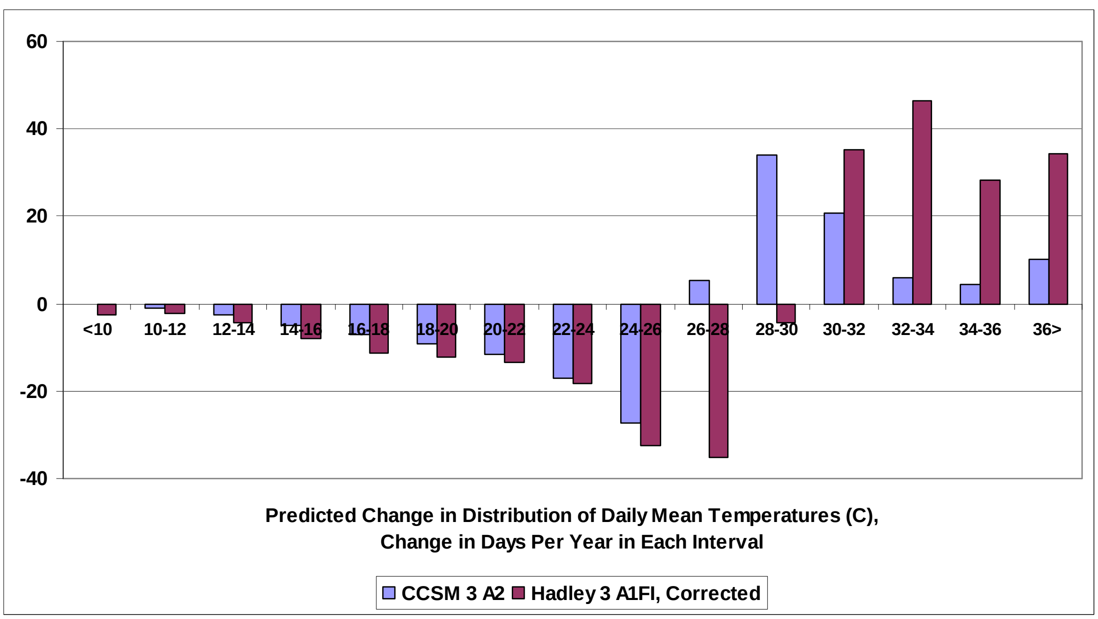

Figure 10: Predicted Change in Distribution of Daily Temperatures in India to 2070-2099. Notes: Temperature distributions (daily averages) for two leading global circulation models under an increase in greenhouse gas emissions and a `business as usual' scenario. Mean temperatures are weighted by average district population between 1957 and 2000. See the text for more details.

Table 1: Descriptive Statistics

	Rural Areas				Urban Areas			
	1957-1969	1970-1979	1980-1989	1990-2000	1957-1969	1970-1979	1980-1989	1990-2000
Total Death Rate Per 1,000 Population	10.74	8.35	4.26	4.30	11.44	8.78	6.21	6.02
	(6.70)	(4.67)	(2.73)	(2.57)	(5.21)	(3.96)	(2.96)	(2.30)
Infant (<1) Death Rate Per 1,000 Live Births	75.70	47.73	28.43	16.25	69.68	50.33	31.38	19.25
	(63.06)	(26.06)	(23.85)	(17.07)	(38.81)	(36.91)	(20.52)	(15.31)
Agricultural Yield Index (kg/hectare)	24.5	30.9	39.2	-	-	-	-	-
	(11.6)	(16.3)	(22.7)	-	-	-	-	-
Agricultural Price Index (Rs/kg)	8.0	7.8	7.1	-	-	-	-	-
	(1.5)	(1.5)	(0.9	-	-	-	-	-
Agricultural Real Wages (Rs/day)	24.80	27.22	33.96	-	-	-	-	-
	(9.85)	(11.00)	(14.05)	-	-	-	-	-
Manufacturing Earnings Per Worker (Rs/annum)					28,330	29,982	32,595	24,493
					(4,741)	(7,596)	(6,378)	(6,149)
Annual Degree-Days (over 32 C)	63.32	61.22	69.45	67.78	55.83	55.29	66.23	(61.18)
	(57.21)	(58.66)	(61.97)	(62.98)	(57.87)	(58.25)	(62.23)	(61.73)
Annual Total Precipitation (cm)	107.73	110.90	105.11	104.52	103.67	107.24	102.01	104.37
	(37.94)	(40.94)	(41.68)	(42.28)	(37.18)	(40.62)	(41.40)	(42.41)

Notes : Note: All statistics are weighted by total district-area (ie rural/urban) population, with the exception of the Agricultural Yield, Price and Real Wage indices, which are weighted total crop area. Standard deviations in parentheses. Monetary values are in year 2000 Rs, deflated by urban/rural-specific deflators.

Table 2: Weather and Death - Rural-Urban Differences

	Rural		Urban	
Dependent Variable: Log (Mortality Rate)	(1)	(2)	(1)	(2)
Temperature (degree-days over 32 C)/10	0.0131***	0.0128***	0.0048**	0.0046**
	0.0031	0.0032	(0.0020)	(0.0020)
Indicator for Rainfall Shock in Lowest Tercile		0.0282*		-0.0050
		0.0147		(0.0105)
Indicator for Rainfall Shock in Highest Tercile		-0.0055		-0.0164
		0.0179		(0.0109)
R-squared	0.626	0.626	0.622	0.622
Observations	11,721	11,721	12,089	12,089

Notes: Regressions are estimated separately by rural/urban sectors and include district fixed effects, year fixed effects, and quadratic region time trends. Regressions are weighted by district population, and standard errors are clustered at the district level. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table 3: Weather and Death - Robustness

Dependent Variable: Log(Mortality Rate)	Rural (1)	Rural (2)	Rural (3)	Rural (4)	Urban (5)	Urban (6)	Urban (7)	Urban (8)
Temperature (degree-days over 32 C)/10	0.0128***	0.0133***		0.0135***	0.0046**	0.0045**		0.0044**
	(0.0032)	(0.0032)		(0.0031)	(0.0020)	(0.0020)		(0.0020)
Temperature (degree-days over 30 C)/10			0.0111***				0.0024	
			(0.0032)				(0.0014)	
Temperature (degree-days under 16 C)/10				0.0017				-0.0014
				(0.0025)				(0.0015)
Temperature-rainfall interactions included?	No	Yes	No	No	No	Yes	No	No
R-squared	0.626	0.628	0.626	0.626	0.622	0.623	0.621	0.622
Observations	11,721	11,721	11,721	11,721	12,089	12,089	12,089	12,089

Notes: Regressions are estimated separately by rural/urban sectors and include district fixed effects, year fixed effects, and quadratic region time trends. All regressions control for rainfall (upper/lower tercile dummies) as in Table 2. Regressions in columns (2) and (6) control for the interaction between temperature (degree-days over 32 C) and each rainfall tercile dummy variable. Regressions are weighted by district population, and standard errors are clustered at the district level. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table 4: Weather and Incomes - Rural-Urban Differences

	Rural			Urban		
Dependent Variable:	Log (Productivity)	Log (Nominal Wages)	Log (Prices)	Log (Productivity)	Log (Nominal Wages)	Log (Prices)
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (degree-days over 32 C)/10	-0.010***	-0.0045**	0.0019**	-0.0000	0.0065	0.0014
	(0.0035)	(0.0015)	(0.0007)	(0.0055)	(0.0057)	(0.0094)
Indicator for Rainfall Shock in Lowest Tercile	-0.0915***	-0.0167***	0.0107***	-0.0435	-0.0223	0.0108
	(0.0097)	(0.0066)	(0.0029)	(0.0327)	(0.0647)	(0.0066)
Indicator for Rainfall Shock in Highest Tercile	0.0036	0.0050	0.0014	-0.0595	-0.0105	0.0035
	(0.0063)	(0.0069)	(0.0029)	(0.0414)	(0.0746)	(0.0051)
Observations	8,604	7,994	7,994	512	592	592
R-squared	0.87	0.95	0.95	0.99	0.99	0.99

Notes: Regressions in columns (1)-(3) use district-level (rural) agricultural data; regressions in columns (4)-(6) use state-level data. 'Productivity' is real agricultural output per cultivated acre in column (1) and real registered manufacturing output in column (4); 'nominal wages' is the nominal agricultural laborer wage in column (2) and per-capita earnings of laborers in the registered manufacturing sector in column (5); 'prices' is a price index of farm harvest prices in column (3) and the urban manufacturing workers' CPI in column (6). Rural regressions include district fixed effects, year fixed effects and quadratic region time trends and are weighted by total cultivated area; urban regressions include state fixed effects, year fixed effects and are weighted by state urban population. Standard errors are clustered at the district level for rural regressions and the state level for urban regressions. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5: Climate Change and Mortality - Forecasted Percentage Impacts in 2070-2099, by Region

	Impact of Change in Days with Temperature			Total Temperature Impact = (1)+(2)+(3)	Temperature and Precipitation Impact
	< 16 C	16C - 32 C	>32 C		
	(1)	(2)	(3)	(4)	(5)
A. Based on Hadley 3, A1F1					
Pooled	-0.010	-0.139	0.659	0.510	0.462
	(0.030)	(0.045)	(0.126)	(0.125)	(0.142)
Rural Areas	-0.030	-0.164	0.853	0.658	0.617
	(0.039)	(0.055)	(0.153)	(0.126)	(0.173)
Urban Areas	0.036	0.013	0.090	0.112	0.116
	(0.033)	(0.058)	(0.105)	(0.101)	(0.116)
B. Based on CCSM3, A2					
Pooled	-0.010	0.039	0.145	0.176	0.116
	(0.013)	(0.042)	(0.028)	(0.061)	(0.084)
Rural Areas	-0.015	0.071	0.189	0.245	0.207
	(0.016)	(0.049)	(0.035)	(0.074)	(0.099)
Urban Areas	0.009	0.016	0.028	0.052	-0.078
	(0.013)	(0.042)	(0.022)	(0.054)	(0.092)

Notes: Forecasted percentage impacts of climate change scenarios in two leading climatological ('global circulation') models, separately by urban/rural/pooled regions. Reported numbers correspond to elements of equation (6), averaged over all districts (weighted by average population between 1957 and 2000). Estimates are based on regression models that control for unrestricted year effects, region-specific quadratic polynomials in time, and unrestricted district-area effects, and use coefficient estimates that are weighted by census population. Projections compare historical period average temperatures (averaged over 1957-2000) with those predicted to occur by the end of the century (averaged over 2070-2099) in each given climatological model. Standard deviations are based on regression standard errors that are clustered by district. See text for more details.

Table 6: Climate Change and Mortality - Forecasted Percentage Impacts, by Time Horizon

	Impact of Change in Days with Temperature			Total Temperature Impact = (1)+(2)+(3)	Temperature and Precipitation Impact
	< 16 C	16C - 32 C	>32 C		
	(1)	(2)	(3)	(4)	(5)
A. Based on Hadley 3, A1F1					
2010-2039	-0.009	0.027	0.057	0.075	0.037
	(0.014)	(0.026)	(0.012)	(0.039)	(0.054)
2040-2069	-0.011	-0.013	0.270	0.246	0.205
	(0.025)	(0.028)	(0.050)	(0.069)	(0.086)
2070-2099	-0.010	-0.139	0.659	0.510	0.462
	(0.030)	(0.045)	(0.126)	(0.125)	(0.142)
B. Based on CCSM3, A2					
2010-2039	-0.006	0.082	-0.073	0.003	-0.054
	(0.010)	(0.016)	(0.015)	(0.018)	(0.041)
2040-2069	-0.008	0.097	0.002	0.091	0.031
	(0.006)	(0.023)	(0.005)	(0.023)	(0.050)
2070-2099	-0.008	0.039	0.145	0.176	0.116
	(0.013)	(0.042)	(0.028)	(0.061)	(0.084)

Notes: Forecasted percentage impacts of climate change scenarios in two leading climatological ('global circulation') models, averaged over all of India (weighted by population), separately for each of three time horizons. Reported numbers correspond to elements of equation (6), averaged over all districts (weighted by average population between 1957 and 2000). Estimates are based on regression models that control for unrestricted year effects, region-specific quadratic polynomials in time, and unrestricted district-area effects, and use coefficient estimates that are weighted by census population. Projections compare historical period average temperatures (averaged over 1957-2000) with those predicted to occur over the average within each of three time horizons. Standard deviations are based on regression standard errors that are clustered by district. See text for more details.