The Unequal Effects of Weather and Climate Change: Evidence from Mortality in India

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Abstract

The industrial revolution in developing countries represents an unfinished process. Urban centers, dominated by manufacturing and services, sit alongside rural hinterlands dominated by subsistence agriculture. This paper uses a 1957-2000 district-level panel data set to test whether hot weather shocks have unequal effects on mortality in rural and urban populations in India. This depends on the degree to which incomes are affected by weather shocks and the extent to which individuals can smooth their survival across these shocks. We find that a one standard deviation increase in high temperature days in a year decreases agricultural yields and real wages by 12.6 % and 9.8 %, respectively, and increases annual mortality among rural populations by 7.3 %. By contrast, in urban areas, there is virtually no evidence of an effect on incomes and a substantially smaller increase in the mortality rate (of about 2.8% for a one standard deviation increase in high temperature days). Importantly, we find that greater availability of credit mitigates the mortality effects of high temperatures in rural areas, presumably by facilitating consumption smoothing. Finally, with all else held constant, the estimates imply that global warming will lead to meaningful reductions in life expectancy in rural India by the 2015-2029 period and quite large declines by the end of the century.

1 Introduction

The industrial revolution in developing countries represents an unfinished process. Whereas in the developed nations the growth of manufacturing and services has made agriculture a small contributor to total production and employment this is not the case in developing countries. In these countries urban centers, dominated by manufacturing and services, sit alongside rural hinterlands dominated by subsistence agriculture. This can be seen starkly in light images of the earth. Whereas the developed nations are lit up, vast tracts of the developing nations remain black with the darkness punctuated only by the bright spots of towns and cities.

This paper is about whether hot weather has an unequal effect on mortality for rural and urban populations in one country—India. This is not only salient for thinking about how current populations can be protected against weather risk but also because global warming will likely mean that rural and urban populations will be exposed to hotter weather in the future. Greater dependence on weather dependent forms of production may imply that rural populations suffer larger income shocks as a result of unusually hot weather and may therefore be less able to smooth survival across these shocks. And the situation may worsen considerably as the number of hot days they are exposed to increase over the current century.

To capture this intuition we build on standard models of health as human capital (as pioneered by Grossman [1972]; see Becker [2007] for a synthesis) to construct a neoclassical model of consumption choices where citizens have to choose to spend the incomes they earn either on health goods (which improve survival chances but provide no utility) or on consumption goods (which provide utility). If incomes fall due to higher temperatures or their health worsens due to the direct effect of exposure to high temperatures, they face a trade-off between survival enhancing expenditures and utlity enhancing expenditures. Through the choice of expenditures on survival enhancing goods (e.g., taking a day off from work in the heat), the model predicts that one margin of adjustment is by assuming the risk of a higher probability of death. The model also describes how the effects of higher temperatures on mortality may be higher for rural populations because the income shocks they suffer from hot weather are more severe. Naturally, we expect these effects to be stronger when credit is relatively expensive or constrained, as the ability to borrow (or decrease savings) will help citizens to smooth consumption and hence survival across periods. This suggests that increased access to banks that reduce the cost of borrowing should mitigate the impact of hot weather on mortality.

We explore these implications empirically by drawing on a unique panel data set on Indian districts which spans almost the entire post-Independence period from 1957 to 2000. For each district, we have annual observations for mortality (both for infants and those aged one and above) which are also recorded seperately for rural and urban populations. Overlaid on this is a dataset on daily records of temperature and precipitation for each Indian district across the 1957-2000 period. This set-up allows us to exploit interannual variation to estimate the mortality effect of

district-level hot weather on constituent rural and urban populations. We can also compare the mortality responses to hot weather observed in Indian district level data to those in county level data from the US.

Figure 1 plots, for India and the US, the impact of having an extra day whose *daily mean* temperature lies in each of eleven temperature bins relative to a day in the reference category bin of 70°-72° F.[1] These response functions are based on very rich statistical models that adjust for location (e.g., districts in India and counties in the US) fixed effects and year fixed effects (see the below for further details). As can be seen in the figure, interannual variation in temperature in the US shows only a very weak co-movement 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 89°-91° F range, relative to the 70°-72° F range. And these effects are large - for example, a *single* additional day with a mean temperature above 97° F , relative to a day with a mean temperature in the 70°-72° F range, increases the annual mortality rate by roughly 0.75 %.

The empricial exercise begins by examining the effects of hot temperature days on productivity, wages and prices for rural and urban areas of India. We find that hot weather sharply depresses agricultual yields and the wages of agricultural laborers in rural areas but exerts no impact on urban productivity, wages or prices. What is more, when we divide weather into that for the growing season and the non-growing season we find that it is growing season weather that has a significantly larger effect on rural incomes and rural mortality. Both these facts are consistent with the income effect of hot weather being more severe for rural versus urban populations.

We then turn to the first large-scale effort to examine the relationship between weather and death in a modern, developing economy. We begin by looking at whether hot weather affects the mortality of rural and urban populations differentially. We find that it is effects on the rural population that push mortality up as temperatures rise above 90° F. In contrast, the mortality effects for urban India are limited to the very hottest days that occur infrequently (e.g., days where temperature exceeds 97° F). Pulling it together, the same district-level hot weather shocks have a much more profound impact on mortality in rural versus urban populations in India. Urbanization and structural change appears to have conferred an advantage in terms of largely uncoupling survival from weather related risk.

These results match well with a development literature on lean or hungry seasons (e.g. Khandker [2012]). Hunger during pre-harvest lean seasons is widespread in the agrarian areas of Asia and Sub-Saharan Africa (e.g. Bryan, Chowdhury, and Mobarak [2013], Paxson [1993], and Dercon and Krishnan [2000]). 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 89°-91° F) limit the formation of grains in key crops such as rice and wheat and therefore negatively affects the

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[1]The US line comes from the 1968-2002 analysis of US counties Deschenes and Greenstone [2011].

sizes of harvest and accentuates income downturns for those dependent on agriculture. Therefore hot weather 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. In effect, when a large income shock collides with high and rising levels of malnutrition the effect can be lethal. Ceteris paribus, this lack of seasonality (both in nutritional status and in incomes) coupled with limited exposure to income volatility induced by weather shocks is a key advantage of living in urban areas.

A variety of behaviours have evolved to deal with weather shocks during the lean season in rural areas—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 (Dreze and Sen [1989], Paxson [1993], Townsend [1994], and Deaton [1997]). Whilst these responses may help smooth income across local, idiosynchratic shocks they may be less successful in dealing with aggregate weather shocks. The state can step in on these occasions (for example by distributing food or by enabling access to financial institutions) and one of India's succeses has been the ending of famine in the post-Independence era. However, our results suggest that the interaction between chronic hunger (for example, amongst landless laborers and small cultivators) and weather shocks still result in significant excess mortality in the rural hinterlands of India. Much of this excess mortality will not be on a mass scale in a local area and may therefore may be 'below the radar' of the state. However, our finding that the survival of large numbers of rural citizens is still at the mercy of the weather in modern day India represents an uncomfortable and striking finding.

Given this situation a key prediction from our model is that access to banks should mitigate the impact of hot weather on mortality. Using the identification strategy of Burgess and Pande [2005] we find some evidence that rural bank branch expansion in India mitigated the impact of hot weather on mortality. This is a preliminary result that we are currently probing further, but it is potentialy important for two reasons. First, because it confirms the key prediction in our model that technologies which enable citizens to smooth consumption across hot weather shocks should assist them in avoiding mortality. And second, because it provides confirmation that the state can take actions which protect citizens from the mortality impacts hot weather shocks.

The latter concern will become increasingly pressing as climate change proceeds. 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. To see this, consider an average Indian born in a rural area during the 2015-29 period, a period in the future in which climatological models predict that temperatures will be warmer than in 1957-2000. Our results imply that, if this Indian lived the rest of her life in a world where there is no further warming beyond what has occurred by 2015-29, then she would be expected to have life expectancy that is 1 year shorter than were she born in our within-sample period. This estimated effect increases to life expectancy reductions of 2.7 years and 6.9 years for individuals born in 2045-59 and 2075-2099, respectively (again, in a scenario in

which there is no further warming than what has occured under business-as-usual scenarios by the period in question.[2] In contrast, life expectancy at birth for urban populations in India will largely be unaffected by climate change as will populations in developed countries like the US.

This is a striking difference in health trajectories. The direction of travel is clear and though we fully expect rural Indians to adapt to an anticipated and slowly warming climate in various ways the fact that rural Indian citizens are already not fully protected from the mortality effects of hot weather implies that much more careful thinking has to be applied to understanding how such protection might be afforded. Famines may have indeed come to an end in India. However, our results suggest that the citizens of rural India still live in a world where inclement weather can significantly elevate mortality. The fact that the weather will likely become more inclement via global warming is then likely to pose particular challenges in these poor, rural settings.

The remainder of this paper proceeds as follows. The next section outlines a theoretical model 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 the key results from the paper, and finally Section 6 concludes.

2 A Model of Weather and Survival Choice

In this section we describe a theoretical framework within which to examine the potential for weather variation to pass through into mortality. Weather variation could cause human health to suffer because extreme weather conditions put human physiology under stress or exacerbates the disease environment. In our framework 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 such a 'direct' weather-induced health shock. Complicating matters, however, is the fact that agriculturally-engaged agents' real incomes also depend on the weather. That is, even absent direct effects of weather on death, agents' mortality risk may rise due to their reduction in income and subsequent reduction in health-improving goods. We extend the canonical framework presented in Becker [2007] in order to elucidate these interacting effects of weather on death.

2.1 Basic Setup

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's survival chances are endogenous. Let $s_t = s(h_t, T_t)$, where h_t is the amount of health-improving

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[2]As we discuss below, there are good reasons to believe that these estimates are biased upwards and others to suggest that they might be biased downwards so that the net bias is ambiguous.

inputs that are consumed by the agent and T_t is a variable 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 (weakly) decreasing in T_t. Finally, we assume that $\frac{\partial s_t}{\partial h_t}$ is increasing in T_t, such that the marginal impact of health inputs on survival is greater when the weather shock T_t is extreme.

When alive, the agent derives utility in period t from consumption c_t according to the intra-temporal utility function, $u(c_t)$. Utility when dead is normalized to zero. Finally, we assume that the agent discounts each future period with a constant discount factor $\beta < 1$. The agent therefore obtains an expected value of lifetime utility given by

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

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

There are two types of goods in this framework. 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 (i.e. $\frac{\partial s_t}{\partial T_t} \geq 0$) allows for a direct effect of weather on 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 weather 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

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[3]Extremely cold temperatures can also affect human health adversely through cardiovascular stress due to vasoconstriction and increased blood viscosity. Deschenes 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. Days in this temperature range are extremely rare in India.

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, but this is testable, as we show below. In contrast, following well-known effects in the agronomic literature, as well as the literature on expected effects of hotter climates on Indian agriculture (e.g. Kumar, Kumar, Ashrit, Deshpande, and Hansen [2004] and Guiteras [2009]), we expect a strong negative relationship between incomes in rural areas (i.e. agricultural incomes) and temperatures; we document further evidence of this relationship below.

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 (i.e. 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 uncertainty is resolved through time in this model. At the beginning of a period (for example, period $t = 0$), the temperature in the current period (e.g. T_0) is drawn. The agent then makes his choices in the current period (i.e. c_0 and h_0) as a function of the current temperature (i.e. $c_0 = c_0(T_0)$ and $h_0 = h_0(T_0)$). After the agent's decision has been made, the agent's survival shock arrives (i.e., 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 or subsequent periods (though the assumption of zero utility in death is merely a normalization).

2.2 A Baseline Model Without Credit or Savings Constraints

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, after T_0 is known, 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 $R \equiv (1+r)$. That is, if total expenditure in period 0 (i.e. $p^c c_0 + p^h h_0$) 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:

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

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 (i.e. $u'(c_1)$) will only bring utility if the agent survives (i.e.. if $s_1 = 1$), and adjusted also for the fact that opportunity cost of consumption in period 0 is also reduced by the possibility of non-survival (i.e.. $\mathbb{E}[s_1] < 1$).

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 (i.e. $u(c_0)$) 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

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that, at the optimal choice, the marginal benefit of spending more income 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 income 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:

$$\frac{\partial s_0(h_0, T_0)}{\partial h} \frac{V_0}{\lambda s_0} = \beta R \mathbb{E} \left[\frac{\frac{\partial s_1}{\partial h} \frac{V_1}{s_1 \lambda}}{1 + \frac{\partial s_1}{\partial h} \frac{W_1}{s_1}} \right]. \tag{3}$$

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 (i.e. $W_1 = 0$), 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—in this benchmark model of frictionless borrowing and saving, and a perfect annuity market—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. 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.

2.3 Implications for Empirical Analysis of the Relationship Between Weather and Death

Our empirical analysis below explores the impact of weather (temperature and rainfall extremes) on the mortality rate. We do so across a number of different settings (urban vs. rural India, India vs. the United States) and weather shocks (notably across those times of the year in which we expect weather shocks to affect, or not affect, agricultural incomes) that differ, as we will demonstrate empirically, in the extent to which weather shocks affect incomes. These comparisons

shed light on how the exogenous impact of weather on incomes (summarized by the relation $y(T_t)$ in the model above) affects the extent to which weather affects death.

In the perfect markets model outlined above, how do we expect an income shock (as induced by a weather shock) to affect the death rate? The answer lies in the standard permanent income hypothesis which holds in this perfect markets model: an income shock in perod 0, caused by a weather shock T_0, only affects an agent's contemporaneous survival chances s_0 via the extent to which the income shock reduces the agent's total income (in present value terms) over the remainder of his life. This is a simple implication of the strong smoothing implied by the Euler equation (3) above. That is, if two identical agents, A and B, face the same weather shock T_0, and agent A has an income stream that depends on the weather (i.e. $\frac{dy(T_0)}{dT_0} < 0$ for agent A) but agent B does not, then we expect the impact of this shock on death to be stronger for agent A than agent B. However, for shocks at annual frequencies, as in our empirical setting, it might be expected that the impact of weather shocks on incomes of the magnitudes we estimate would have too small an impact on (remaining) lifetime incomes to lead to substantial effects of weather shocks on survival.

It is important to stress that, in this simple model in which income can be spent on either consumption or health goods (and there is a linear budget constraint governing the choice between the two consumption goods), a given weather shock harms the agent's survival chances either through income or through the survival function directly. In the former case, the budget constraint is simply affected directly. In the latter case, the agent simply uses income to buy health goods so as to offset the direct effect of weather on survival, which effectively reduces the budget remaining for consumption goods. That is, whether a given weather shock leads to death via the direct health channel or the indirect income channel is, at a fundamental level, irrelevant.

2.4   Implications of Credit Constraints

The Euler equation (3) derived above hinges on an agent's ablity to move lifetime resources between periods, in response to a shock to T_0, so as to equalize expected marginal utility across time periods. We now consider the possibility that agents face constraints on their ability to borrow. While the general implications of liquidity constraints for consumption smoothing are a difficult problem (see, e.g., Besley [1995], for a review in a developing country context), the intuition here is simple. If the agent has insufficient wealth on hand in period 0 to buy the health goods required to equate marginal survival odds in period 0 to those in period 1, rather than these odds equating as in equation (3), these odds will satisfy the following inequality

$$\frac{\partial s_0(h_0, T_0)}{\partial h} \frac{V_0}{\lambda s_0} > \beta R \mathbb{E} \left[\frac{\frac{\partial s_1}{\partial h} \frac{V_1}{s_1 \lambda}}{1 + \frac{\partial s_1}{\partial h} \frac{W_1}{s_1}} \right].$$

This expression implies that, in the presence of borrowing constraints (and the need to borrow), the marginal value of health spending on survival in period 0 will exceed the marginal value of health spending on survival in future periods (such as period 1). This then implies that the impact of a weather shock in period 0 on survival in period 0 will be greater than in a setting without credit constraints. Again, the intuition comes from a comparison with the permanent income hypothesis that prevails in the setting without borrowing (or other) constraints: without credit constraints, a weather shock in period 0 is likely to be small relative to lifetime income and lifetime weather exposure; but with binding credit constraints, lifetime income and lifetime weather exposure are irrelevant if the agent can't access those future resources in period 0. A simple implication of the logic here is that any improvement in the financial system that relaxes borrowing constraints will increase the likelihood of returning to a world in which the Euler equation holds with equality, as in equation (3), and hence in which the permanent income hypothesis benchmark prevails, and period 0 shock is unlikely to much affect period 0 outcomes such as consumption or survival.

2.5 The Implied Willingness to Pay for Avoiding Inclement Weather

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 small worsening in the weather ($dT_0 > 0$) in period 0. We do so in the setting of section 2.1 above in which there are no liquidity constraints; adding such constraints would only raise the agent's WTP to avoid a weather shock since the unconstrained WTP to mitigate a shock will always be weakly lower than the constrained WTP.

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 by $y^*(T_0)$. 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 (i.e. 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 (i.e. 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 (i.e. $\frac{ds(h_0,T_0)}{dT_0}$) 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, i.e. $\frac{ds(h_0,T_0)}{dT_0}$, and the effect of weather extremes on income, i.e. $\frac{dy(T_0)}{dT_0}$. Armed with these two essential ingredients and an estimate of the value of a statistical life in our setting (i.e. $\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$) 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, as discussed briefly above, in this model 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 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 (i.e. $\frac{ds(h_0,T_0)}{dT_0}$) and the effect of weather on incomes (i.e. $\frac{dy(T_0)}{dT_0}$).

We conclude with a final word about policy in this environment. There are no market failures in the baseline model above. There is therefore no efficiency-based 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. We believe that our implied empirical WTP estimates, which are themselves a lower bound due to our ignorance about the magnitude of $\frac{\partial h_0}{\partial T_0}$ and our simplification to a setting without credit constraints, are provocative from this perspective.

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 conceptual framework in Section 2 above 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 depth 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 Mortality

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

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[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)."

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 temperatures.

3.2 Weather

A key finding from Deschenes and Greenstone [2011] 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 [2009] and use data from a gridded daily dataset that uses non-public data and sophisticated climate models to construct daily temperature and precipitation

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[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.

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 eleven temperature categories—as already seen in Figure 1. These categories are defined to include daily mean temperature less than 70° F, greater than 97° F, and the thirteen 3° F-wide bins in between. The 365 daily weather realizations within a year are then distributed over these eleven 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 eleven 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. In Figure 2 we also plot the average temperature distribution for the 2070-2099 period predicted by a leading climatological model of climate change (described further below). As can be seen from this polt the temperature distribution in India will move sharply to the right with there being many more hot days at the end of this century.

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) 90° F are particularly severe. We therefore construct a measure of the cumulative number of degrees-times-days that exceed 90° F in a district and year. We also experiment with 70° F and 80° F cutoffs. 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.

While the primary focus of our study is the effect of high temperatures on mortality, we use

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[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.

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 1st 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

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 1987. From this source we utilize three distinct variables on the agricultural economy: yields, prices, and wages.

3.3.1   Agricultural Yields

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

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

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 and further afield). We explore further the extent of this market integration below.

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 households' 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.

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

[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.

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 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 Method

This section describes the econometric methods used to establish relationships between a series of outcomes and temperature realizations. Several of the relationships appear non-linear and we have chosen specifications that allow for flexibility in the response function while retaining some parsimony. Our *first approach* to estimating these relationships was introduced briefly in the Introduction, and results based on it were presented in Figure 1, but we provide details here. The estimating equation uses a very flexible specification to model the effects of daily temperature on outcomes:

$$
\begin{aligned}
Y_{dt} &= \sum_{j=1}^{11} \theta_j \text{TMEAN}_{dtj} + \sum_k \delta_k \mathbf{1}\left\{\text{RAIN}_{dt} \text{in tercile } k\right\} \\
&+ \alpha_d + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{dt},
\end{aligned} \tag{5}
$$

where Y_{dt} is the outcome variable (e.g., ln mortality rate or ln agricultural output) in district d in year t. The r subscript refers to a 'climatic region'; India has five climatic regions or groupings of states that are judged by India's Meteorological Department to have similar climates. The last term in the equation is a stochastic error term, ε_{dt}.

The key variables of interest are those that capture the distribution of 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 eleven bins that correspond to days with mean temperatures $<70°$ F, $\geq 97°$ F, and the nine $3°$ degree-wide bins in between. It is noteworthy that the daily mean is calculated as the simple average of the daily minimum and daily maximum, so, for example, a day in the $89°$ F -$91°$ F bin is a quite hot day. 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, we use the bin for temperatures between $70°$ F and $72°$ F as a reference category whose coefficient is therefore normalized to zero. Importantly, across our outcome variables we cannot reject the null hypothesis that the impact of days with a mean temperature $<70°$ F have zero effect on the outcome. Further, there are not enough high temperature days to to obtain meaningful estimates for separate temperature bins $\geq 97°$ F.

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, this assumption is unavoidable. Second, the approach assumes that the impact of a day's mean temperature on the annual mortality rate is constant within $3°$ F degree intervals; our decision to estimate separate coefficients θ_j on each of eleven 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 spanning 44 years. Third, by using as a regressor the number of days in each bin, we assume 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.

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, we model the effect of rainfall as the impact of sums over

daily accumulations. Specifically, 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 $\mathbf{1}\{\text{RAIN}_{dt}\text{in tercile } k\}$. We estimate a separate coefficient on each of the three tercile regressors, though we treat the middle tercile regressor as the omitted reference category.

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 outcomes. So, for example, permanent differences in the supply of medical facilities will not confound the weather variables in equations for the ln mortality rate. The equation also includes unrestricted year effects, γ_t. These fixed effects control for time-varying differences in the dependent variable that are common across districts (e.g., changes in health related to the 1991 economic reforms). Since shocks or time-varying factors that affect health may not be common across districts, we emphasize specifications that include separate quadratic time trends for each region.

We use the *first approach* for graphical analyses, like Figure 1, throughout the paper but ten coefficients of interest is too much information for the tables. Consequently, our *second approach* to modeling the temperature-death relationship estimates fewer parameters while still doing some justice to the non-linear nature of the relationships. This second approach, which we refer to as the 'single-index' approach, estimates the parameters in:

$$Y_{dt} = \beta\text{CDD80}_{dt} + \sum_{k=1}^{3} \delta_k \mathbf{1}\{\text{RAIN}_{dt}\text{in tercile } k\} + \alpha_d + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{dt}, \qquad (6)$$

where the variable $CDD80_{dt}$ is the number of cumulative degree-days in district d and year t that exceeded 80° F.[11] This is a particular restriction on the flexible approach in equation (5)—where all of the temperature bin coefficients θ_j below 80° F are restricted to be zero and the three coefficients above 80° F are restricted to be linearly increasing in their average temperatures—for which we find some support below. This approach to modeling temperature has the advantage of estimating only one temperature coefficient rather than 11 coefficients, while still capturing the essential features of non-linearity evident from the 11 coefficient estimates in Figure 1. We will also report on specifications that use $CDD70_{dt}$ and $CDD90_{dt}$ to model temperature.

Our assumptions in pursuing this simplification are that: (i) on days during which the mean temperature is below 80° F temperature is irrelevant for determining the outcome variable (e.g. mortality) Y_{dt}; and (ii), the effect of days whose mean temperatures exceed 80° F 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. Another advantage of this single-index approach is that by estimating one coefficient rather than eleven we

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[11]For example, if a given district-year had only two days over 80° F, one at 82° F and the other at 84° C, its value of $CDD80_{dt}$ would be 6 (i.e. 2+4).

have more statistical power for teasing out the heterogeneous effects of temperature in order to learn more about the relationships between temperature and the outcomes.

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. These parameters are identified from district-specific deviations in weather about the district averages that remain after adjustment for the year fixed effects and region-specific quadratic time trends. Due to the randomness and unpredictability of weather fluctuations, it seems reasonable to presume that this variation is orthogonal to unobserved determinants of the outcomes.

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 districts 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 (or, in the case of agricultural specificatio, the average plot of land) rather than on the average district, which we believe to be more meaningful.

Finally, guided by our theoretical model, we also implement a variant of our second approach where we interact $CDD80_{dt}$ with a bank branch expansion variable $banks_{dt}$ in models for ln mortality rates. The $banks_{dt}$ variable measures the number of commercial bank branches opened in a rural, unbanked areas in a given district and year. During our sample period commercial banks were forced to open more branches in rural areas of India. We use the identification strategy of Burgess and Pande [2005] to instrument both $banks_{dt}$ and the interaction between $banks_{dt}$ and $CDD80_{dt}$. The coefficient on the interaction between $banks_{dt}$ and $CDD80_{dt}$ measures whether bank branch expansions alter the impact of hot weather on death. The intuition is that access to a bank may increase people's opportunities to smooth survival across weather shocks by moving consumption across periods through drawing down deposits or taking out loans.

5 Results

This section presents the main results of the paper that are guided by the conceptual framework in Section 2. We first demonstrate that high temperature days reduce incomes (measured by agricultural yields, wages, and prices) in rural areas, but not urban ones, and this is largely due to hot days during the growing season, rather than the growing season. This allows us to establish whether or not the income effect of hot weather is more pronounced for rural versus

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[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.

urban populations and for growing season versus non-growing season weather. We then move to the central results of the paper where we examine whether hot weather has an unequal effect on rural and urban populations. Both populations within a district experience the same weather fluctuations so, in effect, we are testing whether the same temperature shock affects the two populations differently. Pairing income effects with mortality effects allows us to explore empirically a central implication of Section 2 that, ceteris paribus, mortality effects on rural populations should be larger than mortality effects on urban populations if hot weather has a larger income effect on rural populations. We then turn further evaluate the extent to which banks appear to mitigate the effect of hot weather on mortality, as one would expect if banks facilitate the smoothing of survival chances. Finally, using coffecients from our 1957-2000 analysis of the weather-mortality relationship and predicted changes in district distributions of temperature and precipitation we analyse how climate change is likely to affect mortality and life expectancy in the future in India.

5.1 Weather and Income

5.1.1 Rural and Urban Incomes

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-income relationship differs for these two populations. An agricultural income channel relating weather to death in rural India would begin with an effect of weather shocks on agricultural productivity.

Figure 3 plots the 11 temperature bin coefficients when agricultural yields are regressed on the 11 temperature bin regressors, as well as our rainfall controls, district and year fixed effects, and quadratic region-specific polynomials in time, from the estimation of equation (5).[13] Figure 3 indicates that daily temperatures above 80° F harm annual agricultural yields and the damage is greater at higher temperatures, both of which are consistent with experimental evidence in agronomy (as discussed in, e.g., Guiteras [2009]). The magnitude of the estimated effect of hot weather on agricultural productivity is large—the coefficient estimates for days with mean temperatures exceeding 85° F implies that every *single* day in this category (relative to a day in the 70° - 72° F reference category) reduces agricultural yields by about 0.5% or more. Consequently, a year

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[13]One small difference here, when compared to the mortality regressions below, 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.

with 10 additional days above 85°, and drawn from the reference category, would have a roughly 5% decline in agricultural production. Finally, it is noteworthy that the point estimates on the $79 - 81°$ temperature bin and above would all be judged, even taken individually, as statistically significant at the 5% level or better.

Figure 4 repeats this exercise for our measure of real agricultural wages, which is measured as the average district-level wage of agricultural day laborers (which is calculated only among those working) deflated by our district-specific agricultural price index (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 3, so too do wages in the agricultural sector reflecting their lower marginal product. Along these lines, we see pattern in Figure 4 that is similar to that in Figure 3, with real wages for agricultural laborers falling for temperatures above 82° - 84°F; each day above 85°, relative to a day in the 70° - 72° F range, leads to a 0.25 to 0.5% decline in the annual wage. This finding is particularly significant as agricultural laborers constitute one of the largest and poorest groups in India (as described in, e.g., Deaton and Dreze [2009]) and one of the most affected by weather shocks.[14] Interestingly, the decline in real wages largely reflects a decline in nominal wages as the evidently high degree of market integration for agricultural products in India limits price movements in response to these district-specific temperature shocks.[15]

Table 2 provide details from estimating the relationship between weather and income in the more parsimonious manner specified in equation (6). Panels A, B, and C report on separate versions where the cumulative degree-days (CDD) variable uses a base of 90°, 80°, and 70° F, respectively. The table reports the coefficient on the relevant CDD variable, its standard error (in parentheses), and the effect of a 1 standard deviation increase in the CDD variable on ln annual agricultural yield (in brackets). We will use a goodness of fit measure to guide our choice among the three possible CDD variables for the subsequent analysis below; specifically, we will emphasize the functional form that produces the highest t-statistic (i.e., the square root of the F statistic).

In column (1), the dependent variable is the log of agriculture yields, as in Figure 2. There is a statistically significant relationship between yields in all three panels, however it is evident that the CDD80 and CDD70 variables fit the data best (as is also apparent visually in Figure 3). Both of these specifications indicate that a year with a 1 standard deviation increase in high temperature days (as measured by the CDD80 and CDD70) variables leads to a roughly 13% decline in agricultural yields. The results in column (2) find a similar relationship between log real wages and high temperature days. Again, the CDD70 and CDD80 variables fit the data best and here those regressions suggest that a 1 standard deviation increase in high temperature days

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[14]According to the 2001 Indian census about 1 in 4 workers in India are agricultural laborers.

[15]Seperate price-temperature response plots obtained from the estimation of equation (5) reveals a similar, but reversed pattern of effects because adverse production raises the agricultural price index. Notably the coefficients on the highest temperature bin regressors are smaller in absolute value than those in Figure 3 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.

is associated with a roughly 10% decrease in real daily agricultural wages.

Overall, we conclude that during the 1956 - 1987 period, high temperature days depress agricultural incomes whether they are measured with yields or real wages. Further, we will emphasize the CDD80 variable for these outcomes in the subsequent analysis as it appears to fit the data at least as well as the CDD70 variable and better than the CDD90 one.

Columns (3) and (4) explore the relationship between temperature shocks and measures of urban income, manufacturing productivity (output per worker in the registered manufacturing sector) and wages (nominal earnings per worker in the registered manufacturing sectors). While a large body of agronomic work documents how plants suffer at high temperatures, this enquiry into the weather-urban income relationship is more speculative because it cannot draw on a rich theoretical and experimental literature.[16] An important caveat regarding these results 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 (3) and (4) is available only at the state-level so the state-by-year is the unit of observation. This means that all of these estimates will be considerably less precise, given the smaller sample size.[17] While in many ways these are not perfect analogues of the rural, agricultural income variables in columns (1) and (2), we believe that they are reasonable proxies for urban incomes.

The regressions fail to reveal a meaningful relationship between high temperatures and urban incomes. None of the temperature coefficients would be judged to be statistically significant by conventional criteria and the magnitudes are relatively small. From the available data, we conclude that there is no strong temperature-income relationship in urban India, which stands in stark contrast to the column (1) and (2) results that found that incomes are temperature dependent in rural areas.

5.1.2 Growing versus Non-Growing Season Temperatures

Our analysis so far has documented a strong effect of a given year's temperature on rural incomes. But it is natural to expect the effect of weather on mortality to differ according to the seasons. As many rural citizens depend on agriculture, either as laborers or cultivators, weather shocks in the growing season might depress productivity employment more in the growing season than outside of it. In particular, the agronomy literature suggests that high temperatures can retard plant development, which primarily occurs during the growing season. In addition, there is a nascent literature indicating that individuals are less productive in high temperatures and for health reasons may even choose not to work. In the case of the non-growing season, the effect on individual productivity remains and it is possible that high temperatures affect agricultural yields (e.g., by reducing groundwater or soil moisture) although this effect is less direct than during the

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[16]See Olken, Dell and Jones (2012).

[17]For the purposes of the results in Table 2, we aggregate our district-level weather data to the state-level by using weights proportional to size of each district's urban population.

growing season.

To empirically evaluate the separate effects of growning and non-growing season temperatures, we take a parsimonious approach to determining the 'growing' and 'non-growing' seasons of Indian agriculture. The agricultural calendar in India is driven by the arrival of the southwest monsoon rains, which marks the beginning of the growing season. After its arrival, 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 1st 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.[18] This three month period tends to be the hottest part of the year.

Figure 5 reports results from the estimation of a version of equation (5) that allows the eleven temperature bins to enter separately for the growing and non-growing season portions of the year. There are two key findings. First, high temperature days during the growing season substantially retard agricultural yields. For example, a growing season day where the temperature exceeds 85°F, relative to a day in the 70° - 72° F reference range, reduces annual agricultural yields by roughly 0.7% to 1.0%. Further, all of the coefficients associated with temperatures greater than 75°F are negative and statistically different from zero at the 5% level or better. Second, temperatures in the non-growing season, even days above 90°F, do not have a statistically or economically meaningful impact on agricultural yields. Indeed, none of the coefficients would be judged to differ from zero at conventional significance levels.

Table 3 is structured similarly to Table 2 and provides a more parsimonious summary of the relationship between growing and non-growing season temperatures and incomes, as well as reporting on the parameters associated with the rainfall indicators. Throughout the table, we use CDD80 based on the results in Table 2. In column (1) the strongly negative relationship between high temperature days and agricultural yields is immediately evident; a 1 standard deviation increase in CDD80 leads to a 14.7% decline in yields. As is apparent in the figure, high temperature days in the non-growing season have little impact on yields and the null that the growing and

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[18]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.

non-growing season coefficients for CDD80 are equal is easily rejected. There is also a strong relationship between rainfall shortfalls and agricultural yields, with a year in the lowest terciles leading to a roughly 8% decline in yields. This squares with the sense that damaging scenarios concerning rainfall for Indian agriculture involve a surfeit rather than a surplus of rainfall.

The entries in column (2) indicate that high temperature days reduce real agricultural wages among the employed in rural areas during the growing season with a 1 standard deviation increase in CDD80 implying a 8.6% decline in the wage rate among the employed. There is a modest negative effect of hot days during the non-growing season that is statistically distinguishable from the growing season parameter. A rainfall shortfall has a much weaker relationship with the real wage than with yields.[19]

Columns (3) and (4) report on manufacturing productivity and wages in urban areas. There is little evidence that growing season temperatures, non-growing season temperatures, or rainfall are an important contributor to incomes. The bottom line appears to be that weather shocks, especially hot temperatures during the growing season, substantially affect rural incomes but not urban ones.

5.2 Weather and Death

Figure 1 in the Introduction revealed a strong relationship between hot temperature days and mortality rates for the full (rural plus urban) Indian population. This subsection unpacks this relationship by exploring whether it differs in rural versus urban areas of each Indian district. This cut of the data will shed some light on whether 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 the weather data also allows us to examine if weather during the growing season affects mortality differently from weather in the non-growing season and how these results correspond with the analogous income results.

5.2.1 Urban versus Rural

Figure 6 begins the analysis by plotting the estimated response functions between log annual mortality rate and temperature exposure from fitting equation (5), separately for urban and rural populations. The mortality rate is calculated among all people older than age 1 (finer age gradations are not available) and pertains to the total urban and rural populations in each district.

The results reveal a significant and increasing relationship between log mortality rates and high temeprature days in rural areas. Specifically, days with a temperature exceeding 87° F, relative to a day in the 70°-72°F range, increase the annual mortality rate by at least 0.5% with the ef-

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[19]An analogous graph for the real agricultural wage reveals that the negative effect of high temperature days during the growing season is immediately evident visually, while the non-growing season effect is more difficult to discern.

fect increasing with temperature. In contrast, there is little evidence of a relationship between high temperature days and mortality in urban India, except in the $> 97°$ F bin. Although the 95% confidence intervals for the urban estimates are not depicted here to aid the graph's visual accessibility, it is notable that none of the other temperature effects is statistically significant and all are relatively small in magnitude. It is apparent that the response of the all-India mortality rate to high temperature days in Figure 1 is driven almost entirely by the rural response function. Appendix Figure 1 repeats this graphical exercise for the infant mortaliy rate and leads to qualitatively similar conclusions.

Table 5 explores different approaches to summarizing these results with more parsimonious approaches to modelling temperatures. Across the panels, high temperature days increase annual mortality rates for people older than age 1 as in column (1) and infants in column (2). The CDD90 specification suggests that a 1 standard deviation increase in CDD90 increases the annual mortality rate by 7.4% for those above age 1. The other specifications explain the data less well, but project larger increases in mortality for a 1 standard deviation increase in the relevant variable. Going forward, we will emphasize the specifications that model daily temperature with CDD90 based on the goodness of fit criteria. In the case of infants, CDD70 fits the data best and a 1 standard deviation increase in that variable leads to a 19% increase in the infant mortality rate.

This exercise is repeated for urban areas in columns (3) and (4). The CDD90 variable is associated with a statistically significant increase in the age 1+ mortality rate but there is little other evidence of a relationship between hot days and infant mortality in these columns. 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 largely protected from 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.

Columns (1) through (5) of Table 6 explore whether there are heterogeneous effects of temperature on mortality in rural areas and probes the robustness of the relationship. Column (2) shows that the magnitude of the parameter associated with the CDD90 variable in rural areas was greater before 1980 than afterward but that the difference is not statistically significant. Figure 8 provides some further insight by plotting the CDD90 coefficient from a specification that allows it to vary across the four eleven year periods that span our entire sample of 1957-2000. It is noteworthy that there was a decline in the coefficient between the 1957-67 and 1968-1978 periods but there has been no decline since then which includes years during which the Green Revolution in Indian farming took hold, significant economic reforms were introduced, and there were important improvements in rural incomes and in rural health practices. The takeaway from Figure 8 is that the effect of hot weather in increasing the mortality of rural populations in India has been suprisingly constant over time. Column (3) finds that the effect of CDD90 is essentially equal in districts above and

below the median in terms of CDD90. Column (4) suggests that there is little evidence that days below 50° F affect mortality rates in rural India and the column (5) results demonstrate that the estimate of CDD90 on log mortality rates is insensitive to replacing the region by year time trends with region by year fixed effects.

The remaining five columns of Table 6 repeat the above analysis on urban areas. A similar pattern prevails, although if one ignores the sampling errors there seems to be some evidence that the effect of high temperature days was greater before 1980 and is larger in "cold" districts.

To summarize, the results in this sub-section demonstrate that ambient temperatures play an important role in determining the starkest aspect of health, the probability of dying, in rural areas. 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.

5.2.2 Growing versus Non-Growing Seasons

The analysis of rural incomes found that the effect of high temperature days on rural incomes was predominantly due to high temperature days during the growing season. Here we test whether the mortality regressions reveal a similar pattern.

Table 6 reports on the estimation of versions of equation (5) for log mortality rates for non-infants where we experiment with allowing CDD90 to enter separately for the growing season. In the case of rural areas (column (2)), the point estimate for growing season CDD90 is roughly double the non-growing season coefficient. However, these models that separately estimate the effect of hot temperature days in the growing and non-growing season days are demanding of the data and we cannot reject that the coefficients on these variables are equal. This imprecision is evident in Appendix Figure 2, especially for the growing season which has fewer high temperature days. Just as was the case with the income results, too little rainfall has negative consequences for well-being in rural areas; a rainfall realization in the lowest tercile, relative to the middle tercile, increases the annual mortality rate by about 3.2% in rural areas.

The urban results are presented in columns (3) and (4). It is evident that the mortality effect of high temperature days in urban areas is being driven by the effect of non-growing season days. As Appendix Figure 3 reveals, however, there is an increase in mortality on days where the average temperature exceeds $\geq 97°$ F in both seasons, at least when the coefficients are take literally.

The model emphasized that temperature shocks can reduce incomes and consequently the resources available for individuals to consume standard goods like food and shelter and health preserving goods and directly affect health. In this framework, however, whether a given weather shock leads to a change in the probability of death via the indirect income channel or the direct health channel is irrelevant because a linear budget constraint allows agents to use income to substitute perfectly, on the margin, between consumption and health goods. Nevertheless, it

remains an interesting question as to whether the mortality effect operates through both channels or just one of them. Table 3 made clear that the income channel largely operates through high temperature days in the growing season. This subsection's finding that high temperature days in the non-growing season days affect mortality in rural areas and urban areas (where there was no evidence of an income effect in either season) suggests that both channels are important in explaining the mortality impacts. It is clear, however, from examining the results in Tables 3 and 6, that a key difference in the effect of hot weather on rural and urban populations in India is that the indirect income effect which is concentrated during the agricultural growing season has a more pronounced effect in rural versus urban populations. This is significant as it is during the growing season (which is furthest from the previous harvest) when malnutrition and hunger are at their peak and therefore when income shocks are likely to be most lethal.[20]

5.3 Bank Branch Expansion and the Weather-Death Effect

Our model indicates that if rural citizens had access to improved means of smoothing their consumption (and hence their survival) then this should mitigate the impact of hot weather on mortality. Particularly important in this respect is the credit channel which is central for smoothing survival in our model and the subject of an extensive theoretical and empirical literature (e.g. Townsend [1994] and Besley [1995]). Specifically in the context of the model, improved access to banks should reduce the interest rate at which individuals can borrow to smooth consumption across shocks which, in turn, should reduce the mortality impact of hot weather by facilitating greater consumption.

We explore a preliminary test of this possibility by exploiting the rapid expansion of commercial bank branches into unbanked, rural areas in India during our sample period (see Burgess and Pande [2005]). Before this expansion rural areas had been largely unbanked. A policy enforced by the central bank which was introduced in 1977 and removed in 1990 stipulated for each branch opened in a (typically urban) banked location banks had to open four branches in (typically rural) unbanked locations. In effect, this policy forced banks to open branches in rural, unbanked locations with more of these occuring in financially underdeveloped states and reversed the pre-existing trend of banks opening more branches in financially developed states. By using the deviations, between 1977 and 1990 and post-1990, from the pre-program linear trend relationship between a state's initial financial development and rural branch expansion as instruments, we are able to identify the policy driven element of rural branch expansion.[21] Specifically, we fit an

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[20]The work of nutritionists elucidates how poor nutritional status exacerbates a range of morbidities making it an important (though albeit indirect) cause of mortality in the developing world (see Victoria, Adair, Fall, Hallal, Martorell, and Richter [2008]).

[21]Burgess and Pande [2005] carried their analysis out at the state level. Here we extend their instrumental variable method to the district level. In Burgess and Pande [2005] the focus was on the impact of rural branch expansion on poverty. Here the the focus is on the interaction of bank branch expansion and hot weather in a mortality regression so we use the identification strategy of Burgess and Pande [2005] to instrument both $banks_{dt}$

augmented version of equation (6) for the log mortality rate that includes the number of bank branches and the interaction of bank branches with the CDD90 variable. These two endogenous variables are instrumented with the number of bank branches in a district in 1961 interacted with the a post-1976 time trend and the 1961 number of branches interacted with a post-1989 trend and the interactions of these variables with the CDD90 variable.

Table 7 presents the results for rural areas in columns (1) and (2) where CDD is calculated over the entire year and separately for the growing and non-growing seasons, respectively. The top panel reports the key parameter estimates. The middle panel reports the effect of the relevant temperature variables on the log mortality rate at district-year observations that represent the 25th and 75th percentile of the bank branches variable. When the full year temperature is used, there is little evidence that banks mitigate the impacts of high temeprature days on the mortality rate. The column (2) results, however, indicate that moving from the 25th to 75th percentile of the banks variable essentially eliminates the entire effect of CDD90 on the log mortality rate and this change is statistically significant. In contrast, there is little evidence that banks mitigate the mortality consequences of high temperature days that occur outside the growing season. It is noteworthy that the presence of banks appears most effective at mitigating the temperature shocks that are most closely related to income shocks. Column (3) provides a falsification exercise by testing whether the presence of banks in rural areas of a district mitigate the mortality impacts of high temperature days in urban areas in the same district. This exercise fails to contradict the results in column (2) as the interaction term is of a small magnitude and statistically insignifcant.

Although these results are preliminary, they point to access to banks and access to credit, more generally, playing an important role in enabling citizens to withstand the income shocks induced by hot weather in the growing season. This is a key finding as it suggests that investments in smoothing technologies like banking systems can play a role in reducing mortality rates, not just in smoothing consumption. The commercial banks offered lower interest rates than those that were formerly available via moneylenders which would have improved the ability to borrow. Bank branches were also required to target priority sectors which included small businesses and small-scale entrepreneurs, and agriculture. As Burgess and Pande [2005] illustrate, the value of banks entering rural areas thus extended beyond the financial services they offer. The poorest citizens (for example agricultural laborers) could benefit from agricultural wages going up (as bank borrowers shift labor away from this market and into self-employment) and from rising non-agricultural employment opportunities (which weakened dependence on seasonal, subsistence agriculture) even if they do not hold bank accounts. Put another way, providing access to banks in rural areas both as a means of smoothing consumption and of promoting diversification of the rural economy may be an important means of protecting rural citizens from temperature shocks. Finding means of making rural citizens more resilient to weather shocks is also likely to become a more pressing concern as India becomes warmer due to climate change, a subject to which we now turn.

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and the interaction between $banks_{dt}$ and $CDD90_{dt}$.

5.4 Climate Change and Death

The results in Section 5 above suggest that weather extremes, in the form of hot or dry years, have strong effects on income and mortality in rural areas and modest impacts on mortality in urban areas. 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 today. However, these estimates may also lend some insight into the consequences of climate change in India.

To shed light on this we have obtained data on the predicted change in India's climate that emerges from 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 this model as 'Hadley 3' (the preferred model in use by the Hadley Centre, which provided climate change predictions for the influential Stern Review) and which has been used in the Intergovernmental Panel on Climate Change (IPCC) reports. In the Data Appendix we describe the construction of this model in more detail.

Hadley 3 make predictions about the evolution of daily maximum and minimum temperatures and precipitation at finely spaced gridpoints all over the world, on every day for the remainder of the 21st century. We use these predictions (averaged over hundreds of simulations of the models) to construct a set of temperature predictions for each of India's districts using a procedure detailed in the Data Appendix. To align the predicted climatic variation with the inter-annual climatic variation we use throughout the paper, we use Haldey 3 to predict the average number of days in which the mean temperature will fall into each of the temperature bins used in the above analysis for each year from 2015-2099. This generates a variable that we denote $TMEAN_{dj}^t$, 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 for year t; we also calculate the average of this variable over 15 year periods to smooth out noise in the annual climate projections.

Predictions of climate change 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 scenario which is a "business-as-usual" scenarios that assumes the world does not implement significant greenhouse gas mitigation policies. See the Data Appendix for more details.

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 predictions should be conceived of as a single realization from a superpopulation of models and scenarios. The sources of uncertainty in these models and scenarios are unclear, so this source of uncertainty cannot readily be incorporated

into the below estimates of the impacts of climate change.

Figure 2 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 18 temperature bins (i.e. $TMEAN_{dj}^{2070-2099}$ averaged over districts d, for each temperature bin j) with the actual historical average equivalent over the observed period used in this paper (i.e., 1957-2000). The resulting plot reveals that there will be large reductions in the number of days with temperatures $\leq 81°$ F. These reductions are predicted to be offset by increases in days with temperatures exceeding $\geq 85°$ F. For example, the annual aveage number of days where the mean temperature is at least 88°is projected to increase between the 1957-2000 and 2070-2099 periods by more than 55 days. Thus, the predicted mortality impacts of climate change rest on the differential mortality impact of the days in the $\leq 81°$ F range, relative to days with temperatures $\geq 85°$. 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, India will exchange days that we have estimated to be relatively low mortality days for days that we have estimated to be high mortality ones.

We now turn to a more precise calculation of the predicted effect of climate change on life expectancy in rural and urban India. We do this in three steps:

1. Calculate the change in the mortality rate by age group (i.e., infants and age 1+) for each year. This is simply: $\Delta \widehat{Y}_t = \sum_j \widehat{\theta}_j \Delta TMEAN_j^t$, where $\Delta \widehat{Y}_t$ is the predicted change in the log mortality rate, $\widehat{\theta}_j$ is the estimated coefficient on temperature bin j obtained from Table 4, and $\Delta TMEAN_j^t$ is the predicted (according to Hadley 3 A1FI) change in the number of days on which the mean temperature will fall into temperature bin j in period t averaged across all districts.

2. Apply $\Delta \widehat{Y}_t$ for infants and age 1+ to the 1980 life tables for India.

3. Calculate the change in life expectancy at birth due to the projected change in the life tables for each year, relative to baseline 1980 life expectancy, for every year 2015-2099. Calculate the change in life expectancy for the 15 year periods, 2015-2029, ..., 2075-2099.

Since there are separte 1980 life tables for rural and urban India, these calculations are done separately for each of them.

Before turning to a discussion of the results, it is important to be clear about the meaning of each of these calculations. Specifically for each of the 15 year periods, the exercise produces an estimate of the life expectancy effect for a person born in that period with a 1980 Indian's life expectancy who will experience the climate of the period in which they were born throughout their life. Consequently, this calculation does not capture the life expectancy effect for a person

who is born during the 21st century and faces the full set of projected changes in climate. In this respect, it is appropriate to interpret the calculation as the life expectancy effect of alternative climate change scenarios or greenhouse gas stabilization scenarios.

Figure 9 reports on the results from this exercise. The rural results are striking as they reveal a substantial predicted change in life expectancy that begin in the next 15 years and grows dramatically throughout the remainder of the 21st century. Specifically, the average Indian born in a rural area during the 2015-2029 period is expected to lose about 1 year of life expectancy over the course of their life. This increases to losses of 2.7 years and 6.9 years by 2045-59 and 2075-2099, respectively. The impact on life expectancies in urban areas is projected to be modestly positive throughout the 21st century although this estimate may not be statistically significant.[22]

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.

There are several reasons that the estimates' connection to climate change is not 1 to 1. For example, they may provide upper bound estimates due to individuals' adaptations to climate change that will mitigate the consequences of climate change. It seems likely that more heat resistant agriculture technologies will be developed, technologies to better protect people from the physical harms of high temperatures are likely to proliferate (e.g., fans and air conditioning), occupations will shift away from climate-exposed ones, and the balance of populations will shift from rural to urban areas. Additionally, 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 (e.g. 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.

On the other hand, these estimates are unlikely to adequately capture all of the negative health impacts of climate change as there may be other changes that increase people's vulnerability. For example, changes in the timing of the monsoon or desertification of soil could greatly increase the income losses. Further if there is any scope for cross-regional insurance against differential regional-level shocks, then our estimates are derived from settings in which that insurance is potentially

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[22]We have not calculated the standard errors of these estimates yet. They will be in the next version of the paper.

mitigating the effects of a region's shock on its own fortunes.

6   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 [2012]). 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 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 $T_{dt,1957-2000}^{NCC}$.

5. The predicted end of century climate for each day of the year is equal to $T_{dt,1957-2000}^{NCC} + \Delta T_{dt}^{H}$. 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 Daily Temperature in India and United States.

Estimated Impact of a Day in 10 Temperature-Day Bins on Log Annual Mortality Rate, Relative to a Day in the 70-72 Farenheit Bin

●——— India Estimate	– – – India 95% C.I.
●——— US Estimate	
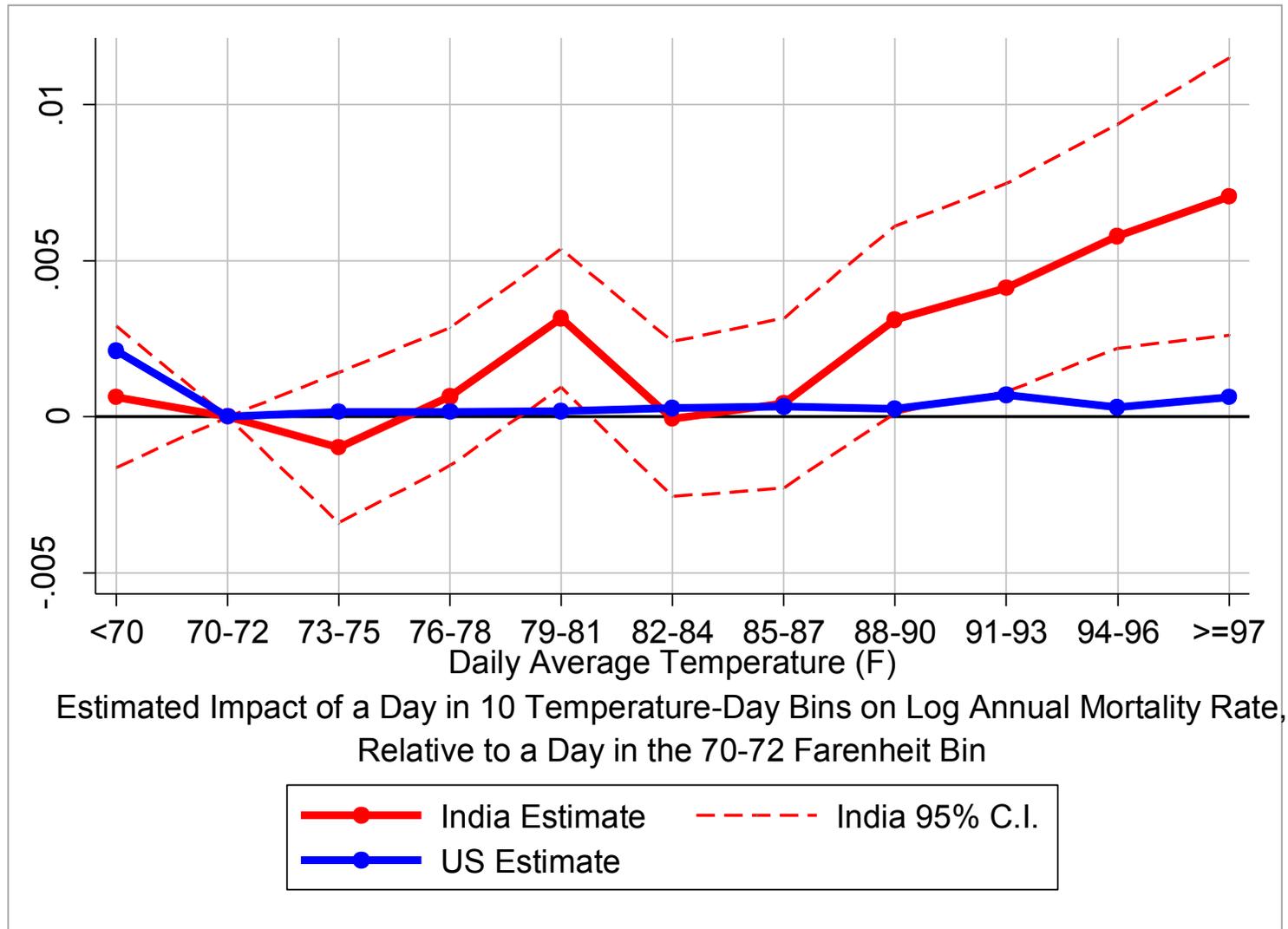
Note: The two solid 'impact' lines report 10 coefficient estimates, representing the effect on annual (all ages) mortality of a single day in each of the corresponding 10 temperature bins, relative to the effect of a day in the 70-72F bin. Dashed lines represent the 95% confidence interval of the estimates. See the text for more details.

Figure 2: Historical and Prediction Distribution of Daily Average Temperatures in India
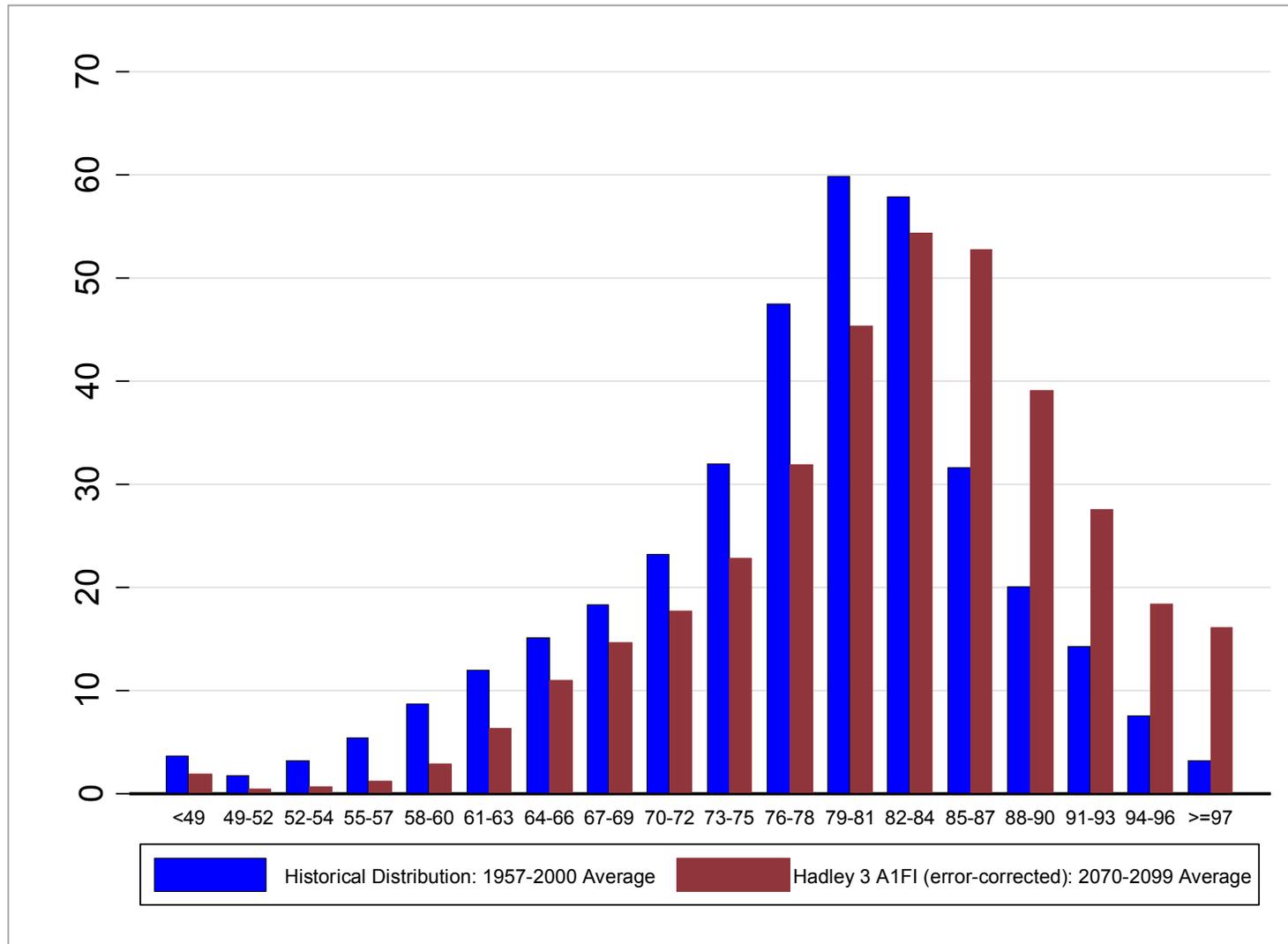
Notes: Historical distribution given by mean daily temperature for each district and year, averaged while weighting by district population. Predicted distribution derived using daily data from error-corrected Hadley 3 A1FI model output. Both averaged weighted by 1957-2000 district population. See the text for more details.

Figure 3: The Effect of Daily Average Temperatures on Log Agricultural Yields.
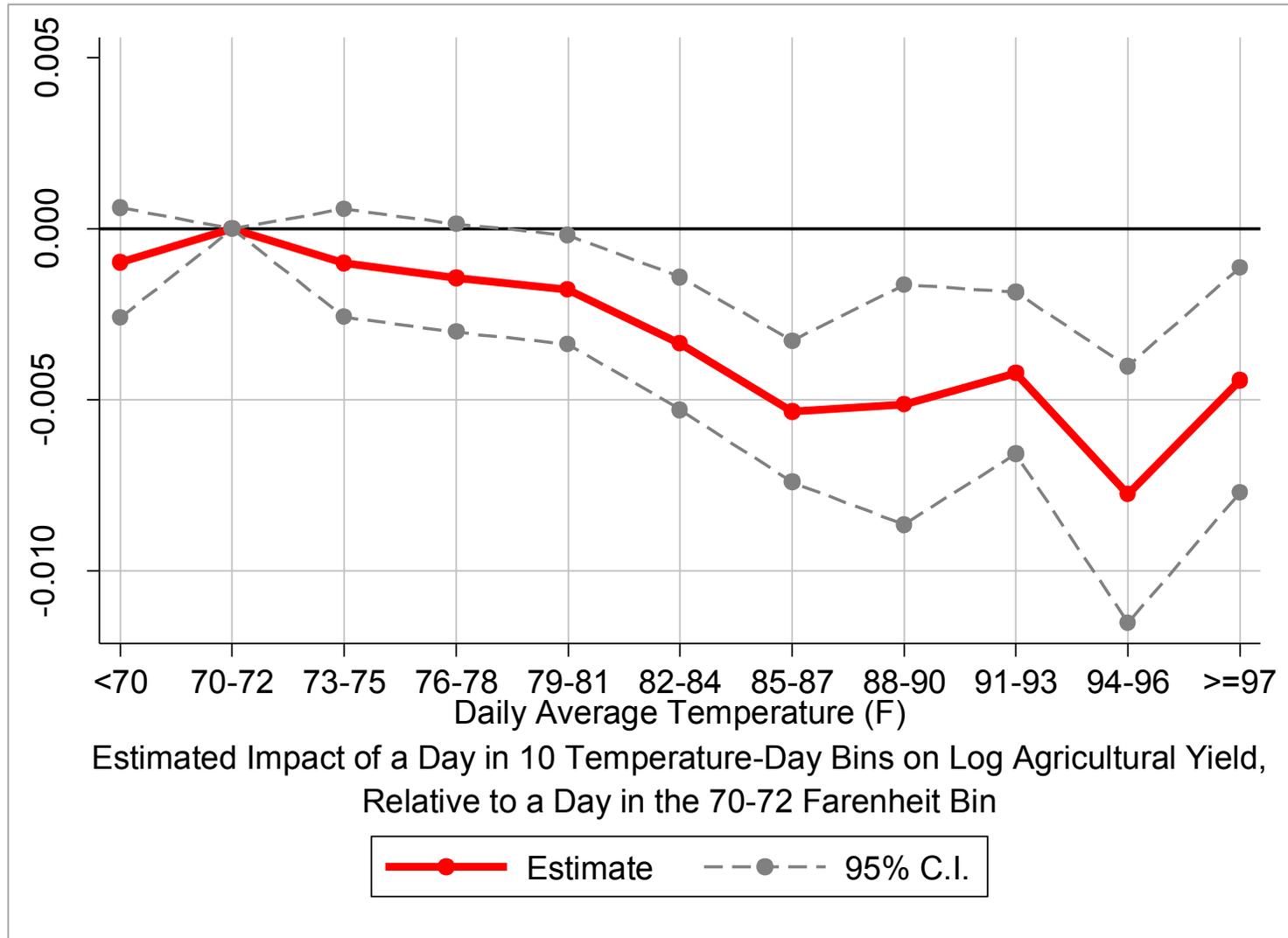
Estimated Impact of a Day in 10 Temperature-Day Bins on Log Agricultural Yield, Relative to a Day in the 70-72 Farenheit Bin

Note: The solid 'coefficient' line reports 10 coefficient estimates, representing the effect on log annual agricultural yields of a single day in each of the corresponding 10 temperature bins, relative to the effect of a day in the 70-72°F 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 4: The Effect of Daily Average Temperatures on Log Real Agricultural Wages.
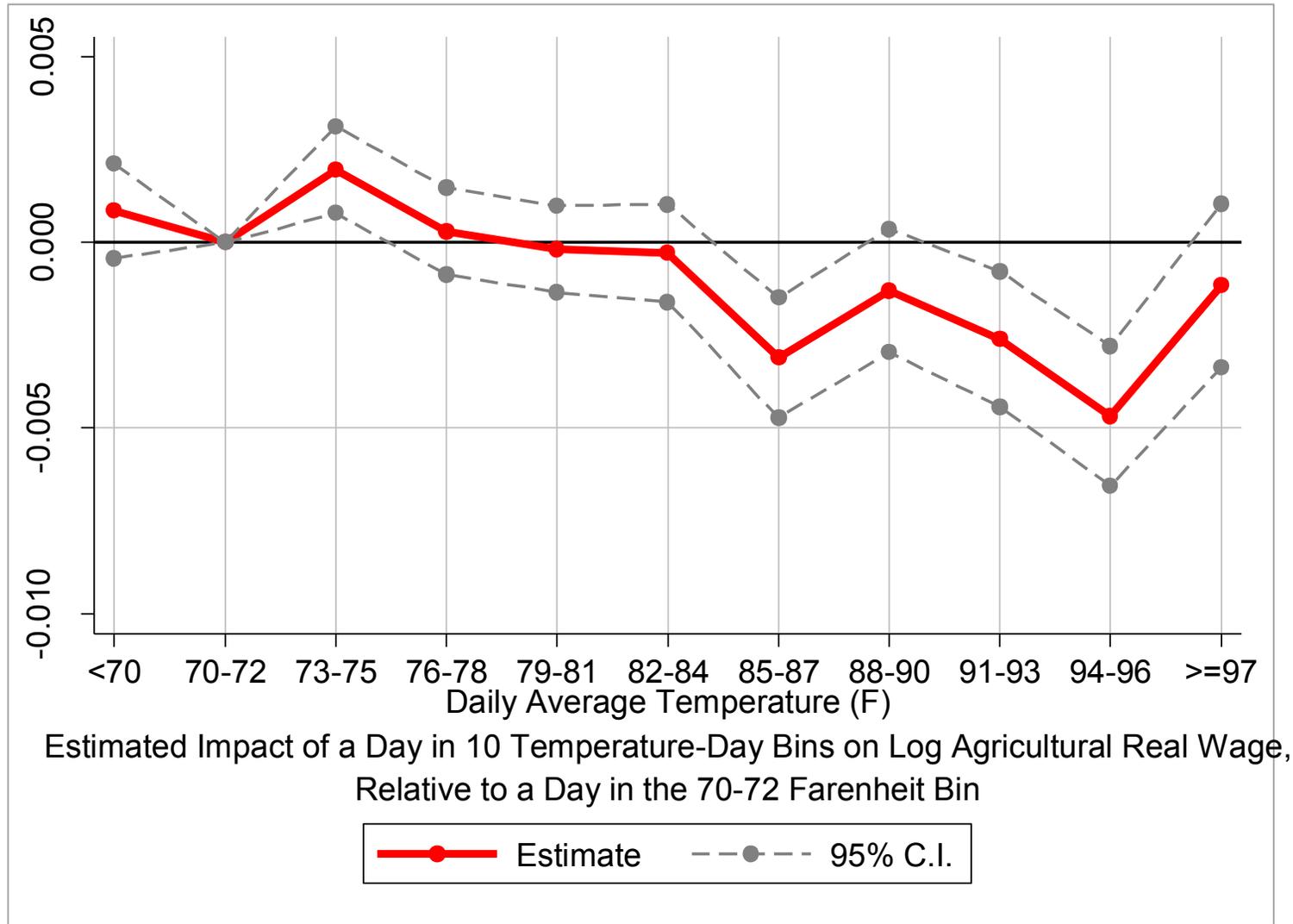
Note: The solid 'coefficient' line reports 10 coefficient estimates, representing the effect on log real agricultural wages of a single day in each of the corresponding 10 temperature bins, relative to the effect of a day in the 70-72°F bin. The dashed lines represent the coefficient plus/minus two standard errors. The methodology used to estimate these coefficients is explained in detail in Section 4.1.

Figure 5: The Effect of Daily Average Temperatures on Log Agricultural Yields, by Agricultural Growing Season.

Estimated Impact of a Day in 10 Temperature-Day Bins on Log Agricultural Yield, Relative to a Day in the 70-72 Farenheit Bin
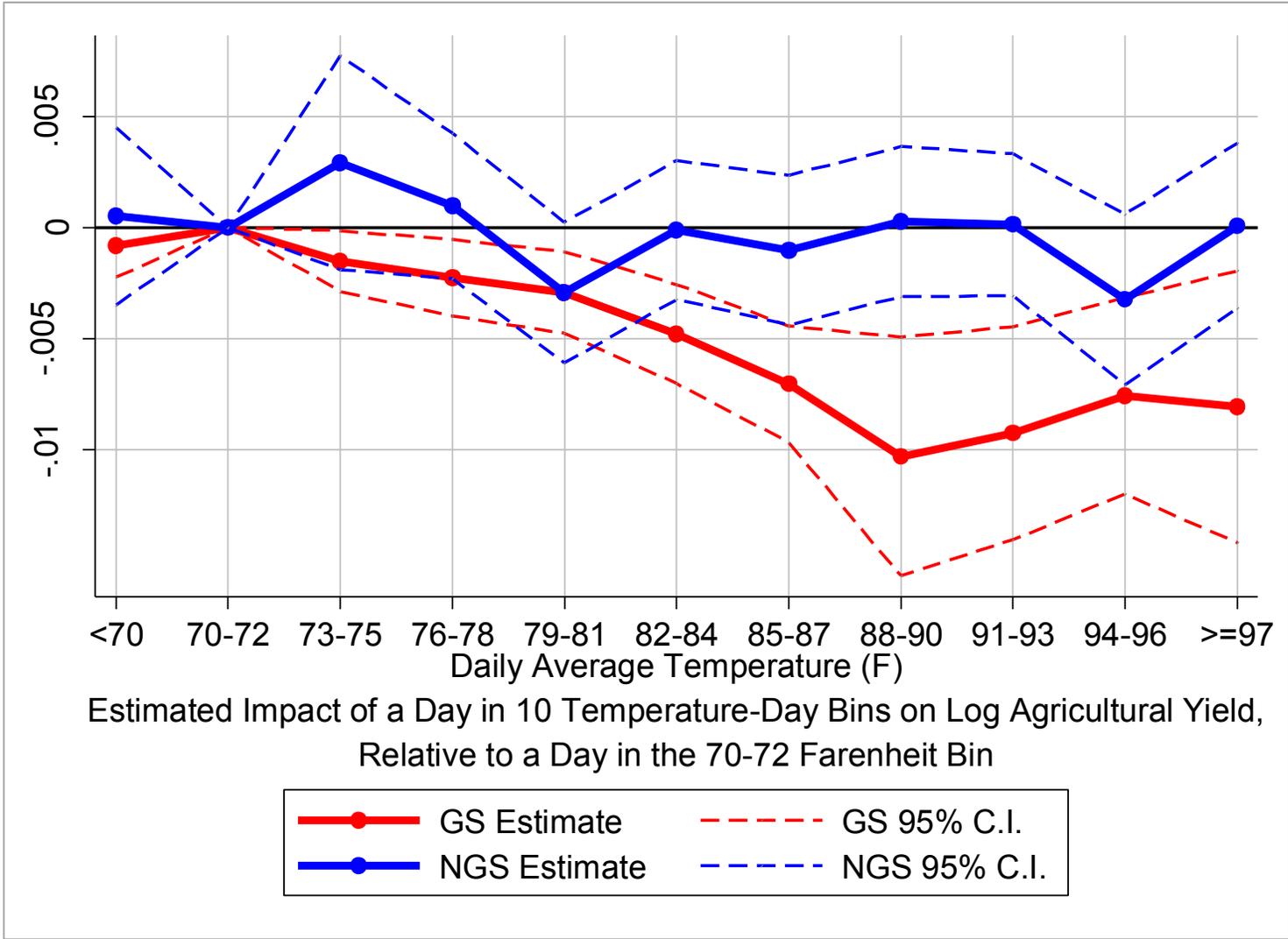
Figure 6: Mortality Impact of Daily Temperature in Rural and Urban India.

Estimated Impact of a Day in 10 Temperature-Day Bins on Log Annual Mortality Rate, Relative to a Day in the 70-72 Farenheit Bin

Daily Average Temperature (F)

Rural   95% C.I.
Urban
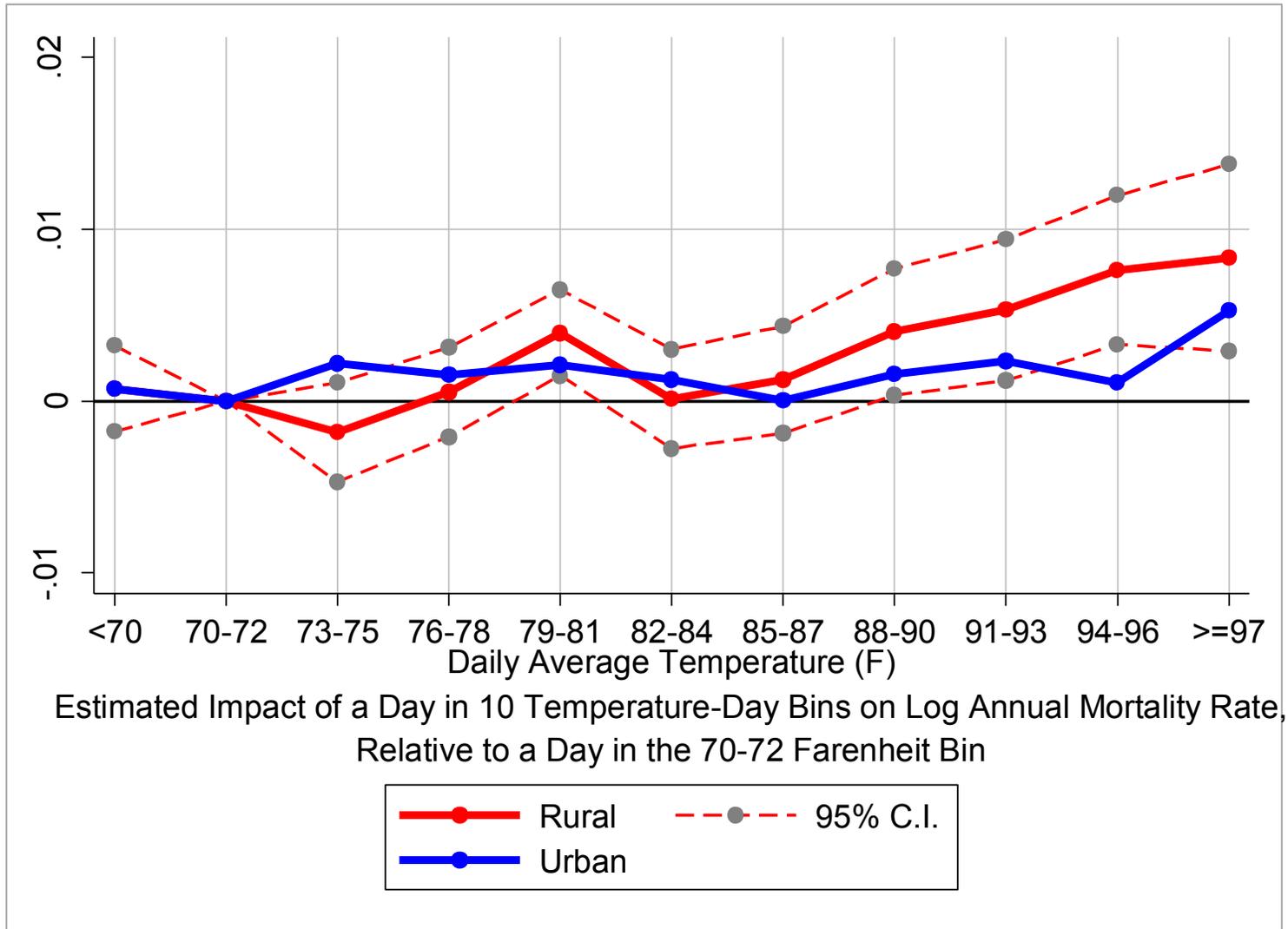
Figure 7: Mortality Impact of Degree-Days Above 90F in Rural India by Time Period.

Estimated Impact of Temperature-Days Above 90F/10 on Log Annual Mortality Rate
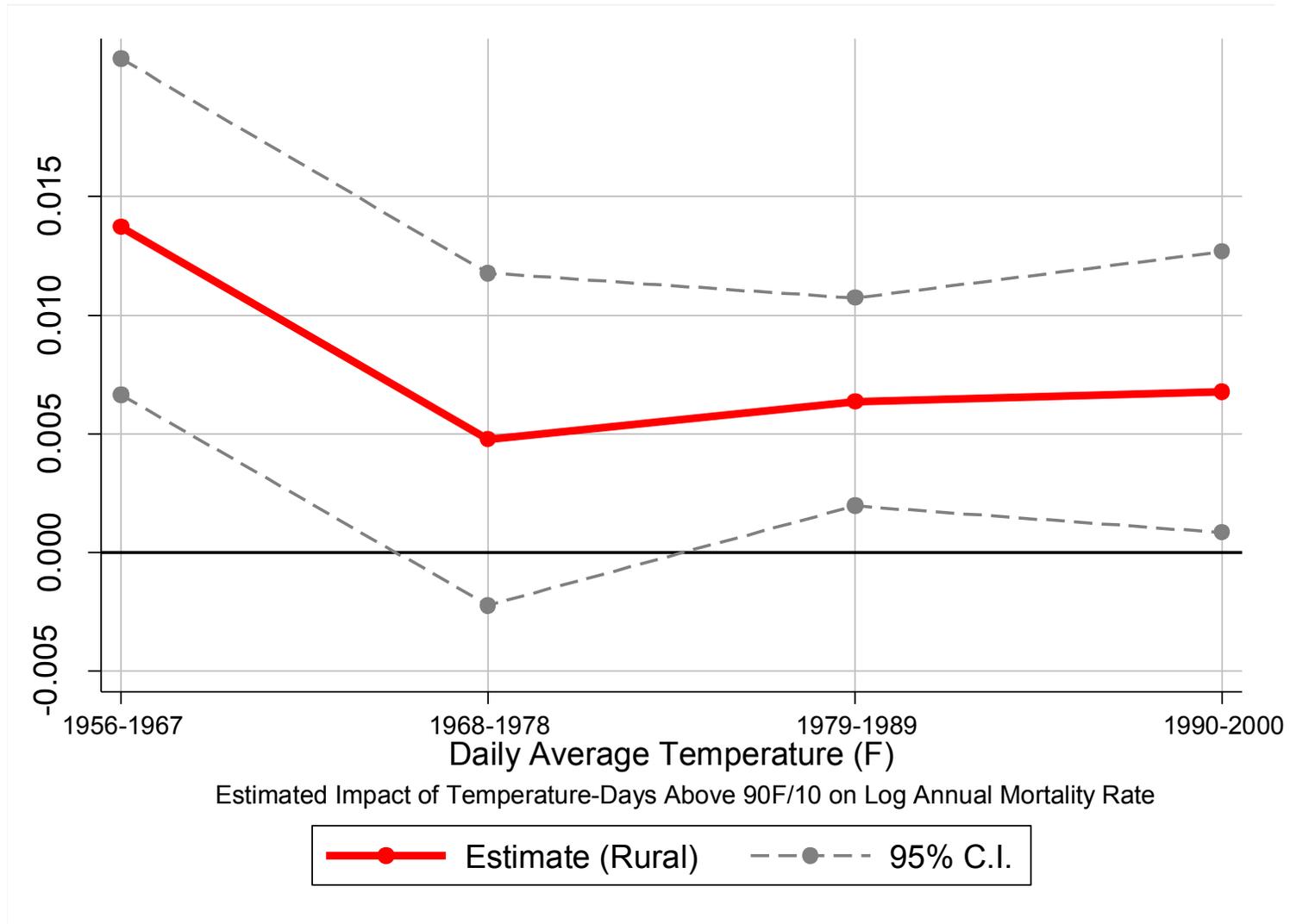
Figure 8: Predicted Impact of Climate Change on Indian Life Expectancy at Birth, Based on Error-Corrected Hadley 3 A1FI Model: 2015-2099
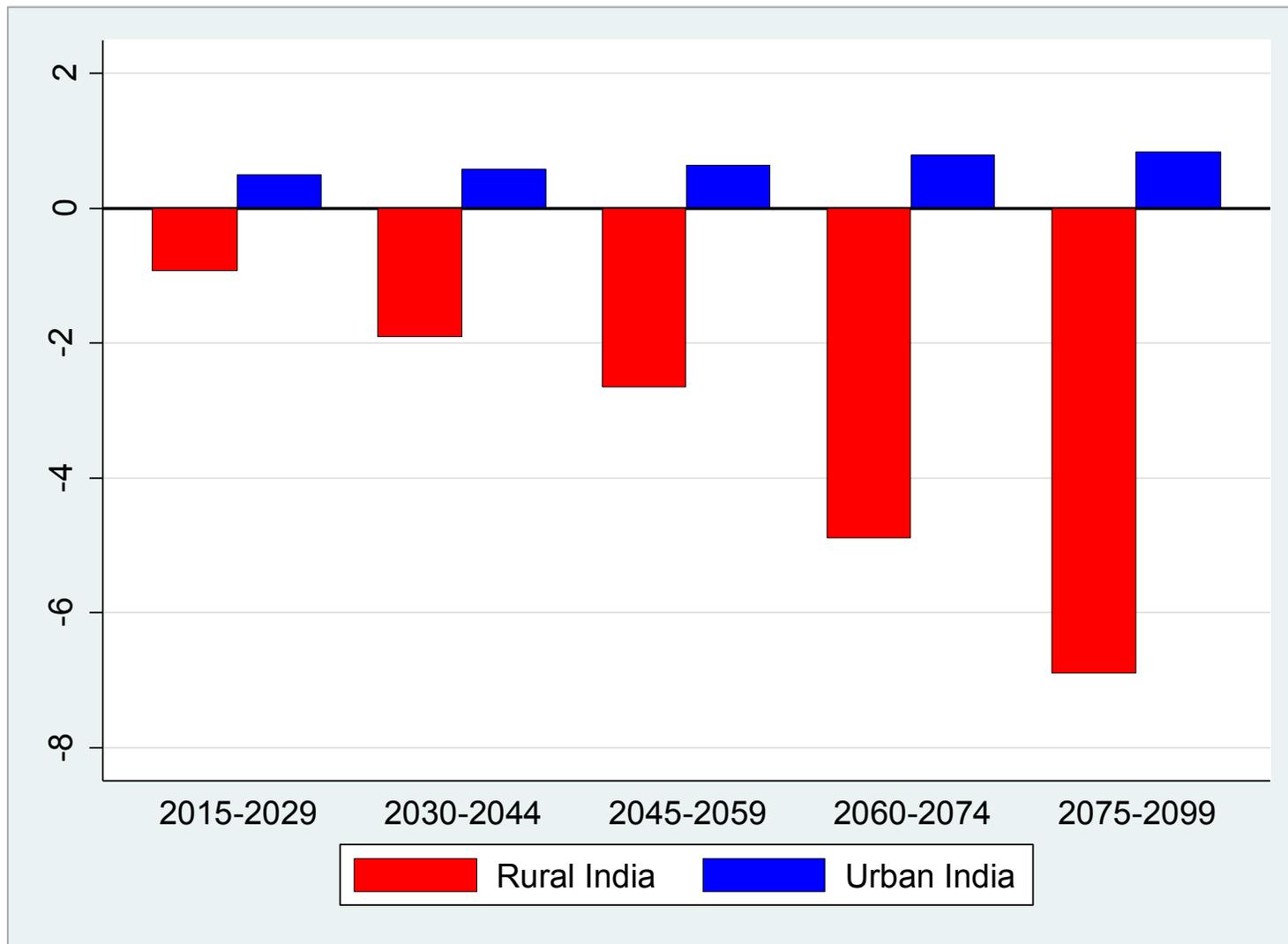
Table 1: Descriptive Statistics

	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	9.06 (5.99)	7.50 (4.24)	3.87 (2.44)	4.03 (2.47)	9.74 (4.48)	7.67 (3.39)	5.67 (2.75)	5.72 (2.24)
Infant (<1) Death Rate Per 1,000 Live Births	75.70 (63.06)	47.73 (26.06)	28.43 (23.85)	16.25 (17.07)	69.68 (38.81)	50.33 (36.91)	31.38 (20.52)	19.25 (15.31)
Life Expectancy at Birth	45.2	50.6	56.1	60.1	-	60.1	63.4	66.8
Agricultural Yield Index (kg/hectare)	24.62 (11.74)	30.91 (16.27)	39.20 (22.74)	- -	- -	- -	- -	- -
Agricultural Real Wages (Rs/day)	3.20 (1.43)	3.64 (1.75)	4.89 (2.16)	- -	- -	- -	- -	- -
Manufacturing Earnings Per Worker (Rs/annum)	-	-	-	-	27,310 (3,770)	28,910 (7,059)	31,369 (6,348)	23,670 (7,308)
Annual Degree-Days (over 90° F)	99.22 (95.34)	95.39 (97.41)	109.40 (103.06)	106.86 (104.60)	88.86 (95.65)	90.33 (97.18)	109.66 (104.58)	100.13 (102.36)
Annual Total Precipitation (cm)	118.31 (65.28)	117.57 (64.02)	114.88 (63.98)	118.49 (67.25)	118.52 (68.68)	120.14 (67.71)	115.24 (67.33)	123.57 (72.33)

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 valu

Table 2: Weather and Incomes - Rural-Urban Differences, Exposure by Calendar Year

Dependent Variable:	Rural		Urban	
	Log (Productivity)	Log (Real Wages)	Log (Productivity)	Log (Real Wages)
	(1)	(2)	(3)	(4)
A. Temperature (degree-days over 90F)/10	-0.0023*	-0.0023***	0.0003	0.0012
(std error)	(0.0009)	(0.0006)	(0.0033)	(0.0036)
[Effect of 1 std dev in CDD90]	[-0.023]	[-0.022]	[0.002]	[0.009]
B. Temperature (degree-days over 80F)/10	-0.0034***	-0.0026***	-0.0006	0.0006
(std error)	(0.0006)	(0.0004)	(0.0013)	(0.0013)
[Effect of 1 std dev in CDD80]	[-0.126]	[-0.098]	[-0.021]	[0.021]
C. Temperature (degree-days over 70F)/10	-0.0023***	-0.0018***	-0.0010	0.0005
(std error)	(0.0004)	(0.0003)	(0.0008)	(0.0008)
[Effect of 1 std dev in CDD70]	[-0.132]	[-0.101]	[-0.053]	[0.023]
Observations	8,304	8,304	512	592

Notes: Regressions in columns (1)-(2) use district-level (rural) agricultural data; regressions in columns (3)-(4) use state-level data. 'Productivity' is real agricultural output per cultivated acre in column (1) and real registered manufacturing output

Table 3: Weather and Incomes - Rural-Urban Differences, Exposure by Growing Season

	Rural		Urban	
	Log (Productivity)	Log (Real Wages)	Log (Productivity)	Log (Real Wages)
Dependent Variable:				
	(1)	(2)	(3)	(4)
Temperature (degree-days over 80F)/10				
Growing Season Temperature	-0.0065***	-0.0040***	-0.0001	0.0006
(std error)	(0.0011)	(0.0005)	(0.0017)	(0.0015)
[Effect of 1 std dev in CDD80]	[-0.147]	[-0.086]	[-0.002]	[0.012]
Non-Growing Season Temperature	-0.0007	-0.0013**	-0.0013	0.0009
(std error)	(0.0004)	(0.0005)	(0.0016)	(0.0017)
[Effect of 1 std dev in CDD80]	[-0.013]	[-0.041]	[-0.034]	[0.024]
Test of Equality (GS = NGS)	0.001	0.001	0.565	0.856
Indicator for Rainfall Shock in Lowest Tercile	-0.0808***	-0.0134	-0.0306	-0.0264
	(0.0083)	(0.0073)	(0.0283)	(0.0656)
Indicator for Rainfall Shock in Highest Tercile	-0.0092	-0.0001	-0.0517	-0.0199
	(0.0059)	(0.0076)	(0.0424)	(0.0732)
Observations	8,304	8,304	512	592

Notes: Regressions in columns (1)-(2) use district-level (rural) agricultural data; regressions in columns (3)-(4) use state-level data. 'Productivity' is real agricultural output per cultivated acre in column (1) and real registered manufacturing output

Table 4: Weather and Death - Rural-Urban Differences, Exposure by Calendar Year

	Rural		Urban	
	Effect of Temperature on Log Mortality Rate		Effect of Temperature on Log Mortality Rate	
Dependent Variable: Log (Mortality Rate)	Age 1+	Infants	Age 1+	Infants
	(1)	(2)	(4)	(5)
A. Temperature (degree-days over 90F)/10	0.0073***	0.0038*	0.0027*	-0.0032
(std error)	(0.0018)	(0.0018)	(0.0011)	(0.0031)
[Effect of 1 std dev in CDD90]	[0.074]	[0.037]	[0.028]	[-0.032]
B. Temperature (degree-days over 80F)/10	0.0024**	0.0025**	-0.0001	-0.0022*
(std error)	(0.0008)	(0.0008)	(0.0005)	(0.0010)
[Effect of 1 std dev in CDD80]	[0.103]	[0.108]	[-0.003]	[-0.101]
C. Temperature (degree-days over 70F)/10	0.0023***	0.0026***	0.0003	-0.0012
(std error)	(0.0007)	(0.0006)	(0.0004)	(0.0007)
[Effect of 1 std dev in CDD70]	[0.173]	[0.190]	[0.021]	[-0.090]
Observations	11,721	11,433	12,089	11,483

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. Estimates in panels A, B, and C are from separate regressions. All regressions control for rainfall (upper/lower tercile dummies). *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level. Residual life expectancy at birth and conditional on surviving past age 1 are 51.01 and 13.85 (Rural) and 59.63 and 15.38 (Urban)

Table 5: Weather and Death - Robustness Analysis

Dependent Variable: Log(Mortality Rate)	Rural						Urban					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature (degree-days over 90F)/10	0.0073*** (0.0018)	0.0082*** (0.0020)			0.0073*** (0.0018)	0.0075*** (0.0022)	0.0027* (0.0011)	0.0018 (0.0016)			0.0027* (0.0011)	0.0037** (0.0012)
Pre-1980			0.0092** (0.0029)						0.0050* (0.0020)			
Post-1980			0.0064* (0.0025)						0.0019 (0.0016)			
"Hot" districts				0.0074*** (0.0019)						0.0025* (0.0011)		
"Cold" districts				0.0072 (0.0047)						0.0048 (0.0032)		
Temperature (degree-days below 50F)/10					-0.0001 (0.0018)						-0.0010 (0.0010)	
P-value of equality test			0.484	0.973					0.266	0.450		
Same years as the agricultural data	No	Yes	No	No	No	No	No	Yes	No	No	No	No
Region*Year fixed effects?	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Observations	11,721	7,964	11,721	11,721	11,721	11,721	12,089	8,327	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 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 6: Weather and Death - Rural-Urban Differences, Exposure by Growing Season

Dependent Variable: Log (Mortality Rate)	Rural		Urban	
	Age 1+	Age 1+	Age 1+	Age 1+
	(1)	(2)	(3)	(4)
A. Temperature (degree-days over 90F)/10				
Growing Season Temperature	0.0105*	0.0108*	0.0010	0.0013
(std error)	(0.0050)	(0.0049)	(0.0035)	(0.0036)
[Effect of 1 std dev in CDD90]	[0.026]	[0.026]	[0.002]	[0.003]
Non-Growing Season Temperature	---	0.0064**	---	0.0030*
(std error)		(0.0020)		(0.0013)
[Effect of 1 std dev in CDD90]		[0.055]		[0.026]
P-value for test of equality	---	0.407	---	0.668
Indicator for Rainfall Shock in Lowest Tercile	0.0324*	0.0318*	0.0007	0.0005
	(0.0155)	(0.0155)	(0.0103)	(0.0103)
Indicator for Rainfall Shock in Highest Tercile	-0.0007	0.0004	-0.0137	-0.0129
	(0.0183)	(0.0184)	(0.0106)	(0.0106)
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 distric

Table 7: Weather and Death - Smoothing via Expansion of Rural Banks

| Dependent Variable: Log (Mortality Rate)	Rural IV (1)	Rural IV (2)	Urban IV (3)
All-year temperature (degree-days over 90 F)/10	0.0100*** (0.0038)		
[Temperature (degree-days over 90 F)/10] x [Bank branches (in previously unbanked rural locations) per 10,000 capita]	-0.0041 (0.0106)		
Growing season temperature (degree-days over 90 F)/10		0.0364*** (0.0123)	0.0021 (0.0085)
[Growing season temperature (degree-days over 90 F)/10] x [Bank branches (in previously unbanked rural locations) per 10,000 capita]		-0.0902** (0.0401)	-0.0010 (0.0068)
Non-growing season temperature (degree-days over 90 F)/10		0.0031 (0.0042)	0.0038*** (0.0013)
[Non-growing season temperature (degree-days over 90 F)/10] x [Bank branches (in previously unbanked rural locations) per 10,000 capita]		0.0145 (0.0117)	
Effect of temperature variable on log (mortality rate) for 25th-percentile district-year in terms of banks	0.0099** (0.0035)	GS: 0.0337** (0.0112), NGS: 0.0035 (0.0040)	0.0021 (0.0059)
Effect of temperature variable on log (mortality rate) for 75th-percentile district-year in terms of banks	0.0082*** (0.0022)	GS: -0.0031 (0.0078), NGS: 0.0094 (0.0023)	0.0017 (0.0060)
p-value of difference	0.695	GS: 0.025 NGS: 0.216	0.884
F-statistic (Angrist-Pischke) from first-stage, bank-temperature interaction instrument(s)	14.22	GS: 13.09 NGS: 8.33	16.52
Observations	10,960	10,960	11,359

Notes: Regressions are IV regressions in which the endogenous variable (the temperature-bank branch interaction variable(s), for a given temperature variable(s), as differs across columns) are instrumented with, following Burgess and Pande (2005), the number of bank branches in a district in 1961 times a post-1976 trend and times a post-1989 trend, each interacted with the relevant temperature variable(s). The level of the banks variable is omitted but we control for the level effect of the two Burgess-Pande instruments. In the middle panel we report the effect of the relevant temperature variable(s) (as differ(s) across columns) on the log(mortaltiy rate) at district-year observations that represent the 25th and 75th percentile of the banks variable (that is, the number of bank branches in previously unbanked rural locations per 10,000 capita) distribution (weighted by rural population). As a test for potentially weak instruments, in the bottom panel we report the Angrist-Pischke F-statistic(s) for the first-stage equation(s) of bank branches interacted with the relevant temperature variable(s) regressed on the Burgess and Pande (2005) instruments interacted with the relevant temperature variable(s). All regressions also include district fixed effects, year fixed

Appendix Figure 1: Infant Mortality Impact of Daily Temperature in Rural and Urban India.

Estimated Impact of a Day in 10 Temperature-Day Bins on Log Annual Mortality Rate, Relative to a Day in the 70-72 Farenheit Bin
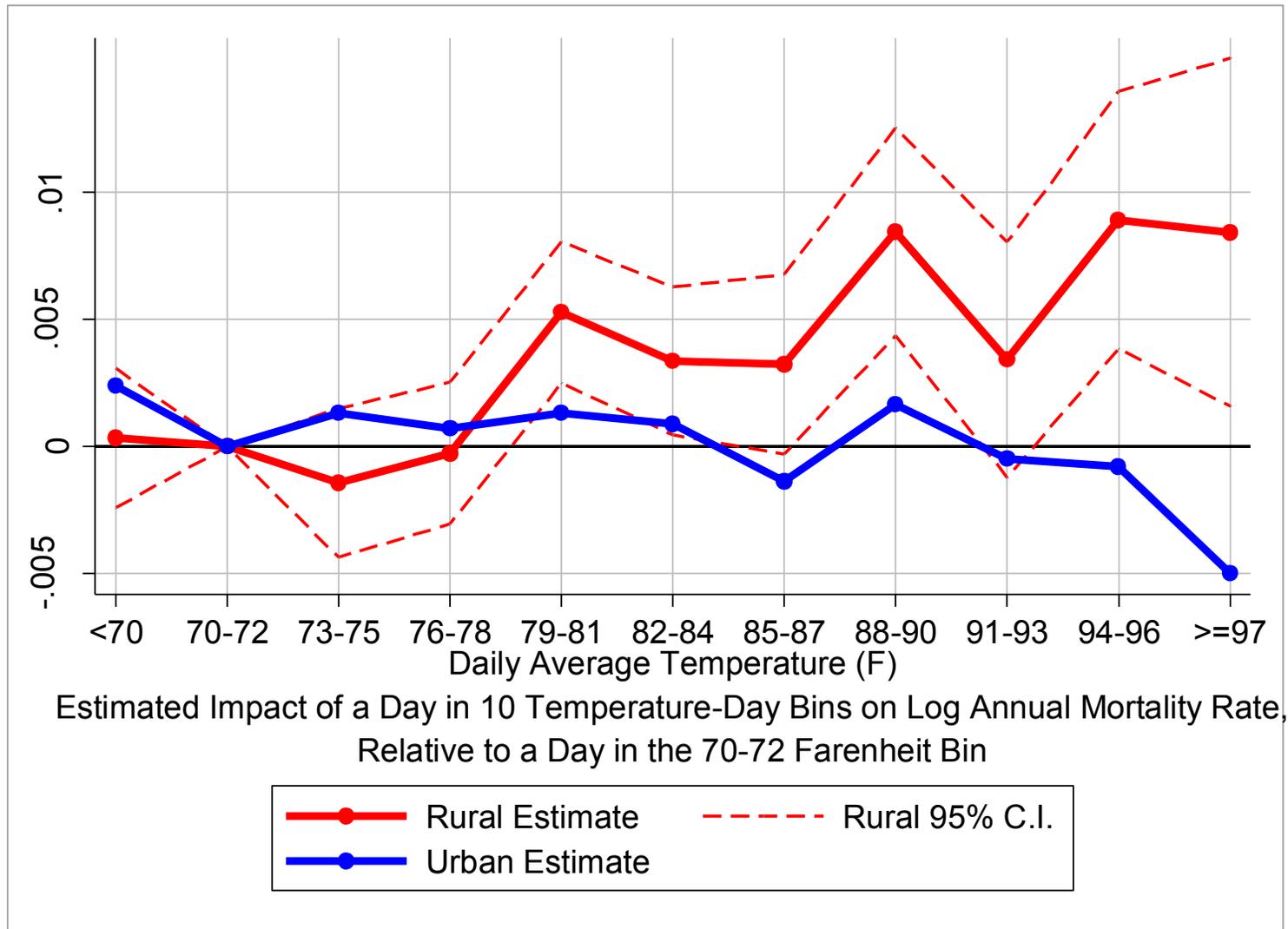
Appendix Figure 2: Mortality Impact of Daily Temperature in Rural India, by Agricultural Growing Season.

Estimated Impact of a Day in 10 Temperature-Day Bins on Log Annual Mortality Rate, Relative to a Day in the 70-72 Farenheit Bin
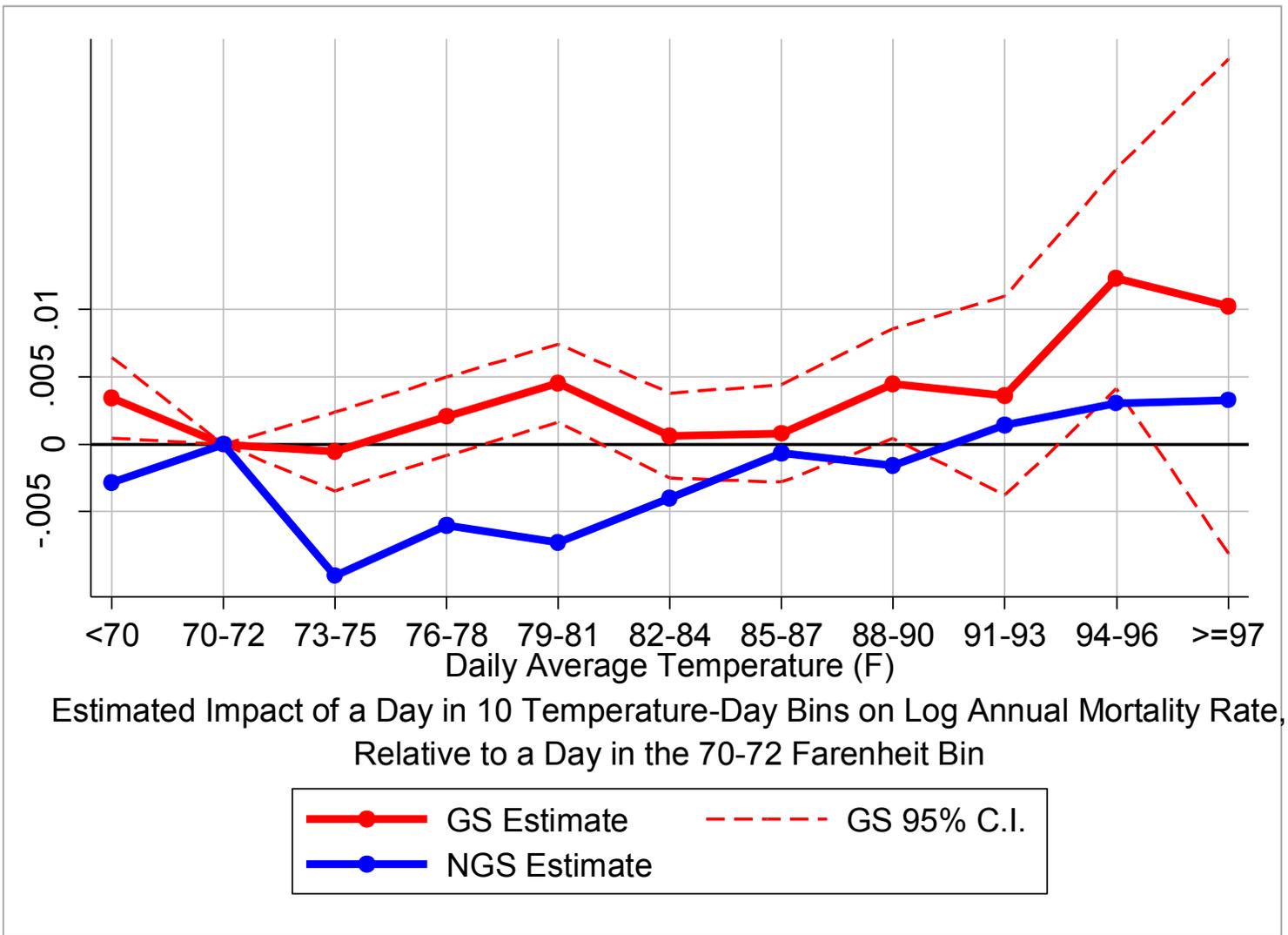
Appendix Figure 3: Mortality Impact of Daily Temperature in Urban India, by Agricultural Growing Season.

Estimated Impact of a Day in 10 Temperature-Day Bins on Log Annual Mortality Rate, Relative to a Day in the 70-72 Farenheit Bin