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Weather and Welfare:

Health and Agricultural Impacts of Climate Extremes, Evidence from Mexico

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Abstract[1]

Using data for all 2,454 municipalities of Mexico for the period 1980-2010, this paper analyzes the relationship between exposure to extreme temperatures and precipitation and death, as well as the relationship between severe weather and agricultural income and crop production in the country. It is found that extreme heat increases mortality, while the health effect of extreme cold is generally trivial. Precipitation extremes seem to affect the agricultural system, but their impact on mortality is ambiguous. More specifically, exchanging one day with a temperature of 16-18 °C for one day with temperatures higher than 30 °C increases the crude mortality rate by 0.15 percentage points, a result robust to several model specifications. It is also found that the extreme heat effect on death is significantly more acute in rural regions, leading to increases of up to 0.2 percentage points vis-à-vis a 0.07-point increase in urban areas. The timing of climate extremes is relevant: if a weather shock takes place during the agricultural growing season, the effects on mortality and agricultural output, productivity, prices, and crop yields are large and significant, but not so if such shocks occur during the non-growing season.

JEL classifications: I12, Q12, Q51, Q54
Keywords: Weather shocks, Climate extremes, Mortality, Agricultural income, Mexico

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1. Introduction

The mechanisms through which weather impacts human welfare are complex and rarely linear. In addition, they often encompass a wide variety of factors ranging from geographical location, economic development, settlement patterns and behavioral adaptation to intra-seasonal acclimatization, demographic characteristics, urbanization, and environmental pollutants. Inherent features of the developing world make people residing in industrializing regions more exposed to the negative impacts of weather than their developed-world counterparts. On average, people in developing countries spend more time outdoors (Basu and Samet, 2002), whether at their workplace, producing goods for their household's own use and maintenance, commuting, or even carrying out activities to meet biological needs such as eating, sleeping, and relaxing. Even indoors, households in developing countries are more likely to lack air conditioning or display other features providing insulation from extreme weather (Rothman and Greenland, 1998).

In developing settings specifically, the power of weather can be generally understood through two specific types of channels. One is direct: weather impacts human physiology through thermal stress and changes in metabolic rates, as well as increased incidence of diseases caused or spread by severe climatic conditions. In an extreme situation, these negative impacts may ultimately lead to death. In fact, the effect of extreme weather on mortality is a public health threat of considerable magnitude: even though *economic* (including insured) disaster losses associated with climate and geophysical events are higher in developed countries, *fatality rates* are higher in developing countries. During the period from 1970 to 2008, over 95 percent of deaths from inclement weather occurred in developing countries (IPCC, 2012.)

Substantial epidemiological evidence documents a strong relation between severe weather and morbidity and mortality. The body adapts thermally to survive in drastic temperature environments, typically through thermoregulatory control mechanisms, such as shivering, arteriovenous shunt vasoconstriction, sweating and precapillary vasodilation in cold and hot environments, respectively. But these physiological processes are only effective within certain limits. Weather can be so extreme that such adjustments fail to balance body and ambient temperature, which in turn leads to strokes, hypothermia and hyperthermia, and other conditions that may be fatal.

Many studies focusing on both industrial and developing countries have consistently shown that extreme heat is a natural hazard that can have a pronounced effect on human wellbeing. This relationship has been considered relevant to public health for millennia[2] and empirically researched as early as the 1930s: in a classic study, Gover (1938) reports excess deaths associated with elevated ambient temperature exposure in 86 U.S. cities from 1925 to 1937. Studies of army recruits published in the 1940s (Schickele, 1947) and 1950s (Stallones, Gauld and Dodge, 1957) also underscore an association between ambient heat exposure and death. More recently, Hajat, O'Connor and Kosatsky (2010) observe that in Europe, increases in emergency hospital admissions among individuals with respiratory diseases have been noted during hot weather, while in studies from the United States, heat-related increases were noted in admissions for heart disease, acute myocardial infarction, and congestive heart failure. Using district-level data for India, Burgess et al. (2011) show that hot days and deficient rainfall cause large increases in mortality within a year of their occurrence in rural regions. Basu and Samet (2002) and Kovats and Hajat (2008) present a general review of the literature on the effects of hot temperature on mortality rates.

Evidence is also robust for cold climate. Deschênes and Moretti (2009) estimate that the aggregate effect of cold weather on mortality is quantitatively large, the number of annual deaths attributable to cold temperature being equivalent to 0.8 percent of total deaths in the United States. This effect is even larger in low-income areas. Hashizume et al. (2009) characterize the daily temperature-mortality relationship in rural Bangladesh and find that for the period between 1994 and 2002, a 1°C decrease in mean temperature was associated with a 3.2 percent (95 percent confidence interval: 0.9–5.5) increase in mortality, with deaths resulting from perinatal causes sharply increasing with low temperatures. In an international study of temperature and weather in urban areas using data from 12 cities in developing countries, including Mexico City and Monterrey, McMichael et al. (2008) find a U-shaped temperature-mortality relationship, with significant death rate increases at lower temperatures. Analitis et al. (2008) study the short-term effects of cold weather on mortality in 15 European cities and find that a 1°C decrease in temperature was associated with a 1.3 percent increase in the daily number of total natural deaths and increases of 1.2 percent, 1.7 percent and 3.3 percent in cerebrovascular, cardiovascular and

[2] Already in Περί Αέρων, Υδάτων, Τόπων (*On Airs, Waters, Places*), a fifth-century B.C. medical treatise ascribed to Hippocrates, the author deals with the effects of climate on health. He argues that "whoever wishes to investigate medicine properly, should proceed thus: in the first place to consider the seasons of the year, and what effects each of them produces for they are not at all alike, but differ much from themselves in regard to their changes. Then the winds, the hot and the cold, especially such as are common to all countries, and then such as are peculiar to each locality."

respiratory deaths, respectively, the increase being greater for the older age groups. Hassi (2005) presents a review of the literature on cold exposure mortality.

The other mechanism through which weather exerts a human impact, especially in developing countries, is indirect. It can be understood as a "food-security mechanism," characterized in general terms by two different channels. One channel could be described as an "income-based channel" in which health outcomes are negatively influenced as a result of adverse weather disrupting the household's sources of income on which it relies for subsistence (Burgess et al., 2011). Indeed, many regions in the world, and particularly the poorest, rely almost solely on small-scale, climate-sensitive subsistence farming, which is especially susceptible to inclement weather (IPCC, 2012.) The other channel could take the form of a "consumption-based channel" whereby consumption of basic goods and food intake is restrained as a result of natural-calamity-induced supply shortages, speculative behavior, and increased demand to deal with uncertainty. The economic consequence of extreme weather is thus higher food prices, which ultimately affect the poor as a result of reduced purchasing power, thus increasing their likelihood of becoming famine victims (Lin and Yang, 2000.) In all, weather has played a major role in 17 out of 24 major famines from 1693 through 2005 (for a listing of famines, see Ó Gráda, 2007, p. 20), suggesting that the food-security mechanism is as relevant as the direct human physiology channel.[3]

There are many instances in the development and agricultural economics literature exposing how the income-based channel operates in a self-sufficiency farming context. For instance, in an influential article, Sen (1981, p. 449) discusses the Ethiopian and Bangladeshi famines of the early 1970s and weather (droughts and floods, respectively), and points out that in both cases farmers were disproportionally affected: "The farming population faced starvation, because their own food output was insufficient, and they did not have the ability to buy food from others, as food output is also their source of income." Food output is also negatively impacted by extreme temperature, as shown by Hatfield et al. (2011). Wheeler et al. (2000) find that crops are especially at risk when extreme temperatures take place near or during their pollination phase, while Prasad et al. (2006) document the adverse impact of extreme

[3] Intuitively, given that both channels of the food-security mechanism ultimately affect human health, it is also useful to consider both income and consumption-based channels as two specific mechanisms through which human physiology is impacted. In this sense, the physiological mechanism can be seen as the "aggregate effect" of weather on mortality.

temperatures on crop yields. In addition, Porter and Semenov (2005) and Hurkman et al. (2009) have found that even if inclement climate does not lead to harvest loss, weather extremes do affect photosynthesis and respiration rates, among other crop development and growth processes, which, in turn, implies lower crop quality and micronutrient malnutrition as a result. Kettlewell, Sothern and Koukkari (1999), Gooding et al. (2003), and Martre et al. (2003) show that there is a significant negative association between extreme weather and both protein content and nutritional properties.

The role of weather in the consumption-based channel is also studied by many analysts. In the same study on famines presented above, Sen (1981) discusses that the wages paid to farm laborers in 1942 did not keep up with the rising price of food caused, inter alia, by a hurricane that affected rice harvests, along with inflation in Calcutta, which was going through a boom as the Raj put money into war production. This resulted in farmers suffering a reduction in their ability to command power over food, which eventually resulted in the Bengal famine of 1943. Similar cases in Africa and Europe are discussed at length by Drèze and Sen (1989) and Ó Gráda (2007.) Staff in a recent report by the Food and Agriculture Organization of the United Nations (FAO, 2008) examine the multiple weather hazards that potentially affect food supply chains when agricultural production is not consumed where it is produced: transporting food is contingent upon transport, storage, and distribution infrastructure that is vulnerable to the destructive nature of severe weather. The more extreme climate events are, the more pronounced the damage to that infrastructure, which is likely to result in disrupted processing and delivery chains. This, in turn, is reflected in higher food prices, acutely impacting the poorest households, who spend a larger share of their income on food (IPCC, 2012.)

In the next section, I show both the direct and the indirect channels through a theoretical model.

2. A Theoretical Framework of Extreme Weather

A theoretical model that portrays the relationship between extreme weather and mortality or other health outcomes should include the direct and indirect mechanisms through which weather impacts human life. A starting point for this purpose is an extension of the health as human capital developed by Becker (2007) and adjusted by Burgess et al. (2011) to incorporate choices that increase agents' probability of survival under extreme heat. I further expand it in order also to account for the negative effects of extreme cold weather.

Consider the following utility function specified with a constant discount factor for different time periods for an infinitely lived agent:

$$V = \mathbb{E}\left[\sum_{t=0}^{\infty} D^t S_t u_t(c_t)\right] \qquad (1)$$

where u_t is the utility at period *t* that depends on consumption during the same period, c_t. D is the discount factor, and S_t is the probability of the agent being alive (i.e., $1 - S_t$ is the probability of death) during period *t*, which equals the product of the conditional probabilities of being alive given that the agent was alive during the previous period:

$$S_t = s_0 s_1 s_2 \dots s_{t-1} = \prod_{t=0}^{t-1} s_t \qquad (2)$$

Suppose now that the probability of survival in period *t* is a function of nutrition, *N*, which is under the agent's control, subject to a budget constraint, and weather, *W*, which is assumed to be exogenous. For the purposes of this paper, operationalize nutrition as caloric intake and weather as the number of days throughout the period with inclement (i.e., excessively cold or excessively hot) climate. Hence, let $s_t = (N_t, W_t)$ and assume that such a function is increasing in *N*, but decreasing in *W*. We thus have two types of consumption goods: food, denoted by *N*, and a composite good, *G*, whose consumption is directly valued by the agent.

In this specification, extreme weather, ceteris paribus, has a direct impact on the probability of the agent's survival, which was defined as the *direct* impact of weather on human physiology in the previous section. Likewise, the assumption that *s* is increasing in *N* is what was previously identified as the food-security mechanism, which impacts human wellbeing *indirectly* through disruptions in the income stream or subsistence consumption that lead to severe reductions in caloric intake.

In this formulation, I follow the event timing specification of Burgess et al. (2011): given weather conditions for period *t*, the agent chooses her bundle of goods $(N_t(W_t), G_t(W_t))$. Then the agent's death shock takes place, with the probability of surviving death $s_t = (N_t, W_t)$. If the agent does survive through the next period, the function *V* gives her intra-period utility.

For simplicity, the budget constraint assumes a constant interest rate, and perfect and fair annuity and capital markets. Likewise, assume that the price of food is p^N, while that of the composite good equals p^G, with both being constant over time. Notice that if expenditures in a given period surpass income, future savings will have to pay off for the due balance. Thus

$$s_T(y - p^N N_T - p^G G_T) = \mathbb{E}\left[\sum_{t=1}^{\infty} \frac{S_t(p^N N_T + p^G G_T - y)}{(1+r)^t}\right] \qquad (3)$$

If the agent maximizes her utility function (1) in period 0 subject to the budget constraint (3), we arrive at the optimal intertemporal consumption choice

$$\frac{u'(c_0)\mathbb{E}[s_1]}{D\mathbb{E}[s_1 u'(c_1)]} = 1 + r \qquad (4)$$

whereby the first order condition for the choice of caloric intake is

$$\frac{\partial s_0}{\partial N}\left(u(c_0) + \mathbb{E}\left[\sum_{t=1}^{\infty} D^t S_t u_t(c_t)\right]\right) = \frac{\partial s_0}{\partial N}\mathbb{E}[V_0] = \lambda p^N s_0 \qquad (5)$$

This is an intertemporal characterization of optimal food choice whereby the marginal benefit of spending on food at time *t* equals the marginal cost of spending on food at time *t*. Equation (5) implies that the optimizing agent equalizes the present-value marginal flow benefit from the control across periods.

This first-order condition can be used to determine the extent to which the agent would be willing to pay to insulate herself from inclement weather in period 0. Burgess et al. (2011) characterize a transfer $\tau*$ that is a function of weather, *W*, in period 0. Such a transfer holds expected lifetime utility *V* constant regardless of the value of *W*, so that

$$\frac{d\tau*(W_0)}{dW_0} = -\frac{dy(W_0)}{dW_0} + \frac{\partial N_0}{\partial W_0} - \frac{ds(N_0,W_0)}{dW_0}\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right] \qquad (6)$$

The amount the agent would be willing to pay to insulate herself from inclement weather in period 0 depends on three conditions. One is the willingness to avoid the risk of being exposed to the negative physiological impacts of weather, which as discussed in the previous section, may ultimately lead to death. This is represented by the third term in equation (6), $-\frac{ds(N_0,W_0)}{dW_0}\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$, which is the product of the probability of surviving given weather conditions *W*, $\frac{ds(N_0,W_0)}{dW_0}$, and what Becker (2007, p. 384) refers to as “the statistical value of life,” which is the monetary value given by the agent of surviving through period 0, $\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$.

Also, given that extreme weather puts food-security at risk, the agent would be willing to pay an amount equal to the first term of equation (6), $-\frac{dy(W_0)}{dW_0}$, to avoid any loss of income resulting from extreme weather. Finally, the agent would need to be compensated for any changes in terms of food expenditure derived from the agent trying to reduce her chance of dying by counterweighing the negative effects of severe climate through the acquisition of more nutrients. This is expressed by the second term of Equation (6), $\frac{\partial N_0}{\partial W_0}$.

Based on equation (6), I propose an empirical approach that estimates the effect of weather on human physiology, particularly on death, as well as that of climate on variables that determine incomes. As a result of money fungibility, it does not matter whether the agent faces a climate shock through either the human physiology or the food-security channel. The agent is only concerned about being insulated from inclement weather, for which she is willing to pay a price. A consideration that needs to be emphasized is that, given that markets are complete in this model, a policy that corrects market failure is irrelevant. However, as Burgess et al. (2011, p. 10) argue, such a model "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."

In the next section, I discuss the data I use to carry out an empirical analysis based on this theoretical framework.

3. Data

As I have argued throughout this paper so far, weather impacts humans via two channels, one that is direct, resulting from severe climate affecting human physiology, and another that is indirect, whereby weather disturbs the mechanisms through which households secure their food consumption. The extreme consequence of both channels is death.

An empirical specification of the theoretical framework presented above, which illustrates the human impact of weather, requires data on three types of variables: one that operationalizes human physiology, one that operationalizes food security, and one that operationalizes climate.

Typical variables that may work well to assess the impact of weather variation on human physiology include the incidence of particular water and vector-borne diseases, hospital admissions, clinic attendance, morbidity rates, and mortality rates (WHO, WMO and UNEP, 2003.) In terms of variables that are likely to reflect a given community's degree of food security—especially in low and middle-income area contexts—income, job productivity and nature of job, crop production, and food consumption are all plausible proxies (USAID, 1992.) Finally, the natural choices for studying climatic phenomena are temperature, pressure, rainfall, hail, aridity, wind, as well as the occurrence of certain weather events like tornados and cyclones (WMO 2012.)

As good evidence requires good data, I selected those variables generated with high frequency, high spatial disaggregation, and high-quality monitoring. The following constitute the variables that I employ for the following empirical analysis.

3.1 Mortality

To calculate mortality rates, information on deaths, births, and population are needed. I obtained death and birth counts data at the municipal level through each state's Civil Registry Office. Since each state has its own registration data and formats, I digitized and harmonized the 32 datasets (31 state datasets and one dataset for Mexico City) using standardized codes for births, deaths, and fetal deaths. I collected monthly data for the period January 1990-December 2010 for 2,454 Mexican municipalities (99.9 percent of the total.)

Given that annual population data are not available in Mexico, I constructed a population monthly time series using censal information for population in combination with migration flow data obtained from Mexico's National Council of Population Demographic Indicators and the State and Municipal Database System of Mexico's National Institute of Statistics (INEGI.) These data are available for years 1990, 1995, 2000, and 2010. For intercensal years, I estimated (midyear) population using the component method, which is defined by the use of estimates or projections of births, deaths, and net migration to update a population (Hollmann, Mulder and Kallan, 2000.) In its simplest statement, the component method is expressed by the following equation:

$$P_t = P_{t-1} + B_{t-1,t} - D_{t-1,t} + M_{t-1,t} \qquad (7)$$

where P_t = population at time t;

P_{t-1} = population at time $t-1$;

$B_{t-1,t}$ = births, in the interval from time $t-1$ to time t;

$D_{t-1,t}$ = deaths, in the interval from time $t-1$ to time t; and

$M_{t-1,t}$ = net migration, in the interval from time $t-1$ to time t.

For simplicity, I computed intercensal net migration using what demographers refer to as the Das Gupta method (Das Gupta 1991.) This technique assumes that the ratio of the intercensal estimate to the postcensal estimate should follow a geometric progression over the five-year period. Naturally, there is no universal norm for producing intercensal migration estimates, and other methodologies could have also been employed.

With these variables, I constructed a crude (total) mortality rate, which I define as the total number of deaths (excluding fetal deaths) per period per 1,000 people. In addition to the crude mortality rate, I also distinguish among two subtypes of mortality indicators: infant mortality rate (i.e., the number of deaths of children less than 1 year old per period per 1,000 live births); and fetal mortality rate (i.e., the number of stillbirths per period per 1,000 live births). I also compare these mortality rates by area, defining the rural mortality rate as the mortality rate in communities with fewer than 2,500 residents, and urban mortality rate as the mortality rate in communities with 2,500 residents or more. Table 1 presents relevant descriptive statistics.

Of particular relevance is the comparative analysis of urban and rural areas. The distinction follows an intuitive logic: the food-security mechanism is more likely to find empirical support in rural communities. The reason is twofold: on the one hand, extreme weather has a clear and direct impact on agriculture, and this sector is the main source of employment for rural regions: the latest Household Income and Expenditures National Survey (INEGI, 2011) is indicative: in 2010, almost 62 percent of surveyed households living in rural communities worked in the agricultural sector, while only 7 percent of households residing in urban areas did. On the other hand, this spatial imbalance translates into significant differences in income: the same survey reports that, also in 2010, households where no members were employed in agriculture had an income, on average, of 13,365 Mexican pesos per month (1,062 USD).[4] Households with some (but not all) members being employed in the primary sector of the economy earned, on average, 8,618 pesos (686 USD). Finally, in the case where the entire

[4] Based on the average midpoint exchange rate of 0.0796 MXN/USD from August 21, 2010 through November 28, 2010, the period when the survey was carried out.

household is engaged in agricultural work, monthly income averages 4,841 pesos (385 USD), or roughly a third of income in non-agricultural households.

These differences, in turn, are reflected in two different patterns of household consumption: monthly expenditures in urban areas are high (relative to rural communities) and food consumption has a relatively smaller share of total expenditures. Urban households spend on average 8,878 pesos (707 USD) per month, of which almost 32 percent is spent on food. In contrast, rural households spend on average 4,602 (366 USD) pesos per month, of which 40 percent is spent on food. Table 2 summarizes these discrepancies.

3.2 Agricultural Outcomes

I obtained data for agricultural outcomes for the period 1994-2009 using Mexico's Agro-alimentary and Fishing Information System. Information on the value of agricultural output (in thousands of pesos), and I obtained total hectares under crop cultivation (planted and harvested) at the municipal level for 2,454 municipalities.

In addition to totals, I collected municipal data for 10 major crops[5] for the volume of production (in tons) and average prices per ton. Using this dataset, I created two additional indicators: I define agricultural productivity as the value of agricultural output divided by harvested hectare, whereas crop yields are expressed as the volume of production divided by harvested hectare. Monetary values are expressed in Mexican pesos of 2009. Prices were deflated using a price index that weights the municipal price of each of the 10 major crops by the value of agricultural output of that crop in a given year.

Given the nature of the agricultural cycle in Mexico, the calendar year and the agricultural year differ. By convention, the agricultural year in Mexico lasts 18 months: it begins on October 1 of year $t - 1$ and ends on March 30 of year $t + 1$, and thus the first three months of a given agricultural year overlap with the last three months of the previous agricultural year. It should be noticed that I collected annual agricultural data based on agricultural years. The empirical analysis reconciles calendar years and agricultural cycles by synchronizing weather data accordingly. In addition, an analysis of my agricultural data shows that, even though there are differences resulting from geographical location, elevation, rainfall, coastal proximity, and varying photoperiods, the period when crop growing intensifies starts typically in early April and

[5] These crops are green alfalfa, beans, corn, green chili, oats, pastures, sorghum, tomato, tomatillo, and wheat.

ends in late August. For my empirical analysis, I thus define this period as Mexico's growing season. Similarly, the period of November through February is characterized by crop-growing inactivity, and throughout this paper I will refer to this timespan as the non-growing season. Table 3 presents summary statistics for several agricultural outcomes, including yields and volume of production for corn, Mexico's main staple.

3.3 Weather

The ultimate essential data to carry out any empirical analysis on weather and its impacts are, of course, climatic records. There is a variety of models that provide environmental analysts with climatic observations and some have been employed to assess weather impacts in Mexico in terms of human, environmental, and agricultural outcomes. In studying the impact of severe weather on health and cognitive development, Aguilar and Vicarelli (2011) use precipitation data at 0.5 degree resolution climate grids, which were generated by the Climate Research Unit and the Tyndall Centre for Climate Change Research, both at the University of East Anglia. Sáenz Romero et al. (2010) develop spatial climate models to estimate plant-climate relationships using thin plate smoothing splines of ANUSPLIN software, created by the Australian National University. Pollak and Corbett (1993) use spatial agroclimatic data to determine corn ecologies.

The underlying problem with these and other works that follow similar methodologies is their use of monthly climatic data. Using monthly climatic data is problematic due to the nonlinear effects of weather, which may be concealed when, for example, daily observations are averaged into monthly or seasonal variables. In effect, daily and even finer-scale weather data facilitate estimation of models that aim to identify nonlinearities and breakpoints in the effect of weather. Using daily temperature data, Schlenker and Roberts (2009) find a nonlinear asymmetric relationship between weather and crops yields in the United States, with yields decreasing more rapidly above the optimal temperature vis-à-vis their increasing below the optimal temperature. The assumption of nonlinearity is particularly critical for studies like this one, where the researcher attempts to represent the relationship between weather and human physiology. In many studies, for the case of mortality, a J-or U-shaped curve has been found appropriate to describe the association, with elevated mortality being observed at temperature extremes and relatively lower mortality at moderate temperatures (Burgess et al., 2011; Curriero et al., 2002; Deschênes and Greenstone, 2011; Huynen et al., 2001; Kunst, Looman and Mackenbach, 1993.)

For this paper, I use daily temperature and precipitation data from the North American Regional Reanalysis (NARR) model (NOAA, 2012.) The NARR project is a long-term, high-frequency, dynamically consistent meteorological and land surface hydrology dataset developed by the National Centers for Environmental Prediction (NCEP) as an extension of the NCEP Global Reanalysis, which is run over the North American Region. It covers 1979 to 2010 and is provided eight times daily on a Northern Hemisphere Lambert Conformal Conic grid with a resolution of 0.3 degrees (32km)/45 layers at the lowest latitude. In addition to the modeling benefits of high spatial resolution, I chose to work with the NARR due to the model's good representation of extreme weather events, resulting from the model outputting all "native" (Eta) grid time-integrated quantities of water budget. Mesinger et al. (2006), for instance, compare the NARR precipitation for January 1998 (when the El Niño effect was underway) with observed precipitation. Their comparison shows that over land there is an extremely high agreement between NARR and observed precipitation, even over the complex western topography of Mexico.

Other variables could be employed for future work. The NARR dataset also includes information on wind speed, humidity, elevation, and other common climatic factors, but evidence shows that, at least for the most important crops of Mexico in terms of output (i.e., corn, sorghum, and wheat), temperature and precipitation are the two weather elements that can effectively inhibit plant growth and development to the point of crop failure (Ministry of Agriculture of Mexico, 2012b.) Conversely, non-optimal values in altitude, soil quality, or light intensity requirements may only retard growth or reduce yields, but these factors are not likely to put crops at imminent risk (FAO, 2007.)

Daily temperature and precipitation data were constructed in two simple steps. First, a spherical interpolation routine needs to be applied to the data: I took weighted averages of the daily mean temperature and accumulated precipitation of every NARR gridpoint within 30 kilometers of each municipality's geographic center, with the inverse squared haversine distance between the NARR gridpoint and the municipality centroid as the weighting factor.[6] Second, all

[6] The haversine distance measure is useful when the units are located on the surface of the earth and the coordinate variables represent the geographical coordinates of the spatial units and a spherical distance between the spatial units

the (365, or 366 for leap years) daily temperature estimates in a given year are distributed over 14 ranges or bins: daily mean temperature lower than 10°C; daily mean temperature higher than 30°C, and 10 two-degree-wide ranges (i.e., 10°C-12°C, 12°C-14°C,…, 28°C-30°C) in between. Similarly, the daily accumulated rainfall estimates are distributed over 15 two-millimeter-wide ranges (i.e., 0-2mm, 2-4mm,…, 28-30mm) plus an extra bin for daily accumulated precipitation exceeding 30mm, and another bin containing exclusively days without rainfall. The binning of the weather data is important for the empirical strategy that will follow, for it would maintain weather variation in any given specification, thus accounting for the nonlinear effects of weather extremes discussed above.

Figures 1 and 2 illustrate this binning for the period 1979-2009. The height of the bars represents the weighted average number of days across municipality-by-year temperature and rainfall realizations, where the municipality-by-year's total population is the weight. The weighted average temperature is 18.6°C, while the weighted average daily accumulated precipitation is approximately 2mm.

An alternative approach to binning is suggested by Burgess et al. (2011). They construct a measure of the cumulative number of degrees-times-days that exceed 32°C in a year, in an attempt to reflect the nonlinear effects of temperature.[7] Although it collapses daily weather observations into a single metric, this measure, by taking into account the number of degrees per day above a certain threshold, still indirectly accounts for the nonlinear effects of weather. For this paper, I follow a similar strategy by constructing four aggregate measures: the cumulative degrees-times-days that exceed 30°C in a year, the cumulative degrees-times-days below 10°C in a year, the total millimeters-times-days that exceed 8 millimeters, and the total millimeters-times-days below 3 millimeters. The rationale behind these thresholds is ecological. These are the minimum and maximum temperature and precipitation requirements for corn, Mexico's staple crop. Beyond these values, corn usually begins to stress, putting at serious risk its survival (Gómez Rojas and Esquivel Mota, 2002; Ministry of Agriculture of Mexico, 2012a; Neild and Newman, 1990; North Dakota Corn Utilization Council, 1997.)

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needs to be calculated. This is accomplished by calculating $d_{st} = r \times c$, where r is the mean radius of the Earth (6,371.009 kms); $c = 2\arcsin\left(\min\left(1, \sqrt{a}\right)\right)$; $a = \sin^2\phi + \cos(\phi_1)\cos(\phi_2)\sin^2\lambda$; $\phi = \frac{1}{2}(\phi_2 - \phi_1) = \frac{1}{2}(x_2[t] - x_2[s])$; $\lambda = \frac{1}{2}(\lambda_2 - \lambda_1) = \frac{1}{2}(x_1[t] - x_1[s])$; $x_1[s]$ and $x_1[t]$ are the longitudes of point s and point t, respectively; and $x_2[s]$ and $x_2[t]$ are the latitudes of point s and point t, respectively.

[7] The authors' choice of using 32°C as their threshold is based on the public health and agronomy research that has consistently shown that temperatures higher than 32°C are severe for both human and crop physiology.

Table 4 summarizes the descriptive statistics for the temperature and precipitation variables employed.

4. Empirical Strategy

Two empirical specifications are employed to establish the relationship between weather and mortality. The first one is an attempt to capture the full distribution of annual fluctuations in weather and based on the following equation:

$$Y_{mt} = \sum_{j=1}^{12} \theta_j tempbin_{mtj} + \sum_{k=1}^{17} \rho_k rainbin_{mtk} + \alpha_m + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{mt} \qquad (8)$$

where Y_{mt} is the log (crude or an alternative) mortality rate (or agricultural outcome of interest) in municipality *m* in year *t* (using levels virtually leaves the results unchanged, but for the sake of clarity, my analysis is carried out using logs). $tempbin_{mtj}$ and $rainbin_{mtk}$ are the separate temperature and precipitation bins described above for municipality *m* in year *t*.

The impact of temperature thus equals the sum of all j bins, whereas the impact of precipitation is equivalent to the sum of all k bins. Notice that the only functional form restrictions in this specification are i) that the mortality impacts of temperature and precipitation are constant within each 2-degree and 2-millimeter range, respectively, and ii) that all days with temperatures/rainfall above (below or equal to) 30°C/30mm (10°C/0mm) have the same impact in terms of mortality.

α_m is the fixed effect of municipality *m*. Including municipality fixed effects controls for the average differences across municipalities in any observable or unobservable predictors of log mortality rate, so that, say, demographic, socioeconomic, or clinical impacts will not be confused with that of weather. Similarly, γ_t is the unrestricted time fixed effect of year *t*. These fixed effects control for time-varying differences in the dependent variable that are common across municipalities, such as the introduction of the Seguro Popular in 2003. Because such shocks are unlikely to have the same effect at the regional level (for instance, among Seguro Popular delegations, the pricing of prescription drugs varies greatly across regions), equation (8) also includes quadratic polynomial time trends λ_r for the *r*=5 mesoregions of Mexico (Northeast, Northwest, South, Center, and Center-West) which, at least in terms of weather, are fairly homogenous. Finally, ε_{mt} is the stochastic error term.

The second specification fits the following equation:

$$Y_{mt} = \beta CDD30_{mt} + \delta CDD10_{mt} + \varphi CMMD8_{mt} + \eta CMMD3_{mt} + \alpha_m + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{mt} \quad (9)$$

where $CDD30_{mt}$ ($CDD10_{mt}$) is the cumulative degrees-times-days that exceed 30°C (below 10°C) in municipality m in year t. Similarly, $CMMD8_{mt}$ ($CMMD3_{mt}$) is the cumulative millimeters-times-days that exceed 8mm (below 3mm) in municipality m in year t. This specification also includes municipal fixed effects α_m, time fixed effects γ_t, quadratic polynomial time trends λ_r, and a stochastic error term ε_{mt}.

Although by definition a more restrictive approach than equation (8), for it assumes that the impact of weather on mortality is determined by extreme temperatures and rainfall only, equation (9), with only four estimated coefficients instead of 29, results in sensitivity gains due to improved statistical power to detect weather effects.

As discussed by Burgess et al. (2011) and Deschênes and Greenstone (2011), the validity of my empirical strategy for studying the weather-mortality relationship relies on the assumption that equations (8) and (9) yield unbiased estimates of the $\theta_j, \rho_k, \beta, \delta, \varphi,$ and η vectors. Given the two-way fixed effect identification strategy employed, any omitted variables that are constant over time and/or particular to one municipality will not bias the estimates, even if the omitted variables are correlated with the explanatory variables. If weather variability is supposed to be random, then it is plausible to assume it is uncorrelated to unobserved mortality determinants.

5. Results

I present two different sets of results, based on the two hypothesized channels through which severe weather affects humans to the point of causing death: i) the human physiology channel (severe weather impacts human physiology through thermal stress and disease, which in an extreme situation may ultimately lead to death) and ii) the food-security channel (mortality rates are driven as a result of adverse weather disrupting either the household's sources of income on which it relies for subsistence or its purchasing-power capacity, or both, increasing their likelihood of becoming famine victims as a result).

These results are derived from the empirical specification introduced above. Because observing a common variance structure over time is unlikely, my results are based on a cluster-correlated Huber-White covariance matrix estimator, which avoids the assumption of homoskedasticity (Wooldridge, 2004.) In addition, my empirical specification is weighted by the square root of the total municipal population, in an effort to correct for heteroskedasticity associated with municipal differences in estimation precision of mortality rates, having the additional advantage of presenting impacts on one person, rather than one municipality (Deschênes and Greenstone, 2011).

5.1 The Physiology Channel

Figures 3 and 4 present the results of the impact of temperature and precipitation on mortality rates. More specifically, these figures show the estimated impact of an additional day in 12 temperature ranges and 17 precipitation ranges, relative to a reference range, which in this case is the 16°-18°C range for temperature and the 4-6mm range for precipitation.

In the case of temperature, two patterns emerge. First, notice that, graphically, a J-shaped curve is fairly appropriate to describe the weather-death association. As theory predicts, moderate temperature ranges do not seem to have an impact on mortality rates. In fact, among the eight bins that account for temperatures between 12°-26°C, only two are statistically significant at the conventional levels. Colder ranges in general do not have an effect statistically different from the reference bin. Second, extreme hot weather does seem to have a sustained impact on death. All three bins including the hotter temperature ranges are statistically different from the reference category. For instance, *one additional day* with an average temperature above 26°C increases mortality rates by at least 0.1 percent relative to a day with a mean temperature in the 16°C-18°C range.

Precipitation impacts are typically insignificant at the conventional levels, with the exception of the extreme-precipitation bins (i.e., the far-left and far-right categories including days with no precipitation and rainfall exceeding 30mm., respectively) Although what can be thought of as the "drought bin" (i.e., the bin that includes day with no precipitation) does not comparatively have an important impact on death, extreme rainfall does pose significant threats to human wellbeing. *One single day* with rainfall higher than 30mm increases mortality rates by 0.7 percent relative to one with rainfall ranging from 6-8mm.

As I pointed out before, some studies have investigated the impact of extreme weather on perinatal and infant mortality. Hashizume et al. (2009) find that perinatal mortality sharply increases with low temperatures. Dadvand et al. (2011) conclude that extreme heat was associated with a reduction in the average gestational age of children, which is associated with perinatal mortality and morbidity. Burgess et al. (2011) show that weather extremes appear to increase infant mortality in rural India, but not in urban areas. Scheers-Masters, Schootman and Thach (2004) find no evidence that elevated environmental temperatures have a significant role in the development of sudden infant death syndrome.

Figures 5 and 6 show that there is no clear relationship between weather, either extreme or moderate, and fetal mortality. If anything, colder temperatures seem to be associated with *lower* fetal mortality rates, but the effect is minimal. All the temperature ranges above 12°C are small in magnitude and insignificant. As for infant mortality, extreme heat is positively associated with infant mortality rates, but in terms of extreme cold, it is not possible to reject the null of equality with the base category. It is noteworthy to mention that the point estimate of days with temperatures higher than 30°C relative to the reference 16°-18°C bin is 0.15 percent for the crude mortality response function, while it is 50 percent larger (0.23 percent) for the infant mortality specification. This finding echoes Deschênes and Greenstone's (2011) result that the impact on annual mortality of hot weather (i.e., higher than 90°F) for infants is twice as large as the point estimate for the general population. The impact of precipitation on both fetal and infant mortality is, with frequency, statistically nil.

Figures 9 through 12 show the relationship between weather and death by type of area. I analyze two types of areas: rural and urban. Recall that I define rural mortality rate as the mortality rate in communities with fewer than 2,500 residents, and urban mortality rate as the mortality rate in communities with 2,500 residents or more. It is important to emphasize that this differentiation is relevant because it would indicate that people living in rural areas are potentially more exposed to the negative impacts of weather, given that their main economic activity, agriculture, is easily upended by climate shocks.

From the analysis of these plots, several interesting findings emerge. In terms of temperature, the effect on death is virtually zero for urban areas: only two out of the 12 temperature bins are significant, but small in magnitude, with no temperature bins being associated with increases in mortality rates greater than 0.1 percent. Conversely, the response function between log rural mortality rate and temperature indicates that rural areas are especially vulnerable to the negative effects of extreme (particularly hot) temperatures. Although the variance of rural mortality is high (see Table 1), which results in wider confidence intervals, the five hottest temperature bins (i.e., temperatures higher than 26°C) are all statistically significant and of higher magnitude than the urban coefficients. For example, exchanging a single day in the

16°C-18°C range for one in the >30°C range would lead to an increase in annual mortality rates of 0.2 percent in rural areas (for urban areas the coefficient is not statistically different from the reference bin.) In terms of the precipitation response functions, with the exception of a couple of bins, for all the coefficients, both for urban and rural areas, it is not possible to reject the null of equality with the base temperature/precipitation bin.

To evaluate the robustness of these results, I present in Table 5 several versions of Equation (9) which, in spite of being less flexible than previous specifications of Equation (8), offers sensitivity gains due to improved statistical power to detect weather effects. Column (1) shows the relationship between extreme weather and annual mortality. Once again, cold temperatures do not seem to have an effect on crude mortality rates. The impact of hot weather is, in comparison, as found before, considerable: each additional degree above 30°C per year is associated with a 0.02 percent increase in the crude mortality rate. In other words, a one-standard deviation (34.3 percent) increase in the cumulative-degree-days above 30°C would lead to a 0.7 percent increase in the crude mortality rates. Exposure to extreme precipitation patterns, defined as the cumulative-millimeter-days above 8mm or below 3mm, is positively associated with crude mortality rates. Each additional millimeter above or below the threshold causes a 0.01-0.02 percent increase in the crude mortality rate.

Columns (2) and (3) show the relationship between extreme weather and infant and fetal mortality rates. As with the previous specification, severe weather events do not seem in general to lead to an increase in mortality in infants or stillbirths, with the exception of extreme heat, which is associated with a 0.04 percent increase in infant mortality rates. Extreme precipitation patterns seem to be *negatively associated* with these types of mortality indicators, or at most, have a negligible positive effect.

Columns (5) and (6) compare the effect of weather on mortality by type of area. Once again, the impact of cold weather is statistically zero. In terms of extreme heat and precipitation, it is again found that rural areas are more vulnerable than urban zones. According to equation (9), the effect of an additional degree above 30°C per year on mortality rates is twice as large for rural regions relative to urban areas. In terms of precipitation, differences are more prominent, with exposure to an additional millimeter-day above 8mm having an impact on rural mortality rates approximately eight times larger than on urban mortality rates.

The story told so far is that hot temperatures are associated with higher mortality rates. In particular, infants seem to be a segment of the population particularly vulnerable to extreme heat. The impact of cold temperatures is normally trivial. In addition, the impact of (hot) temperature seems to be differentiated: it is larger for rural regions than for urban areas. As for rainfall, the effect is ambiguous: depending on the specification, precipitation extremes may be strongly associated with higher mortality or reflect habitually insignificant estimates.

The rural/urban differentiation is to be expected if the food-security mechanism is at work. In particular, the "income-based channel," in which health outcomes are negatively influenced as a result of adverse weather disrupting the household's sources of income on which it relies for subsistence is more likely to operate in rural regions. Agriculture, which is the economic sector most susceptible to weather variability, is the main income-generating activity in rural communities, while in urban centers industry and services play a more significant role (see Table 2).

This hypothesis is tested below, first by comparing the impact of weather during the growing season vis-à-vis the non-growing season. If weather leads to contractions in agricultural output, which in turn decreases income, constraining consumption and ultimately causing death, then extreme weather taking place during the growing season should be particularly damaging, but severe weather events occurring in the non-growing season should have an inconsequential impact on mortality.

5.2 The Food-Security Channel

The timing of extreme weather is important: a look at Figures 13-20 validates once more the negative effect of high temperatures on mortality, *provided that such high temperatures take place during the growing season.* This effect is statistically significant for rural areas, but not for urban areas, which suggests that rural specialization in agriculture may explain differences in mortality rates, as discussed above. Even though signs and magnitudes seem to be correct for the temperature impacts during the non-growing season, the null hypothesis of equality with the base category is not rejected for most of the temperature bins. The three higher temperature bins for rural areas are statistically different from zero: an additional single day with temperatures higher than 26°C increases mortality on average by 0.2 percent, relative to the base category of 16°C-18°C, which indicates that virtually all the effect that temperature exerts on mortality is explained by the occurrence of extreme events during the growing season. Precipitation impacts are generally insignificant at the conventional levels, both for urban and rural areas, regardless of the timing of rainfall.

Figures 21-26 point to a similar conclusion in terms of the effect of weather on agricultural output. Notice that the effect of extreme weather on agricultural output is not apparent at first sight. The number of extreme hot (or cold) days in a given agricultural year does not seem to have a significant impact on agricultural output (see Figure 21.) However, when the regressors consist of temperature and precipitation bins for growing-season days only, a clear negative relationship emerges: the higher the temperature, the lower the agricultural output (see Figure 22.) On the contrary, as expected, when one regresses agricultural productivity against non-growing-season weather bins, one finds that there is no relationship between temperature and agricultural output that is statistically significant at the conventional levels, which is reflected in the fairly flat line shown in Figure 23. As in the mortality analysis, the relationship between precipitation and agricultural output, as modeled, yields insignificant results (see Figures 23-26.)

It is important to notice that, because of the reduced number of observations per bin (instead of 365 days per year, the growing season, as defined, has 153 days, while the non-growing season comprises only 120 days), parameter estimation precision is reduced. Yet, the same results are found when estimating equation (9) for urban and rural areas. In terms of temperature, hot weather is substantially more dangerous than cold temperatures in Mexico. Again, severe temperature impacts on mortality are typically zero or slightly positive during the non-growing season. Conversely, they are large in magnitude and statistically significant during the growing season (with the exception of cold weather in rural areas, whose impact is statistically zero.)

Similarly, extreme precipitation patterns have a more profound mortality impact in rural areas, with rural estimates being approximately three times larger than urban estimates. Cumulative-millimeter-day variables are always significant for the growing-season specifications, but typically equal to zero in statistical terms for the non-growing season regressions.

An analysis of key variables of the agricultural cycle provides further evidence of the food-security channel being at work. Table 7 presents estimates of the impact of extreme temperatures on agricultural output, agricultural productivity and crop prices, both for the growing and the non-growing season, based only on equation (9), given the estimate precision issues pointed out above. It is worth noting that these results support the food-security channel hypothesis: extreme weather is indeed negatively affecting productivity and prices. In turn, as the abundant literature on famines, food supply chains, and agroecology has recurrently shown, this reduces income and consumption.

Columns (1) and (2) in Table 7 report the impact of extreme weather on agricultural income. In terms of temperature, the findings are similar to those of the mortality analysis in the previous section. Extreme heat, operationalized as the number of cumulative-degree-days above 30°C, is associated with lower agricultural income, and the association is significant at the conventional levels. This is true for the growing season, but not so for the non-growing season. In effect, while one additional degree-day above 30°C during the growing season leads to a 5 percent decrease in agricultural income, one extra degree-day above 30°C during the non-growing season has an effect that is not statistically different from zero. Once again, consistent with the results of the mortality analysis, cold days do not seem to have an impact, either during the growing season or during the non-growing season, on agricultural income. In terms of the precipitation variables, both “dry” and “wet” days during the growing season lead to decreases in income. Both coefficients are negative and statistically significant, but dry days are roughly three times more damaging than wet days: an additional millimeter-day above 8 mm. is associated with a 0.04 percent decrease in output, while an additional millimeter-day below 3 mm. is associated with a 0.13 percent decrease in income. Conversely, precipitation impact estimates for the non-growing-season regression are statistically equal to zero.

Columns (3) and (4) in Table 7 replicate this exercise for agricultural productivity, measured as the value of output per cultivated hectare. The impact of extreme weather on productivity is very similar to that on agricultural income. First, notice that severe precipitation and temperatures taking place during the non-growing season do not seem to have a significant effect on agricultural productivity. The null of equality to zero is not rejected for any weather coefficient. Second, the effect of abnormally high and low temperature on productivity is negative, and comparable in magnitude to the effect on agricultural output, but not statistically significant. Finally, both the coefficients for the cumulative-millimeter-days above 8 mm. and the cumulative-millimeter-days below 3 mm. are, as expected, negative and significant at the conventional levels, with productivity decreases ranging from 0.02 percent in the case of an extra millimeter above 8 mm/day to 0.08 percent for the case of an additional millimeter below 3mm/day.

Table 8 presents more specific results, in terms of yields, defined as tons per cultivated hectare, for five of the most important crops in Mexico: corn, beans, chilies, tomato, and wheat, for which sufficient data are available. Together, these crops make up for more than 55 percent of the total value of agricultural output of the country. Columns (1) through (6) show the results of estimating equation (8). As in previous versions of Equation (8), moderate temperature and precipitation ranges are in general equal to the reference bin, so that only the three most extreme bins at both ends of the distribution are presented for the sake of conciseness. An analogous pattern to previous estimations arises: cold temperatures usually do not have a significant effect on yields; if anything, colder temperatures increase yields. Severely hot temperatures, on the contrary, do seem to negatively impact crop yields. For the five crops analyzed, all show a clear negative relation between temperature and yields, and three are statistically significant at the conventional levels. In the case of Mexico's staple crop, corn, for which the largest number of observations is available, an additional day in any of the three coldest temperature ranges leads to an approximate yield increase of 0.1 percent relative to the reference temperature bin of 16°-18°C. Conversely, an additional day in any of the three hottest temperature ranges, leads, on average, to a 0.1 percent yield decrease relative to the reference temperature bin. For other crops, the impact of hot temperatures is even more acute: for instance, one single day with temperatures higher than 30°C leads to a 0.3 percent decrease in tomato yields and to a 0.5 percent decrease in wheat yields.

The results of precipitation ranges are fairly parallel to those of temperature extremes. Precipitation bins for ranges below 4 mm., with the exception of wheat, are negative, and in general, significant. Days with limited rainfall, relative to the reference precipitation bin, lead to yield decreases ranging from 0.2 percent to 0.9 percent. Days with extreme rainfall, relative to the reference precipitation bin, lead to yield decreases ranging from 0.4 percent to 3 percent. Once again, taking as an example the representative case of corn, an additional day in the 0 mm. bin leads to a 0.2 percent yield decrease (relative to the reference category of 6-8 mm.), while an extra day with rainfall surpassing 30 mm. leads to a 0.4 percent yield decrease.

If extreme weather, both in terms of precipitation and temperature, leads to decreases in output, yields and productivity, then price increases ought to be expected. The price mechanism in market economies adjusts in response to constraints in crop supplies. Columns (5) and (6) in Table 7 present the results of estimating equation (9) for a bundle of agricultural prices for 10 representative crops that make up approximately 70 percent of the total value of agricultural production in Mexico (Servicio de Información Agroalimentaria y Pesquera, 2012.)

Indeed, extreme weather does increase agricultural prices, with hot temperatures being the weather condition that exacerbates prices most. This pattern once again holds for the growing season only. An additional degree-day above 30°C is associated with a sharp 7 percent increase in crop prices. Any other severe weather impact is considerably weaker. An additional degree-day below 10°C leads to a 0.4 percent increase in agricultural prices. Likewise, an extra millimeter-day above the 8 mm. threshold is associated with a 0.02 percent increase in crop prices, while an extra millimeter-day below the 3 mm. threshold leads to an increase of approximately 0.06 percent in agricultural prices. Unsurprisingly, when agricultural income and productivity seems to be unaffected by weather, that is, during the non-growing season, prices are not affected by severe climate either.[8]

6. Conclusion

Extreme weather exerts negative effects on humans, particularly on the most vulnerable. Using data for all the 2,454 municipalities of Mexico for the period 1980-2010, I analyzed the impact of exposure to severe weather, here defined as extreme temperatures and precipitation, on death and agricultural outcomes.

I present empirical evidence for the hypothesis that extreme weather increases mortality rates and decreases agricultural income and productivity, in addition to increasing crop prices. In particular, I find that extreme heat is the most damaging form severe weather may take. I find that extremely hot temperatures increase mortality and crop prices, while they at the same time decrease agricultural income, agricultural productivity, and yields of critical crops such as corn,

[8] The findings throughout this paper should be interpreted taking into account the inherent limitations of the empirical specification. For instance, given that the effect of weather on mortality was estimated based on inter-annual climate variation, the estimates should be understood as short-term impacts of unanticipated severe weather, which provide an upper-bound to the impact of less unpredictable extreme weather. As Burgess et al. (2011, p. 33) point out: "individuals are likely to be better able to adapt to long-run, predictable change, for example through migration (for example, from rural to urban areas), technology adoption, or occupational change away from climate-exposed industries such as agriculture."

which a large number of poor households in rural Mexico depend upon for their subsistence. As expected, given that Mexico does not have harshly cold seasons, I do not find any statistically significant effect of cold weather on health or agricultural outcomes. I find that precipitation extremes have an ambiguous effect on mortality depending on the model specification. Evidence is more coherent in terms of agricultural outcomes, as I find that both limited and extreme rainfall pose negative consequences for crop yields, agricultural incomes and productivity, with these effects being observed during the growing season only.

I find that rural areas are substantially more vulnerable to severe weather than urban areas. In addition, I also find that, for rural areas, if extreme weather takes place during the peak of the growing season, the effects are considerably stronger than in a situation where climate extremes are observed during non-growing times. This echoes the conclusion of Burgess et al. (2011) for their study in India. As they put it: "quasi-random weather fluctuations introduce a lottery in the survival chances of citizens. But this lottery only affects people living in the rural parts where agricultural yields, wages and prices are adversely affected by hot and dry weather" (p. 34).

These results have an important policy implication: under severe weather conditions, a free market economy can produce socially unfair outcomes: climate extremes cause crop prices to rise precisely when incomes fall (farmers have less output, productivity falls), which in an extreme situation may lead to death, as evidenced in this paper. In other words, the price mechanism aggravates the problem instead of being self-correcting. Technically speaking, the problem is one of missing markets rather than market failure: if regions specialized in agriculture (usually rural communities) had sufficient insurance and credit mechanisms catering to the poor, these would provide safety nets in the event of a weather shock. As a result, the government may play a key role in creating the conditions to mitigate the adverse effects of climate, even though these risks cannot be fully eliminated.

Furthermore, if extreme heat is the most lethal mechanism through which weather affects human physiology, and this impact is considerably stronger in rural regions, given their dependence on agriculture, the consequences of climate change are likely to be unevenly distributed across communities. There is empirical evidence that there has been an overall decrease in the number of cold days, while the number of warm spells and heat waves has increased (IPCC, 2012). As a result, development policy must encompass differential vulnerability and capacity mechanisms in order for communities to better adapt to these changing conditions. Future research should focus on these environmental and institutional aspects.

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Table 1. Mortality Rates in Mexico, 1990-2010, by Type of Area

	Pooled (1)	Rural (2)	Urban (3)
Crude mortality rate	4.8	9.1	4.9
	(1.4)	(34.5)	(1.9)
Infant mortality rate	15.4	31.6	19.8
	(9.6)	(160.3)	(64.9)
Fetal mortality rate	10.5	16.4	13.6
	(6.7)	(99.6)	(51.5)

Note: Municipalities may consist of urban areas only, rural areas only, or a combination of both. All statistics are weighted by total municipal population. Standard deviations in parentheses.

Table 2. Household Income and Expenditures (in Mexican Pesos), by Type of Household

	Income (1)	Expenditures (2)	Food Consumption (3)	% Households Employed in Agriculture* (4)
Pooled	11,667	7,964	2,607	18.9
Urban	13,026	8,878	2,816	7.2
Rural	6,673	4,602	1,839	61.9

Source: Encuesta Nacional de Ingresos y Gastos de los Hogares 2010.

Table 3. Relevant Agricultural Outcomes in Mexico, 1994-2009, by Type of Area

	Pooled (1)	Rural (2)	Urban (3)
Agricultural output ($1,000)	658,092.4	664,831.9	84,092.1
	(1,959,499)	(1,96,9799)	(259,492)
Agricultural productivity ($/ha)	21.5	21.6	11.9
	(817.3)	(822.0)	(54.1)
Harvested hectares (ha)	36,791.8	37,154.2	6,388.6
	(46,923)	(47,070)	(10,285)
Yield (corn) (tons/ha)	2.7	2.7	1.3
	(2.1)	(2.1)	(0.9)
Volume (corn) (tons)	54,114.5	54,709.9	1,138.9
	(155,137)	(155,904)	(1,740)
Price index	2.3	2.3	2.3
	(2.2)	(2.2)	(2.3)

Note: If fewer than 2,500 residents live in a given municipality, that municipality is considered "rural." Data refer to the agricultural cycle, rather than calendar years. Monetary values are in thousands of pesos of 2009. All statistics are weighted by total harvested hectares, except descriptive statistics for corn, which are weighted by harvested hectares of corn. Standard deviations in parentheses.

Table 4. Relevant Agricultural Outcomes in Mexico, 1979-2009, by Type of Area

Rates	Pooled (1)	Rural (2)	Urban (3)
Daily mean temperature (°C)	18.5	17.4	18.5
	(4.4)	(3.9)	(4.4)
Annual average rainfall (mm)	712.8	678.9	713.0
	(419.1)	(332.7)	(419.5)
Annual degree-days (over 30°C)	11.6	6.8	11.6
	(45.5)	(30.0)	(45.5)
Annual degree-days (below 10°C)	30.1	38.7	30.1
	(54.7)	(57.8)	(54.7)
Annual millimeters-days (over 8mm)	174.8	129.3	175.1
	(225.1)	(139.8)	(225.4)
Annual millimeters-days (below 3mm)	779.7	764.9	779.8
	(122.7)	(120.6)	(122.8)

Note: If fewer than 2,500 residents live in a given municipality, such a municipality is considered "rural." All statistics are weighted by total municipal population. Standard deviations in parentheses.

Table 5. Estimates of the Impact of Extreme Weather on Relevant Mortality Rates

	Crude mortality		Infant mortality		Fetal mortality		Urban mortality		Rural mortality	
	(1)		(2)		(3)		(4)		(5)	
Cumulative-degree-days above 30	0.00022	***	0.00038	**	0.00008		0.00018	**	0.00034	*
	(0.00007)		(0.00019)		(0.00028)		(0.00007)		(0.00021)	
Cumulative-degree-days below 10	0.00004		-0.00017		-0.00041	**	0.00005		-0.00028	
	(0.00005)		(0.00012)		(0.00018)		(0.00009)		(0.00022)	
Cumulative-mm-days above 8	0.00010	***	0.00006	*	-0.00017	***	0.00003	**	0.00022	***
	(0.00001)		(0.00003)		(0.00004)		(0.00002)		(0.00004)	
Cumulative-mm-days below 3	0.00019	***	-0.00004		-0.00021	***	0.00012	***	0.00040	***
	(0.00003)		(0.00007)		(0.00008)		(0.00004)		(0.00009)	
n	48,583		40,425		35,104		29,206		46,384	

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6. Estimates of the Impact of Extreme Weather on Relevant Mortality Rates, by Season

	Agricultural year				Growing season				Non-growing season			
	Urban mortality		Rural mortality		Urban mortality		Rural mortality		Urban mortality		Rural mortality	
	(1)		(2)		(3)		(4)		(5)		(6)	
Cumulative-degree-days above 30	0.00018	**	0.00034	*	0.02484	***	0.06166	***	0.00017	**	0.00022	
	(0.00007)		(0.00021)		(0.00649)		(0.00821)		(0.00008)		(0.00022)	
Cumulative-degree-days below 10	0.00005		-0.00028		0.00261	**	0.00014		0.00002		-0.00016	
	(0.00009)		(0.00022)		(0.00122)		(0.00190)		(0.00010)		(0.00025)	
Cumulative-millimeter-days above 8	0.00003	**	0.00022	***	0.00001		0.00033	***	0.00013	***	0.00009	
	(0.00002)		(0.00004)		(0.00003)		(0.00008)		(0.00005)		(0.00009)	
Cumulative-millimeter-days below 3	0.00012	***	0.00040	***	0.00019	***	0.00070	***	-0.00006		0.00063	**
	(0.00004)		(0.00009)		(0.00006)		(0.00014)		(0.00013)		(0.00031)	
n	29,206		46,384		29,206		46,384		29,206		46,384	

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. Estimates of the Impact of Extreme Weather on Relevant Agricultural Outcomes, by Season

	Agricultural income			Agricultural productivity (output/ha)			Crop prices		
	Growing season		Non-growing season	Growing season		Non-growing season	Growing season		Non-growing season
	(1)		(2)	(3)		(4)	(5)		(6)
Cumulative-degree-days above 30	-0.04935	**	0.00030	-0.05122		0.00102	0.06983	***	-0.00066
	(0.02298)		(0.00057)	(0.03389)		(0.00055)	(0.01951)		(0.00040)
Cumulative-degree-days below 10	0.00014		0.00054	-0.00556		0.00046	0.00407	*	-0.00000
	(0.00373)		(0.00035)	(0.00344)		(0.00034)	(0.00241)		(0.00024)
Cumulative-millimeter-days above 8	-0.00040	***	-0.00056	-0.00024	**	-0.00055	0.00017	**	0.00011
	(0.00010)		(0.00043)	(0.00010)		(0.00043)	(0.00008)		(0.00023)
Cumulative-millimeter-days below 3	-0.00133	***	-0.00148	-0.00079	***	-0.00112	0.00056	**	0.00076
	(0.00030)		(0.00121)	(0.00031)		(0.00123)	(0.00023)		(0.00055)
n	27,562		27,562	27,562		27,562	27,715		27,715

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total harvested hectares. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8. Estimates of the Impact of Extreme Weather on Relevant Crop Yields (tons/ha), by Season

	Impact on log crop yields											
	Days < 10°C		Days 10°-12°C		Days 12°-14°C		Days 26°-28°C		Days 28°-30°C		Days > 30°C	
	(1)		(2)		(3)		(4)		(5)		(6)	
Corn	0.00123	***	0.00089	**	0.00103	***	-0.00155	***	-0.00093	**	-0.00066	*
(*n*=26,343)	(0.00039)		(0.00036)		(0.00027)		(0.00036)		(0.00043)		(0.00036)	
Beans	0.00237	***	-0.00041		0.00113		-0.00259	***	-0.00159	*	-0.00258	**
(*n*=20,054)	(0.00075)		(0.00091)		(0.00089)		(0.00099)		(0.00093)		(0.00107)	
Chillies	-0.00003		-0.00496	**	0.00265		-0.00107		-0.00107		-0.00103	
(*n*=7,863)	(0.00239)		(0.00206)		(0.00232)		(0.00226)		(0.00217)		(0.00225)	
Tomato	-0.00393	***	-0.00012		0.00066		-0.00117		-0.00122		-0.00099	
(*n*=6,270)	(0.00152)		(0.00129)		(0.00099)		(0.00132)		(0.00115)		(0.00186)	
Wheat	0.00020		-0.0018		0.00079		-0.00101		-0.00443	**	-0.00511	***
(*n*=6,261)	(0.00074)		(0.00084)		(0.00056)		(0.00125)		(0.00221)		(0.00188)	

Table 8., continued

	Impact on log crop yields											
	Days 0mm		Days 0-2mm		Days 2-4mm		Days 26-28mm		Days 28-30mm		Days > 30mm	
	(1)		(2)		(3)		(4)		(5)		(6)	
Corn	-0.00183	**	-0.00219	***	-0.00265	***	-0.00728		0.00300		-0.00386	*
(*n*=26,343)	(0.00077)		(0.00082)		(0.00096)		(0.00491)		(0.00871)		(0.00200)	
Beans	-0.00205		-0.00232		-0.00076		-0.00133		0.01481		-0.00436	
(*n*=20,054)	(0.00268)		(0.00262)		(0.00355)		(0.00615)		(0.00952)		(0.00365)	
Chillies	-0.00671	**	-0.00648	**	-0.00875	**	-0.00020		-0.01627		0.00087	
(*n*=7,863)	(0.00285)		(0.00294)		(0.00350)		(0.01243)		(0.01491)		(0.00727)	
Tomato	-0.00260		-0.00304		-0.00251		-0.02802	**	0.00606		-0.01581	**
(*n*=6,270)	(0.00246)		(0.00240)		(0.00293)		(0.01156)		(0.01396)		(0.00652)	
Wheat	0.00516	***	0.00617	***	0.00503	**	0.02770	***	0.03279	***	-0.01076	**
(*n*=6,261)	(0.00188)		(0.00189)		(0.00203)		(0.01035)		(0.01228)		(0.00543)	

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by each crop's total harvested hectares. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1. Temperature Distribution in Mexico, 1979-2010.

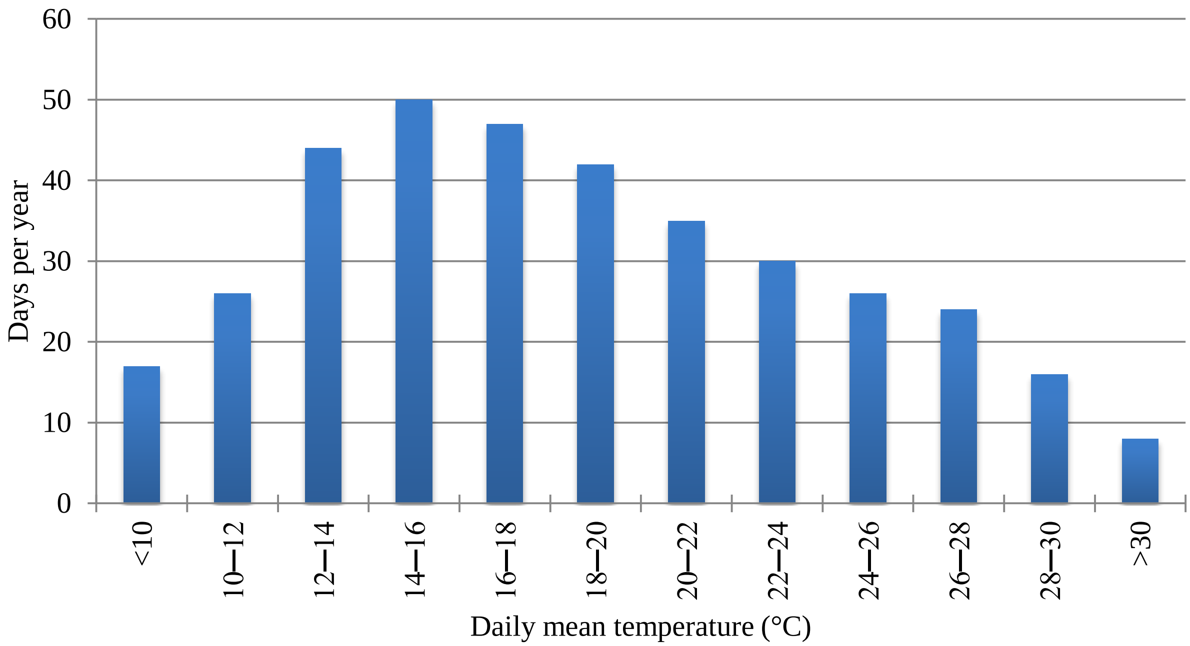

Figure 2. Rainfall Distribution in Mexico, 1979-2010.

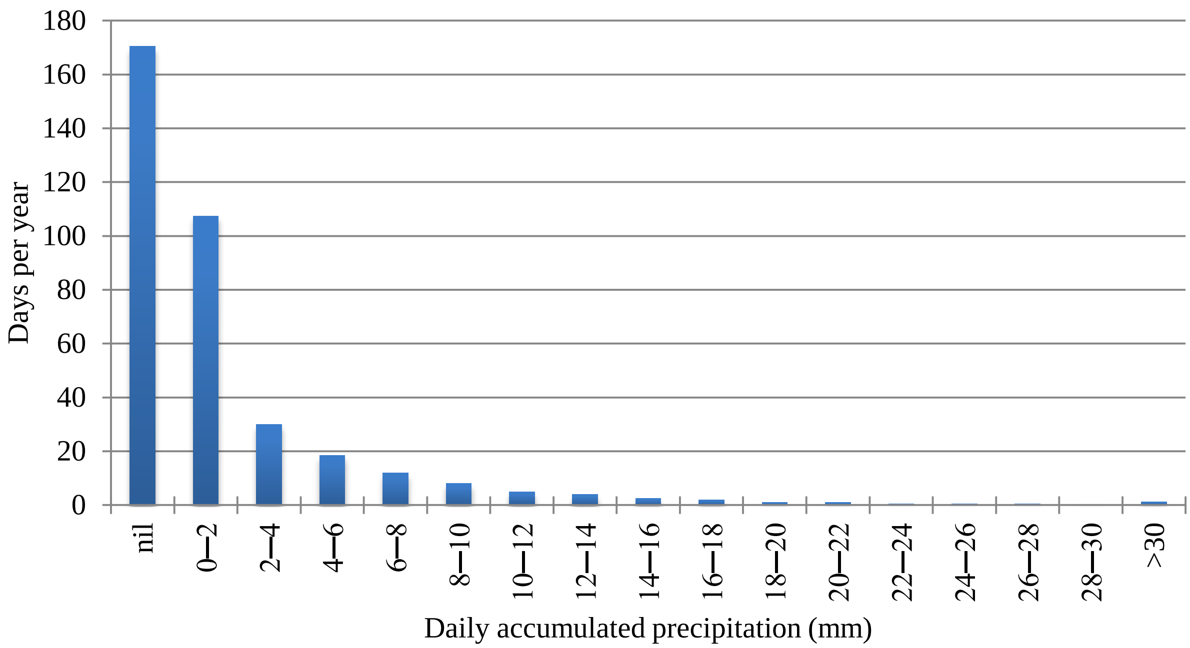

Figure 3. Estimated Impact of a Day in 12 Temperature Bins on Log Annual Mortality Rate, Relative to a Day in the 16°-18°C Bin

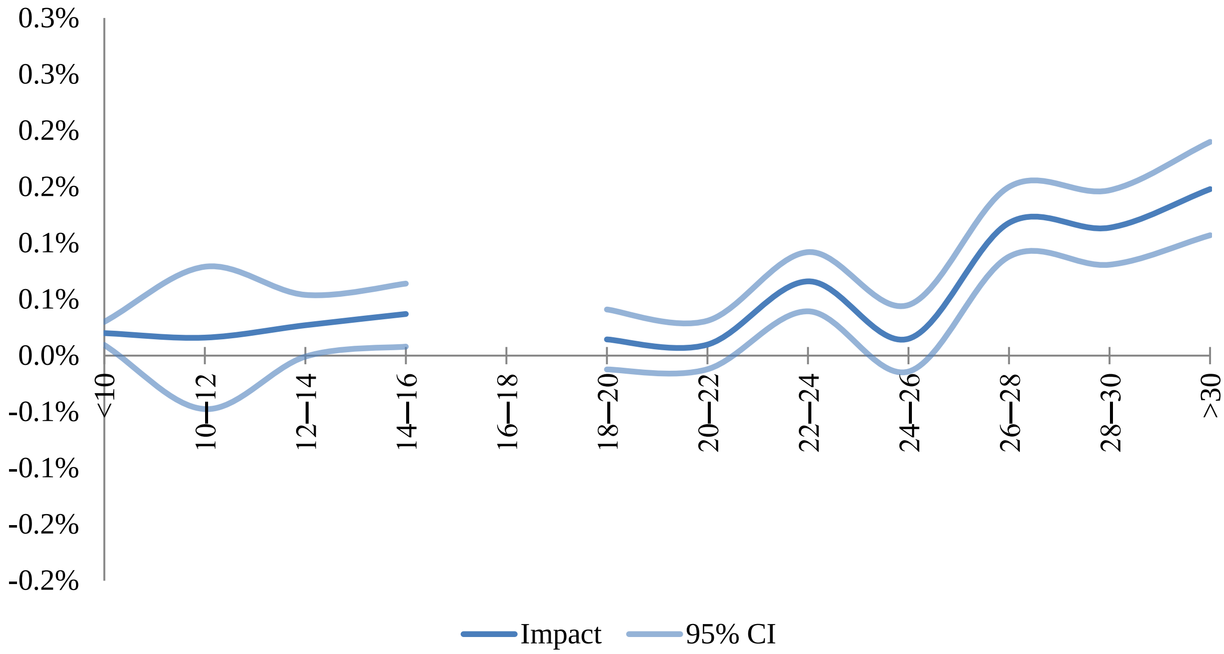

Figure 4. Estimated Impact of a Day in 17 Precipitation Bins on Log Annual Mortality Rate, Relative to a Day in the 6-8mm Bin

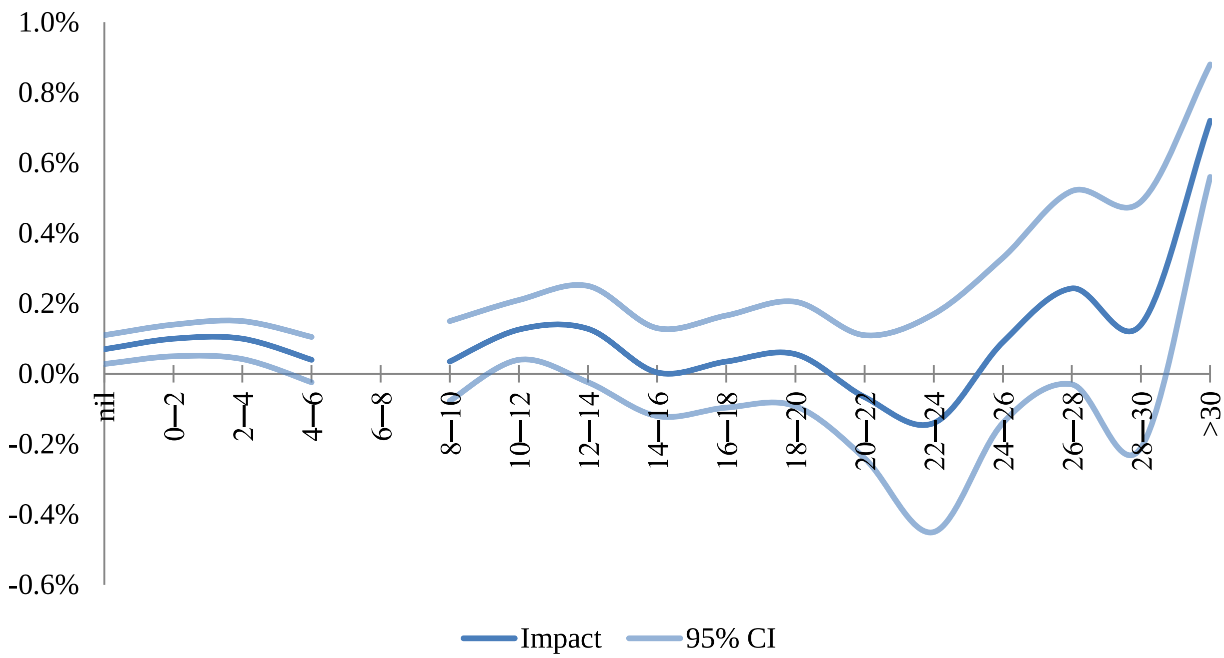

Figure 5. Estimated Impact of a Day in 12 Temperature Bins on Log Annual Fetal Mortality Rate, Relative to a Day in the 16°-18°C Bin

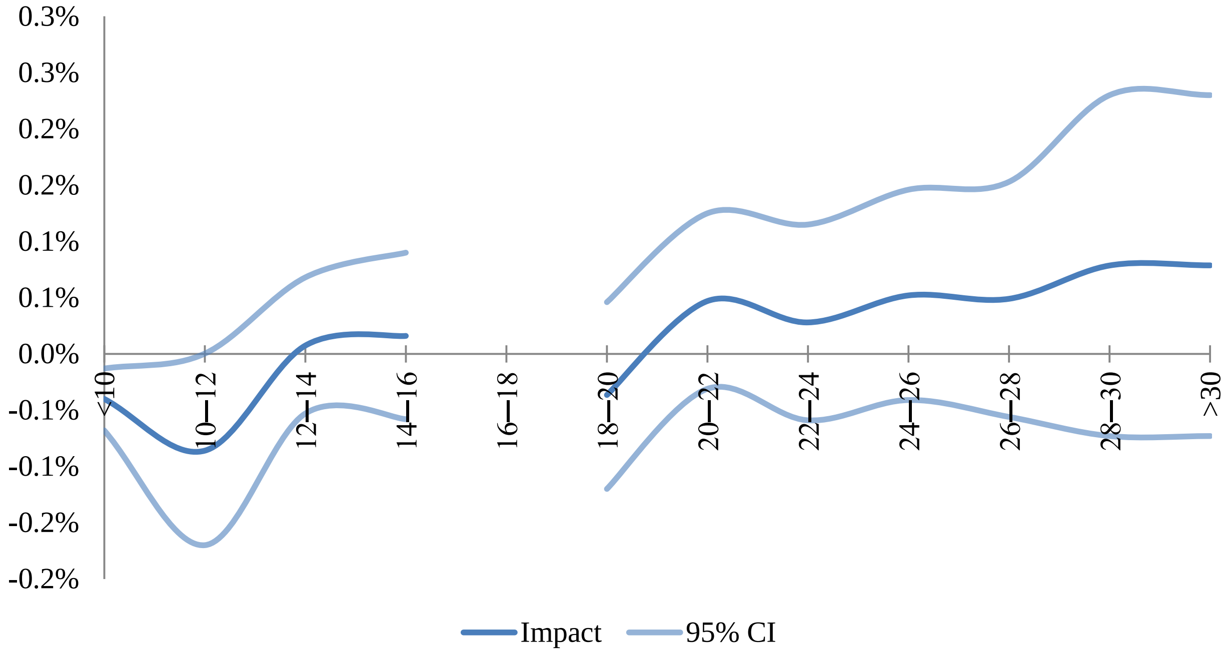

Figure 6. Estimated Impact of a Day in 17 Precipitation Bins on Log Annual Fetal Mortality Rate, Relative to a day in the 6-8mm Bin

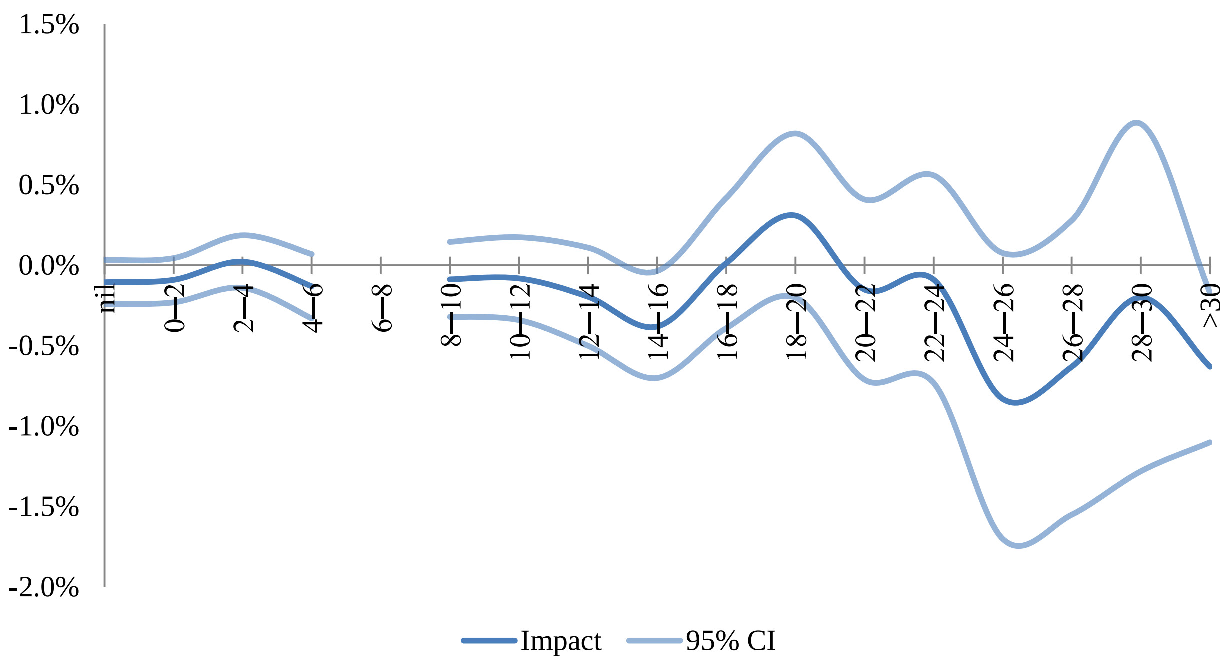

Figure 7. Estimated Impact of a Day in 12 Temperature Bins on Log Annual Infant Mortality Rate, Relative to a Day in the 16°-18°C Bin

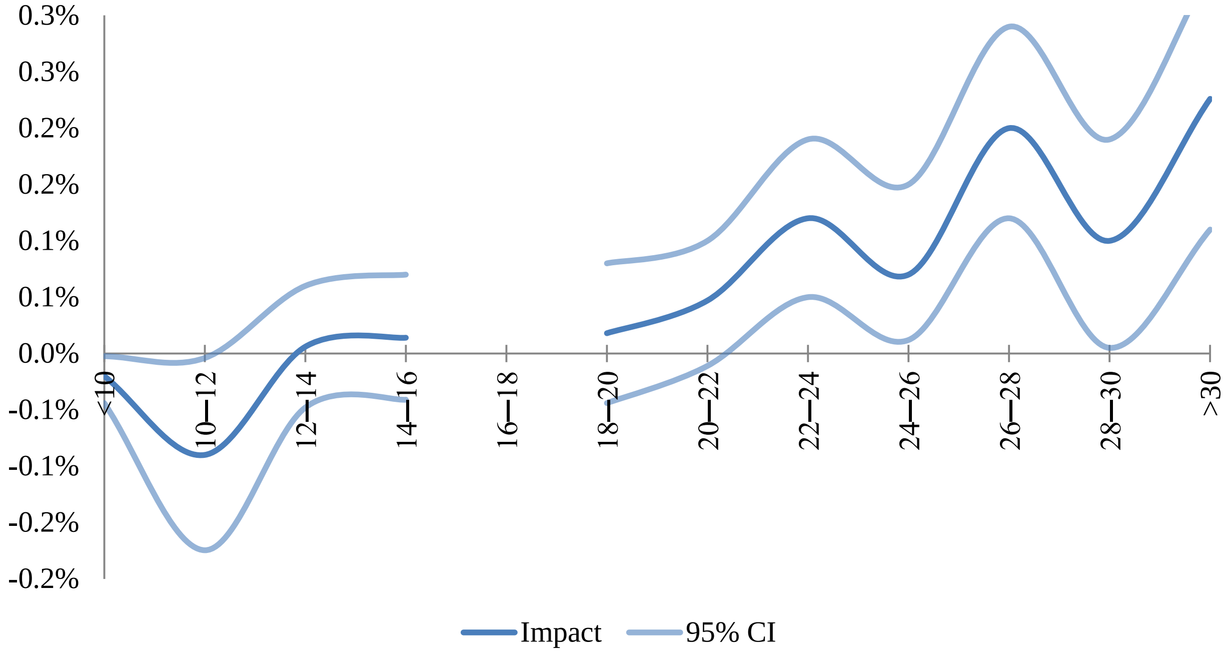

Figure 8. Estimated Impact of a Day in 17 Precipitation Bins on Log Annual Infant Mortality Rate, Relative to a Day in the 6-8mm Bin

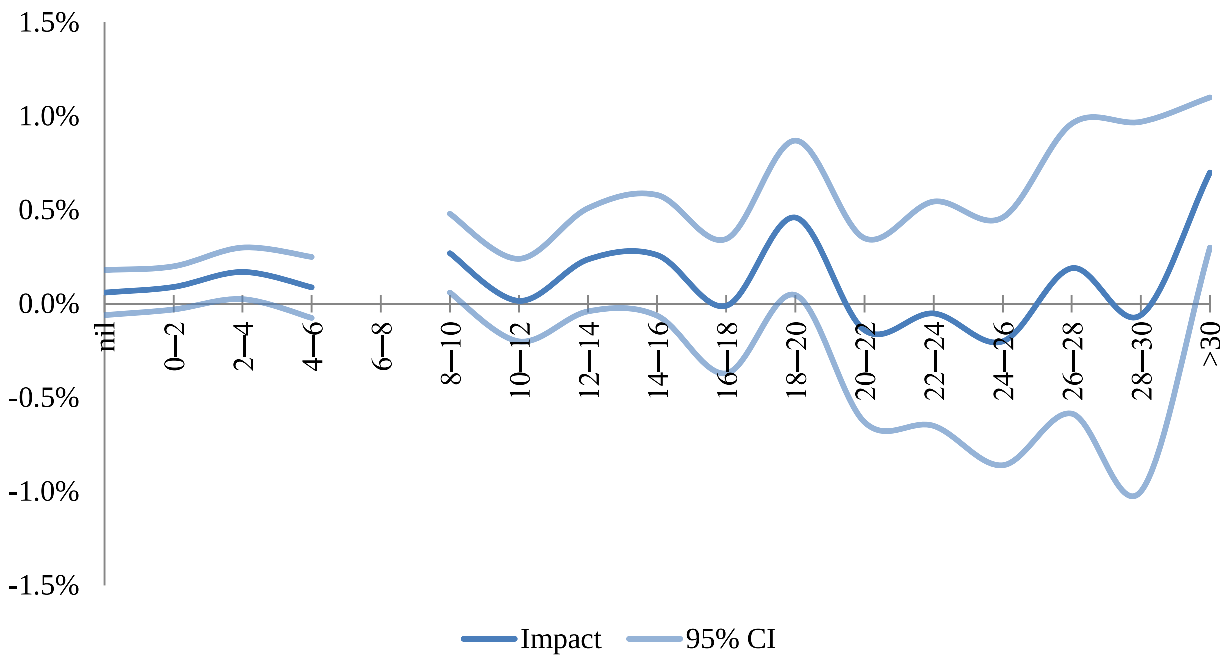

Figure 9. Estimated Impact of a Day in 12 Temperature Bins on Log Annual Urban Mortality Rate, Relative to a Day in the 16°-18°C Bin

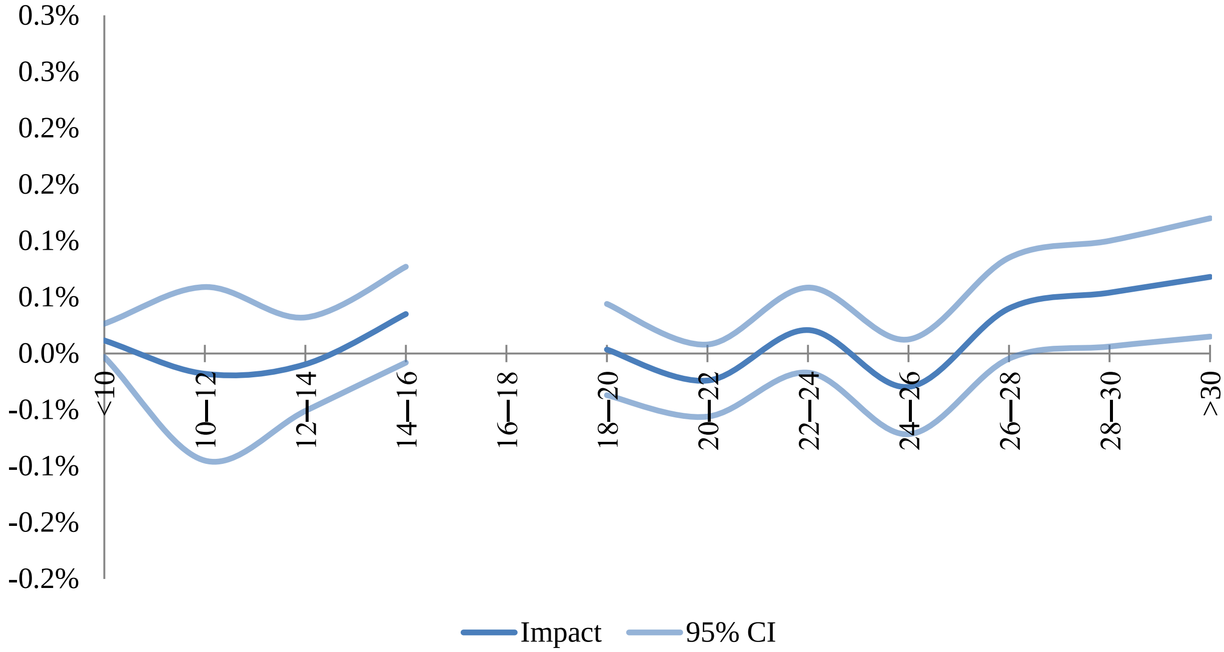

Figure 10. Estimated Impact of a Day in 12 Temperature Bins on Log Annual Rural Mortality Rate, Relative to a Day in the 16°-18°C Bin

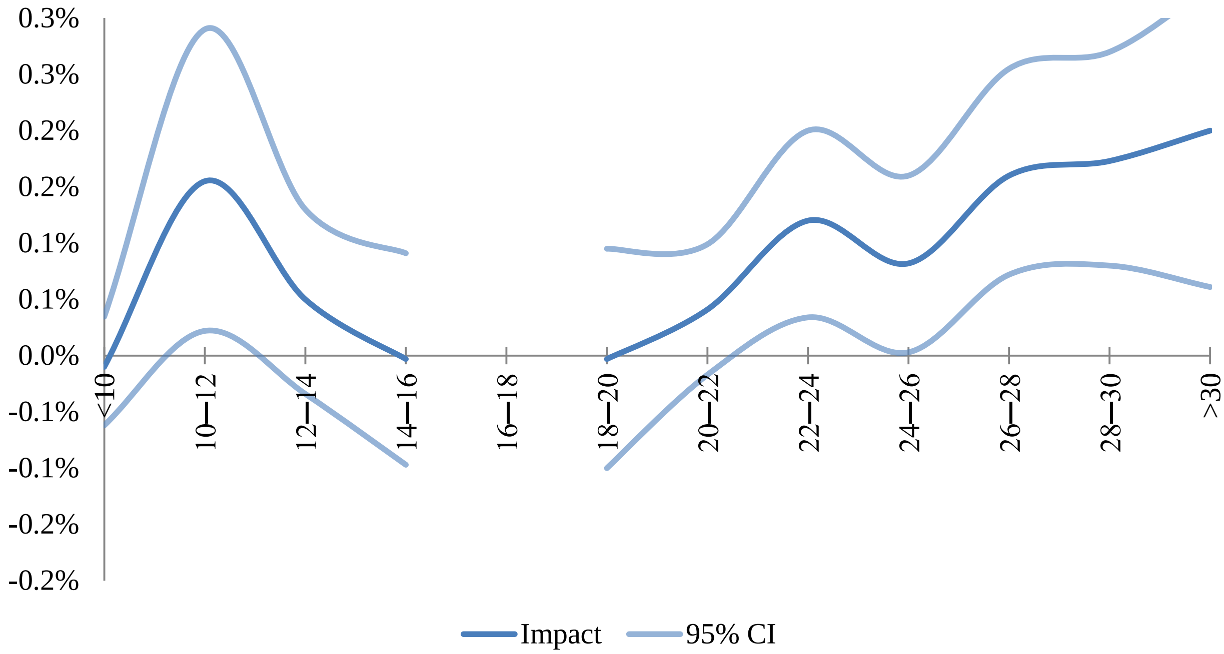

Figure 11. Estimated Impact of a Day in 17 Precipitation Bins on Log Annual urban Mortality Rate, Relative to a Day in the 6-8mm Bin

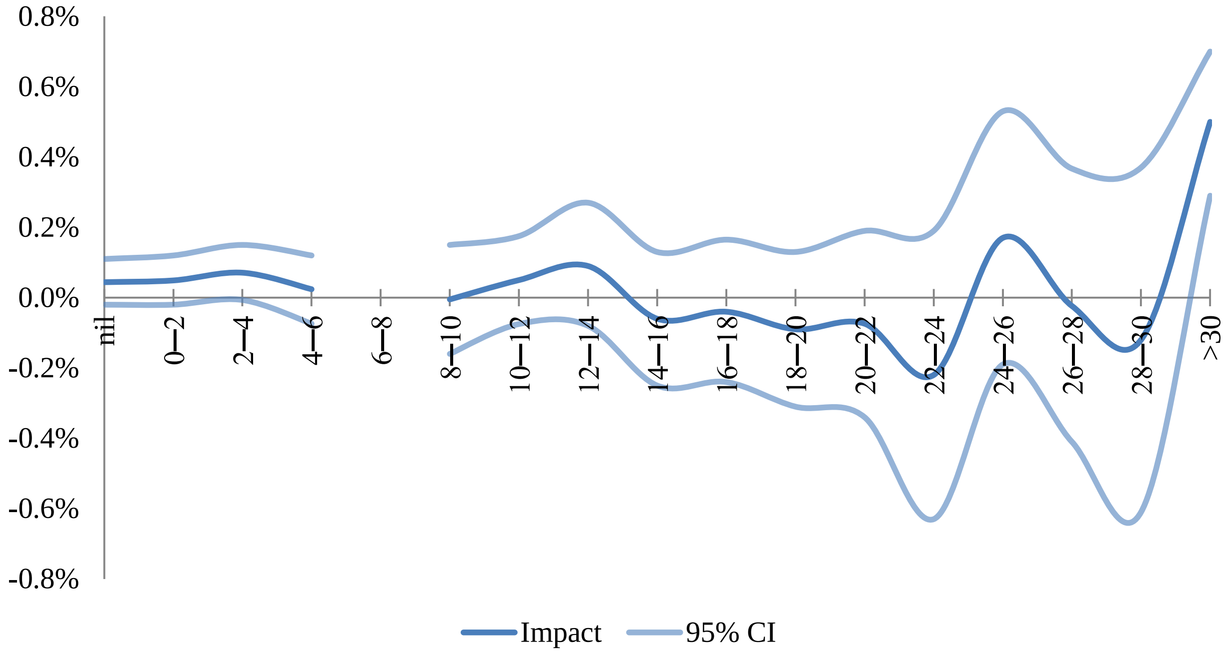

Figure 12. Estimated Impact of a Day in 17 Precipitation Bins on Log Annual Rural Mortality Rate, Relative to a Day in the 6-8mm Bin

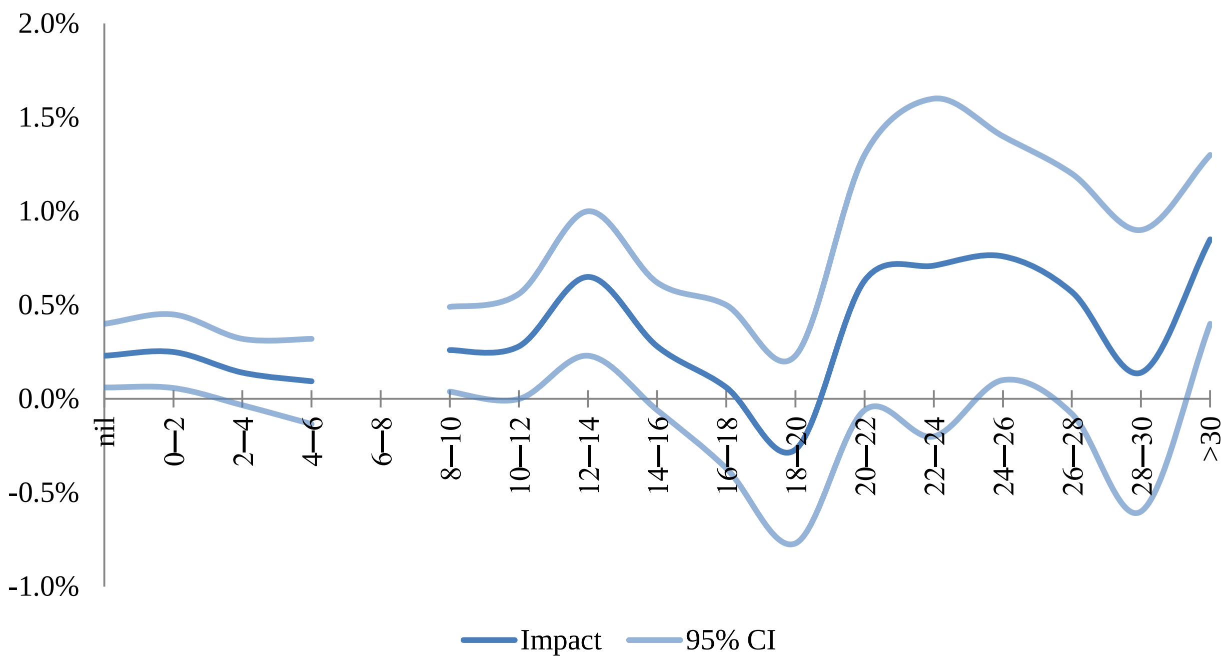

Figure 13. Estimated Impact of a Growing-Season Day in 12 Temperature Bins on Log Annual Urban Mortality Rate, Relative to a Day in the 16°-18°C Bin

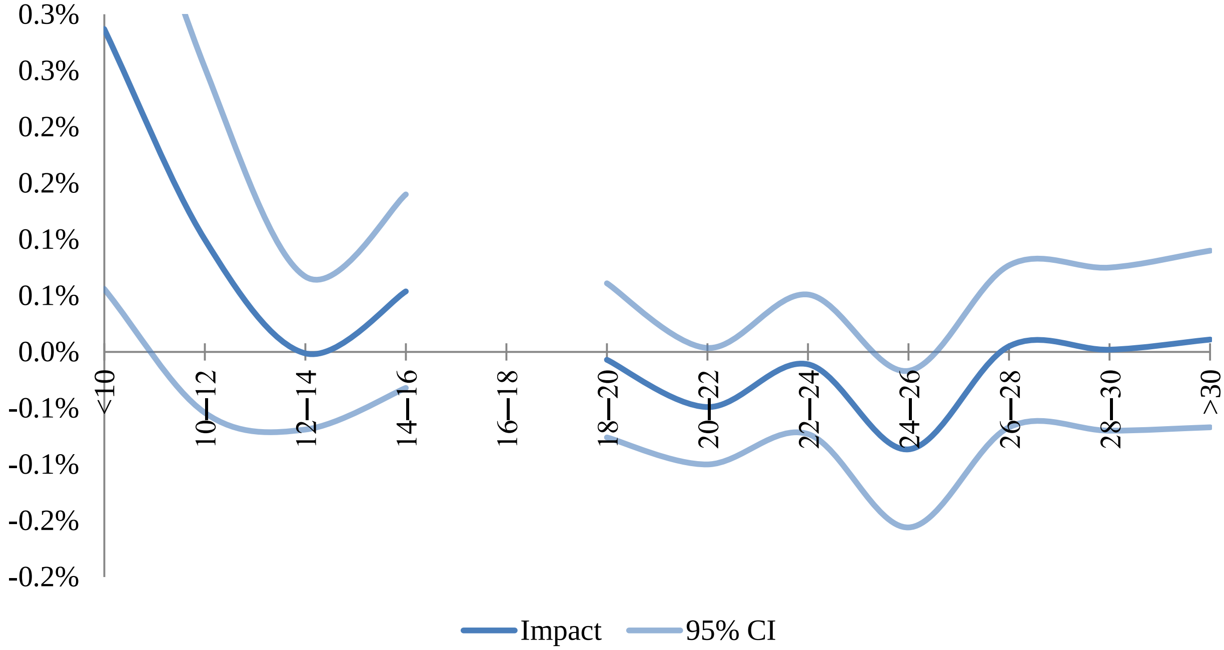

Figure 14. Estimated Impact of a Growing-Season Day in 12 Temperature Bins on Log Annual Rural Mortality Rate, Relative to a Day in the 16°-18°C Bin

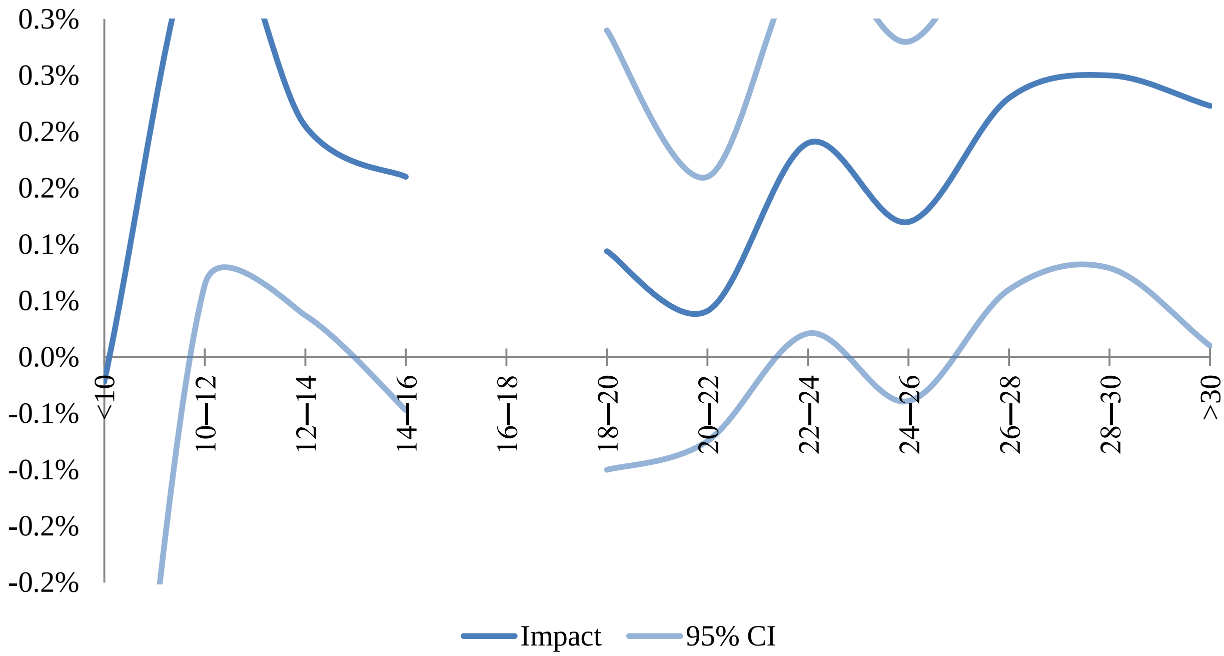

Figure 15. Estimated Impact of a Growing-Season Day in 17 Precipitation Bins on Log Annual Urban Mortality Rate, Relative to a Day in the 6-8mm Bin

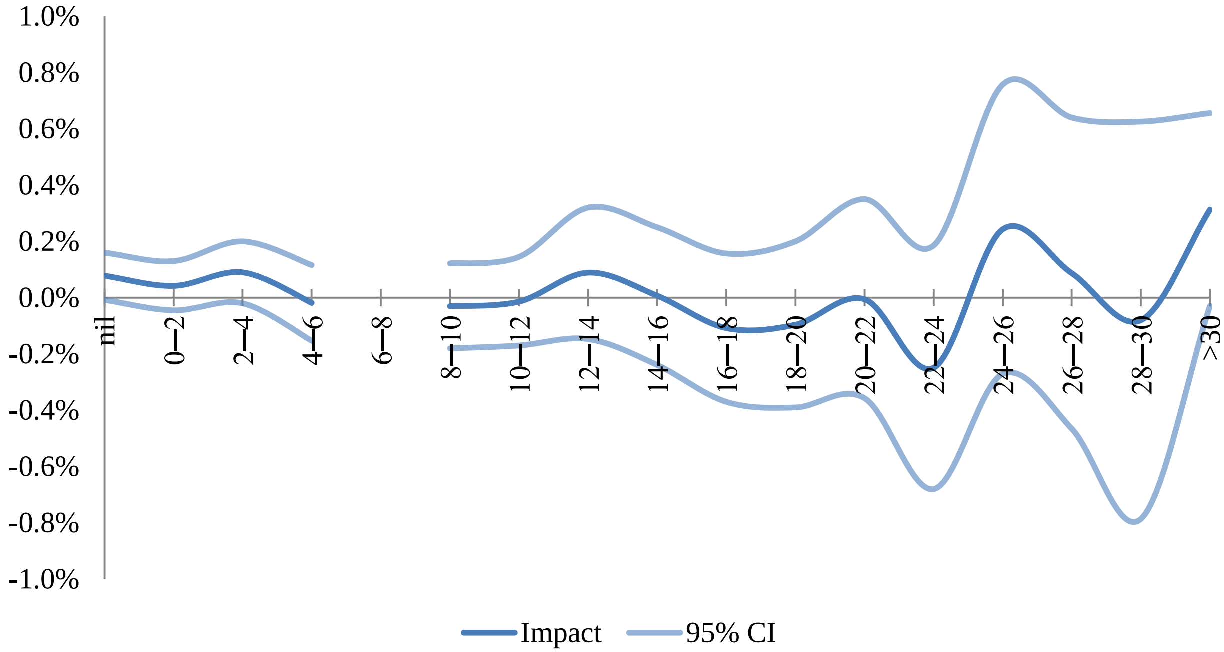

Figure 16. Estimated Impact of a Growing-Season Day in 17 Precipitation Bins on Log Annual Rural Mortality Rate, Relative to a Day in the 6-8mm Bin

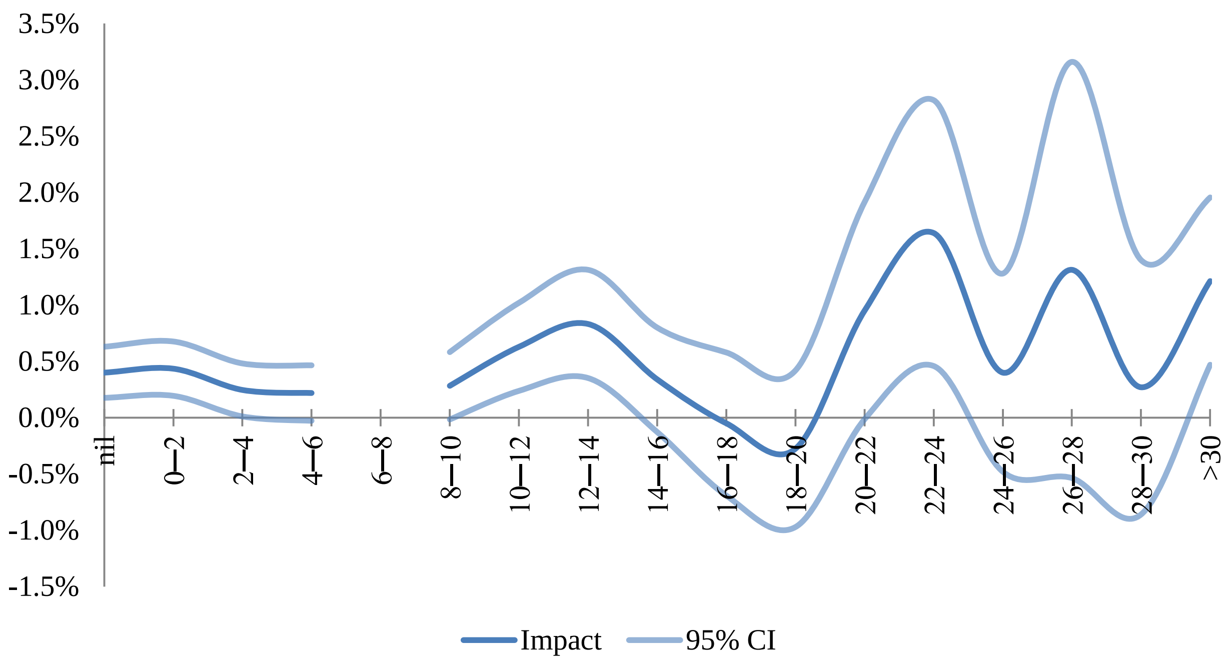

Figure 17. Estimated Impact of a Non-Growing-Season Day in 12 Temperature Bins on Log Annual Urban Mortality Rate, Relative to a Day in the 16°-18°C Bin

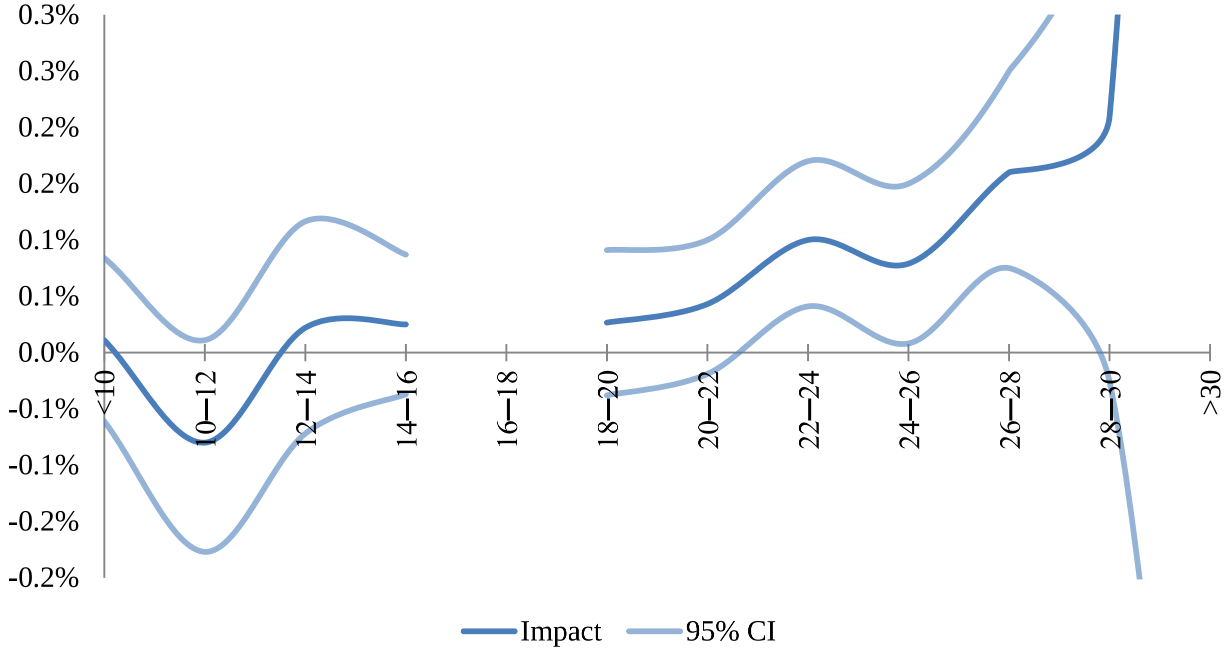

Figure 18. Estimated Impact of a Non-Growing-Season Day in 12 Temperature Bins on Log Annual Rural Mortality Rate, Relative to a Day in the 16°-18°C Bin

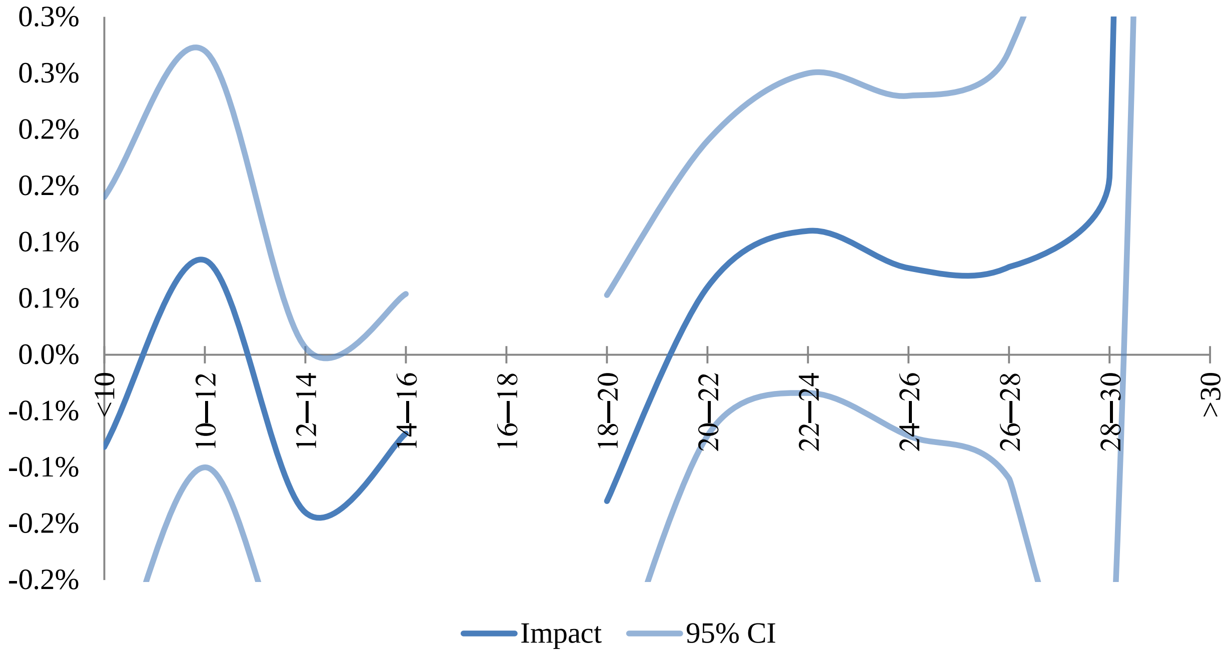

Figure 19. Estimated Impact of a Non-Growing-Season Day in 17 Precipitation Bins on Log Annual Urban Mortality Rate, Relative to a Day in the 6-8mm Bin

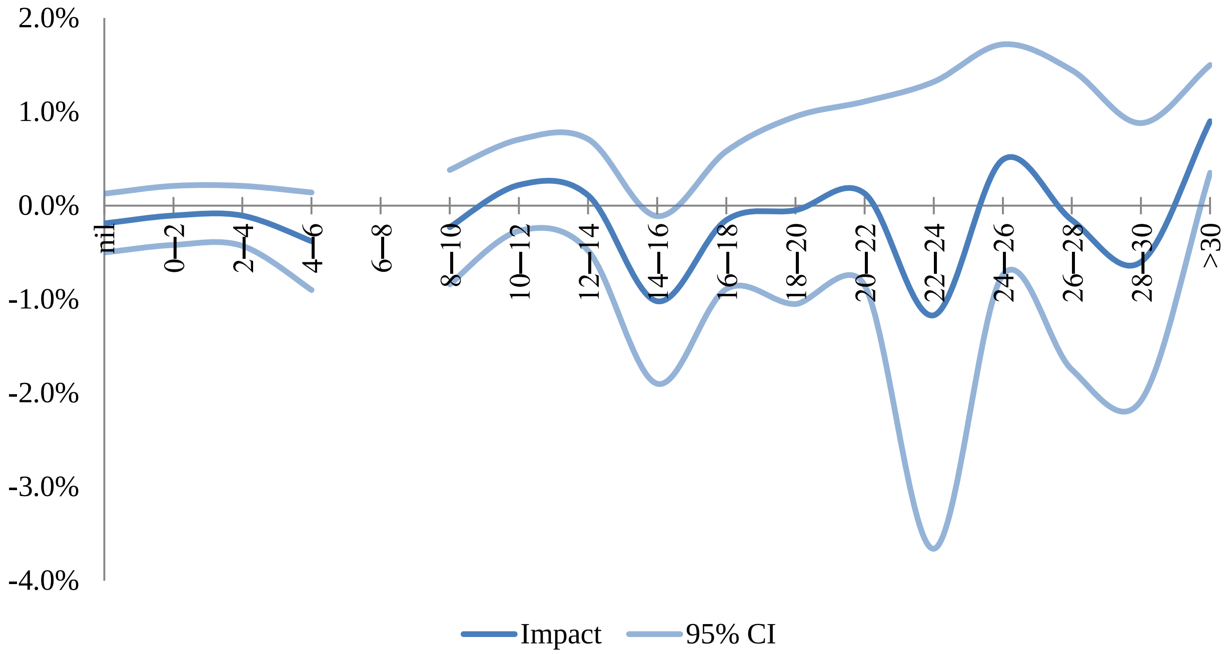

Figure 20. Estimated Impact of a Non-Growing-Season Day in 17 Precipitation Bins on Log Annual Rural Mortality Rate, Relative to a Day in the 6-8mm Bin

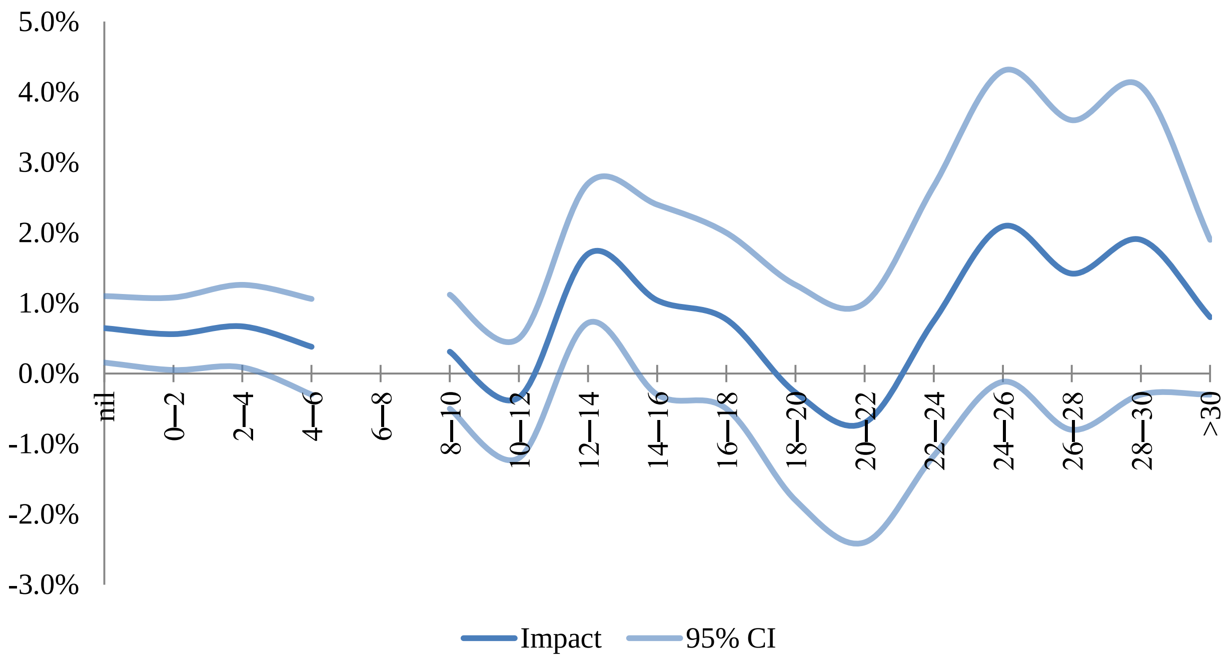

Figure 21. Estimated Impact of a Day in 12 Temperature Bins on Log Annual Agricultural Output, Relative to a Day in the 16°-18°C Bin

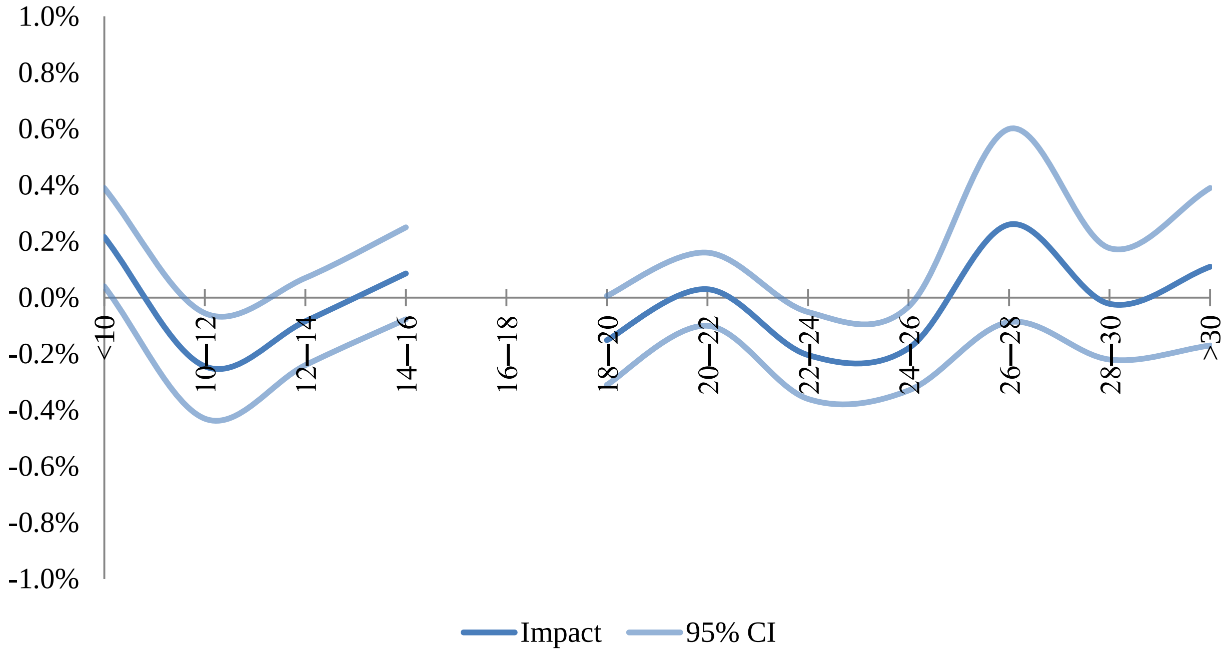

Figure 22. Estimated Impact of a Growing-Season Day in 12 Temperature Bins on Log Annual Agricultural Output, Relative to a Day in the 16°-18°C Bin

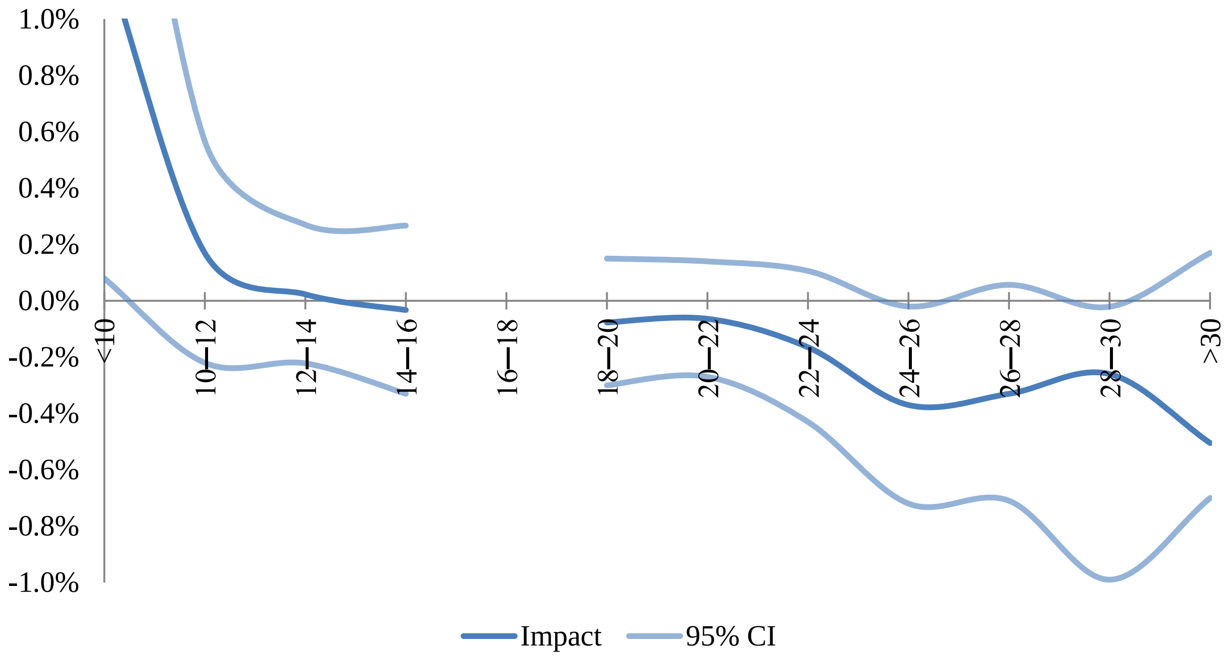

Figure 23. Estimated Impact of a Non-Growing-Season Day in 12 Temperature Bins on Log Annual Agricultural Output, Relative to a Day in the 16°-18°C Bin

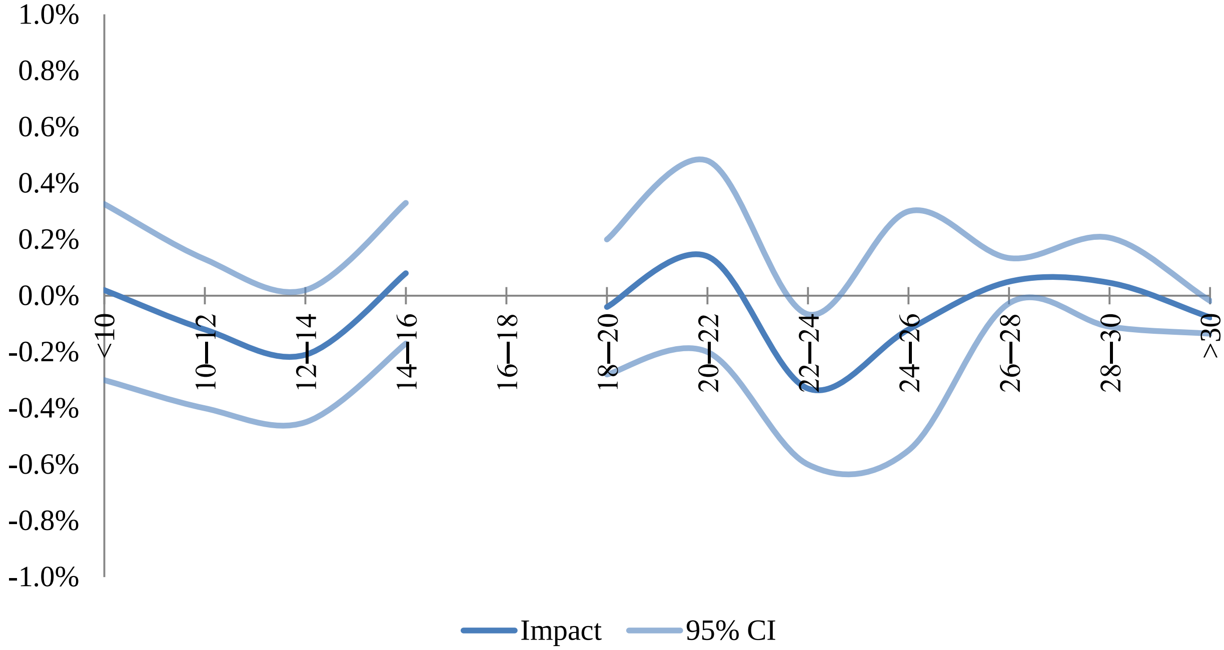

Figure 24. Estimated Impact of a Day in 17 Precipitation Bins on Log Annual Agricultural Output, Relative to a Day in the 6-8mm Bin

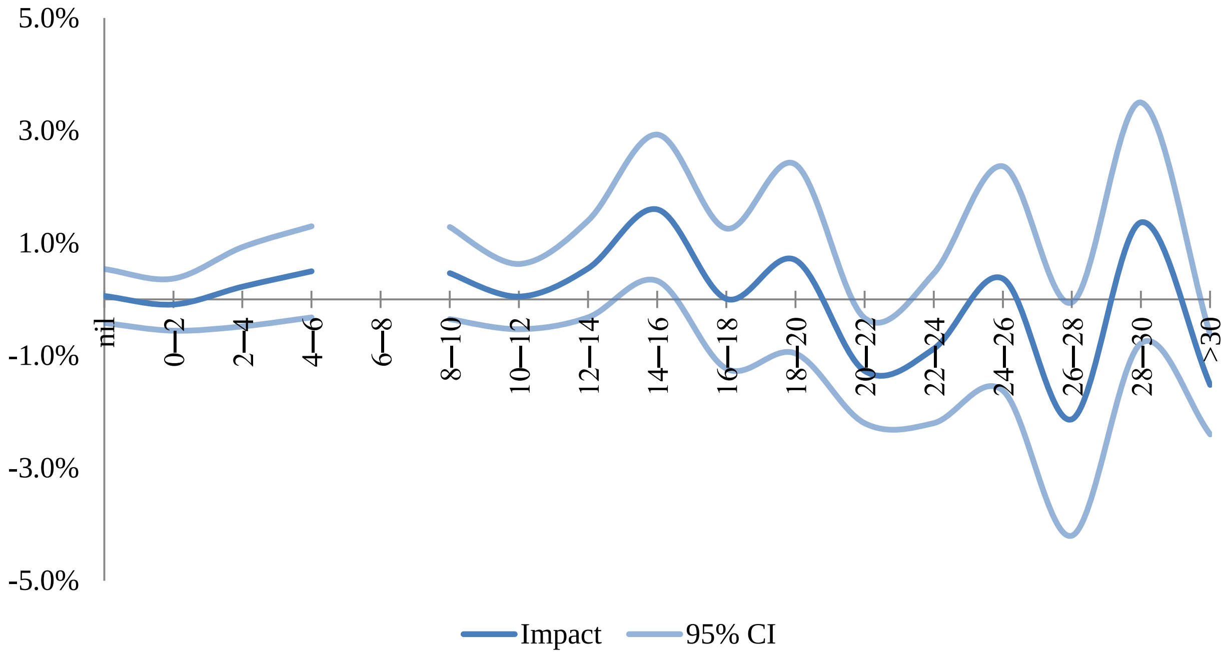

Figure 25. Estimated Impact of a Growing-Season Day in 17 Precipitation Bins on Log Annual Agricultural Output, Relative to a Day in the 6-8mm Bin

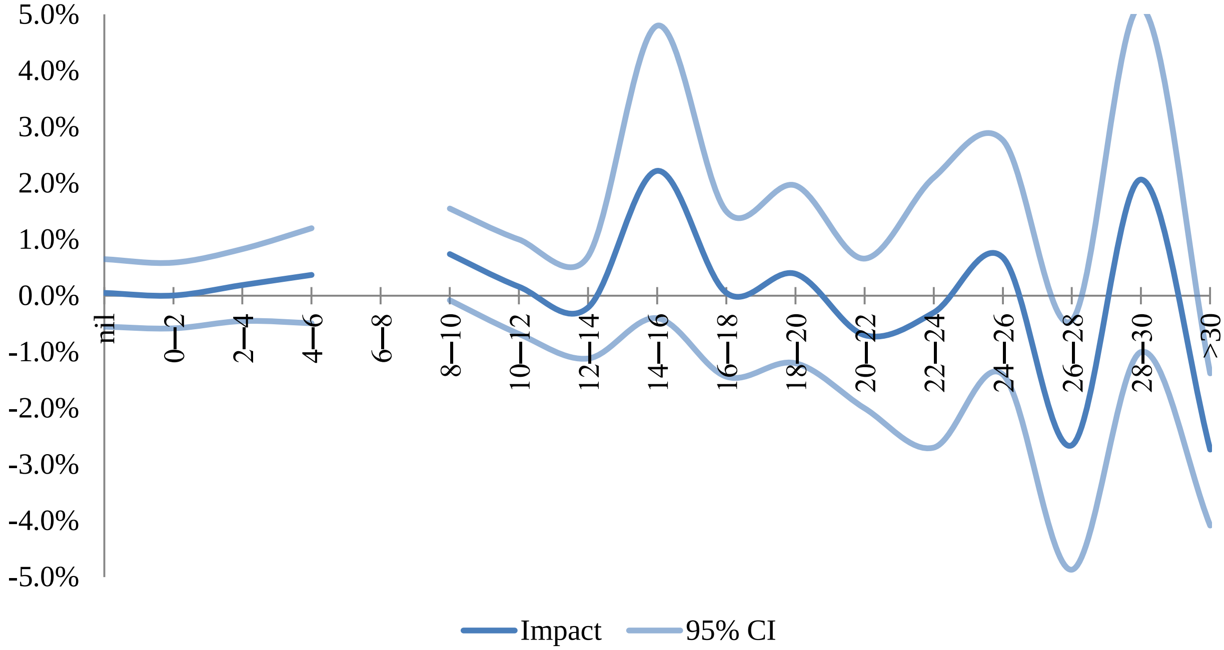

Figure 26. Estimated Impact of a Non-Growing-Season Day in 17 Precipitation Bins on Log Annual Agricultural Output, Relative to a Day in the 6-8mm Bin