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Mortality, Temperature, and Public Health Provision: Evidence from Mexico

François Cohen and Antoine Dechezleprêtre*

Abstract

We examine the impact of temperature on mortality in Mexico using daily data over the period 1998-2017 and find that weather shocks trigger 11 percent of deaths in Mexico (75,000 every year). However, 89 percent of weather-related deaths are induced by cold (<10°C) or mildly cold (10-20°C) days and only 1 percent by outstandingly hot days (>32°C). Furthermore, temperatures are 60% more likely to kill people in the bottom half of the income distribution. Finally, we show causal evidence that the *Seguro Popular*, a universal healthcare policy, has saved 3,000 lives per year from cold weather (<20°C) since 2004.

Keywords: temperature; mortality; inequality; universal healthcare; distributed lag model

JEL codes: I13, I14, Q54

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Introduction

Climate change is a major threat for human health in the 21st century. The World Health Organisation estimates that it could result in 250,000 additional deaths every year between 2030 and 2050. However, these effects will likely be unequally distributed across countries and regions. The effects of temperature shocks on mortality – one of the most direct ways in which climate change may affect health – have been shown to be quite mild in the US (Braga *et al.*, 2001; Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; Barreca, 2012), but recent evidence from developing countries suggests much greater impacts (Burgess *et al.*, 2017; Carleton *et al.*, 2018). Lower-income countries are expected to be affected the most not only because they already have warmer climates but also because they have lower adaptive capacity. Indeed, access to individual protection measures such as air conditioning explains the declining heat-related mortality that has been observed in the US over time (Barreca *et al.*, 2016; Heutel, Miller and Molitor, 2017), but such strategies are unlikely to be available to poorer households in the developing world (Kahn, 2016). Therefore, understanding how much weather shocks affect human health in low- and middle-income countries, and to what extent public policies can alleviate the impact of these shocks, is of major research interest and of great policy importance.

In this paper, we make a key contribution to this literature by investigating the relationship between temperature, mortality, inequality and public health provision in Mexico based on data of unprecedented quality. We use a large dataset of over 14 million daily mortality rates from 1998 to 2017 for 2,297 Mexican municipalities, representing around 90 percent of the country's population, in combination with weather data from the closest meteorological stations, to analyse the impact of weather shocks on mortality. The use of daily data at the local level has major advantages: the inclusion of municipality-by-month-by-year fixed effects allows us to purge the estimates from a large number of confounding factors that might be correlated with both temperatures and mortality, while distributed lag models account for possible mortality displacement effects.

We then match the characteristics of individuals as reported in death records to the Mexican census data. This allows us to estimate the income level of each individual in our dataset at the time of their death and to analyse the vulnerability to temperature shocks across income groups. This paper is the first analysis of the heterogeneous relationship between temperature and mortality in a middle-income country that combines daily mortality data with individual estimates of income level. Findings coincide with the general expectation that the poor are more vulnerable to inclement weather, and that this may explain part of the life expectancy gap between and within countries. Finally, we exploit the progressive implementation of a large social insurance programme targeted at low-income households – the *Seguro Popular* – to analyze the impact that extending universal healthcare has on reducing weather vulnerability. To our knowledge, this paper is also the first to assess the causal impact of pro-poor public health policies on resilience to weather shocks.

The paper begins by confirming the extent to which the population of a middle-income country like Mexico is vulnerable to weather compared to those in developed countries. In Mexico, 11 percent of deaths – around 75,000 annually – are induced by weather shocks. To put things in perspective, this is three times more than road-related deaths in the country. However, the first interesting contribution of this study is to document the impact of mildly cold temperatures on mortality. Whereas the media usually pay attention to extreme heat and cold, these events are infrequent and only account for a minority of weather-related deaths in our analysis. In a hot country like Mexico, even days with a mean temperature below 20°C (68°F) are associated with statistically significant increases in the daily mortality rate compared to a day at 26-28°C. Therefore, while very cold days with a mean temperature below 10°C are responsible for the deaths of around 4,750 people each year, we estimate that 83 percent of weather-induced deaths – around 62,000 people per year – occur in the aftermath of days with mean temperatures between 10°C and 20°C.[1] This is because these days still record low temperatures at night, which favour the development of respiratory pathologies and put the human body at higher cardiovascular risk. Infants, the elderly and people with metabolic diseases such as diabetes are also more at risk while poor housing conditions across Mexico may exacerbate the impact of mildly cold temperatures on mortality. In contrast, extremely hot days over 32°C trigger a comparably small amount of additional deaths (around 700 annually).[2]

[1] Daily average temperatures are calculated as the average between the minimum and maximum daily temperatures. On average, in our dataset, daily minimum temperatures are 8.6°C below the daily average. Days recording an average temperature of 10°C typically imply a minimum temperature of around 2-3°C at night. This is well below the comfort zone of the human body which lies between 20 and 25°C. Likewise, mildly cold days, e.g. averaging 14-16°C, expose people to fairly cold temperatures (on average 7-8°C) at night.

[2] This finding is for the direct impact of weather on mortality only. It stands in sharp contrast with most recent economic analyses of both developed and developing countries, which tend to predict that climate change will significantly increase temperature-induced mortality (e.g. Deschenes and Greenstone, 2011; Burgess et al. 2017). The difference in findings can be partly explained by our focus on short-term impacts: we do not account for the indirect effects of temperature, e.g. on agriculture and income, which influence health outcomes. In that regard, our results strongly align with the scientific literature on the direct, physiological impact of cold and heat waves on mortality (Barnett et al., 2012; Guo et al., 2014; Ma, Chen, and Kan, 2014; Gasparrini et al., 2015; Yang et al., 2015; Hajat and Gasparrini, 2016; Gasparrini et al., 2017). Recent epidemiological research insists on the strong health burden of cold, especially during the winter.

The second contribution of this study is to show that vulnerability to extreme weather is negatively correlated with personal income. Controlling for differences in the age structure across income groups, we show that vulnerability to unusual cold (defined as a day with mean temperature below 10°C) is 37 percent higher for people in the first quartile of the income distribution compared to people in the last quartile. Death following mildly cold days (10°C-20°C) are 60% more frequent for people living below the national median personal income. Hence, a large majority of cold-related deaths concentrates on the poorest income groups. Analyses by death causes show that the higher vulnerability of the poor comes to a large extent from respiratory diseases, but also from non-transmissible diseases such as diabetes and circulatory system diseases. In contrast, we find no statistically significant differences in vulnerability to heat across income groups.

The final and most important contribution of this study is to assess the impact that improved access to healthcare has on reducing weather-related vulnerability. Our epidemiological analysis shows that policies targeting the most vulnerable people (particularly young children and the elderly in low-income households) could significantly reduce weather-related mortality. However, such policies should not focus on extremely cold days – unlike, for example, early warning systems – but provide protection all year round, since mildly cold days are responsible for the vast majority of weather-related deaths. This suggests that expanding access to healthcare (particularly for vulnerable groups) may significantly reduce weather vulnerability. During our study period, Mexico implemented a nationwide policy, the *Seguro Popular*, to increase access to healthcare for low-income households. This policy provides protection against a set of diseases that happen to be particularly sensitive to weather conditions (e.g. pneumonia and diabetes).[3]

We assess if the rollout of the *Seguro Popular* led to a reduction in the extra mortality triggered by unusually cold and mildly cold temperatures. To do so, we interact the number of consultations per capita performed under the *Seguro Popular* with temperature bins. To control for the endogenous enrolment of municipalities into the policy, we include a full range of interaction terms between municipality fixed effects and temperature bins. In addition, we use year fixed effects interacted with temperature bins to control for the autonomous evolution of weather vulnerability over time. We furthermore take advantage of the fact that the Seguro Popular targeted a specific subset of diseases, and run regressions separately for covered vs.

[3] Access to healthcare is a major issue in Mexico: according to the 2000 Mexican Census, over 80% of people in the first income quartile do not have access to social security.

non-covered diseases. We find that the *Seguro Popular* saved around 3,000 lives per year from cold weather between 2004 and 2015, representing 5.0 percent of deaths induced by days below 20°C during the same period as estimated in the paper. While our analysis focuses on weather vulnerability, which is only one specific aspect of the impacts of the *Seguro Popular* on mortality, it is in fact the first assessment of the impact of the *Seguro Popular* on mortality[4] and thus also contributes to the literature assessing the impact of healthcare extensions in emerging countries more generally, where important data constraints usually exist (Dupas and Miguel, 2017).

The relevance of this paper goes beyond the borders of Mexico. Even in hot countries where coldest temperatures almost never reach 0°C, cold remains a risk factor with potentially high health impacts. Low-income households, particularly in the developing world, are ill-equipped to protect themselves against low temperatures. This puts them at a higher risk at all ages, and particularly when they become older. Furthermore, these households are at risk over longer time periods in the year than richer households, since they appear to be vulnerable to even mildly cold temperatures. We show that access to universal healthcare can successfully reduce this high vulnerability.

The remainder of this paper is structured as follows. Section I discusses the previous empirical literature on the impact of weather on mortality. Section II describes the data. The general impact of temperatures on mortality is presented in Section III. Results by quartiles of income are presented in section IV, and the impact assessment of universal healthcare on reducing weather-related mortality is presented in section V. A concluding section summarizes our findings and discusses the implications of our results.

I. Previous empirical literature on temperature and mortality

A review of the epidemiological literature focusing on the physiological impact of cold and heat on human health is presented in Appendix A1, but we summarize the most important results of this literature in this section. To quantify heat- and cold-related mortality, epidemiological studies usually correlate daily death counts with temperature data at the city level and rely on a Poisson regression framework. Recent studies have established the existence of a U-shape relationship between temperature and mortality at the daily level (Curriero *et al.*, 2002; Hajat *et al.*, 2006; Hajat *et al.*, 2007; McMichael *et al.*, 2008). Human beings face lowest

[4] Other papers looking at the *Seguro Popular* have focused on health spending (King et al., 2009), health expenditure and self-declared information on health issues (Barros, 2008), access to obstetrical services (Sosa-Rubi, Galarraga and Harris, 2009) and prenatal services (Harris and Sosa-Rubi, 2009).

mortality risk at a given threshold temperature, which differs from one location to another (e.g. due to acclimation) and may possibly change over time. Above and below this threshold, mortality increases and, the farther away from the threshold, the greater the numbers of heat- and cold-related mortalities. This is in line with medical evidence that the human body starts being at risk outside a comfort zone which varies across individuals but is generally believed to lie in the range of 20°C to 25°C. From a methodological perspective, such a nonlinear relationship between mortality and temperature calls for the use of temperature bins in panel data analyses (Deschenes and Greenstone, 2011): the impact between temperature and mortality is then separately evaluated at different levels of temperature stress.

Despite evidence from the medical literature that even mildly cold or hot days can negatively affect human health, the economic literature has primarily focused on the impact of extremely hot and cold days (see for example Deschenes and Moretti, 2009; and Deschenes and Greenstone, 2011), plausibly because these extreme weather events tend to concentrate media attention. However, while the impact of a mildly cold or hot day is definitely less dangerous than that of an extremely hot or cold day, days lying just outside the typical human body comfort zone are much more frequent. This media misrepresentation of the relative burden of extreme temperatures is particularly striking in the case of very hot days. Whereas unusually hot days receive significant media attention, the question of their actual impact on mortality remains controversial once account is taken of displacement effects, i.e. the impact of a day's temperature on the mortality levels of the following days. Extra deaths on hot days were often found to be offset by lower mortality rates on the following days, suggesting that mortality on hot days largely corresponds to a "harvesting" effect (Braga *et al.*, 2001; Hajat *et al.*, 2005; Deschenes and Moretti, 2009).[5] Recent developments in epidemiology show that the impact of cold days on human health are in fact seemingly much stronger than the impact of hot days (Barnett et al., 2012; Guo et al., 2014; Ma, Chen, and Kan, 2014; Gasparrini et al., 2015; Yang et al., 2015; Hajat and Gasparrini, 2016; Gasparrini et al., 2017). In particular, Gasparrini et al. (2015) collect data from 384 locations in 13 countries and find that 7.29% of all deaths are attributable to cold while only 0.42% are caused by heat, with most cold-related deaths caused by pathologies triggered by mildly cold temperatures. Extremely cold and hot temperatures are jointly responsible for only 0.86% of total mortality.

[5] For example, Gouveia et al. (2003) show that the positive relationship between mortality and heat in Sao Paulo dissipates within three weeks. Based on data for Beirut (Lebanon), El-Zein et al. (2004) show that the statistically significant effect of hot days on mortality dissipates within fourteen days.

However, uncertainty remains on the true mortality impact of hot days because extreme weather events may not only directly affect human physiology, they may also reduce agricultural output, drinkable water availability and household income. These impacts may in turn affect health or access to healthcare and lead to extra mortality. In order to account for these longer-term impacts, a few economic studies have used monthly or annual panel data rather than daily data (Deschenes and Greenstone, 2011; Barreca, 2012; Burgess *et al.*, 2017; Barreca *et al.*, 2016).[6] These studies establish a clear correlation between hot temperatures and monthly or annual mortality. Burgess *et al.* (2017) find a strong impact of extreme temperatures on annual mortality in India, plausibly because temperature shocks affect agricultural productivity, and therefore the food intake and income of populations located in rural areas.

The existence of such economic factors in addition to the standard epidemiologic ones suggests that people's vulnerability to cold and hot temperatures depends on their access to protection measures. For example, Barreca *et al.* (2016) establish a strong correlation between the declining heat-related mortality that has been observed in the US over time and the gradual deployment of air conditioning. Heutel, Miller and Molitor (2017) similarly argue that the deployment of air conditioning explains regional differences in the health impact of heat on the elderly in the US. Deschenes and Greenstone (2011) predict that climate change in the US would lead to a 3 percent increase in age-adjusted mortality by the end of the 21st century and to a 12 percent increase in electricity consumption as households resort to air-conditioning to protect themselves from the negative consequences of temperature rises. Other potential adaptation measures include migration to places with a more temperate climate (Deschenes and Moretti, 2009) or a reduction in the time spent outdoors (Graff-Zivin and Neidell, 2010).

Differences in the ability of populations to adapt to temperature shocks have been documented both within and between countries, with potentially large effects on economic development (Dell, Jones and Olken, 2012). In epidemiological studies, McMichael *et al.* (2008) show vast heterogeneity in the impact of temperature on mortality across twelve cities in medium- and low-income countries. Using long-term climate change scenarios, Barreca (2012) finds a very small reduction in mortality for the US as a whole (-0.08 percent), but this hides significant heterogeneity: mortality would decrease in the coldest States whereas it would significantly increase (by up to 3 percent) in the warmest and most humid States. In India, Burgess et al. (2017) find a significant increase in heat-related mortality, but only in rural areas. In these

[6] See Bupa (2008) and Deschenes (2014) for thorough literature reviews.

regions, climate change impacts would translate into a large increase in mortality by the end of the century of 12 to 46 percent.

Overall, evidence suggests that weather vulnerability in middle-income economies may substantially differ from that in developed countries. In particular, developed countries have already experienced an epidemiological transition: cancers and other non-transmissible diseases have long been the leading cause of death in these countries, contrary to many developing countries. Furthermore, elemental protection measures (e.g. proper clothing) are available to all in industrialized countries, and national programs such as Medicare and Medicaid provide universal healthcare coverage in life-threatening cases.

II. Data and summary statistics

To evaluate the relationship between temperature and mortality in Mexico, we combine mortality data from the Mexican National Institute of Statistics and Geography (INEGI) and weather data from the National Climatological Database of Mexico.

II.A Mortality data

Our mortality data comes from the Mexican general mortality records (*defunciones generales*) from 1990 onwards as assembled by INEGI. The micro-data provides information about each case of death in Mexico, including cause, municipality, date and time of death along with socioeconomic information on the deceased. A template of the death certificate used in Mexico is provided in Appendix A2. Based on this dataset, we are able to construct daily municipal mortality rates for all Mexican municipalities over the period 1998-2017. The exact date of death is not available before 1998. Table 1 displays the average daily mortality rate by cause of death, gender and age, together with the average population within each group for the period 1998-2017.[7] The average daily mortality rate across all municipalities is around 1.4 deaths per 100,000 inhabitants. This figure is about twice as low as the current rate in the United States (see Deschênes and Moretti 2009), a feature that is explained by the larger proportion of young people in Mexico. The death rate is lowest for children aged 4-9 and rises non-linearly until it reaches 21.3 per 100,000 inhabitants for people aged 75 years and above.

[7] We calculate daily municipal mortality rates by dividing the amount of deaths in a municipality on a specific day with the population in this municipality. To do so, we use municipal population data available from the INEGI for the years of the national censuses (1990, 1995, 2000, 2005 and 2010). We perform a linear interpolation of the population for the years between two censuses to obtain estimates of the Mexican population in each municipality for each year between 1998 and 2017. This may introduce measurement errors in the dependent variable, a problem known to reduce model efficiency but not the consistency of estimates.

We break down mortality rates by cause of death, based on the typology of the 10th version of the International Classification of Diseases (10-ICD) of the World Health Organization (WHO). We consider seven types of cause of death: infectious and parasitic diseases; malign neoplasms; endocrine, nutritional and metabolic deaths (including diabetes which account for 80 percent of deaths in this category, followed by malnutrition); diseases of the circulatory system; diseases of the respiratory system; and violent and accidental deaths. As reported elsewhere, the primary cause of death is circulatory system diseases, which has been shown to be affected by temperature in the epidemiologic literature. The importance of each cause of death differs by age and gender. For example, the prevalence of violent and accidental death is four to five times greater among men than among women. It is also the main cause of death for people aged between 10 and 44. The significance of circulatory system diseases rises with age and peaks above 75, when it becomes the primary cause of death.

[TABLE 1 ABOUT HERE]

II.B Weather and climate data

The National Climatological Database of Mexico provides daily temperature and precipitation records for around 5,500 operating and formerly operating land-based stations in Mexico. Information on the longitude and latitude of the stations is also provided. In order to compute mean temperatures and precipitations at municipal level, we match the municipalities in Mexico with the closest land-based stations.[8] This leads us to exclude a few municipalities that are either located too far from any weather station, or close to a weather station that did not efficiently record both minimum and maximum temperatures. Our combined daily temperature-mortality dataset covers 2,297 Mexican municipalities over the period 1998-2017[9] and includes over 14 million observations. Figure 1 presents the historical distribution of daily average temperature in Mexico from 1998 to 2017.[10] The temperature data is weighted according to the population

[8] To do so, we use the information on the longitude and latitude of municipalities from the INEGI's National Geostatistical Framework (marco geoestadístico nacional). We calculate the longitude and latitude of the centroid of each municipality (averaging the coordinates of all locations that are part of a municipality), and then the distance between this centroid and all the land-based stations in the climatological data. Based on their distance from the centroid of each municipality, land-based stations are matched with municipalities. We consider a land-based station to be within a municipality if it is less than 20km from its centroid. Municipalities in very remote zones feature less than 5 active stations in the 20km radius. In this case, we match each municipality with the five closest stations within a maximum radius of 50km. Once we have identified the land-based stations relevant to a municipality, we compute the daily mean temperature and precipitation levels in a municipality by averaging the records of all stations considered to be relevant to a given municipality.

[9] In 2008, there were 2,454 municipalities in Mexico (INEGI, 2008).

[10] Daily average temperature is defined as the average between the maximum and minimum temperatures of that day, following recommendations by the World Meteorological Organization (2011).

of each municipality to reflect the average exposure of Mexican people to low and high temperatures. We use 13 temperature bins: “below 10°C”, “above 32°C” and eleven 2°C bins in between. In the empirical models presented hereafter, we use the same temperature bins to estimate the relationship between temperature and mortality. In Figure 1, each bar represents the average number of days in each temperature category for the average person in Mexico. The mode of the distribution is between 16°C and 18°C, and 55 percent of days lie in the range 14°C-22°C. At the extremes of the distribution, the average Mexican is exposed to 4.9 days per year below 10°C (50°F) and 2.2 days per year above 32°C (90°F). Mexico’s climate is much warmer than that of the US, featuring fewer days below 16°C and many more days above 26°C.[11] The distribution is also more spread out in the US. In addition, Figure 1 also provides estimates of the distribution of cold and hot days under three climate change scenarios. These estimates are derived from the output of the third version of the Coupled Physical Model of the Geophysical Fluid Dynamics Laboratory (GFDL CM3) by the National Oceanic and Atmospheric Administration (NOAA).[12] We observe that the distribution of daily temperature shifts sharply to the right in all climate change scenarios with much fewer cold days and many more hot days by the end of the century.

[FIGURE 1 ABOUT HERE]

II.C Socioeconomic data

Information from the Mexican 2000 census of population and housing is used in this paper to estimate the income of the deceased. In particular, we extract socioeconomic information on income, educational attainment, social insurance coverage, profession, age, etc. This data source is described in detail in Appendix A3. In a nutshell, the 2000 Census shows large differences in the average personal income between the poorest and richest households. The average personal income of people in the first income quartile is 18 times lower than that of

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[11] Deschenes and Greenstone (2011) provide a distribution of daily mean temperatures in the U.S. On average, temperatures are much lower: there are around 120 days with a mean temperature below 10°C and 1.3 days with temperatures greater than 90°F (32.2°C).

[12] We extract monthly average temperature forecasts for Mexico and 2075-2099 based on three IPCC emissions scenarios (RCP2.6, RCP4.5 and RCP8.5). We obtain the model output from the Atlas Climático Digital de México. This Atlas provides climate model output for Mexico online and is monitored by Centro de Ciencias de la Atmósfera of the Universidad Nacional Autónoma de México (UNAM). We extrapolate the number of days falling within each temperature bin for each climate scenario and municipality. To do so, we calculate the difference between the monthly average temperature as observed in the historical data (1998-2017) and the forecasts of GFDL CM3: this gives estimates of monthly increases in average temperature due to climate change. Assuming that the distribution of daily temperatures around the monthly average temperature in one location and the population distribution across municipalities would remain constant under climate change, we can evaluate the proportion of days falling within each temperature bin under each climate change scenario. The result of this exercise is synthetically provided in Figure 1 for the three climate scenarios.

people in the top quartile. This high inequality is a feature of the Mexican economy that we will use in the next sections to investigate differences in the weather-mortality relationship across income groups. In addition, these high inequalities translate into low healthcare coverage of the very poor: more than 80 percent of the people in the 1st income quartile have no social security.

III. The effect of temperatures on mortality in Mexico

III.A Method

One of the simplest approaches to assess the impact of daily temperatures on mortality is to correlate daily temperatures with daily mortality rates using a fixed-effect linear regression. To control for differences in mortality rates due to seasonal phenomena and structural differences between municipalities (e.g. in the quality of medical services), the model includes municipality by month by year fixed effects. Thus, in the baseline regressions, parameters are identified from deviations in temperature from the municipality average in a given month and year. These fixed effects strongly improve the comparability of observations across municipalities and time. However, they could be eating up some of the effect since our model will only compare mortality between days that have relatively similar temperatures (within a month). Prior to running such models, we concluded that there was enough variance within a month and location to estimate differences in effects across temperature bins.[13] Another limitation of such a model is that it assumes similar mortality levels across days within a municipality/month. Therefore, it does not control for day-specific mortality levels, something that either day by month by year fixed effects (e.g. July 21st, 1999 vs. July 22nd, 1999) or municipality by day by month fixed effects would capture (e.g. Tijuana on July 21st vs. Tijuana on July 22nd). In Appendix B4, we use alternative sets of fixed effects and conclude that municipality by month by year fixed effects are the best fit to the data, and that alternative sets of fixed effects tend to underestimate the effect of cold temperature. Our approach with municipality by month by year fixed effects is justified because vulnerability has strongly evolved over time but heterogeneously so across municipalities (especially because of population ageing). We furthermore expect the effect of hot and cold days to be different across seasons. In particular, respiratory diseases account for a large share of the pathologies associated with cold weather, and respiratory viruses have much stronger prevalence in the autumn and winter than in the summer. Our main result that mildly

[13] The difference between the maximum and the minimum daily average temperatures recorded within each municipality over the course of a month is equal to 5.6°C on average. This difference naturally increases in months that record extreme temperatures. For example, the average difference between the maximum and minimum average daily temperatures recorded during the months in which days above 32°C occurred is equal to 6.6°C. This difference equals 8.6°C in months in which days below 10°C occurred. Therefore, the model can generally compare a day at 8°C with days in the range of 8-16.6°C, and days at 33°C with days in the range of 26.4-33°C.

cold days have the strongest impact on mortality is robust to any change in the choice of the fixed effects, as shown in the robustness checks section below.

To model the temperature-mortality relationship, we estimate equations of the following form:

$$(1) \qquad Y_{i,d,m,t} = \theta . T_{i,d,m,t} + \mu_{i,m,t} + \varepsilon_{i,d,m,t}$$

where $Y_{i,d,m,t}$ is the mortality rate of municipality i on day d of month m and year t, θ is a vector of parameters, $T_{i,d,m,t}$ is a vector of climatic variables that we discuss in detail below, $\mu_{i,m,t}$ is a vector of municipality-by-month-by-year fixed effects and $\varepsilon_{i,d,m,t}$ is the error term.[14] Standard errors are clustered at the municipality level.[15] In addition, the regression coefficients are weighted by the population in each municipality.[16]

$T_{i,d,m,t}$ includes our climatic variables of interest. One issue of importance is to account for non-linearity (Dell, Jones and Olken, 2014). The most conservative approach consists in using temperature bins to specify the relationship between temperature and mortality (Deschenes and Greenstone, 2011). The model requires as many dummy variables in $T_{i,d,m,t}$ as temperature bins (excluding a baseline temperature bin), each one taking the value of 1 when the day's temperature falls within the range of the bin. We use 2°C temperature bins (e.g. 10°C-12°C, 12°C-14°C and so on) to construct the vector $T_{i,d,m,t}$. The lowest bin covers days with a temperature below 10°C, and the highest bin covers days with a temperature above 32°C.

Furthermore, $T_{i,d,m,t}$ cannot only consist of the impact of today's temperature on today's mortality. The temperatures of previous days also have an impact on mortality (e.g. because some people may catch influenza on a cold day and die a few days later) and are obviously correlated to today's temperature. Empirically, Deschenes and Moretti (2009) show that dynamic effects related to the impact of temperature on mortality can spread over 30 days and need to be accounted for. To simultaneously account for non-linearities in the temperature-

[14] The specification being used is fully linear. Alternatively, we could have opted for a log-linear specification. In the present case, the linear specification is preferable because there are many zeros in the dependent variable since it corresponds to daily mortality rates. A log-linear specification would drop these zeros. A convenient transformation could be using the logarithm of the death rate plus 1, i.e. ln(Y+1) instead of Y. We have run our model with such a transformation and the results were very similar.

[15] In a preliminary test, we also checked that our main results were robust to the use of larger clusters, namely State-level clusters. Standard errors increase but the statistical significance of the effects remains. State-level clusters would strongly relax the assumption of zero correlation between municipalities. Later on, we do not State-level clusters because this choice for the clusters would be overly restrictive. We would assume some correlation between two daily death rates occurring during different years and geographical areas, i.e. 28th June 1999 in Tijuana and the 3rd of December 2006 in Bahía de los Ángeles.

[16] This is because, without any weights, coefficients would be representative of municipalities and not of the population.

mortality relationship and for dynamic effects, Deschenes and Greenstone (2011) suggest combining temperature bins with a distributed lag model. Thus, we consider 12 temperature bins and include 30 lags for each bin. In practice, this choice is rather conservative since all effects seem to fade out after 15-20 days. The expression for the distributed lag model is as follows:

$$(2) \qquad Y_{i,d,m,t} = \sum_{k=0}^{K=30} \sum_{s} \theta_{s,-k} . B_{s,i,d-k,m,t} + \sigma . P_{i,d,m,t} + \mu_{i,m,t} + \varepsilon_{i,d,m,t}$$

The subscript *s* stands for the various temperature bins, and $B_{s,d-k,i}$ is a dummy variable equal to one if the temperature on day (d-k) in municipality i falls within bin *s*. We use 26-28°C as the baseline temperature bin, but check that the choice of the reference temperature has no impact on the results.[17] Furthermore, we use on-the-day average precipitation ($P_{i,d,m,t}$) to control for the confounding effect of precipitations on mortality. Due to the lag structure of the model, the effect of a cold or hot day on mortality is the sum of all the coefficients for the contemporaneous and lagged variables representing this temperature bin. This model is computationally intensive, but our very large sample allows us to overcome the multicollinearity problems arising when many lags and temperature bins are considered simultaneously.

III.B Main results

We now present the results obtained with the distributed lag model. In Appendix A4, we also present the results obtained with a simpler model with no lags, therefore considering only the contemporaneous relationship between temperature and mortality.

Figure 2 displays the cumulative impact of temperature on 31-day mortality for the whole population and all causes of death, as estimated with our distributed lag model. We find the classic U-shaped relationship between temperatures and mortality identified in previous studies. However, looking at the two extremes of the temperature distribution observed in Mexico, low temperatures appear to lead to much more extra mortality than high temperatures. A day with an average temperature below 10°C kills about 3.5 times more than a day with an average temperature above 32°C. Interestingly, we find statistically significant impacts of days above 32°C, suggesting that extremely hot days displace death by more than one month and not only

[17] For example, using 18-20°C as the baseline temperature bin has no impact on the magnitude of the estimates.

a few days.[18] Furthermore, we find statistically significant and strong impacts on mortality of all temperatures bins below 20°C. In fact, the contrast between a day below 10°C and a day between 10°C-12°C is not sharp. A day between 10°C-12°C increases mortality by around 0.56 deaths per 100,000 inhabitants, whereas a day below 10°C increases mortality by 0.72 deaths per 100,000 inhabitants. Likewise, a day between 16°C-18°C increases mortality by 0.14 deaths per 100,000 inhabitants, so that a week of mildly cold days at 16°C-18°C conveys a higher mortality impact than one unusually cold day below 10°C. This comparison is interesting when we consider that there are around 60 days at 16°C-18°C per year in Mexico and only 4.9 days per year below 10°C. In Mexico, the effects of temperatures below 20°C and above 32°C have long-lasting effects that can reduce longevity.

[FIGURE 2 ABOUT HERE]

These results are consistent with the dynamic effects of hot and cold days on mortality as reported previously (e.g. Deschenes and Moretti, 2009; Guo et al., 2014; Gasparrini et al., 2015). Like these authors, we find evidence of strong harvesting for hot days whereas the impact of cold days accumulates after the event. These short-term dynamics can be observed on Figure 3, which present the impact on mortality of extremely hot/cold days on the day of the weather event and for each of the following 30 days. A cold day below 10°C has a statistically significant effect on mortality every day during the first week at least. By contrast, we find that a hot day above 32°C has a strong and immediate effect on mortality but this effect is statistically significant only for the first two days, after which the coefficients become systematically negative although not statistically significantly so.

[FIGURE 3 ABOUT HERE]

Table 2 combines the results presented in Figure 2 with the distribution of hot and cold days in Mexico shown in Figure 1. Days under 10°C cause the death of around 4,750 people each year (95 percent confidence interval is 4,281–5,207).[19] This represents 0.7 percent of the number of deaths in Mexico in 2017. However, because mild temperatures between 10°C and 20°C are much more frequent, the total number of additional deaths associated with moderately low

[18] Guerrero Compeán (2013) conducted a similar study on temperature and mortality in Mexico. Our results differ from Guerrero Compeán (2013) since this study finds that heat could have a stronger impact than cold on mortality. Nonetheless, the point estimates of Guerrero Compeán (2013) are imprecisely estimated (e.g. the 10-12°C bin is not statistically different from any other bin, except for the 26-28°C bin). Furthermore, Guerrero Compeán (2013) uses a specification at annual level. Specifications with annual variations recover the impact that temperatures may have on health through indirect channels, e.g. reductions in agricultural yields or income. Results are therefore not directly comparable.

[19] This is obtained for the 2017 population estimate of 129 million people, a death rate of about 0.75 deaths per 100,000 inhabitants for a day below 10°C compared to a day at 26-28°C and around 4.9 days below 10°C per year.

temperatures between 10°C and 20°C is around 62,000 per year[20] (95 percent CI: 52,139–72,415), or 9 percent of the number of deaths in Mexico in 2017. This suggests that the total impact of mild temperatures on mortality is much stronger than the impact of unusually cold days.[21] At the other end of the spectrum, extremely hot days over 32°C trigger a comparably small amount of additional deaths (around 700 annually, 95 percent CI: 476–876).

[TABLE 2 ABOUT HERE]

III.C Impacts by gender, age and cause of death

We now look at the impact of temperature on mortality by gender, age and cause of death. This exercise is useful to identify the type of people at risk during cold waves. We focus on the two extremes of the temperature distribution: days with an average temperature below 10°C (corresponding to the left-hand side of Figure 2) and days with an average temperature above 32°C (corresponding to the right-hand side of Figure 2). The full results are presented in Appendix A5; here, we briefly discuss the main results from this analysis.

We find that the 31-day effects of cold are much stronger for people over 75: the coefficient for cold-related mortality is 22 times higher than for the whole population. In addition, the very young (<5 years old) and senior people (>55) are also more vulnerable to cold. Cold appears to have a particularly strong impact on metabolic, circulatory and respiratory diseases. These three causes of death are estimated to concentrate 76 percent of deaths due to days below 10°C. Interestingly, unusually cold days induce more accidental and violent deaths. As for extreme heat, we likewise find a much stronger impact on people over 75. Most heat-related deaths seem to be due to circulatory system diseases and metabolic diseases.

Existing studies similarly report that people over 75 are much more vulnerable than the rest of the population. The causes of cold-related deaths in Mexico look different than in the U.S., where two-thirds of cold-related deaths have a cardiovascular origin and around 20 percent are caused by respiratory diseases, while diabetes and infectious diseases respectively account for only about 3 percent and 2 percent of cold-related deaths (Deschenes and Moretti, 2009). Looking at the corresponding estimates for Mexico, we find that cardiovascular diseases account for 36 percent of cold-related deaths (<20°C), followed by metabolic ones (26 percent, including mostly diabetes), and respiratory diseases (23 percent). However, a large share of the

[20] This excludes the impact of days below 10°C.

[21] We are comparing days with an average temperature between 10°C and 20°C with days with an average temperature between 26°C and 28°C. Minimal temperatures at night can be cold (e.g. 0-10°C) for mildly cold days, whereas maximal temperatures can be high in the reference bin (depending on intra-day variations).

difference in the causes of weather-induced deaths between Mexico and the US is likely due to differences in the classification of diseases. Diabetes doubles the risk of cardiovascular disease and most deaths from diabetes are due to coronary artery disease. We find no statistically significant impact of cold weather on deaths from infectious diseases.[22]

The output of the regressions by age group can be used to compute annual deaths by age group. These are reported in Table 3 for cold (<10°C), mildly cold (10-20°C) and hot (>32°C) days. The great majority of deaths correspond to people aged 75 and over, mostly on mildly cold days. People aged 55-74 constitute the second age range in terms of number of deaths, followed by people aged 35-54 and children under 5. Individuals over 75 are much more vulnerable than people aged 35-64 and children under 5, explaining the large gap in deaths. However, only around 3.6 million people over 75 lived in Mexico in 2017, whereas the country comprised around 14.6 million people aged 55-74, 33.4 million aged 35-54 and 11.5 million children under 5 that same year. Results by age group suggest that 72 percent of the deaths caused by days over 32°C concentrate on people over 55.

[TABLE 3 ABOUT HERE]

The estimates by age group are informative about the impact of cold on longevity. In Appendix A6, we calculate the annual total of years of life lost associated with outdoor temperature exposure for the Mexican population using life expectancy estimates. We find that the number of years of life lost are high for people under 5 and people over 45. The number of years of life lost due to cold days under 10°C is greater for children under 5 than for any age group, including people aged over 75. There are two reasons. First, the number of years of life lost per child is obviously much greater. Second, Mexico's birth rate is high and, as already explained, many children end up being exposed to cold days.

III.D Implications for climate change

We can use our model to simulate the impact that climate change may have on extra winter mortality in Mexico. This is only a partial effect of climate change since our model only identifies short term responses to cold and hot waves within a reduced time frame. The details of this analysis are provided in Appendix A7. Because the frequency of cold and mildly cold days is expected to decrease, the number of deaths imputable to temperatures reduces with the forecasted temperatures induced by climate change as compared to historical ones. With the

[22] Because death causes represent competing risks, an increase in the likeliness of dying from one cause reduces the likeliness of dying from something else. This element is not taken into account in our regressions, since we are estimating these effects separately.

RCP2.6 scenario (low GHG emissions), temperature-related mortality would be 33 percent lower. The RCP8.5 scenario (high GHG emissions) corresponds to a 50 percent reduction in the estimated relationship between mortality and temperature. These results look high in magnitude. However, this analysis comes with serious caveats: because we only look at short-run impacts, our analysis restricts weather-related deaths to short-term variability in weather. Climate change could also affect mortality through increased frequency of natural catastrophes and not only through temperatures, and these deaths are unaccounted for in the present study. Also, our analysis at the daily level does not allow for acclimatization, and we could be underestimating the impact of increased heat waves if the effect of heat grows non-linearly beyond 32°C days. In addition, our model includes municipality-by-month-by-year fixed effects, which control for income, technologies, and the general health of the population, three factors that climate change could influence. All in all, these simulations predict that extra winter mortality will decrease with climate change and that weather-related mortality will be more equally spread across seasons. In addition, we show below that weather-related mortality more strongly affects people in the first two quartiles of the income distribution, suggesting that the reduction in exposure to cold weather associated with climate change could lead to a reduction in mortality inequality.

III.E Robustness

We conducted an extensive series of robustness checks to confirm the aforementioned findings. These are described in detail in Appendix B but we summarize them in this subsection.

Minimum vs. Maximum Temperature (Appendix B1). We separately estimate the effect of daily minimum and daily maximum temperatures instead of using the daily average temperature. This allows us to consider whether intra-day temperature variations have a strong impact on mortality. We find that minimum temperatures below 0°C are associated with an increase in mortality of 0.62 deaths per 100,000 inhabitants. We record no statistically significant effect on mortality for unusually high minimum temperatures above 25°C. We find an extra mortality impact of around 0.39 deaths per 100,000 inhabitants when daily maximum temperatures are below 15°C, and a smaller effect when they are unusually high (+0.22 deaths per 100,000 inhabitants for maximum temperatures above 40°C). The magnitude of these effects is similar to those found when using daily averages in our base model.

Acclimatization (Appendix B2). We then consider the role of acclimatization. We assume that the temperature-mortality relationship might depend on the usual temperature faced by households in a given location. Heutel, Miller and Molitor (2017) find radically different results on the health impact of climate change in the US when taking into account differences in regional sensitivity. We perform such a test and find that warmer regions seem to be more sensitive to cold than any other region, but confidence intervals are wide and results are not statistically significantly different. In complement, instead of using absolute temperature bins, we calculate deviations from the average temperature in each location to construct relative temperature bins with a 2°C window. The average temperature in each municipality is obtained by averaging all daily temperatures over 1961-2018. We then rerun our distributed lag model with the newly constructed temperature bins. These include deviations between -10°C and +10°C with respect to the average temperature in each municipality. We similarly find that cold and mildly cold days convey strong mortality effects.

Heterogeneous effects (Appendix B3). We also test the sensitivity of the results to different sub-samples. More precisely, we check for coefficient stability by splitting the sample into six periods (1998-2000, 2001-2003, 2004-2006, 2007-2009, 2010-2012 and 2013-2017). We find a decrease in the temperature-mortality relationship between the 1998-2003 and the 2004-2010 periods. There is however a resurgence in the temperature-mortality relationship for 2010-2012, which disappears in 2012-2017 and could be due to statistical variations. We also estimate different effects of temperature on mortality for weekdays and weekends. We find that cold-related mortality is slightly higher during weekends. Finally, we tested for differences in estimates between rural areas and urban areas, and found no differences in estimates, but this could be because estimates are imprecise for rural areas.

Model choice (Appendix B4). We also tested the sensitivity of the results to alternative specifications. First, we ran a placebo test with the leads of the temperature bins used as explanatory variable. To do so, we added 30 leads for all the temperature bins of our distributed lag model. While we observed a clear extra mortality effect for the nearer lags, we observe no clear pattern for leads, as expected. In Figure 4 below, we report the estimates for each coefficient of the 30 leads, the contemporaneous effect and the 30 lags for the "below 10°C" temperature bin. We observe a clear extra mortality effect for the nearer lags: if a cold day occurred less than 1 week ago, then mortality is impacted. We observe no clear pattern for leads.[23]

[FIGURE 4 ABOUT HERE]

[23] In addition, we checked if extending the number of lags in the model to account for the effect of temperatures up to 60 days after the event altered our general results. Results remain similar with 30 additional lags (results not reported for concision).

Most importantly, we use alternative structures for the fixed effects. In the baseline specification, we use fully interacted, municipality-by-year-by-month fixed effects. This restrains the comparison of mortality effects to days within the same month of the year within a given municipality and disregards seasonal patterns in the temperature-mortality relationship, so that mortality could be systematically higher in the winter for example because of cold temperature. In other words, we could underestimate the mortality impacts of direct exposure to temperature in very cold or very hot months by comparing very cold days with already cold days, and very hot days with already hot days within a month. To the contrary, we find that using alternative sets of fixed effects attenuates estimated impacts, plausibly because they could improperly control for the spurious correlation between global warming and population ageing.

Omitted variable bias (Appendix B5). Our results could be driven by an omitted variable correlated with daily changes in temperature and in mortality. In this respect, we look if other climate variables could drive our results. We check if precipitation levels might have delayed impacts on mortality or interact with the temperature-mortality relationship. We find no statistically significant impact of lagged precipitations on mortality. We also look at the confounding effect of humidity. Results are not substantially modified, but we find that mortality due to cold is higher in dry climates.

Another issue would be that our results be driven by air pollution or the interaction between air pollution and temperature. We collected data for outdoor air pollution for Mexico City, where pollution is monitored for several pollutants and daily information on air quality is directly accessible from the Direccion de Monitoreo Atmosferico.[24] The Mexican air quality index data (IMECA) has been downloaded from their website for the period 1998-2017 and we use the data for Central Mexico City as a control variable in our distributed lag model. For this purpose, we produced 4 air quality bins and 30 daily lags for each. We then run the model on all the municipalities located in the Mexican Federal District. Figure 5 displays the impact of temperature on mortality for the Federal District. The maximum temperature bin in Figure 5 is "above 22°C" because Mexico is in the mountains and temperatures rarely go beyond that point. The solid line is the effect obtained after controlling for pollution. The dotted lines correspond to the 95 percent confidence interval. For comparison, we also report the average effect of temperature for the Federal District when we do not control for pollution (dashed line). Results are very similar, suggesting that temperature and pollution convey two separate effects on

[24] http://www.aire.cdmx.gob.mx/default.php

mortality. We report the coefficients obtained for the impact of air pollution on mortality in Appendix B5.

[FIGURE 5 ABOUT HERE]

Indoor air pollution could also be a confounding factor explaining our results. As already mentioned, there is no clear difference in estimates between rural areas (where wood might be sourced and used for heating) and urban areas (Appendix B3). Since 75 percent of the Mexican population live in urban areas,[25] our results cannot be primarily driven by the interaction between temperature and indoor pollution through use of solid fuels for heating (or cooking) . However, the use of solid fuels could still be a contributing factor explaining high vulnerability in Mexico. In the national Income and Household Expenditure Surveys, 15.5 percent of Mexicans used wood (15.24 percent) or coal (0.21 percent) as the main cooking fuel in 1998. This proportion is stable over time: in the 2010 survey, 14.4 percent of households were using either wood or coal, and 14.5 percent in 2016. Yet, we found a decrease in the temperature-mortality relationship between 1998-2003 and 2004-2009 (Appendix B3) which cannot seemingly be attributed to a change in the use of solid fuels indoors.

IV. External validity and the role of income

Our estimates for the temperature–mortality relationship are robust to many specification changes. They are also high in magnitude, considering that we attribute 11 percent of deaths in Mexico to cold and mildly cold temperatures. An important question is whether similar results could be found in other middle-income countries or if Mexico is just a special case. Below, we compare our results with studies on other countries. It appears that richer countries are less vulnerable. We furthermore look at the heterogeneity of the mortality impacts by income groups with our data to understand if weather vulnerability would go down with economic development. All these elements are described in detail in Appendix C but we summarize them in this subsection.

Other studies (Appendix C1). Our estimates can be compared with the results of recent studies conducted with US panel data (Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; and Barreca, 2012) and Indian data (Burgess et al., 2017). In short, our results are higher in magnitude than those obtained in the US, and far smaller in magnitude than those found by Burgess et al. (2017) for extremely hot days in India. Deschenes and Moretti (2009) use a similar 30-day distributed lag model. Their estimate of 0.20 extra deaths per 100,000 inhabitants

[25] Own calculation based on 2000 Census data.

for days between 40°F and 50°F (4.4-10°C) is 3.5 lower than ours in magnitude and both estimates are statistically different from each other. This suggests that Mexico's inhabitants are much more vulnerable to cold than US residents. Burgess et al. (2017) find strong effects on rural populations and not on urban populations. This is because unusually hot weather during the growing season sharply depresses agricultural yield and the wages of agricultural labourers in rural areas, which in turns pushes up mortality rates. For Mexico, we find no clear difference between rural and urban areas (Appendix B3). This suggests that the impact of heat is lower in countries in which rural inhabitants do not entirely rely on subsistence agriculture.

This quick international comparison suggests that income levels might play a strong role in determining one's vulnerability to temperature fluctuations. We suspect that differences in living conditions and access to healthcare play a central role in the vulnerability to temperature variations, because poorer households will not have the same access to protection measures, such as heating, air-conditioning and access to healthcare. This could be a major driver explaining cross-country or within-country differences in weather vulnerability.

Vulnerability by quartiles of income (Appendix C2). Our data allows us to explore the hypothesis that weather vulnerability is correlated with differences in income. To do so, we run our distributed lag model separately for each income quartile. Methodological details on how we construct death rates by income quartile are provided in Appendix C2. In short, since income is not directly available on death certificates, we use data from the 2000 Mexican census to estimate income levels at the moment of death based on individual characteristics provided on deaths certificates (e.g. age, gender, profession) and use predicted income to produce daily mortality rates by income quartile.

The method includes two steps. First, we run a simple regression with data from the Mexican census where we predict income as a function of independent variables also present on death certificates. This includes gender, age, civil status, occupation, education level and registration with public or private healthcare. We also include municipality by rural/urban area fixed effects, to separate rural from urban areas within the same municipality, since we expect people living in the city centre to be richer than those living in nearby rural areas. The model also includes a quadratic term for age and interaction terms between age (and age squared) and occupation, to account for experience at work. Because professions are recorded with a different, non-comparable nomenclature from 2013 onwards, we performed the analysis with data from 1998 to 2012 only. The output of this estimation is presented in Appendix C2. The regression results are consistent with economic theory (higher experience or education is correlated with higher income) and the model captures a large share of the variation in revenues (R2=0.45).

Second, we use the predicted income values to construct income quartiles. Based on the 2000 Mexican census, we first compute the proportion of people in each municipality *i* whose predicted income would have fallen within income quartile κ. We then calculate the proportion of deaths in each municipality with a predicted income in each quartile κ and compute daily mortality rates by income quartile for each municipality *i* at time *t*.[26]

The results of these regressions by income quartile are reported in Figure 6. Results show a strong difference in vulnerability to cold at unusual and mild levels between the first two and last two quartiles. For example, an unusual cold day below 10°C conveys 1.01 deaths per 100,000 inhabitants for the first two quartiles of income, versus 0.60 for the last two. In contrast, we do not find any statistically significant difference in the impact of unusually hot days on mortality across income quartiles. This is likely to be caused by some lack of statistical power since only a minority of weather-related deaths are associated with excessive heat.

[FIGURE 6 ABOUT HERE]

In Table 4, we report the magnitude of the impacts in number of annual deaths for both mildly cold and unusually cold weather (i.e. all temperature bins below 20°C) for each income quartile. Cold days below 20°C lead to around 60% more deaths for the 1st and 2nd quartiles of income than for the last two.[27]

[TABLE 4 ABOUT HERE]

These results might be driven by differences in baseline mortality rates across quartiles. In Table 5, panel A, we normalize the mortality estimates by quartile and express them as a proportion of the average daily mortality rate of each income quartile. After normalization, vulnerability to unusually cold temperatures is nearly 80% higher for people in the first quartile as compared to people in the fourth quartile and the difference is statistically significant at 1 percent (see Table 5 – panel A).

[26] With this method, we are able to assign an income quartile to 73.3% of deaths (not all death certificates record all the sociodemographic variables we need). We finally use the mortality rates by income quartile to run separate distributed lag models for each income quartile. We augment all estimated coefficients by a factor of 1/0.733 to account for the deaths for which no income quartile could be attributed.

[27] The total number of deaths (for all quartiles) estimated in Table 4 is slightly different from the one reported in Table 2. This is because the estimates of Table 4 are based on the results of the regressions reported in Figure 6, while the estimates of Table 2 are based on our baseline regression (Figure 2). However, differences are small: there are 67,021 deaths from days below 20°C in Table 2, and 66,341 in Table 4.

To deepen our understanding of the correlation between income and weather-related deaths, we run the quartile-specific econometric models for separate causes of death for days below 10°C.[28] Results by cause of death are reported in Appendix C2 and corroborate that low-income households are more vulnerable to metabolic, cardiovascular and, above all, respiratory diseases. We find impacts across all quartiles from endocrine, nutritional and metabolic diseases, circulatory system diseases and respiratory system diseases. However, the magnitude of the effect diminishes sharply between the 1st and the 4th quartiles for these types of diseases.

Age-corrected quartiles (Appendix C3). In general, the results by quartiles of income confirm the intuition from the studies performed in other countries that income determines weather-related vulnerability. The interpretation of these results by income quartile is however not straightforward. It is important to keep in mind that these results display a correlation between income and weather-related mortality, and not a causal impact. Causal effects are likely to go both ways: (a) people are more sensitive to weather because they are poor; but, at the same time, (b) people that are sensitive to the weather may display lower general health and, because of this, they may be less capable of generating income.

When running separate regressions by income quartile, demographics are likely to play a role in explaining the differences in vulnerability across income groups. We have shown previously that the elderly constitute by far the most vulnerable group. However, people in the lowest quartiles of income are older on average because access to pensions is insufficient. In addition, poor families tend to have more children and young people tend to be poor. The young and the very old are thus overrepresented in the lowest quartiles. To account for this phenomenon, we also provide results by income quartile while accounting for average differences in income across age groups. We can then interpret the residual difference in vulnerability across the quartiles of income as originating principally from differences in living conditions (and not demographics).[29]

Age-corrected results for cold days below 10°C are provided in Table 5, Panel B. Point estimates show that correcting for age does not affect our general results: the first quartile of income is about 60% more vulnerable than the last quartile. This difference is statistically different at 5 percent. Therefore, a sizeable difference in vulnerability levels correlates with differences in living conditions and social protection. Results by cause of death also clearly

[28] We have also tried to run the model for different age groups. Unfortunately, running the model by age group significantly reduces model efficiency and results are inconclusive. The reader may note that breakdowns by cause of death and income group are not always very efficient.
[29] The methodological details are presented in Appendix C4.

corroborate that low-income households are more vulnerable to respiratory diseases (details in Appendix C3).

[TABLE 5 ABOUT HERE]

Defining quartiles with a poverty indicator (Appendix C4). To make sure that our findings by quartiles of income are robust to a different measure of living conditions, we use a poverty index instead of predicted income. The Mexican Council of Population (CONAPO) defines a marginality index based on a set of questions asked to Mexican households in the 2000 census. The answers to this set of questions are less easy to manipulate by dishonest respondents and are less sensitive than income. We define and predict a poverty index for each deceased person in a way that is very similar to the CONAPO and construct quartiles based on this alternative metric. The detailed results and methodology feature in Appendix C4 but are summarized in Table 5, Panel C. They corroborate the findings obtained with predicted income levels.

The policy implications of Tables 4 and 5 are substantial. They suggest that the poor are not only much more vulnerable to unusually cold temperatures, but they are also more vulnerable to temperatures that are less likely to affect richer households. This definitely puts poor households at risk, since mildly cold days are relatively frequent.

In general, these results by income group are not surprising when we consider that low-income families have insufficient access to quality housing, drinking water and health insurance (as reported on Census data – see Appendix A3). While access to electricity is widespread, it is rarely used for heating. According to the 2018 Mexican National Survey of Energy Use in Residential Housing, only 6.3% of the housing units are equipped with some form of heating equipment.

V. Weather-related mortality and universal healthcare

The analysis of sections III and IV shows strong vulnerability of low-income groups to cold weather. An important question is whether public policies can substantially reduce this vulnerability. During our study period, Mexico implemented a nationwide policy – the *Seguro Popular* – to increase access to healthcare for low-income households.[30] Considering that developing countries may be financially constrained to protect their citizens from cold, targeted

[30] Formerly, low-income families working in the informal sector did not have access to healthcare insurance, and the country still suffers from chronic under-financing of free public hospitals. Mexico is the OECD country with the lowest budget dedicated to health: in 2015, current expenditure per capita in purchasing power parity was $1,052, compared to $3,814 on average in other OECD countries, and $9,451 in the US (see OECD Health Statistics 2016).

health programs may offer the possibility to restrict the population of recipients to vulnerable groups. They can also restrict the range of diseases covered to those that are known to arise because of cold weather. Below, we provide evidence that the *Seguro Popular* has reduced weather-related mortality.

The *Seguro Popular* was initially launched as a pilot exercise (2001-2003) to increase universal healthcare. Access to the *Seguro Popular* was open to all. In practice, it focused on people who were not eligible to employment-based health insurance, i.e. low-income households working in the informal sector. Enrolment was free in most cases even though a fee could be due from families above a certain level of income. This fee then grew in proportion to income. By 2004, the Mexican government decided to progressively extend the program to the entire population, municipality after municipality. In 2004, the Mexican government also promoted the *Fondo de Protección contra Gastos Catastróficos*, which provides financial support to families affected by a series of chronic, long-term diseases, in particular cancer and HIV.[31] Both programs are still ongoing. The extension of the *Seguro Popular* to the whole Mexican population required either integrating the existing medical infrastructure into the scheme or building new infrastructure. The INEGI reports the number of people that received medical attention under the *Seguro Popular* by municipality and year.[32] At its start in 2004, the *Seguro Popular* provided around 315,000 external consultations. This figure radically increased to 11 million in 2005, 61 million in 2010 and up to near-full coverage of Mexican municipalities nowadays.

A specific feature of the *Seguro Popular* and the *Fondo de Protección contra Gastos Catastróficos* is that health coverage is restricted to a reduced list of priority diseases. This list mostly includes preventive health actions (e.g. vaccines), ambulatory medicine (e.g. measles, tuberculosis), reproductive health, selected emergencies (in particular caused by hypertension and diabetes) and surgeries (e.g. appendectomy, treatment of fractures). A wide spectrum of covered diseases are weather-sensitive, especially respiratory pathologies. We therefore expect the policy to have reduced weather-related vulnerability.

[31] Furthermore, additional protection has been provided to children under 5 born after 1 December 2006 with the implementation of a policy called the *Seguro Médico para una Nueva Generación*.

[32] The implementation of the *Fondo de Protección contra Gastos Catastróficos* was done through specialized institutions that required accreditation. The rollout of the program was therefore very similar to that of the *Seguro Popular*. We make the simplifying assumption that the municipalities who benefitted from the *Seguro Popular* also benefitted from the *Fondo de Protección contra Gastos Catastróficos* since we unfortunately do not have this exact piece of information.

V.A Method

We aim to assess if the rollout of the *Seguro Popular* led to a reduction in weather-related vulnerability. To this end, we use a method similar to Barreca, Clay, Deschenes, Greenstone, and Shapiro (2016). These authors look at the impact of air conditioning, electricity access and healthcare on weather vulnerability by interacting temperature bins with key variables of interest, e.g. the number of doctors per capita. To avoid omitted variable biases, they use a large range of fixed effects.

To assess the impact of the *Seguro Popular* on weather vulnerability, we interact temperature bins with the number of consultations per capita provided under the *Seguro Popular* during the study period. We downloaded this information from the Mexican statistical institute (INEGI) for all available years (2004-2015), for each municipality and year. We interact this variable with temperature bins. To increase precision, we rely on fewer temperature bins that in our baseline models above: below 12°C; 12-16°C; 16-20°C; 20-24°C; 24-26°C (reference bin); 26-30°C; and above 30°C. In Appendix D, we also provide the results with the 2°C temperature bins used in the previous sections.

We introduce two types of additional controls. The first one is a full set of interaction parameters between the temperature bins and municipality fixed effects. These parameters allow us to control for the endogenous enrolment of municipalities into the policy: municipalities with different vulnerability levels have different probabilities of adopting the *Seguro Popular*. Early adopters may therefore be structurally different from late adopters. We also include interactions between each temperature bin and year fixed effects. This set of interactions control for the autonomous evolution of weather vulnerability in Mexican municipalities that is unrelated to the deployment of the *Seguro Popular*.

However, with so many additional control variables, the model with daily data becomes unsolvable. This is because we would need to have around 2,000 municipality interaction terms for each of the 6 x 30 bin-specific lags (i.e. 360,000 dummy variables). We circumvent this problem by aggregating the data at monthly level. Our temperature bins are redefined as "the number of days falling within a given bin during month m, at time t and for municipality i". With the data aggregated at monthly level, the number of temperature by municipality interactions becomes manageable. Furthermore, the sample size is divided by 30. A drawback with a dataset aggregated at monthly level is that we can no longer include municipality by year by month fixed effects: they would capture all the variation in our data. Alternatively, we include two sets of overlapping fixed effects: municipality by year and municipality by month fixed effects. This allows the monthly model to be as close as possible to the original daily specification.

Finally, we take advantage of the fact that the *Seguro Popular* targeted a specific set of diseases. We focus on the list of diseases covered by the *Seguro Popular*, and run regressions in which the dependent variable is the mortality rate from covered diseases.[33] In parallel, we run placebo tests for the impact of the *Seguro Popular* on the mortality rate of non-covered diseases. Nonetheless, there is a risk that doctors and patients artificially classify non-covered diseases as covered diseases, so that more patients are covered by the *Seguro Popular*. To mitigate this issue, we also run regressions with the all-cause mortality rate.

V.B Results

In Table 6, we present our estimates for the effect of the *Seguro Popular* on weather vulnerability. Column (1) provides general results for all covered diseases. We find negative correlations for all days below the reference bin (24-26°C), and for days above 30°C. The effect is strong and statistically significant at 1% for days below 12°C.

In column (2), we increase precision and focus on the three categories of diseases that we know to be particularly sensitive to the weather: respiratory diseases, circulatory system diseases, and metabolic diseases. The dependent variable is the mortality rate for the diseases covered by the *Seguro Popular* within these three broad causes of death. Point estimates are very similar, and standard errors reduce: the coefficient for 16-20°C becomes statistically significant at 5%, and the one for >32°C becomes statistically significant at 10%.

Using this specification, we can predict that the *Seguro Popular* saved around 3,000 lives (95% CI is 413–5,603) per year between 2004 and 2015 thanks to increased protection to cold weather (<20°C).[34] Overall, this corresponds to a 5.0% reduction in vulnerability from days below 20°C. Considering population growth, but above all since it took time for the *Seguro Popular* to reach maturity, this average is naturally higher for later years, at around 4,800 lives saved every year on average between 2012 and 2015, or a 7.6% reduction in vulnerability below 20°C.[35]

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[33] We identify these with the 2010 nomenclature of covered diseases. The list of covered diseases has been very stable over time, with only a few additions/subtractions.

[34] The results of column 1 correspond to 3,250 saved lives from cold weather (<20°C) between 2004 and 2015, but are only statistically significant at 10%.

[35] This is considering an average population of 116.5 million inhabitants for 2004-2015, and an average of 123.2 for 2012-2015.

Detailed results by age group and disease type are reported in Appendix D. In column (3), we show that 70% of the reductions in cold-related mortality (<20°C) come from the respiratory diseases covered by the policy. This is consistent with two facts: (1) these diseases are particularly sensitive to the weather, and (2) they affect the poor more strongly than other income groups (according to section IV). In columns (4)-(5), we report results for children under 5 and people over 75. Consistently, we find that the reductions in mortality thanks to the *Seguro Popular* are stronger for these age groups.

In column (6), we run a regression where we look at the mortality reduction for all causes of death, whether they are covered or not by the Seguro Popular. Indeed, columns (1)-(3) could underestimate mortality effects if doctors purposefully misclassify non-covered diseases into covered diseases, so that more patients get access to free healthcare. The results of column (6) are very similar to the baseline results. We find a stronger impact for days below 12°C (even though not statistically different) and lower impacts for days between 12-20°C (likewise not statistically different). This suggests that separating covered from non-covered diseases does not create significant biases, which could have arisen if doctors had manipulated the classification of death causes to provide free healthcare to patients before their death.

Finally, we provide two placebo tests. In column (7), we report the reductions in weather-mortality from the *Seguro Popular* for the diseases that were not covered by the policy. We find no statistically significant reduction in mortality for these diseases. In column (8), we look at the effect of the policy on reducing mortality from neoplasms during cold and hot days. We find no impact. Similar additional placebo tests using mortality rates from non-covered diseases are also reported in appendix D, Table D4, and show no impact of the *Seguro Popular* on the mortality from non-covered diseases.

[TABLE 6 ABOUT HERE]

VI. Conclusion

Because investments in protective measures are determined by income, climate change is generally predicted to have the greatest effect on the poorest people in developing countries. This study analyzes the heterogeneous impact of temperature shocks on mortality across income groups in Mexico using individual death records and census data for the period 1998-2017. We find that random variation in temperatures is responsible for the death of around 75,000 people every year in Mexico, representing 11 percent of annual deaths in the country. However, extreme weather events only account for a small proportion of weather-related deaths:

unusually cold days (<10°C average temperature) trigger around 4,750 deaths each year, extremely hot days (>32°C) kill less than 700 annually, while 83 percent of weather-related deaths are induced by mildly cold days (average temperature between 10°C and 20°C).

A consequence of our findings is that climate change should significantly reduce the number of weather-related deaths in Mexico by at least one third by the end of the 21st century, even in the absence of any adaptation. This illustrates the vast heterogeneity in climate change impacts across countries and regions, even though the reader should be aware that only the short-term impact of weather shocks is considered in this paper.

We find that vulnerability to weather shocks is strongly correlated with individual income. The impact of mildly cold days (10-20°C) is 60 percent greater for those living below the median average income. This suggests that not only are poorer households more vulnerable to unusual cold, but they are also more vulnerable at relatively mild temperatures. Therefore, protecting low-income households from cold all year round should be effective in reducing the life expectancy gap between and within countries.

Under these circumstances, there is a role for public policies to reduce the mortality inequalities caused by inclement weather. Healthcare systems can be used to reduce the mortality of vulnerable groups while targeting diseases that are known to respond to weather shocks. We exploit variation in universal healthcare coverage caused by the deployment of the *Seguro Popular* and the *Fondo de Protección contra Gastos Catastróficos* to assess their contribution to reducing weather vulnerability. We find that the schemes saved around 3,000 lives per year since 2004 from exposure to temperature below 20°C. This represents a 5.0 percent reduction in weather vulnerability from days below 20°C.

The overall welfare implications of weather vulnerability in low- and middle-income countries are very strong: in the sole case of Mexico, we estimate that 75,000 deaths each year are triggered by temperatures from which people in low-income households are inadequately protected. Furthermore, birth rates are higher in low- and middle-income countries than in high-income countries, implying that exposure to cold has a stronger impact on longevity because many young children are exposed. We show that access to universal healthcare can successfully reduce this high vulnerability, but more research is required to assess which protection measures are capable of reducing cold-related vulnerability in the most cost-effective manner.

Conflict of interest

The authors declare having no conflict of interest or financial interest related to the content of this research.

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Tables and figures

Table 1: Summary of death statistics

Group	Average pop. per mun.	All causes	Respir. diseases	Circul. diseases	Metab. diseases	Infect. diseases	Neopl.	Violent and accid.	All other
		Average daily municipal mortality rate (deaths per 100,000 inhabitants)							
Total	44,418	1.36	0.117	0.323	0.221	0.045	0.168	0.151	0.335
			(8.6)	(23.8)	(16.3)	(3.3)	(12.4)	(11.1)	(24.6)
Men	21,696	1.54	0.13	0.337	0.215	0.056	0.168	0.249	0.385
			(8.4)	(21.9)	(14)	(3.6)	(10.9)	(16.2)	(25)
Women	22,722	1.18	0.104	0.309	0.227	0.034	0.168	0.058	0.28
			(8.8)	(26.2)	(19.2)	(2.9)	(14.2)	(4.9)	(23.7)
Aged 0-4	4,317	0.96	0.097	0.014	0.03	0.066	0.013	0.075	0.669
			(10.1)	(1.5)	(3.2)	(6.8)	(1.4)	(7.8)	(69.3)
Aged 5-9	4,533	0.07	0.005	0.002	0.003	0.005	0.013	0.024	0.022
			(6.1)	(3.3)	(4.1)	(7.1)	(17.3)	(32.4)	(29.6)
Aged 10-19	8,861	0.15	0.005	0.007	0.004	0.005	0.016	0.081	0.033
			(3.3)	(4.4)	(2.6)	(3.4)	(10.5)	(54)	(21.8)
Aged 20-34	10,830	0.39	0.012	0.025	0.015	0.029	0.03	0.2	0.076
			(3.2)	(6.5)	(3.9)	(7.5)	(7.7)	(51.7)	(19.6)
Aged 35-44	5,880	0.66	0.025	0.076	0.062	0.046	0.085	0.189	0.175
			(3.9)	(11.6)	(9.4)	(6.9)	(12.9)	(28.8)	(26.6)
Aged 45-54	4,140	1.36	0.056	0.233	0.25	0.056	0.225	0.185	0.355
			(4.1)	(17.1)	(18.4)	(4.1)	(16.5)	(13.6)	(26.1)
Aged 55-64	2,643	3.07	0.159	0.659	0.755	0.082	0.529	0.202	0.684
			(5.2)	(21.5)	(24.6)	(2.7)	(17.2)	(6.6)	(22.3)
Aged 65-74	1,586	5.11	0.265	1.1	1.26	0.136	0.882	0.336	1.131
			(5.2)	(21.5)	(24.7)	(2.7)	(17.3)	(6.6)	(22.1)
Aged 75+	1,032	21.31	2.85	7.71	3.49	0.373	2.21	0.56	4.117
			(13.4)	(36.2)	(16.4)	(1.8)	(10.4)	(2.6)	(19.3)

Notes: The table shows cause-specific daily mortality rates as number of deaths per 100,000 inhabitants. The share of average group mortality is presented in brackets, in percentage points. The sample includes 2,456 municipalities over 19.94 years on average. All means are weighted by the relevant population group in municipalities.

Table 2: Estimated number of deaths per year by temperature bin

Average daily temperature	Average deaths per year	95 percent confidence interval
<10°C	4,744	(4,281; 5,207)
10-12°C	9,465	(8,442; 10,489)
12-14°C	16,115	(14,199; 18,031)
14-16°C	15,669	(12,794; 18,544)
16-18°C	13,466	(10,172; 16,760)
18-20°C	7,562	(5,310; 9,814)
20-22°C	3,674	(1,843; 5,504)
22-24°C	467	(-800; 1,733)
24-26°C*	1,201	(198; 2,204)
26-28°C*	0	-
28-30°C	1,171	(306; 2,036)
30-32°C	712	(311; 1,114)
>32°C	676	(476; 876)
Total	74,922	(61,605; 88,238)

Notes: The 95 percent confidence interval in brackets only takes into account the uncertainty of the impact of temperature bins on mortality. This table is based on the 1998-2017 average and does not take into account the variability of hot and cold days in Mexico from one year to the other. Population is assumed to be 129 million. *: The reference bin been readjusted to 26-28°C for the calculation of deaths since this recorded minimum mortality levels. However, the reference bin of the model is 24-26°C (as per Figure 2).

Table 3: Death estimates by age group and temperature level

Age group	<10°C	10-20°C	>32°C
0-4	344*	1,668*	11
5-9	-12	-911	-5
10-19	37	308	18
20-34	144*	889	48
35-44	178*	2,187*	50*
45-54	430*	5,994*	120*
55-64	695*	13,004*	137*
65-74	688*	12,778*	134*
75+	2,980*	40,498*	339*

Note: These are estimates of the annual number of deaths due to cold (<10°C), mildly cold (10°C-20°C) and hot (>32°C) temperatures, as compared to a day with an average temperature of 26°C-28°C. Estimates take into account the frequency of cold, mildly cold and hot days. Population is assumed to be 129 million and age group estimates are from our linear extrapolation of population for 2017. The reference bin been readjusted to 26-28°C for the calculation of deaths since this bin recorded minimum mortality levels. * means statistically significant at 10 percent.

Table 4: Estimated deaths per year for temperatures below 20°C by income quartile

	Excess number of deaths per year		
Temperature level	**<10°C**	**10-20°C**	**Total <20°C**
1st quartile	1,464 (1,210; 1,718)	18,291 (13,996; 22,585)	19,755 (15,337; 24,174)
2nd quartile	1,740 (1,443; 2,037)	19,324 (13,944; 24,703)	21,064 (15,532; 26,596)
3rd quartile	1,129 (854; 1,403)	13,462 (7,890; 19,035)	14,592 (8,831; 20,353)
4th quartile	793 (489; 1,098)	10,133 (6,128; 14,139)	10,927 (6,750; 15,104)

Notes: All estimated values refer to a day with an average temperature of 26°C-28°C, and have been corrected to account for the 26.7% of deaths that could not be attributed to any quartile using the data on the death certificates. Estimates are made with the same distribution of cold days (corresponding to Figure 2), for a total population of 129 million inhabitants equally spread across quartiles. Lower and upper bounds of a 95 percent confidence interval in brackets and do not account for uncertainty in the variability of the weather.

Table 5: Impact by income quartile on a cold day below 10°C on cumulative 31-day mortality

Model	1st quartile	2nd quartile	3rd quartile	4th quartile	1st vs. 4th	First two versus last two
A. Income quartiles	0.71	0.72	0.56	0.4	+0.31	+0.24
	(0.06)	(0.06)	(0.08)	(0.08)	(0.10)	(0.07)
B. Age-corrected income	0.67	0.63	0.62	0.42	+0.25	+0.13
quartiles	(0.07)	(0.05)	(0.07)	(0.08)	(0.10)	(0.07)
C. Poverty indicator	0.62	0.71	0.45	0.36	+0.26	+0.26
	(0.06)	(0.05)	(0.07)	(0.07)	(0.09)	(0.06)

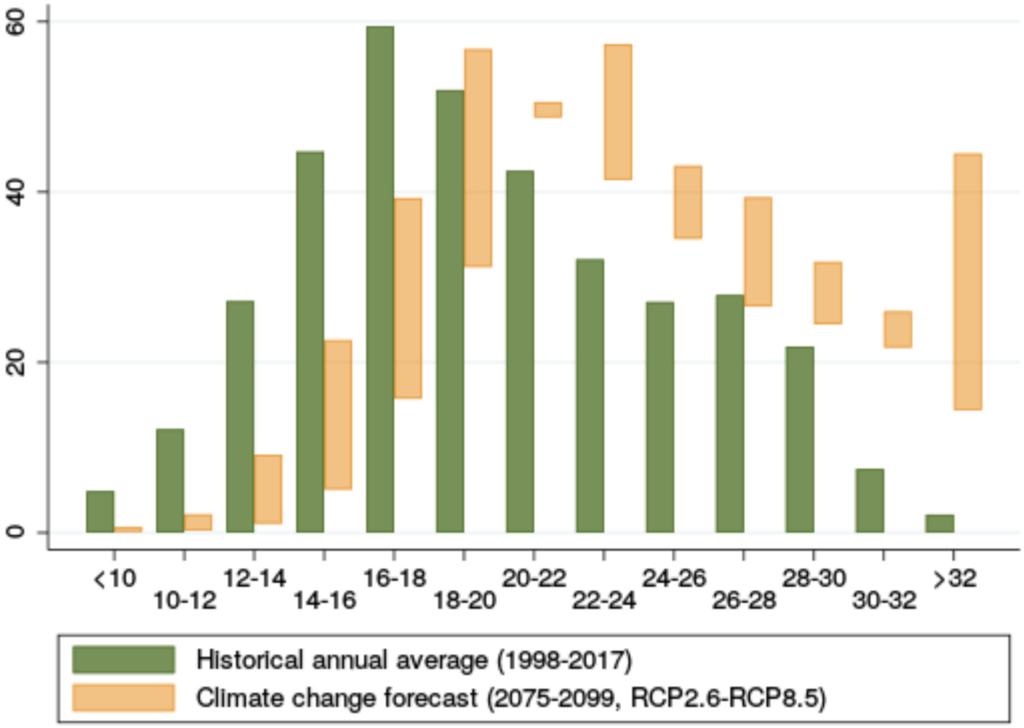
Notes: All of the coefficients come from a different regression and correspond to the 31-day long-run cumulative effect of a day below 10°C on mortality for all death causes. The dependent variable the daily mortality rate in deaths per 100,000 inhabitants, normalised to one according to the average daily mortality rate in each quartile. For example, for the first quartile of income, a day below 10°C leads to a 71% increase in the daily mortality rate. All regressions include the daily precipitation level as a control and municipality by month by year fixed effects. Standard errors in brackets. Reference day is 24-26 degrees Celsius.

Table 6: The impact of the *Seguro Popular* on weather mortality

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disease type/age	Covered	Cov. & 3 causes	Respir.	0-4	>75	All	Non Cov.	Neopl.
Seguro Popular:								
x days below 12°C	-0.055	-0.046	-0.035	-0.116	-0.609	-0.078	-0.014	0.001
	(0.015)	(0.012)	(0.008)	(0.048)	(0.276)	(0.027)	(0.017)	(0.003)
x days at 12-16°C	-0.012	-0.012	-0.009	-0.016	-0.038	-0.008	0.009	0.002
	(0.01)	(0.008)	(0.005)	(0.038)	(0.18)	(0.018)	(0.013)	(0.003)
x days at 16-20°C	-0.015	-0.014	-0.008	-0.016	-0.353	-0.006	0.014	0.001
	(0.011)	(0.007)	(0.005)	(0.047)	(0.155)	(0.018)	(0.012)	(0.003)
x days at 20-24°C	-0.013	-0.007	-0.003	-0.043	-0.183	-0.001	0.017	-0.0002
	(0.008)	(0.006)	(0.004)	(0.023)	(0.181)	(0.015)	(0.011)	(0.002)
x days at 24-26°C	-	-	-	-	-	-	-	-
x days at 26-30°C	0.001	0.003	0.002	-0.003	0.009	0.013	0.018	-0.0001
	(0.008)	(0.006)	(0.003)	(0.024)	(0.166)	(0.015)	(0.011)	(0.002)
x days above 30°C	-0.015	-0.015	-0.003	-0.046	-0.136	-0.024	-0.005	0.001
	(0.01)	(0.008)	(0.005)	(0.032)	(0.264)	(0.022)	(0.016)	(0.003)

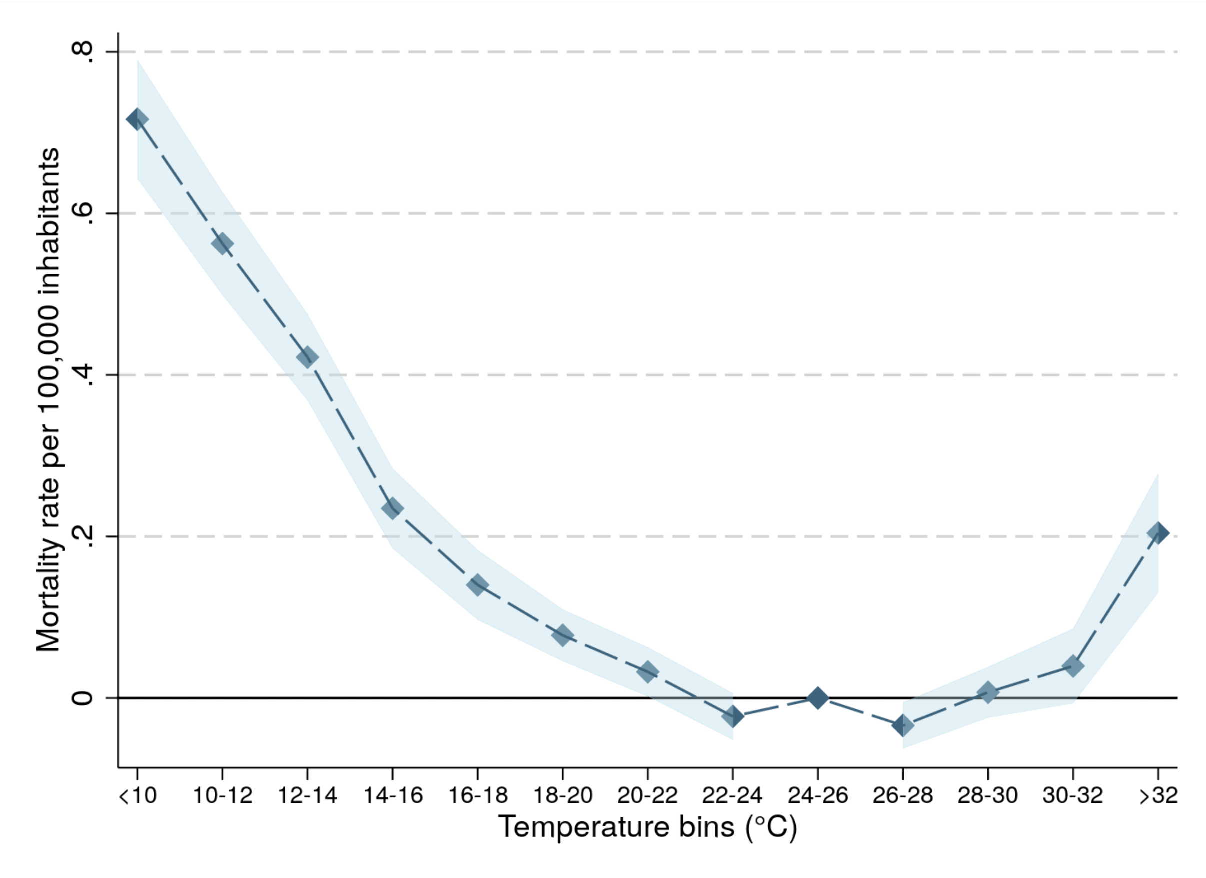
Notes: The dependent variable is the all-cause monthly mortality rate per 100,000 inhabitants. All specifications include municipality by month and municipality by year fixed effects, and interacted fixed effects: municipality by temperature bin fixed effects and year by temperature bin fixed effects. The data is from 1998 to 2015 since information on the number of consultations per capita was unavailable for 2016-2017. Standard errors in brackets clustered at the level of municipalities. Reference day is 24-26 degrees Celsius. The model is estimated using the reghdfe command in Stata based on Guimaraes and Portugal (2010) and Gaure (2010).

Figure 1: Population-weighted number of days per year falling within each temperature bin (in °C) for historical data and 3 climate change scenarios based on GFDL CM3 model output (2075-2099)



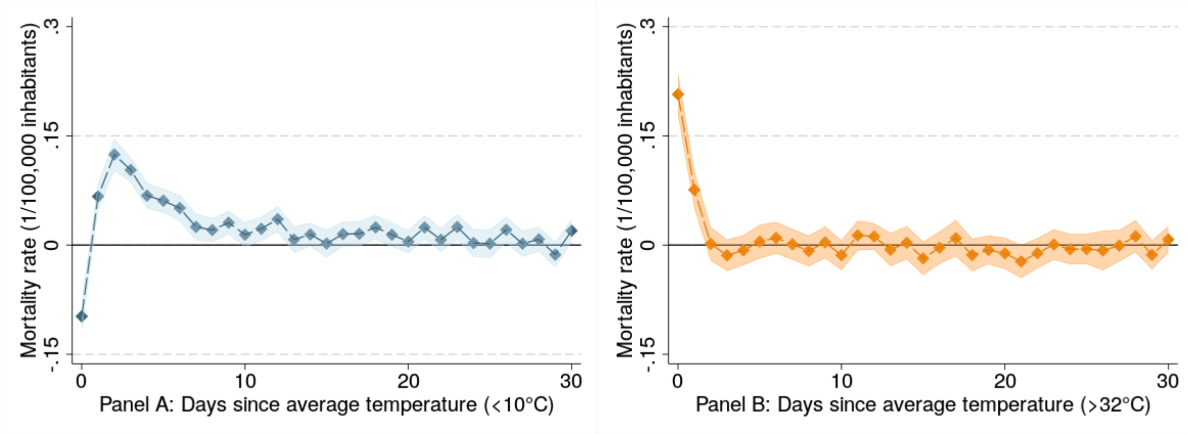
Notes: The figure shows the distribution of daily mean temperatures across 13 temperature-day bins (in °C). Each green bar represents the historical average number of days in each temperature category during a year (calculated over 1998-2017). Municipality averages have been weighted by total population in a municipality. The climate change results (light orange bar) are represented by an interval for 3 different climate scenarios: RCP2.6 (low emissions), RCP4.5 (medium-high emissions), and RCP8.5 (high emissions). The intervals are our own calculations based on GFDL CM3.

Figure 2: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants



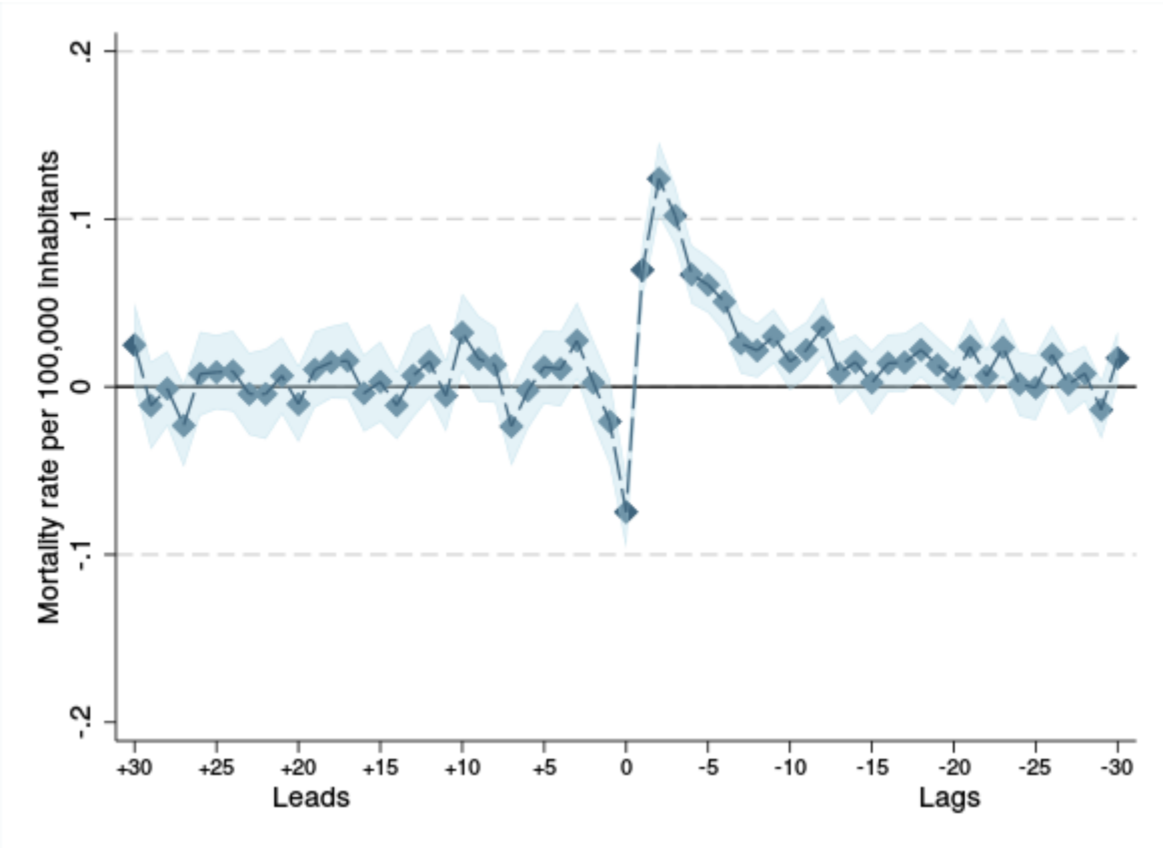
Notes: The graph shows the cumulative effect of a day with a temperature within each bin (relative to the 24°C-26°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area correspond to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level. 467,329 groups and 30.1 observations per group on average. The regression controls for daily precipitation level and includes a range of municipality by year by month fixed effects.

Figure 3: Impact within 31 days of a cold day (<10°C – panel A) or a hot day (>32°C – panel B) on daily mortality rate per 100,000 inhabitants



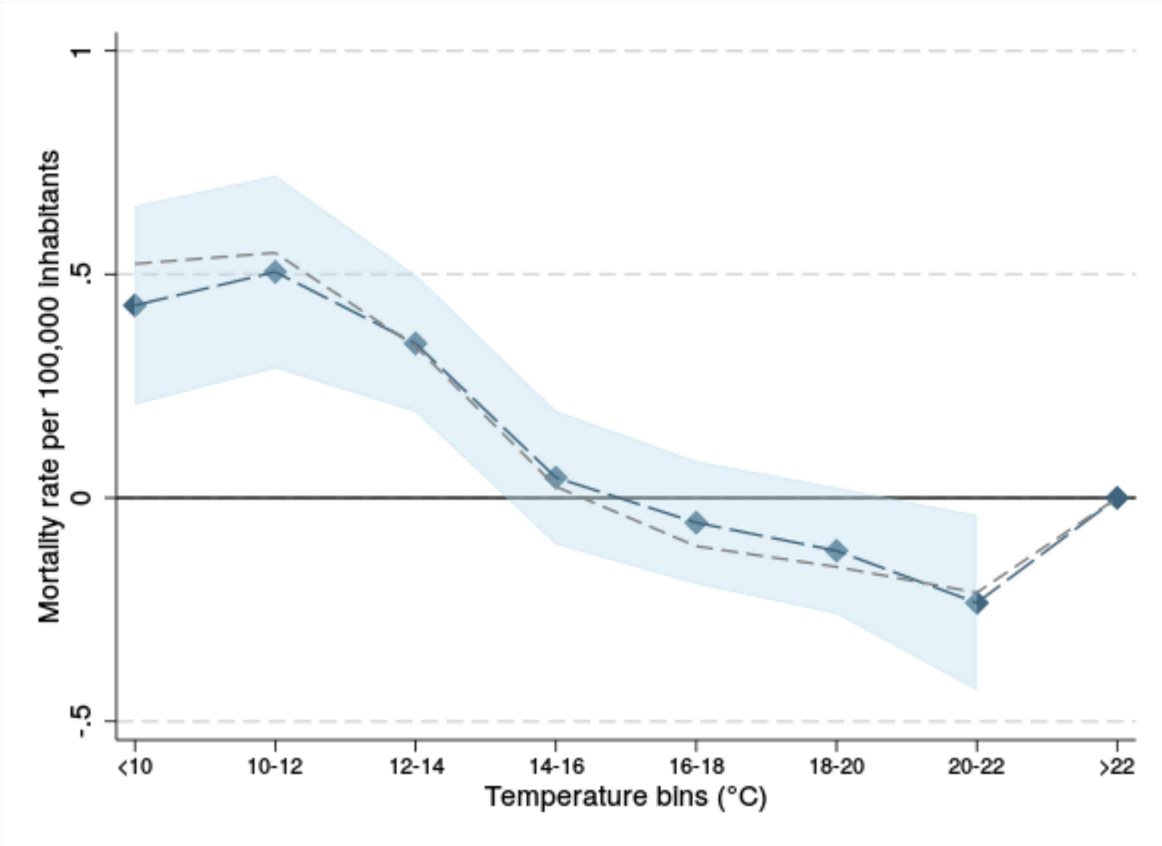
Note: These two graphs are obtained from the same regression, considering all Mexican people and all causes of death (1998-2017). Unit is deaths per 100,000 inhabitants. Each diamond corresponds to an estimated coefficient from the distributed lag model for days below 10°C (Panel A) or above 32°C (Panel B). Shaded areas correspond to the 95 percent confidence interval obtained for each estimated coefficient. 467,329 groups and 30.1 observations per group. The regression controls for daily precipitation level and includes a range of municipality by year by month fixed effects.

Figure 4: Impact of the lags and leads of the "below 10°C" bin on mortality, in deaths per 100,000 inhabitants



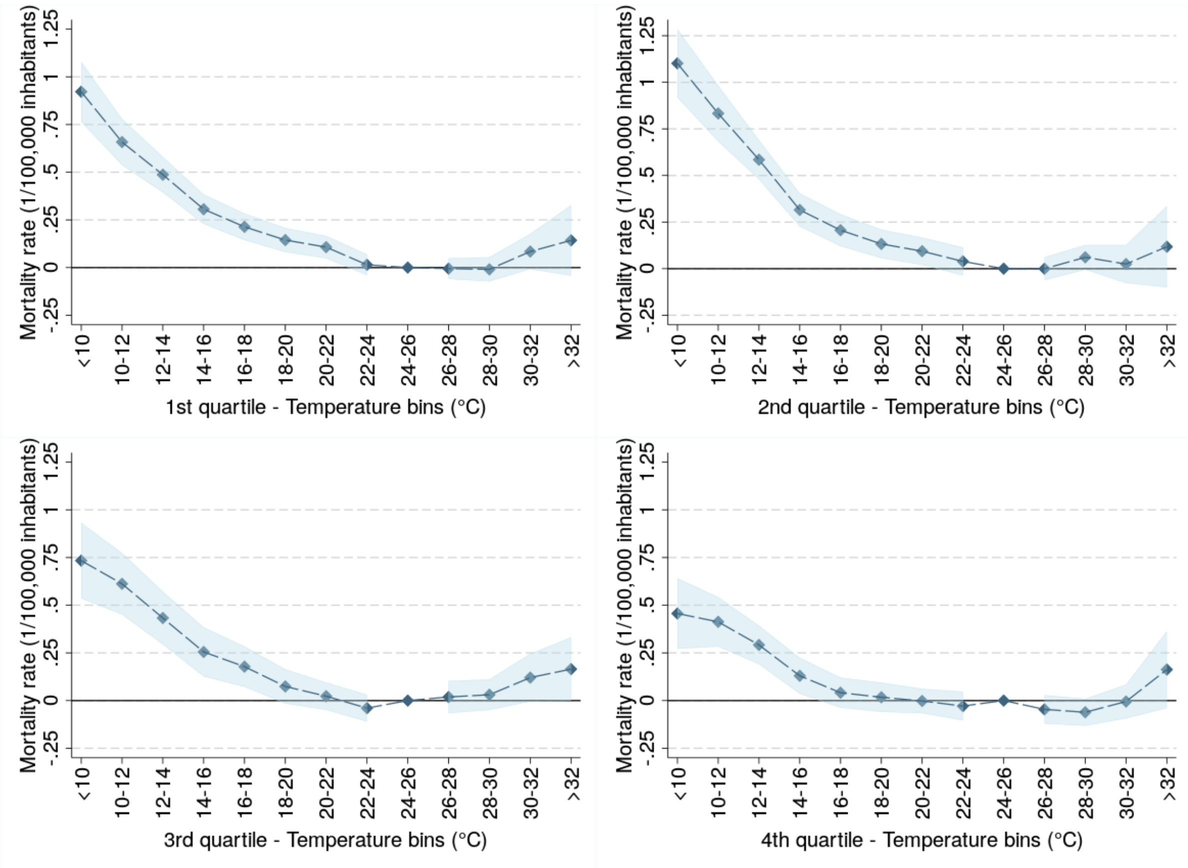
Notes: The graphs show the coefficient value and 95% confidence interval (shaded area) for the below 10°C category (relative to the 24°C-26°C category) obtained from a dynamic model with 30 leads (on the left, from +1 to +30) and 30 lags (on the right, from -1 to -30). The dependent variable is the daily mortality rate at the municipality level. The regression controls for daily precipitation level and includes a range of municipality by year by month fixed effects. It is weighted by municipal population.

Figure 5: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants in the Federal District of Mexico, with (solid line) and without (long dashes) control variables for pollution levels over the past 31 days



Notes. The graph shows the cumulative effect of a day with a temperature within each bin based (relative to the >22°C category) obtained from a dynamic model with 30 lags run for populations living in any municipality part of the Federal District of Mexico. The diamonds on the dashed line show the sum of the coefficients on these thirty lags in each category. The shaded area correspond to the 95 percent confidence interval, with municipality-level clusters. The dependent variable is daily mortality rate per 100,000 inhabitants at the municipality level. The regression controls for daily precipitation level, includes a range of municipality-by-year-by-month fixed effects, and a wide range of controls for pollution on the same day and over the past 30 days. For comparison, the average effects obtained for the Federal District without the air pollution controls are represented by the short-dashed line in grey.

Figure 6: Impact of temperature on cumulative 31-day mortality by income quartile



Note: The results for each quartile are taken from separate regressions. The dependent variable is the mortality per 100,000 inhabitants belonging to the quartile. The y-axis is mortality per 100,000 inhabitants and the x-axis corresponds to the cumulative impact after 31 days for each of the 2°C temperature bins in the regressions. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with municipality-by-month-by-year fixed effects. The shaded areas represent the 95 percent confidence interval for each estimated set of coefficients. Note that all coefficient values have been augmented by a factor of 1/(1-0.267) because 26.7% of the deaths could not be attributed to any quartile using the data on the death certificates.

Mortality, Temperature, and Public Health Provision: Evidence from Mexico

François Cohen and Antoine Dechezleprêtre

APPENDICES – FOR ONLINE PUBLICATION ONLY

Appendices are divided into 4 sections: main appendices (A1 to A7), robustness checks (B1 to B5), external validity and impact of income (C1 to C4) and *Seguro Popular* (D).

MAIN APPENDICES

Appendix A1: Health risks of environmental exposure to heat and cold

The good functioning of the human body requires core body temperature to be around 37°C. However, variations in ambient air temperatures, whether between seasons or throughout a day, induce heat transfers between the organism and the environment. Below or above a comfort zone within which ambient air temperatures are around 20-25°C, the body needs to activate heating or cooling responses.[1] The cooling and heating mechanisms of the human body put stress on the organism by themselves. Above all, they may not be sufficient to maintain core body temperature at 37°C, especially if the heat or the cold received is either intense or prolonged.

High ambient air temperatures can cause increases in core body temperature that are associated with dehydration and the development of pathologies. In a review, Basu and Samet (2005) pinpoint that hot temperatures are associated with excess mortality due to cardiovascular, respiratory, and cerebrovascular diseases. In fact, these pathologies develop much before the body enters severe hyperthermia: mild stress caused by ambient air temperatures above 25°C

[1] The human body relies on three sets of mechanisms to cope with changes in ambient air temperature: one triggering core body heating through voluntary or involuntary muscle contractions, shivering, tachycardia (the heart beats more quickly), vasoconstriction and rapid breathing to avoid hypothermia; another enabling core body cooling that principally consists of vasodilatation and sweating to avoid hyperthermia; and a neural function to monitor core body temperature (in the hypothalamus), activate either heating or cooling when required, and instigate a strong dislike for excessive heat and cold that encourages protective behaviours (Marriott and Carlson, 1996; Chenuel, 2012).

can be sufficient to trigger pathological responses. These pathologies arising because of heat are of the non-transmissible kind (e.g. heart attacks). In addition, mildly high temperatures can also open a window of opportunity for the development of transmissible pathologies. For example, the hosts of some viruses, such as malaria or dengue, develop more easily in hot and humid environments, explaining higher incidence during hot and humid seasons (Colón-González et al., 2011). This constitutes another channel through which high ambient temperatures may provoke excess mortality.

Importantly, not everyone is vulnerable to heat the same way. Some people are at risk very promptly as soon as temperatures go above their comfort zone. Thermoregulation works inefficiently in some people, making them more vulnerable than others for a given temperature level. This is particularly the case for the elderly and younger children.[2]

As much as high temperatures can overwhelm thermoregulation, cold days can also prevent core body temperature from being maintained at 37°C. Very serious cases of hypothermia (<32°C) impair cardiac, cerebrovascular and respiratory functions, which can lead to loss of consciousness and death (Colon *et al.*, 2011). However, strong hypothermia is uncommon whereas mild cold below the comfort zone is a very common situation which affects several functions of the organism, in particular the circulatory and respiratory functions.[3] Like in the case of heat, people with inefficient thermoregulation systems or with preconditions will be more vulnerable to cold, and start being at risk for ambient air temperatures between 10°C and

[2] These groups tend to have low maximal aerobic power, high adiposity and small body stature and body mass compared with young adults. These characteristics imply relatively large surface area-to-mass ratio along with lower sweat rate and cardiac output. In addition, the elderly tend to have poor control of peripheral blood flow. Their hypothalamic system may also be less prompt in detecting hyperthermia and dehydration. All these factors reduce the efficiency of thermoregulation (Inbar et al., 2004). People with specific preconditions, such as diabetes, are more sensible to heat (Scott et al., 1987). Finally, risks depend on exposure. Occupation may play a major role (Thonneau, 1998): people spending much time outdoors and making physical efforts (which naturally produce heat in the body) are more exposed and therefore more at risk than people making less effort and staying indoors during hot days.

[3] This can be exemplified looking at the case of mild hypothermia (32-35°C) (Schubert, 1995). Circulatory effects include higher blood viscosity (by 4-6% for each °C) and higher risk of hypovolemia (decreased volume of circulating blood in the body). Mild hypothermia also affects the coagulation system through reversible platelet sequestration, decreases in enzymatic activity for clotting and increases in fibrinolitic activity. In addition, several organs are affected. The cardiac function suffers from higher stress (e.g. impairment of diastolic relaxation) such that mild hypothermia is correlated with higher risk of angina, myocardial and coronary ischemia. Likewise, lungs can be compromised: pulmonary oedemas have been found in patients after environmental exposure to cold (Morales and Strollo, 1993). More frequently, protective airway reflexes are reduced because of impairment of ciliary function. This predisposes to aspiration and pneumonia (Mallet, 2002). In addition, cerebral activity is reduced due to decreases in cerebral blood flow and cerebral metabolic rate of oxygen (by around 5% for each °C). Furthermore, low body temperature decreases the metabolic rate by 5-7% per °C and moderately affects both the hormonal and immunity systems: e.g. hypothermia reduces leukocyte mobility and the speed of phagocytosis (Schubert, 1995).

20°C when others could sustain much lower temperatures. Older individuals respond poorly to cold stress (Young, 1991). This is because ageing is typically characterised by a loss in muscle mass and body fat.[4] Likewise, malnourished people are vulnerable to cold due to lack of body mass and because core body heating requires the consumption of calories beyond the scope of what they may have in stock (Marriott and Carlson, 1996). In addition, some transmissible diseases develop more easily in cold environments. It is well-known that the transmission of air-borne viruses can be facilitated by low temperatures. Cold environments may also provide increased stability to enveloped viruses, such as influenza. This is why we observe waves of influenza throughout fall and winter. Colder temperatures may also encourage people to spend more time indoors, in closer proximity to one another and in poorly ventilated environments (Pica and Bouvier, 2014).

Consequently, ambient temperatures below or above a comfort zone of 20-25°C may be a contributing factor to the development of pathologies, and even trigger death, in particular among people with pre-existing health conditions. However, heat or cold will not be reported as the primary cause of hospitalisation or death except in the rare cases of severe hypothermia or hyperthermia. In milder cases, which likely constitute the majority of cold- or heat-related deaths, doctors are more likely to report the pathologies that might have arisen because of heat or cold exposure, such as heart attacks or influenza. For the statistician, this implies that looking directly at medical or death records for severe hypothermia and heat strokes underestimates the fraction of weather-related diseases or deaths.

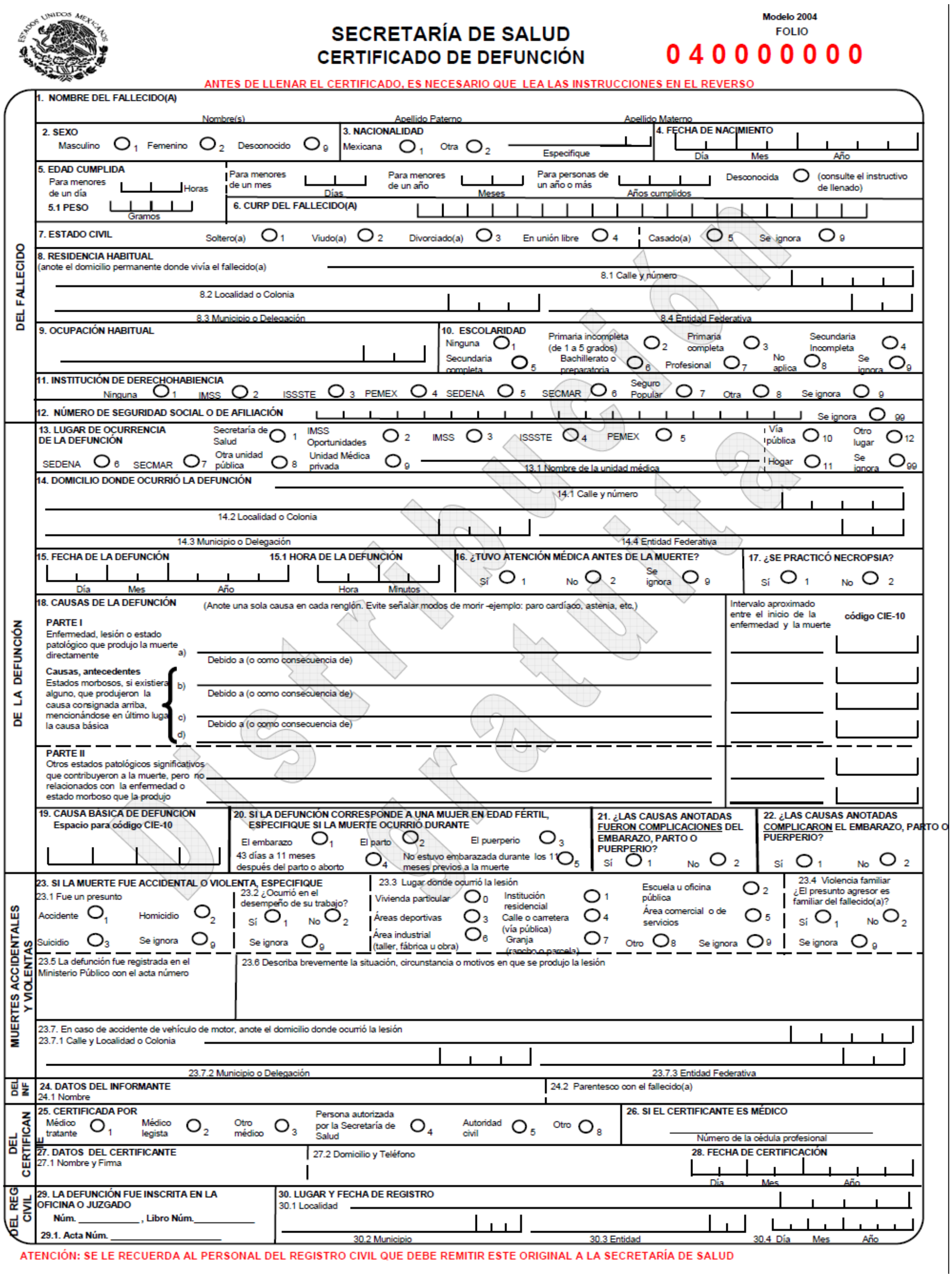
[4] Muscle mass is the essential component of heat production in the body (Horvath, 1981) whereas body fat offers additional protection to cold.

Appendix A2: Template of death certificate used in Mexico

Mexican death certificates include information on many socio-demographic variables: date of birth, gender, civil status, nationality, profession, education level and affiliation to social security. This comes in addition to the information about usual place of residence and specific details about the death, in particular the place of death, date of death, cause of death and whether the deceased received medical assistance or not before dying.

A template of death certificate is provided hereafter (in Spanish).

Figure A2: 2004 Template of a death certificate (source: INEGI)



SECRETARÍA DE SALUD
CERTIFICADO DE DEFUNCIÓN
Modelo 2004
FOLIO
040000000
ANTES DE LLENAR EL CERTIFICADO, ES NECESARIO QUE LEA LAS INSTRUCCIONES EN EL REVERSO

DEL FALLECIDO
1. NOMBRE DEL FALLECIDO(A) — Nombre(s) — Apellido Paterno — Apellido Materno
2. SEXO — Masculino 1 — Femenino 2 — Desconocido 9
3. NACIONALIDAD — Mexicana 1 — Otra 2 — Especifique
4. FECHA DE NACIMIENTO — Día — Mes — Año
5. EDAD CUMPLIDA — Para menores de un día: Horas — Para menores de un mes: Días — Para menores de un año: Meses — Para personas de un año o más: Años cumplidos — Desconocida (consulte el instructivo de llenado)
5.1 PESO — Gramos
6. CURP DEL FALLECIDO(A)
7. ESTADO CIVIL — Soltero(a) 1 — Viudo(a) 2 — Divorciado(a) 3 — En unión libre 4 — Casado(a) 5 — Se ignora 9
8. RESIDENCIA HABITUAL (anote el domicilio permanente donde vivía el fallecido(a)) — 8.1 Calle y número — 8.2 Localidad o Colonia — 8.3 Municipio o Delegación — 8.4 Entidad Federativa
9. OCUPACIÓN HABITUAL
10. ESCOLARIDAD — Ninguna 1 — Primaria incompleta (de 1 a 5 grados) 2 — Primaria completa 3 — Secundaria incompleta 4 — Secundaria completa 5 — Bachillerato o preparatoria 6 — Profesional 7 — No aplica 8 — Se ignora 9
11. INSTITUCIÓN DE DERECHOHABIENCIA — Ninguna 1 — IMSS 2 — ISSSTE 3 — PEMEX 4 — SEDENA 5 — SECMAR 6 — Seguro Popular 7 — Otra 8 — Se ignora 9
12. NÚMERO DE SEGURIDAD SOCIAL O DE AFILIACIÓN — Se ignora 99

DE LA DEFUNCIÓN
13. LUGAR DE OCURRENCIA DE LA DEFUNCIÓN — Secretaría de Salud 1 — IMSS Oportunidades 2 — IMSS 3 — ISSSTE 4 — PEMEX 5 — SEDENA 6 — SECMAR 7 — Otra unidad pública 8 — Unidad Médica privada 9 — Vía pública 10 — Hogar 11 — Otro lugar 12 — Se ignora 99 — 13.1 Nombre de la unidad médica
14. DOMICILIO DONDE OCURRIÓ LA DEFUNCIÓN — 14.1 Calle y número — 14.2 Localidad o Colonia — 14.3 Municipio o Delegación — 14.4 Entidad Federativa
15. FECHA DE LA DEFUNCIÓN — Día — Mes — Año
15.1 HORA DE LA DEFUNCIÓN — Hora — Minutos
16. ¿TUVO ATENCIÓN MÉDICA ANTES DE LA MUERTE? — Sí 1 — No 2 — Se ignora 9
17. ¿SE PRACTICÓ NECROPSIA? — Sí 1 — No 2
18. CAUSAS DE LA DEFUNCIÓN (Anote una sola causa en cada renglón. Evite señalar modos de morir -ejemplo: paro cardíaco, astenia, etc.) — Intervalo aproximado entre el inicio de la enfermedad y la muerte — código CIE-10
PARTE I — Enfermedad, lesión o estado patológico que produjo la muerte directamente a)
Causas, antecedentes — Estados morbosos, si existiera alguno, que produjeron la causa consignada arriba, mencionándose en último lugar la causa básica — b) Debido a (o como consecuencia de) — c) Debido a (o como consecuencia de) — d) Debido a (o como consecuencia de)
PARTE II — Otros estados patológicos significativos que contribuyeron a la muerte, pero no relacionados con la enfermedad o estado morboso que la produjo
19. CAUSA BÁSICA DE DEFUNCIÓN — Espacio para código CIE-10
20. SI LA DEFUNCIÓN CORRESPONDE A UNA MUJER EN EDAD FÉRTIL, ESPECIFIQUE SI LA MUERTE OCURRIÓ DURANTE — El embarazo 1 — El parto 2 — El puerperio 3 — 43 días a 11 meses después del parto o aborto 4 — No estuvo embarazada durante los 11 meses previos a la muerte 5
21. ¿LAS CAUSAS ANOTADAS FUERON COMPLICACIONES DEL EMBARAZO, PARTO O PUERPERIO? — Sí 1 — No 2
22. ¿LAS CAUSAS ANOTADAS COMPLICARON EL EMBARAZO, PARTO O PUERPERIO? — Sí 1 — No 2

MUERTES ACCIDENTALES Y VIOLENTAS
23. SI LA MUERTE FUE ACCIDENTAL O VIOLENTA, ESPECIFIQUE
23.1 Fue un presunto — Accidente 1 — Homicidio 2 — Suicidio 3 — Se ignora 9
23.2 ¿Ocurrió en el desempeño de su trabajo? — Sí 1 — No 2 — Se ignora 9
23.3 Lugar donde ocurrió la lesión — Vivienda particular 0 — Institución residencial 1 — Escuela u oficina pública 2 — Áreas deportivas 3 — Calle o carretera (vía pública) 4 — Área comercial o de servicios 5 — Área industrial (taller, fábrica u obra) 6 — Granja (rancho o parcela) 7 — Otro 8 — Se ignora 9
23.4 Violencia familiar ¿El presunto agresor es familiar del fallecido(a)? — Sí 1 — No 2 — Se ignora 9
23.5 La defunción fue registrada en el Ministerio Público con el acta número
23.6 Describa brevemente la situación, circunstancia o motivos en que se produjo la lesión
23.7. En caso de accidente de vehículo de motor, anote el domicilio donde ocurrió la lesión — 23.7.1 Calle y Localidad o Colonia — 23.7.2 Municipio o Delegación — 23.7.3 Entidad Federativa

DEL INF
24. DATOS DEL INFORMANTE — 24.1 Nombre — 24.2 Parentesco con el fallecido(a)

DEL CERTIFICANTE
25. CERTIFICADA POR — Médico tratante 1 — Médico legista 2 — Otro médico 3 — Persona autorizada por la Secretaría de Salud 4 — Autoridad civil 5 — Otro 8
26. SI EL CERTIFICANTE ES MÉDICO — Número de la cédula profesional
27. DATOS DEL CERTIFICANTE — 27.1 Nombre y Firma — 27.2 Domicilio y Teléfono
28. FECHA DE CERTIFICACIÓN — Día — Mes — Año

DEL REG CIVIL
29. LA DEFUNCIÓN FUE INSCRITA EN LA OFICINA O JUZGADO — Núm. ______, Libro Núm. ______ — 29.1. Acta Núm. ______
30. LUGAR Y FECHA DE REGISTRO — 30.1 Localidad — 30.2 Municipio — 30.3 Entidad — 30.4 Día — Mes — Año

ENTREGUE EL ORIGINAL Y LAS DOS COPIAS AL REGISTRO CIVIL PARA OBTENER EL ACTA DE DEFUNCIÓN

ATENCIÓN: SE LE RECUERDA AL PERSONAL DEL REGISTRO CIVIL QUE DEBE REMITIR ESTE ORIGINAL A LA SECRETARÍA DE SALUD

Appendix A3: Summary statistics from the 2000 Mexican Census

Table A3: Socioeconomic characteristics of the Mexican population based on 2000 Census

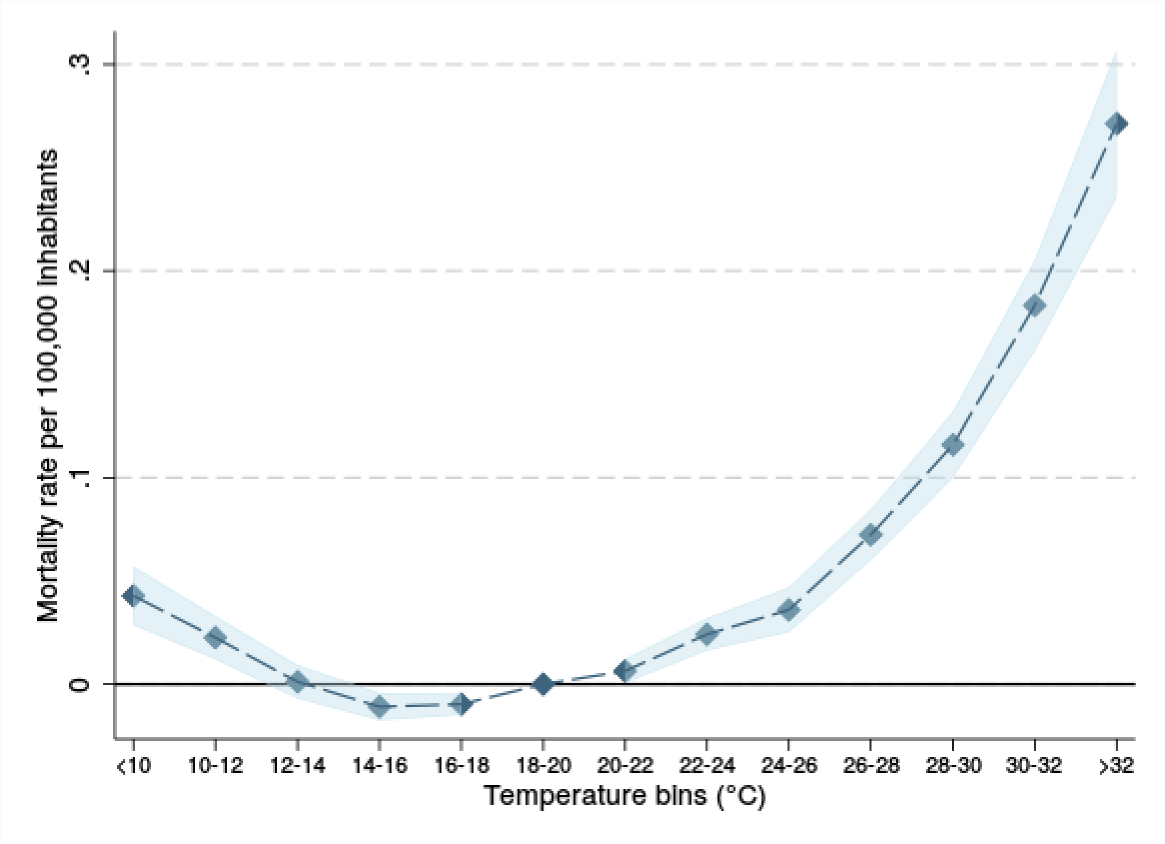
Population	Personal income*	No social security	Completed secondary school†	Age	Male	Share of population
Total	2,876	58.6%	37.1%	26.2	48.7%	100.0%
Rural	1,433	83.7%	17.3%	25.0	49.6%	25.4%
Urban	3,330	50.1%	43.8%	26.5	48.4%	74.6%
By quartile of income						
1st quartile	437	82.9%	18.6%	24.7	48.2%	25.0%
2nd quartile	1,155	60.8%	31.5%	24.5	48.7%	25.0%
3rd quartile	2,119	47.4%	42.3%	26.0	49.2%	25.0%
4th quartile	7,816	36.2%	59.7%	28.6	49.3%	25.0%
By type of profession						
Workers in agriculture, fisheries and hunting activities	1,552	87.1%	18.1%	38.2	92.7%	5.2%
Do not work (under 16)	2,371	62.5%	14.4%	7.7	50.0%	37.3%
Assistants in industrial and handmade production	2,397	62.1%	44.9%	28.5	85.3%	1.5%
Do not work (over 65)	2,647	49.4%	10.9%	74.4	36.5%	4.1%
Do not work (16-65)	2,648	62.4%	47.5%	34.3	21.2%	25.9%
Street vendors	2,679	81.4%	41.5%	38.6	68.8%	0.7%
Workers in industry of transformation	2,784	64.0%	46.9%	34.9	85.7%	5.5%
Workers in army and civil protection	3,059	21.4%	66.3%	36.5	94.3%	0.8%
Drivers of mobile machines and transports	3,061	54.6%	59.5%	35.8	99.3%	1.6%
Workers in personal services in institutions	3,116	47.0%	53.2%	34.2	60.4%	1.9%
Fixed machine operators	3,323	15.6%	61.3%	28.7	61.9%	1.9%
Domestic workers	3,753	78.2%	27.4%	34.0	12.2%	1.4%
Sellers, employees in trade and salesmen	3,817	57.9%	67.5%	35.0	60.6%	3.8%
Low-skilled workers in administrative tasks	4,124	24.1%	91.3%	31.0	38.4%	2.3%
Technicians	4,641	26.4%	91.4%	33.8	56.0%	1.0%
Overseers in industrial production	5,045	16.4%	84.0%	34.4	79.7%	0.6%
Workers in education	5,662	15.0%	98.9%	36.8	39.8%	1.4%
Medium-skilled workers in administrative tasks	5,973	18.3%	93.5%	35.8	67.6%	0.8%
Workers in art, sports and events	6,176	58.0%	81.3%	34.7	74.9%	0.3%
Certified professionals	7,758	32.0%	99.8%	36.5	63.2%	1.3%
Public servants and directors	10,453	29.0%	95.8%	39.7	74.0%	0.7%

Notes. The table shows average values of socioeconomic characteristics of the Mexican population based on the 2000 Census. Statistics are calculated using the sample weights provided by INEGI. *: Personal income (in 2000 Mexican pesos) is calculated as family income divided by the square root of the total number of people in the household. This calculation method allows accounting for economies of scale in larger households. †: includes people that were completing secondary school.

Appendix A4: Contemporaneous effect

Due to an omitted variable bias, correlating today's temperatures with today's mortality will lead to biased estimates of the impact of temperature on mortality if no account of the temperatures of the previous days is made. Figure A4 displays the impact of the day's temperature on mortality for all Mexicans and all causes of death when no lagged temperature bins are included in the model. This can help the reader assess the magnitude and the direction of the bias produced in this case. The Mexican population appears to be very sensitive to high temperatures above 28°C. A statistically significant impact of temperatures below 12°C is also detected. However, an extremely hot day above 32°C is six times more lethal than an unusually cold day below 10°C. Therefore, the model with contemporaneous temperatures underestimates the effect of cold and over-estimates the impact of heat.

Figure A4: Impact of the day's average temperature on daily mortality, in deaths per 100,000 inhabitants



Notes. The dependent variable is the daily mortality rate at the municipality level. The graph shows the contemporaneous effect of a day with a temperature within each bin (relative to the 18°C-20°C category). The diamonds show the average point estimate, reported in deaths per 100,000 inhabitants on the y-axis. The shaded area corresponds to the 95 percent confidence interval. 467,329 groups and 30.1 observations per group on average. The regression controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects. It is weighted by municipal population.

Appendix A5: Impacts by gender, age and cause of death

Table A5 displays the 31-day cumulative impact of a day with average temperature below 10°C in Panel A and the impact of a day with average temperature above 32°C in Panel B.

Table A5: Impact of a day under 10°C and above 32°C on cumulative mortality

	Cause of death						
Group	All causes	Infectious diseases	Neoplasms	Endocrine, nutritional and metabolic diseases	Circulatory system diseases	Respiratory system diseases	Violent and accidental
Panel A: Impact of a day under 10°C							
Total	0.717 (0.0375)	0.012 (0.0048)	0.003 (0.0092)	0.164 (0.0125)	0.209 (0.0159)	0.174 (0.013)	0.0366 (0.0104)
Men	0.775 (0.0497)	0.0135 (0.0082)	0.0123 (0.0121)	0.154 (0.016)	0.224 (0.0224)	0.189 (0.0156)	0.0357 (0.0198)
Women	0.659 (0.0387)	0.0104 (0.0045)	-0.0058 (0.0114)	0.174 (0.0156)	0.194 (0.0174)	0.159 (0.016)	0.0374 (0.0091)
Aged 0-4	0.659 (0.0813)	0.0808 (0.025)	0.0023 (0.0066)	0.0224 (0.0119)	0.0081 (0.0082)	0.29 (0.0333)	0.101 (0.0222)
Aged 4-9	0.0059 (0.0158)	0.0021 (0.0035)	-0.0104 (0.0062)	0.0027 (0.0034)	0.0015 (0.0037)	0.0019 (0.0048)	0.008 (0.0098)
Aged 10-19	0.0369 (0.0184)	0.0058 (0.0033)	-0.0084 (0.0065)	0.0062 (0.003)	-0.0096 (0.0036)	0.0114 (0.004)	0.0171 (0.0139)
Aged 20-34	0.106 (0.0313)	-0.0056 (0.0055)	0.0088 (0.0085)	0.0104 (0.0051)	0.0109 (0.0063)	0.0062 (0.0046)	0.0608 (0.0255)
Aged 35-44	0.159 (0.0568)	-0.0133 (0.0119)	0.0275 (0.0146)	0.0498 (0.0158)	0.0239 (0.0156)	0.017 (0.0128)	-0.0279 (0.0284)
Aged 45-54	0.536 (0.0962)	0.008 (0.017)	-0.0624 (0.0344)	0.236 (0.0385)	0.137 (0.0458)	0.0733 (0.0197)	-0.0165 (0.0366)
Aged 55-64	1.26 (0.173)	0.0099 (0.0279)	-0.0362 (0.0814)	0.456 (0.0778)	0.437 (0.0901)	0.247 (0.0454)	0.0214 (0.0401)
Aged 65-74	2.11 (0.289)	0.0165 (0.0465)	-0.0591 (0.136)	0.764 (0.131)	0.734 (0.152)	0.412 (0.0763)	0.0355 (0.0666)
Aged 75+	16.0 (0.838)	0.189 (0.0809)	0.247 (0.217)	2.78 (0.333)	5.82 (0.434)	4.28 (0.359)	0.38 (0.114)
Panel B: Impact of a day above 32°C							
Total	0.204 (0.0376)	0.006 (0.0041)	0.0217 (0.0102)	0.0296 (0.0136)	0.0437 (0.0205)	0.01 (0.0165)	0.0379 (0.0146)
Men	0.238 (0.0505)	0.0067 (0.0073)	0.0194 (0.0165)	0.0229 (0.0167)	0.0698 (0.024)	0.0178 (0.0261)	0.0504 (0.027)
Women	0.172 (0.0465)	0.0053 (0.0049)	0.0239 (0.0178)	0.0364 (0.0217)	0.0176 (0.0249)	0.0023 (0.0113)	0.0258 (0.0111)
Aged 0-4	0.0911 (0.0614)	-0.0046 (0.0145)	-0.0095 (0.0078)	0.002 (0.011)	-0.0023 (0.0061)	0.0071 (0.015)	0.0001 (0.0197)
Aged 4-9	0.0062 (0.0184)	-0.0068 (0.0045)	0.0041 (0.007)	-0.0018 (0.004)	-0.0019 (0.005)	0.0011 (0.0034)	0.0033 (0.019)
Aged 10-19	0.0387 (0.0208)	-0.00176 (0.003)	0.0026 (0.0073)	0.008 (0.0037)	-0.003 (0.0046)	0.0008 (0.0028)	0.0315 (0.0189)
Aged 20-34	0.082 (0.0493)	-0.009 (0.009)	0.004 (0.0074)	0.0087 (0.0077)	-0.0016 (0.0118)	0.0088 (0.0123)	0.0659 (0.0282)
Aged 35-44	0.0884 (0.0589)	-0.0072 (0.013)	0.0178 (0.0243)	-0.0123 (0.0163)	0.0301 (0.0242)	0.0431 (0.0235)	0.0186 (0.0485)
Aged 45-54	0.301 (0.132)	0.0402 (0.0235)	0.0745 (0.0395)	0.0819 (0.0345)	0.0585 (0.0531)	0.0129 (0.0339)	0.0549 (0.0502)
Aged 55-64	0.393 (0.162)	-0.0326 (0.0318)	0.0583 (0.0987)	0.029 (0.0964)	0.159 (0.12)	-0.0232 (0.0311)	0.0436 (0.0647)
Aged 65-74	0.653 (0.268)	-0.0534 (0.0525)	0.097 (0.163)	0.0493 (0.159)	0.265 (0.196)	-0.0379 (0.051)	0.0723 (0.106)
Aged 75+	3.31 (0.976)	0.209 (0.0995)	0.189 (0.26)	1.04 (0.448)	0.554 (0.569)	-0.0072 (0.314)	0.0983 (0.167)

Notes: In each panel, all the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C (panel A) or above 32°C (panel B) on mortality, for specific age groups and causes of death. The dependent variable is always the daily mortality rate in deaths per 100,000 inhabitants and all regressions include the daily precipitation level as control, along with municipality by month and year fixed effects. Standard errors in brackets (clustered at municipality level). Reference day is 24-26 Celsius degrees. Regressions are weighted by the relevant municipal population.

Appendix A6: Years of life lost estimates

The estimates by age group are informative about the impact of cold on longevity. We calculate the annual total of years of life lost associated with outdoor temperature exposure for the Mexican population by using the life expectancy estimates of the Mexican life table of 2010 available from the Global Health Observatory data repository. Results are calibrated based on the death estimates of Table 3, which assume a population of 129 million (2017 estimate). Results are synthesized in Table A6. Unusually cold days seem to impact age groups quite equally, while mildly cold days mostly affect people over 45. The number of years of life lost due to cold days under 10°C is higher for children under 5 than and people over 75 years old. For days between 10°C and 20°C, we find that the number of years of life lost is larger for people over 75 than for any age group, but people over 45 and children under 5 are also strongly impacted. Deschenes and Moretti (2009) provide similar calculations of years of life lost for the US. In total, they find that people over 75 lose 106,405 years of life annually. However, the cumulative number of years of life lost in a year for children under 5 is only 5,410. The impact of cold weather on infant mortality is therefore much higher in the case of Mexico. We also find high impacts for people above 55. This result implies that priorities for policy makers in both countries should be different. US policies to reduce weather-related mortality may need to focus on the elderly, whereas emerging countries like Mexico may need to tackle mortality effects across a wider age range.

Table A6: Years of life lost estimates by age group and temperature level

Age group	<10°C	10-20°C	>32°C
0-4	25,888*	125,549*	819
5-9	-862	-65,170	-380
10-19	2,362	19,792	1,123
20-34	7,563*	46,817	2,536
35-44	7,295*	89,790*	2,047*
45-54	13,820*	192,417*	3,842*
55-64	16,527*	309,276*	3,257*
65-74	11,274*	209,505*	2,195*
75+	23,334*	317,090*	2,657*

Note: These are estimates of the total number of years of life lost for each age category. They are obtained by multiplying the estimated number of deaths in table 3 with the remaining life expectancy of each age group. Life expectancy is obtained from the life table of 2010 for Mexico, which is accessible from the Global Health Observatory data repository. Note that the calculation of the years of life lost assumes the same life expectancy for those who died from cold as for those who did not. This is an approximation with no consequence on the international comparison: the US figures were obtained based on the same assumption (Deschenes and Moretti, 2009). However, we may overestimate the total years of life lost. An asterisk (*) denotes statistically significant results at 10%.

Appendix A7: Impacts of Climate Change

We calculate the number of weather-related deaths under climate change based on the output of the climate model GFDL CM3 for 2075-2099. Annual death estimates under climate change are provided in Table A7.[5] Because the frequency of cold and mildly cold days is expected to decrease, the number of deaths imputable to temperatures reduces with the forecasted temperatures of GFDL CM3 as compared with the historical ones. With the RCP2.6 scenario (low GHG emissions), temperature-related mortality would be 33% smaller. The RCP8.5 scenario (high GHG emissions) yields a 50% reduction in the estimated relationship between mortality and temperature. We show in section IV.B that weather-related mortality affects mostly people in the first two quartiles of the income distribution, suggesting that the reduction in the exposure to cold weather associated by climate change could lead to a reduction in mortality inequality. Therefore, in Mexico, we predict that climate change will reduce the impact of short-term weather variability on mortality, with significant health benefits. However, this analysis comes with serious warnings: climate change could also affect mortality through increased frequency of natural catastrophes and not only through temperatures; our analysis at the daily level does not allow for acclimatization; and we could be underestimating the impact of increased heat waves if the effect of heat grows non-linearly beyond 32°C days. In addition, our model includes municipality-by-month-by-year fixed effects which control for income and for the general health of the population. Climate change may impact income, or the general health of the population, and these factors may in turn impact mortality.

Table A7: Impact of temperatures on annual deaths in several climate scenarios

Number of deaths	Estimates	95% Confidence interval
Historical	74,922	61,605–88,238
GFDL CM3:		
RCP2.6	49,547	38,456–60,639
RCP4.5	43,670	33,241–54,099
RCP8.5	37,735	27,861–47,609

Note: The 95% confidence intervals only take into account the uncertainty of the impact of temperature bins on mortality. They do not take into account the uncertainty of climate models in the distribution of daily temperatures.

[5] The distributions for hot and cold days obtained with this climate model are reported in Figure 1.

B – ROBUSTNESS CHECKS

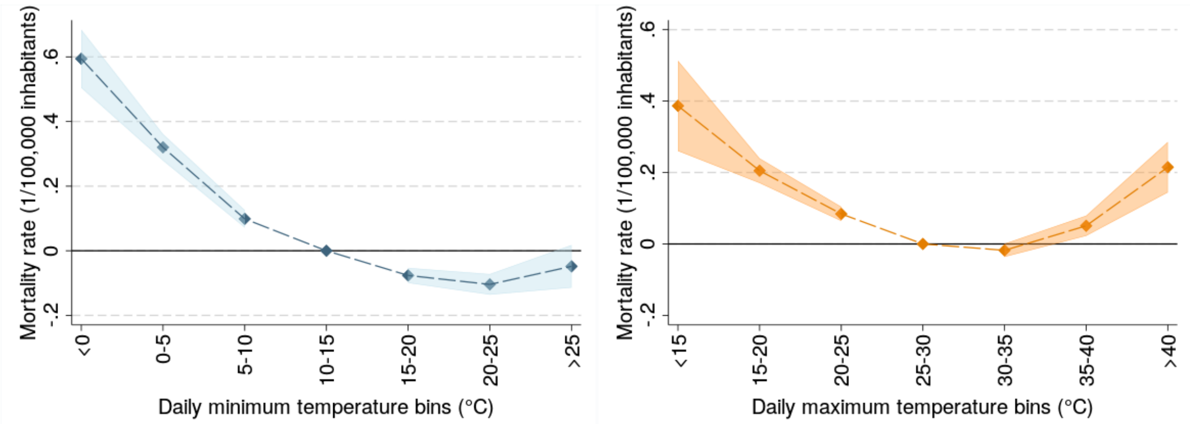
Appendix B1: Minimum vs. maximum temperature

In the baseline model, we correlate mortality with the average temperature in a day. No consideration is made for within-day variation. Yet, intra-day variation is large (see Table B1). To investigate this issue, we run a specification of the distributed lag model where we calculate separate effects for minimum and maximum temperatures. The profile of point estimates is very similar to the baseline results using average daily temperature.

Table B1: Intra-day variation by temperature bin, as characterized by the difference in average daily minimum and maximum temperature bins in our data

	Daily minimum temperature		Daily maximum temperature	
Temperature bin	Average	Standard deviation	Average	Standard deviation
<10°C	1.1	3.7	15.7	3.9
10-12°C	3.2	2.8	19.2	2.8
12-14°C	5.2	2.6	21.2	2.5
14-16°C	7.4	2.5	22.9	2.4
16-18°C	9.4	2.4	24.7	2.4
18-20°C	11.5	2.4	26.7	2.4
20-22°C	13.6	2.3	28.5	2.3
22-24°C	15.6	2.3	30.5	2.3
24-26°C	18.0	2.3	32.1	2.3
26-28°C	20.4	2.0	33.8	2.0
28-30°C	22.1	1.8	35.8	1.9
30-32°C	23.3	1.7	38.4	1.8
>32°C	24.9	1.9	41.3	2.0
Total	12.8	6.0	27.7	5.4

Figure B1: Impact of minimum (left panel) and maximum (right panel) daily temperatures on 31-day cumulative mortality, in deaths per 100,000 inhabitants.

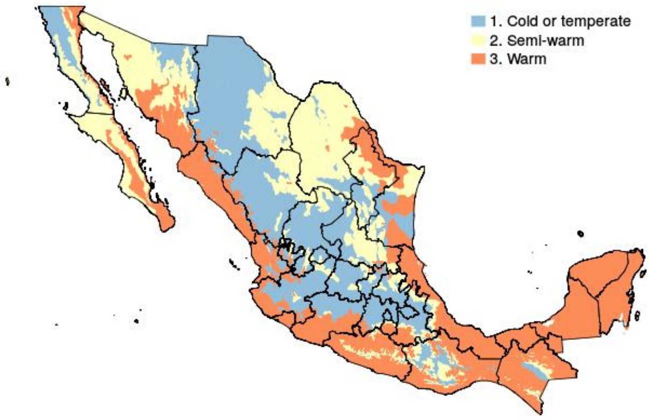


Notes. The dependent variable is the daily mortality rate at the municipality level. The graph shows the cumulative, 31-day effect of a day with a temperature falling within each bin. The diamonds show the 31-day multiplier and it is reported in deaths per 100,000 inhabitants on the y-axis. The estimates displayed on the left panel (minimum temperature) and right panel (maximum temperature) have been estimated jointly and come from the same fixed effect regression. Therefore, the impact of a given day on mortality is given by the effect of the minimum temperature on this day, plus the effect of the maximum temperature on this day. Shaded areas correspond to the 95 percent confidence intervals (standard errors clustered at municipality level). The regression controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects. It is weighted by municipal population.

Appendix B2: Acclimatization

Effects by climate region. The INEGI provides a detailed map of Mexico with a typology of 21 climates. We have simplifiedS this typology and broken down Mexico into 3 climate categories (see Figure B2.1): very warm and warm (covering very dry, dry, semi-dry, humid and semi-humid regions that are also very warm and warm); semi-warm; cold and temperate (covering cold, semi-cold and temperate regions).

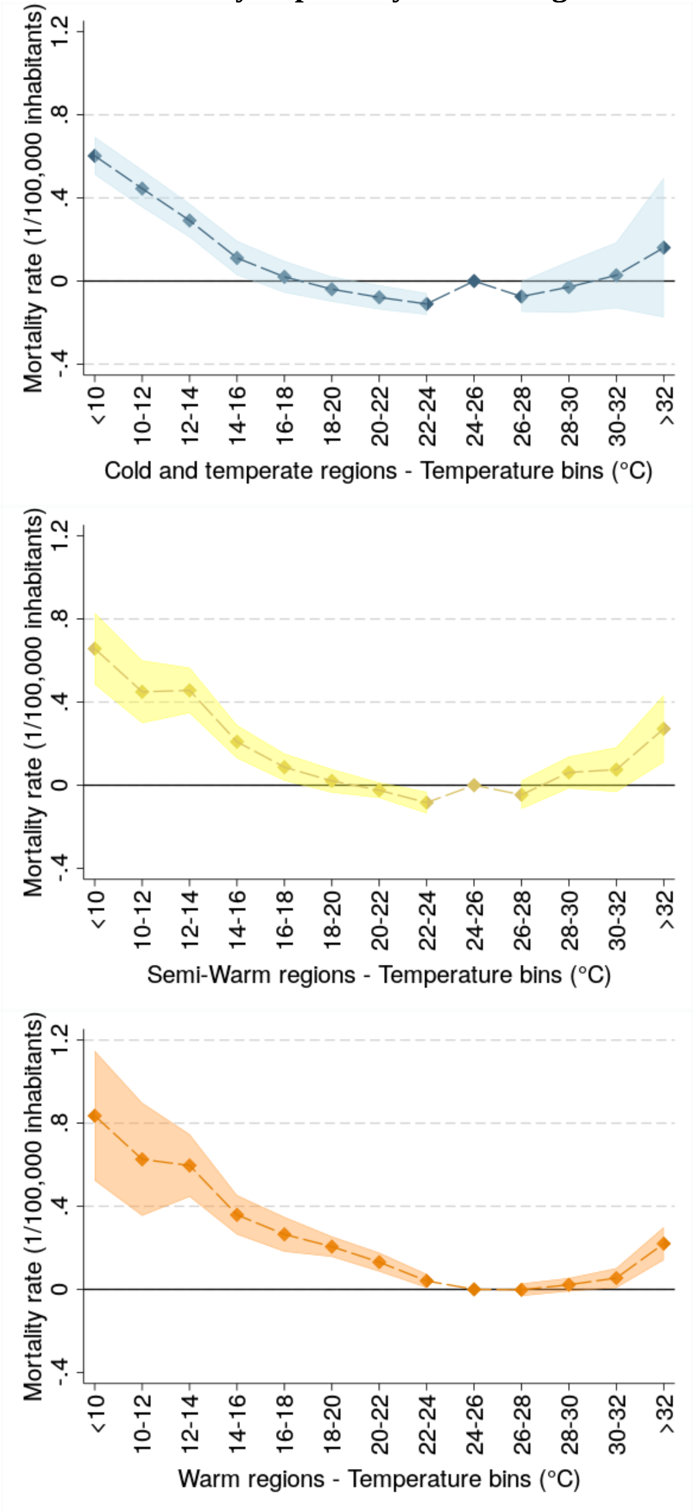
Figure B2.1: Map of Mexico distinguishing between climates



We have matched the boundaries of the Mexican municipalities with the boundaries of our three climatic categories. Our matching strategy assigns a climate to each point of the polygon that corresponds to the boundaries of a municipality. For each municipality, we calculate the share of delimiting data points that fall in a given climate. We then run three regressions by weighting observations based on this share. The output of the separate regressions is provided in Figure B2.2.

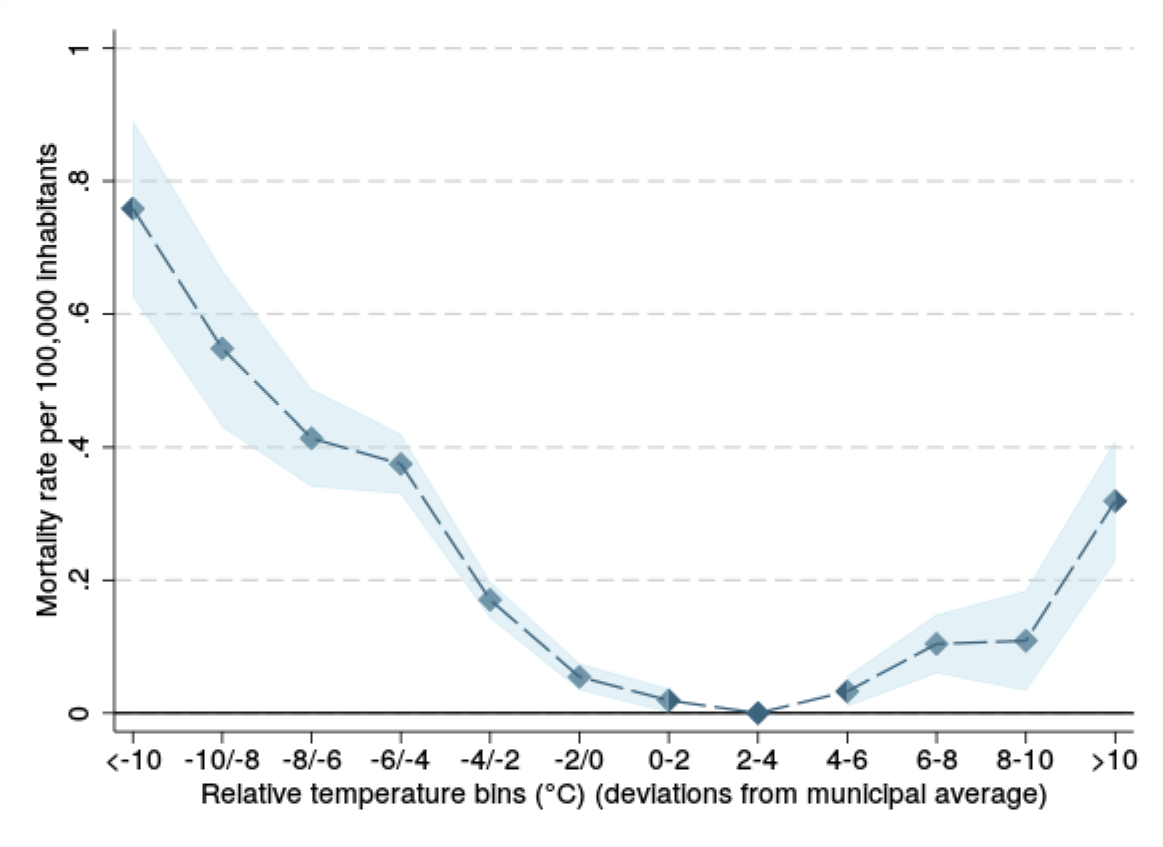
Relative temperature bins. We run a series of specifications where we assume that the impact of temperature on mortality depends on the difference between the temperatures faced during a given day and the ones that are usually experienced: instead of using absolute temperature bins, we calculate deviations from the average temperature in each location to construct relative temperature bins with a 2°C window. The average temperature in each municipality is obtained by averaging all daily temperatures over 1961-2018. Then we rerun our distributed lag model with the newly constructed temperature bins. These include deviations between -10°C and +10°C with respect to the average of each municipality. The 31-day cumulative results for all the population and causes of deaths are displayed in Figure B2.3. Results likewise show a strong impact of cold and mildly cold days on mortality.

Figure B2.2: Mortality impacts by climate region in Mexico



Notes: The graphs show the cumulative effect of a day with a temperature within each bin (relative to the 24°C-26°C category) obtained from a dynamic model with 30 lags, for three different types of regions, sorted according to their climate: cold and temperate regions (upper panel), semi-warm regions (central panel), and warm regions (lower panel). The diamonds show the sum of the coefficients on these thirty lags in each temperature bin. Shaded areas correspond to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regressions control for daily precipitation level and include a range of municipality-by-year-by-month fixed effects.

Figure B2.3: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, using relative temperature bins

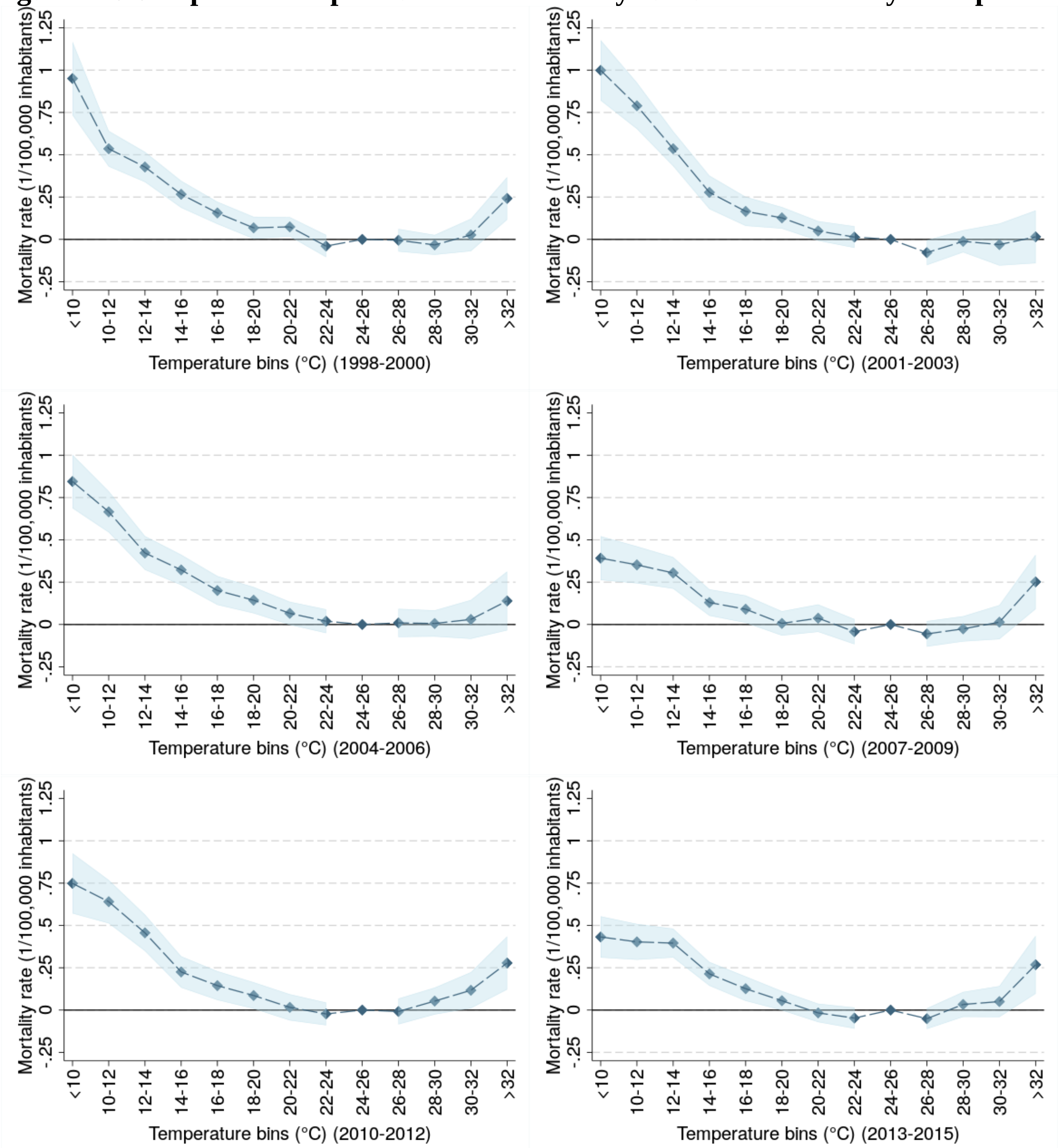


Notes. The graph shows the cumulative effect of a day with a relative temperature within each bin (relative to the +2°C-4°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regression controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects. It is weighted by municipal population.

Appendix B3: Heterogeneous effects

Splitting the sample into six periods. On Figure B3.1, we run our model on six periods: 1998-2000, 2001-2003, 2004-2006, 2007-2009, 2010-2012 and 2013-2017. We find a significant decrease in weather-related vulnerability between 1998 and 2009. The decrease coincides with the implementation of the *Seguro Popular* from 2004 onwards. However, these results cannot be interpreted as the causal impact of the *Seguro Popular*. In addition, there seems to be some resurgence in the temperature-mortality relationship in 2010-2012.

Figure B3.1: Impact of temperature bins on 31-day cumulative mortality for 6 periods

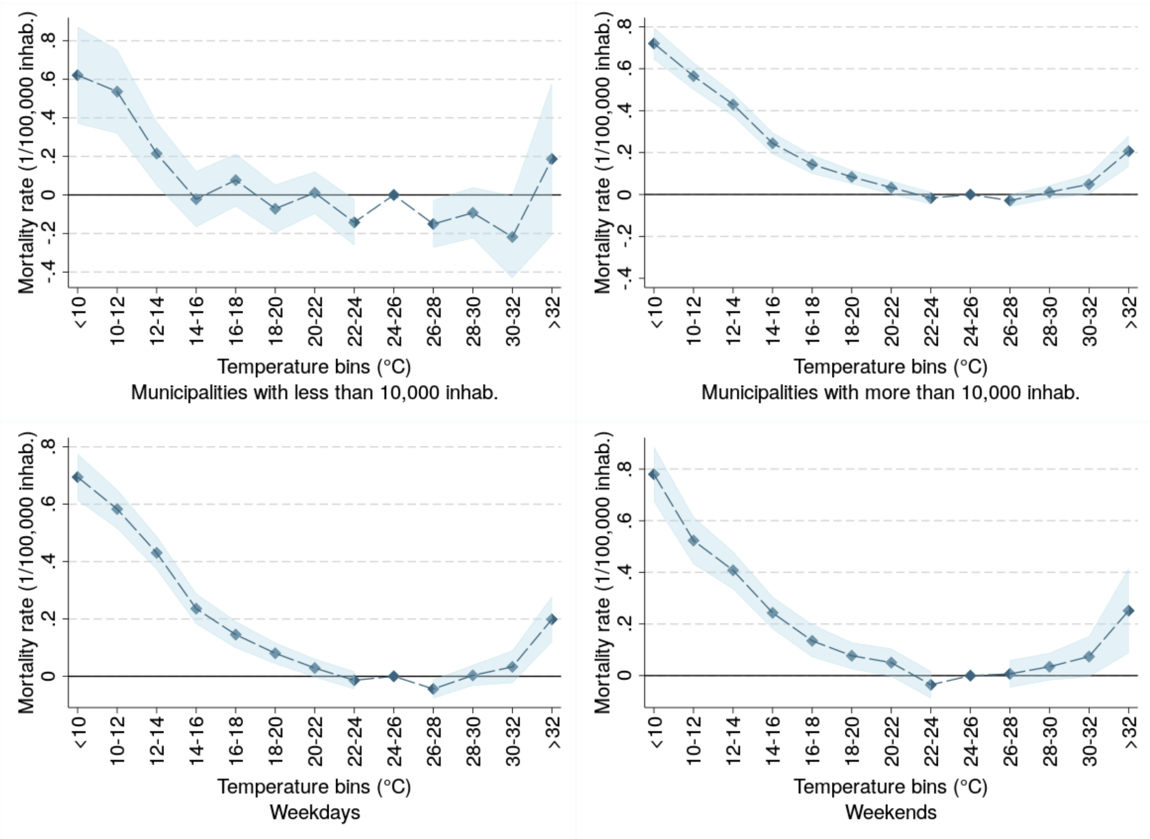


Notes: The graphs are calculated separately for six periods. They show the cumulative effect of a day with a temperature within each bin (relative to the 24°C-26°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. Shaded areas correspond to the 95% confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regressions controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects. They are weighted by municipal population.

Rural versus urban areas. We look here if short-run vulnerability to temperatures may differ between people living in large vs. small municipalities. Results are displayed on the upper panels of Figure B3.2. Impacts are inefficiently estimated for small municipalities. Yet, they suggest similar vulnerability to unusual cold weather for small and large municipalities.

Effects for weekdays and weekends. The lower panels of Figure B3.2. below provide the 31-day cumulative mortality estimates for hot and cold days, depending on whether they fell during a weekday (lower left panel) or the weekend (lower right panel).

Figure B3.2: Impact of temperature bins on 31-day cumulative mortality in small vs. large municipalities, and on weekdays vs. weekends.

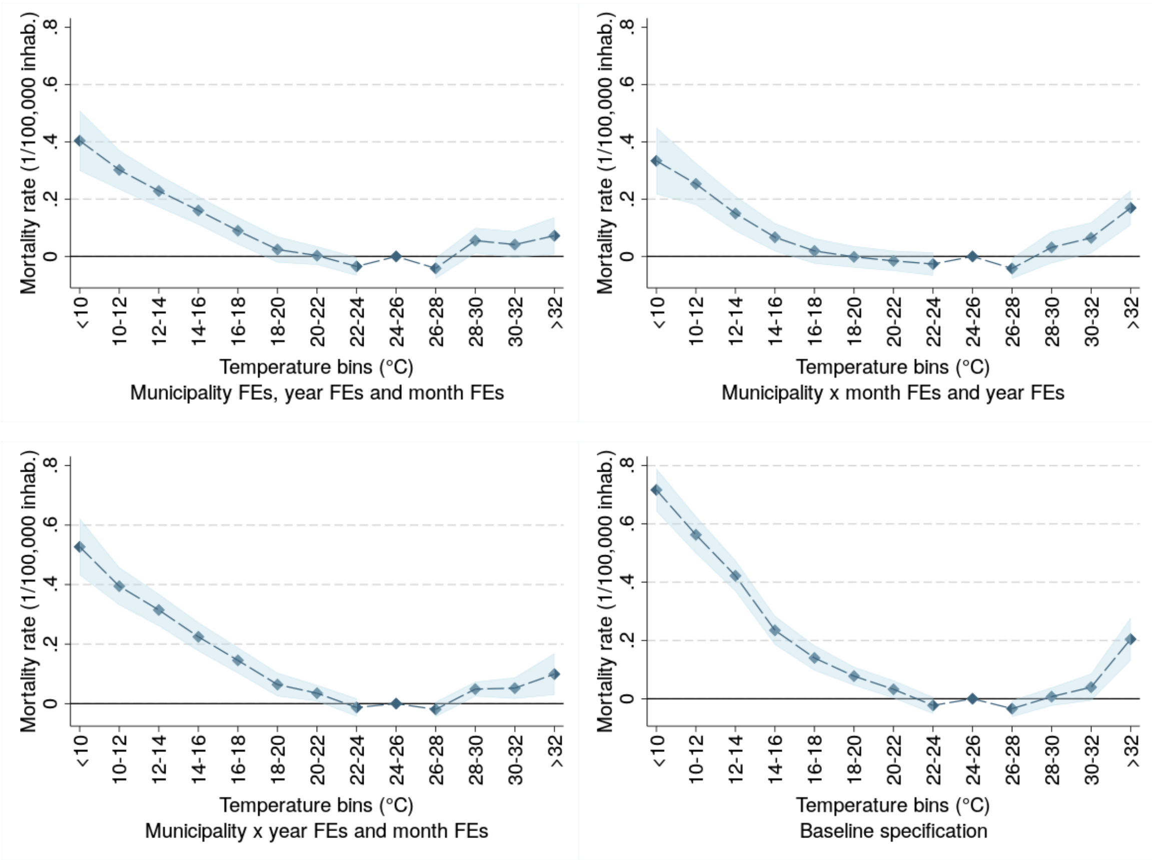


Notes. The graphs have been obtained separately. They show the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags run for populations living in municipalities with less than 10,000 inhabitants (upper left panel) or more than 10,000 inhabitants (upper right panel). Regressions in the lower panels estimate the temperature-mortality relationship separately for weekdays (lower left panel) and weekends (lower right panel). The diamonds show the sum of the coefficients on these thirty lags in each category. Shaded areas correspond to the 95% confidence interval. The dependent variable is daily mortality rate at the municipality level. The regressions control for daily precipitation level and include a range of municipality-by-year-by-month fixed effects. All regressions are weighted by municipal population.

Appendix B4: Alternative fixed effects

In this section, we use different structures for the fixed effects. In the base specification, we have used fully interacted, municipality-by-year-by-month fixed effects. This restrains the comparison of mortality effects to days within the same month of the year within a given municipality and disregards the fact that changes in temperature may affect seasonal patterns, and in turn mortality. Above all, we could underestimate the mortality impacts of direct exposure to temperature in very cold or very hot months by comparing very cold days with already cold days, and very hot days with already hot days within a month. To the contrary, we find that relaxing the controls for within-municipality seasonal patterns attenuates estimated impacts (Figure B4.2).

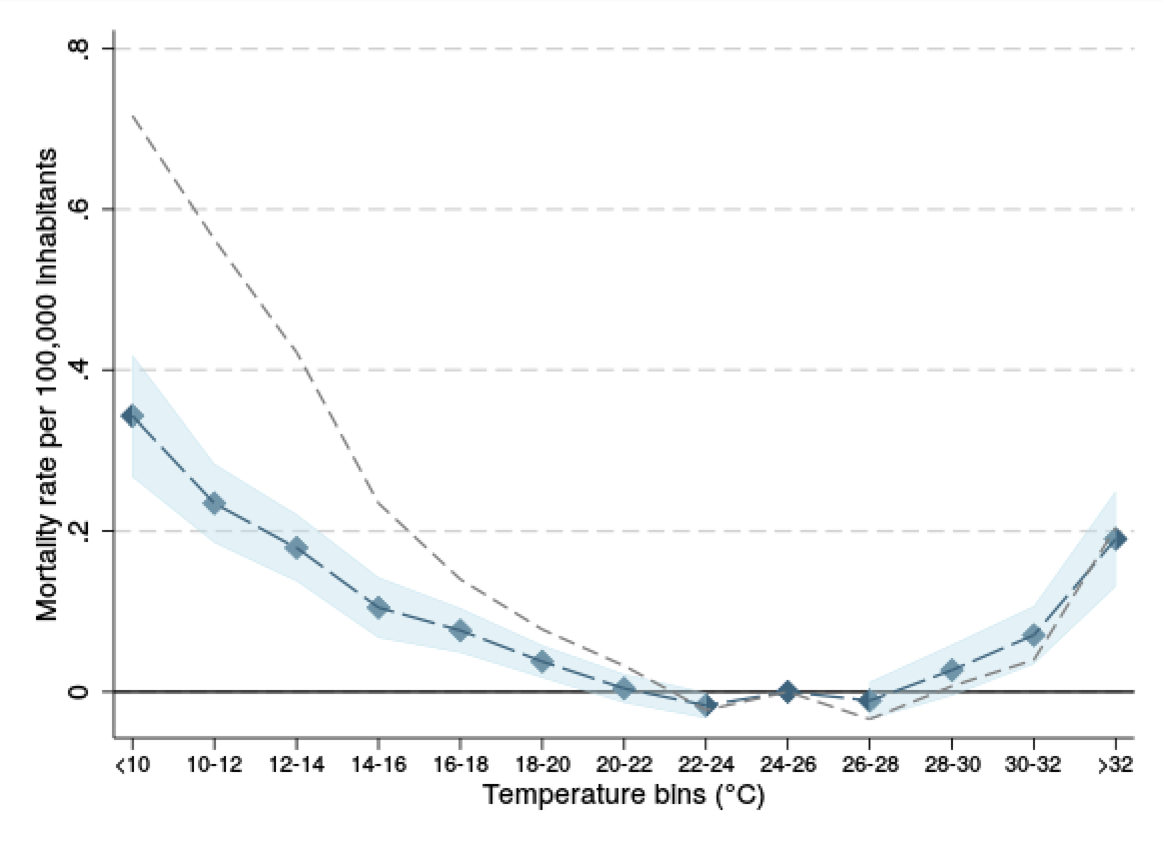
Figure B4.2: Impact of temperature (in °C) on mortality using different sets of fixed effects



Notes. The graphs have been obtained separately. They show the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags. All regressions use the mortality rate in deaths per 100,000 inhabitants as dependent variable and the diamonds show the sum of the coefficients on these thirty lags. The difference in the four panels comes from the nature of the fixed effects used (described below each panel). Shaded areas correspond to the 95% confidence interval. All regressions control for daily precipitation levels. All regressions are weighted by municipal population.

Another concern is that our model does not control for the average mortality levels recorded on specific days. Hereafter, we try a specification with three types of fixed effects: 1) day by month by year fixed effects (e.g. 21st January 2001 vs. 22nd January 2001); 2) municipality by day by month fixed effects (e.g. Tijuana on 21st January vs. Tijuana on 22nd January); and 3) municipality by year fixed effects. Results are reported on Figure B4.3 and estimated impacts are lower than with our baseline specification (dashed lines). This specification would predict an average 31,000 deaths from cold days (<20°C), including 2,300 deaths per year from unusual cold (<10°C), and 1,400 deaths from hot days (>30°C). Therefore, the overall magnitude of mildly cold versus hot days remains, but the impact of mildly cold days is attenuated.

Figure B4.3: Specification with (1) day by month by year fixed effects, (2) municipality by day by month fixed effects, and (3) municipality by year fixed effects.



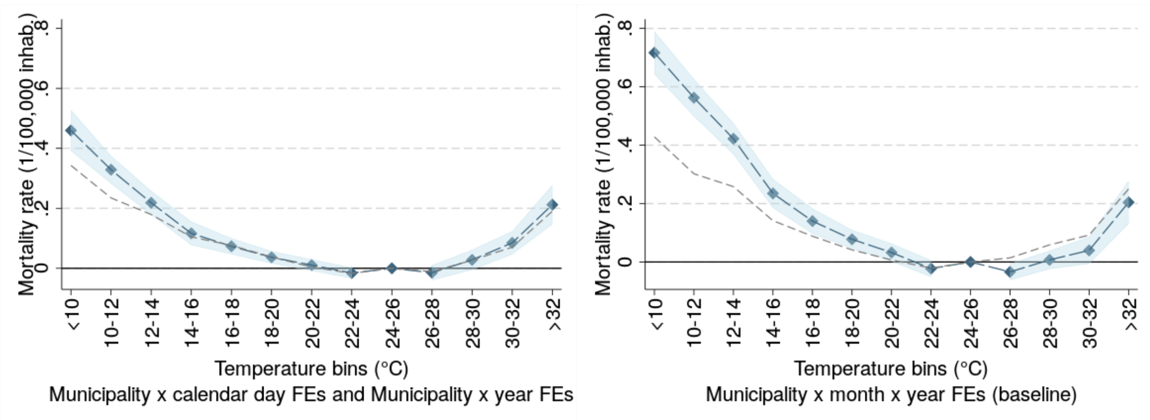
Notes. The graph shows the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags. The regression uses the mortality rate in deaths per 100,000 inhabitants as dependent variable and the diamonds show the sum of the coefficients on these thirty lags. The model includes 1) day by month by year fixed effects; 2) municipality by day by month fixed effects; and 3) municipality by year fixed effects. The shaded area corresponds to the 95% confidence interval, while the dashes in gray correspond to the results of our baseline specification. The regression controls for daily precipitation levels and is weighted by municipal population.

We suspect that this specification might capture some of the mortality effects of cold temperatures because of the day-month-year fixed effects. While absolute temperatures strongly differ across geographies and climates, temperature anomalies (i.e. differences to the mean) are known to be very stable across space. A model with day-month-year fixed effects could therefore attenuate impacts if it captures the effect of the average daily temperature anomaly on mortality.

In order to explore this further, we investigate the impact that adding day-month-year fixed effects has on mortality estimates by (1) removing those fixed effects from the above specification; and (2) adding those fixed effects to our baseline specification with municipality by month by year fixed effects.

The left panel of Figure B4.4 presents the results of a model with municipality by calendar day and municipality by year fixed effects, but no day-month-year fixed effects (the specification of Figure B4.3 without the day-month-year fixed effects). In dashed lines, we provide the results of Figure B4.3 (with day-month-year fixed effects). The right panel of Figure B4.4 provides the results of our baseline specification (with municipality by month by year fixed effects). In dashed line, we provide the point estimates obtained when adding day-month-year fixed effects to our baseline specification. Results in Figure B4.4 imply that adding day-month-year fixed effects (the dashed line on each Figure) attenuates results in both cases.

Figure B4.4: Specifications with and without day-month-year fixed effects

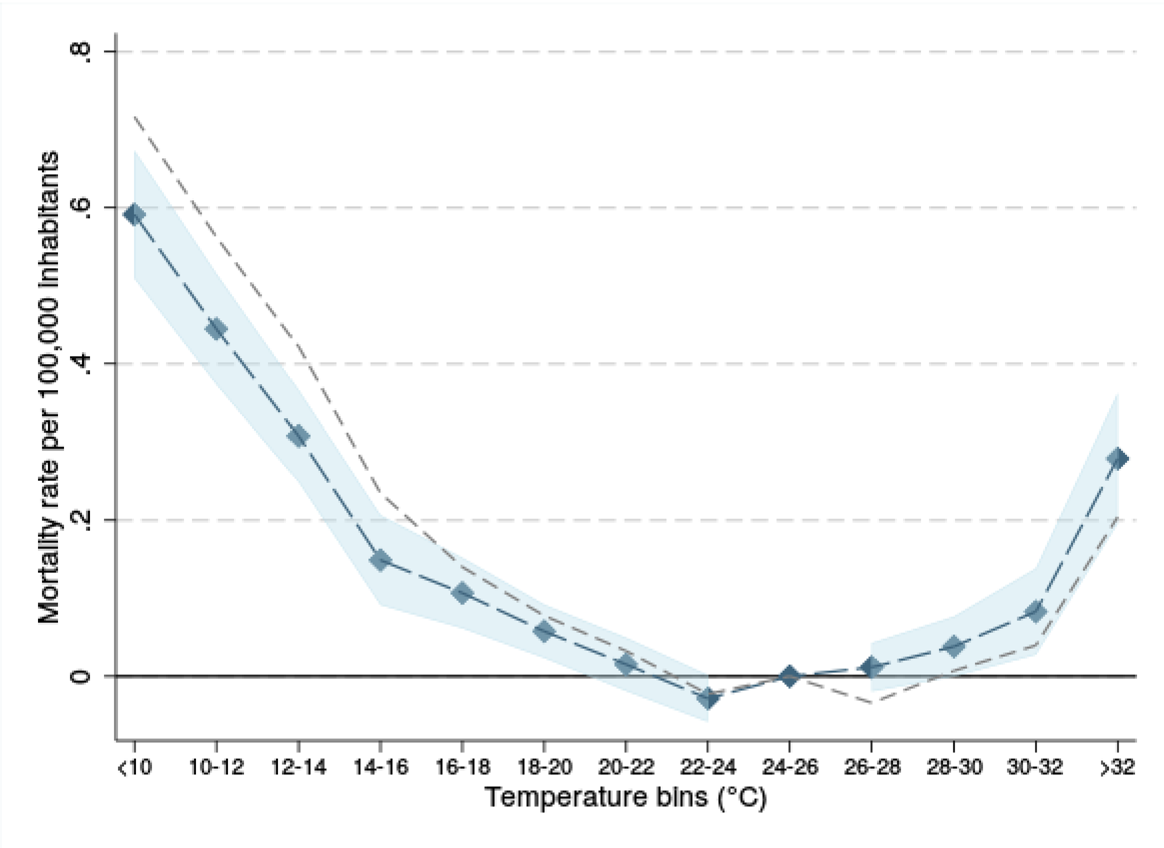


Notes. The graphs have been obtained separately. They show the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags. All regressions use the mortality rate in deaths per 100,000 inhabitants as dependent variable and the diamonds show the sum of the coefficients on these thirty lags. The difference in the two panels comes from the nature of the fixed effects used (described below each panel). The shaded area corresponds to the 95% confidence interval, while the dashes in grey are obtained by adding day by month by year fixed effects to the specification displayed in each panel. All regressions control for daily precipitation levels. All regressions are weighted by municipal population.

Between the model on the left and the model on the right of Figure B4.4, we chose to use the model on the right as baseline specification. The left-panel specification compares mortality on specific days (e.g. March 12th) across different years (1998 vs. 1999, 2000 and so on). Climate change and demographic change (especially population ageing) are concomitant. Therefore, the probability of hot days correlates with demographic change. We can expect this to lead to an over-estimation of the impact of hot days and an underestimation of the impact of cold days, or vice-versa. It is not obvious that the municipality by year fixed effects can fully correct for this, because the probability of a hot day occurring in municipality *i* varies within a year, making municipality-year fixed effects an imperfect set of control variables. This is why we prefer the model with municipality by month by year fixed effects.

However, our baseline specification does not account for seasonality at daily level. To check that this creates no strong bias, we run a last specification in Figure B4.5. In this specification, we add municipality by calendar day fixed effects to our baseline model. The estimates in Figure B4.5 are close to those of our baseline model (reported in long dashes). Naturally, this model with two layers of fixed effects takes much longer to run, so we have decided to use a simpler specification as baseline model.

Figure B4.5: Specification with municipality by month by year fixed effects and municipality by day by month fixed effects



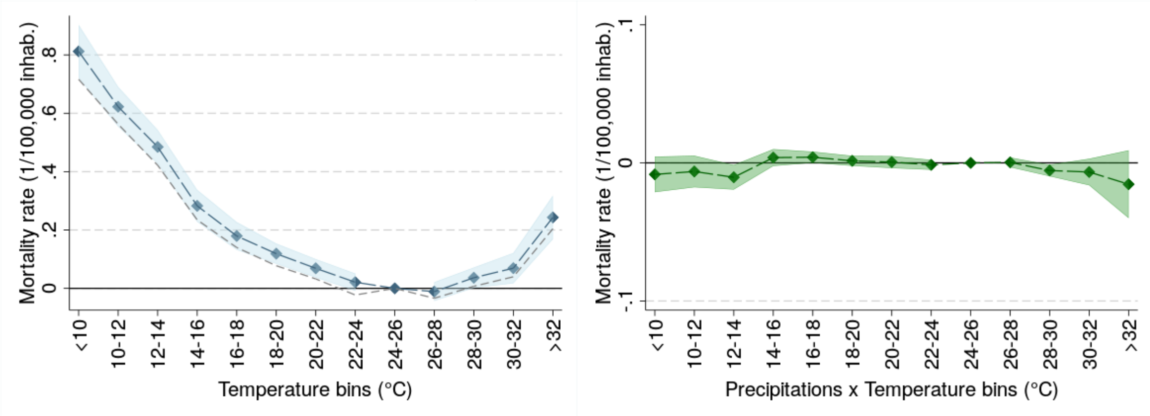
Notes. The graph shows the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags. The regression uses the mortality rate in deaths per 100,000 inhabitants as dependent variable and the diamonds show the sum of the coefficients on these thirty lags. The model includes municipality by month by year fixed effects and municipality by day by month fixed effects. The shaded area corresponds to the 95% confidence interval, while the dashes in grey corresponds to the results of our baseline specification (without municipality by day by month fixed effects). The regression controls for daily precipitation levels and is weighted by municipal population.

Appendix B5: Considerations regarding omitted variable bias

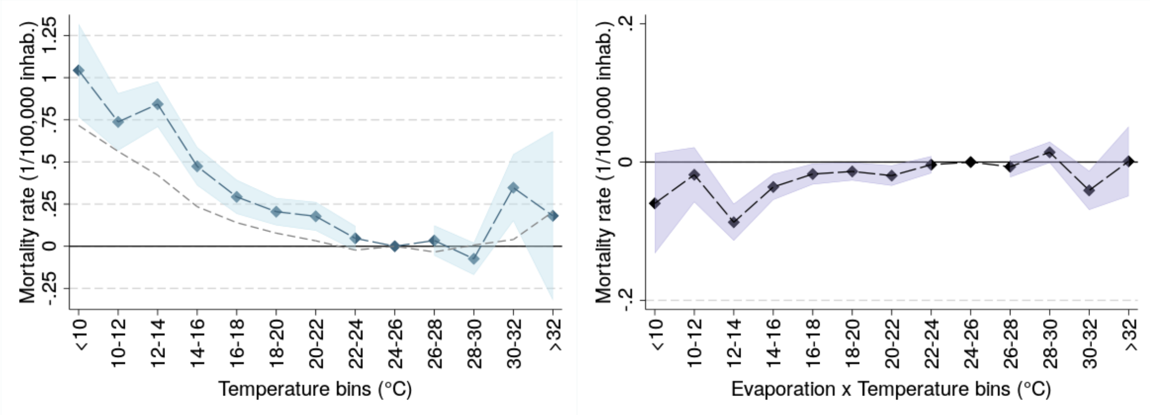
Interactions with precipitations and evaporation levels. We run two additional models and presents their results in Figure B5.1. In the first one (upper panels), we add lagged precipitations ($P_{i,d-k,m,t}$), and interact lagged temperature bins and with the precipitations of same lag ($B_{s,i,d-k,m,t} \cdot P_{i,d-k,m,t}$). In the second (lower panels), we add both lagged precipitations and evaporation levels in the model, and then interact lagged evaporation levels and lagged temperature bins (of the same lag). The results suggest no interaction between precipitations and temperature, but the impact of cold temperatures on mortality seems stronger in dryer areas.

Figure B5.1: Cumulative 31-day impact of temperatures, precipitations and their interactions

a) Specification with precipitation lags, interacted with temperature bins:



b) Specification with precipitation lags and interactions between temperature and humidity

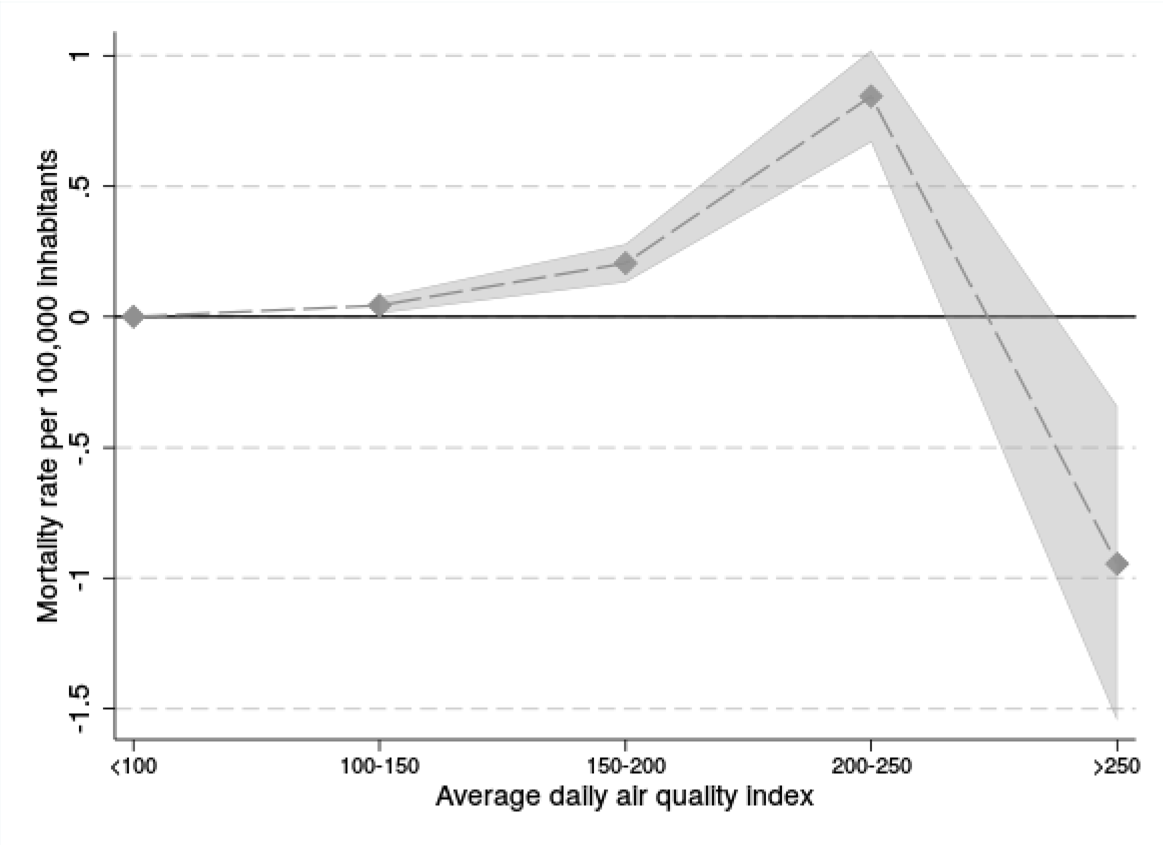


Notes. The upper panels correspond to a regression which includes the lags of precipitations as control variables, and interaction terms between precipitations and temperature. On the upper left panel, the 31-day cumulative impact of temperature bins is reported. The solid line represents the point estimates, the shaded area, the 95% confidence interval and the long dashes in grey correspond to the point estimates of the baseline model. On the upper right panel, we report the 31-day cumulative effect for the interaction terms with precipitations. The lower panels correspond to a different regression, which includes: precipitation lags, evaporation lags, and an interaction between evaporation and temperature. The graphs in the lower panels can be interpreted the same way, with the coefficients for the temperature bins on the left and the interaction term between temperature and evaporation on the right. The unit on the y-axis is deaths per 100,000 inhabitants. Regressions are weighted by municipal population.

Results for pollution in Mexico City. Figure B5.2 reports the results obtained for the effect of pollution in Mexico City, using the Mexican air quality index data (IMECA). We have added 4 air quality bins and 30 daily lags for each to our baseline distributed lag model.

We find significant mortality effects after 31 days caused by poor and very poor air quality (IMECA between 150-200 and 200-250). However, days with extremely poor air quality (IMECA over 250) are correlated with less mortality. These days are extremely rare (around 1 every 400 days), suggesting that people strongly adapt to these terribly polluted days (e.g. do not go out) explaining the lower mortality levels recorded in the data.

Figure B5.2: Impact of the air quality index on 31-day cumulative mortality, in deaths per 100,000 inhabitants in the Federal District of Mexico



Notes. The graph has been obtained from the same regression as for Figure 4. It shows the cumulative effect of a day with an air quality index falling within each bin (relative to the 22-24°C category) obtained from a dynamic model with 30 lags run for populations living in the Federal District of Mexico. The diamonds on the solid line show the effect of the sum of the coefficients on these thirty lags. The shaded area corresponds to the 95% confidence interval. The dependent variable is daily mortality rate at the municipality level. The regression controls for daily precipitation level, includes a range of municipality-by-year-by-month fixed effects, and a wide range of variables for the temperature on the same day and over the past 30 days. The regression is weighted by municipal population.

C – EXTERNAL VALIDITY AND THE ROLE OF INCOME

Appendix C1: Comparison of main results with related studies

The methodology and data used in this paper are very close to Deschenes and Moretti (2009). These authors use a similar 30-day distributed lag model. Their estimate is three times and a half lower than ours (0.20 deaths per 100,000 inhabitants) for days between 40°F and 50°F (4.4-10°C). Both estimates are statistically different from each other suggesting that Mexican residents are more vulnerable to cold than US residents.

Table C1: Main results of similar panel data studies

Study	Country and period	Frequency of data	Day below minus 1.1°C (10°F)	Day between 4.4-10°C (40-50°F)	Day below 10°C (50°F)	Days between 10-14°C (50°F-	Day above 32°C (or 90°F)
Deschenes and Moretti (2009)	USA (1972-1988)	Daily		+0.20 deaths per 100,000 inhabitants			Statistically insignificant
Barreca (2012)	USA (1973-2002)	Monthly		+0.15 deaths per 100,000 inhabitants			+0.17 deaths per 100,000 inhabitants
Deschenes and Greenstone (2011)	USA (1968-2002)	Annual	+0.69 deaths per 100,000 inhabitants				+0.92 deaths per 100,000 inhabitants
Burgess et al. (2014)	India (1957-2000)	Annual				Annual mortality rate increases by about 0.4-0.7%	Annual mortality rate increases by about 0.5-1%

The estimates by Deschenes and Moretti (2009) are in line with those obtained in other studies for the US. Barreca (2012) finds that a day between 40°F and 50°F (4.4-10°C) increases the monthly mortality rate by 4.5 people per 100,000 inhabitants. This corresponds to a daily mortality rate of 0.15 people per 100,000 inhabitants (95% confidence interval = 0.09-0.22). Using annual data, Deschenes and Greenstone (2011) find that a day below 10°F (-12°C) increases mortality by 0.69 people per 100,000 inhabitants and a day between 40°F and 50°F (4-10°C) by 0.27 people per 100,000 inhabitants as compared to a day between 50°F and 60°F (10-15.5°C). The upper bound of the 95% confidence interval for this last estimate is around 0.49 and therefore statistically below ours (at 0.72, with a standard error of 0.038).

One reason why Mexicans could be more vulnerable to cold than Americans could be acclimation: since they live in a hot country, Mexicans may be less prepared to face low temperatures. However, our results suggest that Mexicans could also be more vulnerable to high temperatures. For a day above 90°F (32.2°C), Deschenes and Moretti (2009) find no evidence of an impact of heat on mortality after 30 days. They find a highly positive impact of temperatures on mortality on the first days of heat waves but the latter is compensated for in the short run due to a harvesting effect. For the same level of temperatures, we find a statistically significant and positive impact of hot days on 31-day cumulative mortality: with temperatures above 32°C, the mortality rate is, on average, higher by 0.20 deaths by 100,000 inhabitants in Mexico.

However, Barreca (2012) and Deschenes and Greenstone (2011) do find a mortality impact of hot days: respectively 0.17 and 0.92 deaths per 100,000 inhabitants for temperatures above 90°F (32°C). The impact found by Barreca (2012) using mortality data is therefore comparable to ours in magnitude. As for Deschenes and Greenstone (2011), they use annual data over a long time period (1968-2002) so as to capture indirect effects of temperatures on mortality through other channels (e.g. agricultural and industrial output, and therefore income, employment, access to healthcare, etc.). Their estimates would indicate stronger vulnerability in the US but are not as easily comparable to our results, not only because we use with daily data but also look at a different time period.

Let us now turn our eyes to the results obtained by Burgess et al. (2014) for India. These authors use a log-linear model to estimate the impact of temperatures on annual mortality. They find impacts of a much higher magnitude for India as compared to the US estimates of Deschenes and Moretti (2009). For cold, the coefficient of their model is not statistically significant at the lower limit of 10°C or below possibly due to the small frequency of such cold days in their data. However, they find that the log annual mortality rate increases by 0.004 for each day between 10-12°C and by 0.007 for each day between 14°C. In other words, an additional day between 10-14°C increases the annual mortality rate by about 0.4-0.7% in India. For heat, they find that an additional day above 32°C increases the annual mortality rate by about 0.5-1%.

We may compare these figures with ours, taking into considerations that our study uses daily data and therefore is not fully comparable. The average daily mortality rate is around 1.36 deaths per 100,000 inhabitants in Mexico. Converted to an annual rate, this corresponds to about 496 deaths per 100,000 inhabitants. In this context, our estimate of an extra 0.72 deaths per 100,000 inhabitants caused by a day below 10°C roughly represents a marginal increase of about 0.14% in the annual death rate. Likewise, the estimate of 0.20 deaths per 100,000 due to a day above 32°C corresponds to a marginal increase in the annual death rate by 0.04%. The relative impact of cold on mortality in Mexico seems 3-5 times lower than in India whereas the estimated impact for heat is incomparably lower.

Appendix C2: Method to predict income quartiles

Income is not reported on death certificates. We started our analysis by running our baseline distributed lag model separately for each profession, which is information that is available on death certificates. We did not find clear differences in terms of vulnerability to temperatures across professions, except for workers in agriculture, fisheries and hunting who appear to suffer from cold temperatures. In fact, professional categories are an imperfect depiction of the diversity of living conditions among Mexicans. Whereas the revenues of the 1st quartile are more than 16 times lower than those of the 4th income quartile, the difference between professions is much less contrasted. Therefore, we use data from the 2000 Mexican census to estimate income levels at the moment of death in our mortality dataset.[6] To do so, we run a simple regression with data from the Mexican census where we predict income y_h of each individual h with a series of independent variables also present on death certificates. The regression used to predict income is:

$$\log(\, y_h) = \psi W_h + \omega_{i,r} + \omega_h$$

Where y_h is personal income for individual h in 2000 Mexican pesos, calculated as total household income divided by the square root of the number of people in the household (to account for economies of scale within households). Because personal income has a skewed distribution, we take the natural log to improve the fitness of the model and the accuracy of predictions. W_h is a vector of independent variables that include gender, age, civil status, occupation, education level and registration with public or private healthcare. It also includes a quadratic term for age and interaction terms between age (and age squared) and occupation to account for experience at work. $\omega_{i,r}$ is a fixed effect that takes into account that income may vary by municipality. Because professions are recorded with a different, non-comparable nomenclature from 2013 onwards, we performed the analysis with data from 1998 to 2012 only. Within a given municipality, we also distinguish between people living in urban areas (e.g. the city centre) and those living in rural areas. Thus, $\omega_{i,r}$ is a municipality *i* by-urban/rural area *r* fixed effect ($r\epsilon\{rural, urban\}$). Finally, ω_h is an idiosyncratic error term and ψ is a vector of coefficients estimated from the regression[7]. The output of this estimation is presented below.

[6] We therefore only exploit cross-sectional information to predict income quartiles. A complementary possibility would have been to use the data from the 2010 census as well. However, the 2010 census does not report total income, but only income from work. This is a limitation and we therefore preferred to use the 2000 data only.

[7] The regression coefficients are weighted by population size in each municipality so as to be representative of the Mexican population. The 2000 Census includes about 10% of the Mexican population.

Table C2.1: Regression used to predict income levels

Dependent variable	Log(Personal income)
Age	-0.0088 (0.0008)
Age squared	0.0001 (0.00005)
Female	-0.0036 (0.0014)
Fixed effects	
Civil status	Yes
Occupation	Yes
Social security affiliation	Yes
Educational level	Yes
Municipality and rural/urban area	Yes
Interactions:	
Civil status x gender	Yes
Occupation x age	Yes
Occupation x age squared	Yes
R2	0.45
Number of observations	8,522,132

Notes. Standard errors in brackets.

The regression results are consistent with economic theory (higher experience or education is correlated with higher income) and the model captures a large share of the variation in revenues (R2=0.45).

We use these regression results to predict the income level of deceased people, for whom we have the socio-demographic information reported on the death certificates (see Appendix A3 for the list of demographic variables available and Appendix A2 for an example of a death certificate). We can make income predictions by restricting the independent variables used in the income regression to those that are also present on the death certificates.

We then use predicted income values to construct income quartiles. Based on the 2000 Mexican census, we first compute the proportion of people in each municipality i whose predicted income would have fallen within income quartile κ. We then calculate the proportion of deaths in each municipality with a predicted income in each quartile κ and compute daily mortality rates by income quartile for each municipality i at time t. With this method, we are able to assign an income quartile to 73.3% of deaths. For that reason, we augment all estimated impacts by a factor of 1/0.733.

The daily mortality rates by income quartile can be used to run separate distributed lag models for each income quartile.[8] The advantage of this approach is its high flexibility since the mortality impact of each temperature bin is estimated separately for each income quartile. The results however rely on predicted income values due to the absence of such information on death certificates. The main drawback is a loss of precision in the estimates due to measurement errors in the dependent variable.[9]

We have run separate regressions of Equation 1 for each income quartile. The main results are displayed on Figure 5 in the core of the text. Effects by income quartile and cause of death are reported below. To ease comparison, they have been normalised according to the average death rate in each quartile. We find that differences in vulnerability may come from endocrine, nutritional and metabolic diseases; circulatory system diseases; and above all respiratory system diseases.

Table C2.2: Impact by income quartile and cause of death of a cold day below 10°C on cumulative 31-day mortality

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile
Infectious diseases	0.013 (0.008)	0.02 (0.007)	0.007 (0.012)	0.006 (0.011)
Neoplasms	0.002 (0.016)	-0.006 (0.013)	0.01 (0.022)	0.019 (0.018)
Endocrine, nutritional and metabolic diseases	0.135 (0.021)	0.159 (0.023)	0.153 (0.026)	0.083 (0.022)
Circulatory system diseases	0.208 (0.028)	0.224 (0.028)	0.194 (0.029)	0.118 (0.037)
Respiratory system diseases	0.192 (0.021)	0.197 (0.025)	0.111 (0.021)	0.072 (0.018)
Violent and accidental deaths	0.006 (0.015)	-0.002 (0.015)	0.01 (0.019)	0.037 (0.018)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C on mortality, for specific quartiles and causes of death. The dependent variable the daily mortality rate in deaths per 100,000 inhabitants, normalised to one according to the average daily mortality rate in each age-corrected quartile. For example, for the first quartile of income, a day below 10°C leads to a 19.7% increase in the daily mortality rate because of respiratory system diseases. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with municipality-by-month-by-year fixed effects. Standard errors are in brackets and clustered at municipality level. All regressions are weighted by the municipal population belonging to the relevant quartile.

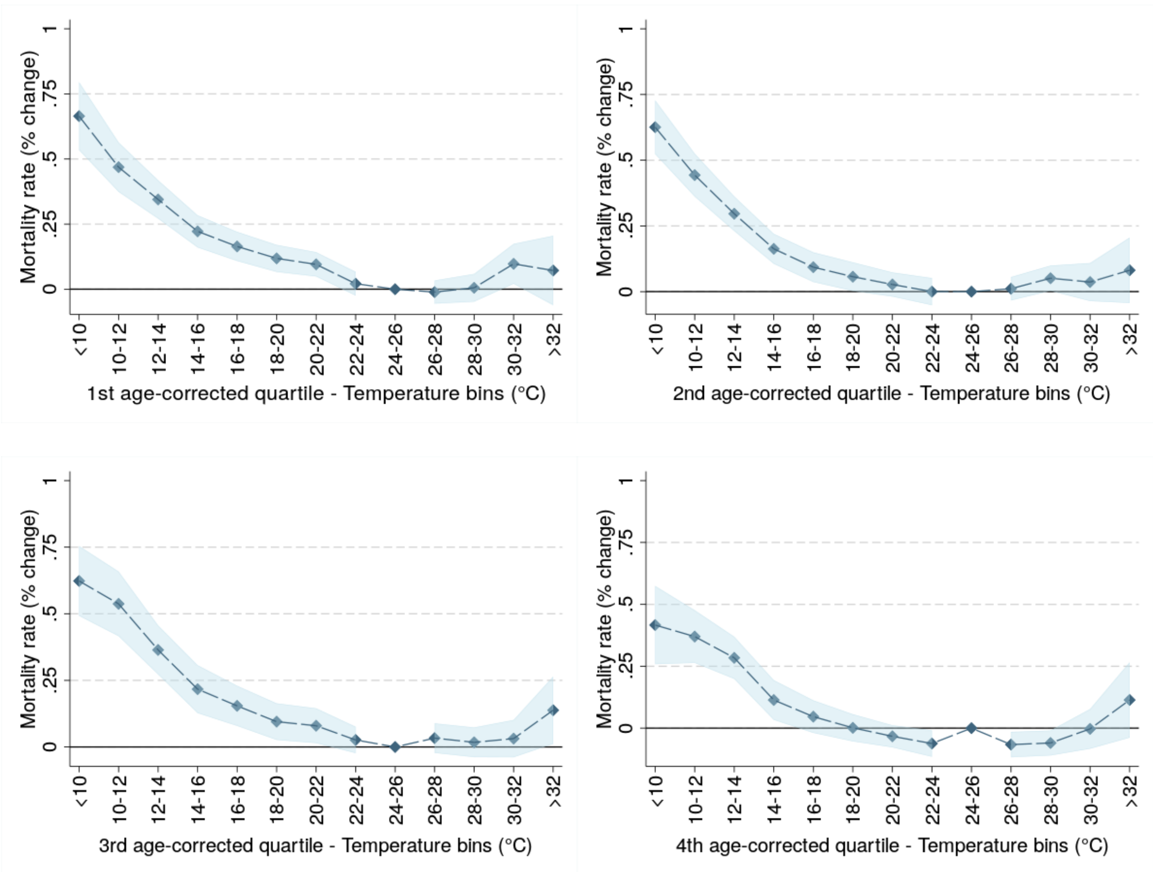
[8] Even though we are using predicted mortality rates, standard errors using clustering are valid and there is no need for bootstrapping: this is because these predicted rates are used as the dependent variable. Using predicted instead of actual values therefore increases measurement errors in the dependent variable and this directly affects the statistical power of our regressions.

[9] The method could also be inconsistent if some households systematically underreport their income levels. We mitigate this risk by excluding observations with doubtful declarations from the regression. After the census, the Mexican administration crosschecks individual declarations on employment status: in the survey, some individuals inaccurately declare that they do not work. We suspect these individuals to have underreported their income levels and exclude them from the regression used to predict income levels. They represent 2.6% of the original sample.

Appendix C3: Age-corrected regressions by income quartiles

For a given age, we can determine the relative position of an individual compared to all the people of the same age. Therefore, we can create age-specific quartiles, and reclassify people in the 1st, 2nd, 3rd or 4th quartile of income depending on whether they are rich or poor given their age. For example, someone relatively old may earn less than the median income of the Mexican population, but still be relatively richer than the median old person. In this case, s/he may belong to the 3rd or 4th age-corrected income quartile, even if his/her income level is lower than the median income level for all Mexicans, including those in working-age. Figure C3 below presents the full results of the age-corrected regressions by income quartiles for all causes of death. To ease comparability, results are normalised according to the average daily death rate registered in each quartile.

Figure C3: Age-corrected impact, by income quartile, on 31-day mortality



Notes. The results for each quartile are taken from separate regressions. The dependent variable the daily mortality rate in deaths per 100,000 inhabitants, normalised to one according to the average daily mortality rate in each age-corrected quartile. For example, for the first quartile of income, a day below 10°C leads to a 67% increase in the daily mortality rate. The y-axis corresponds to the cumulative impact after 31 days for each of the 2°C temperature bins in the regressions. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with municipality-by-month-by-year fixed effects. The shaded areas represent the 95 percent confidence interval for each estimated set of coefficients. All regressions are weighted by the municipal population belonging to the relevant age-corrected quartile.

Effects by age-corrected income quartile and cause of death are reported below. We find that differences in vulnerability may come from endocrine, nutritional and metabolic diseases; circulatory system diseases; and above all respiratory system diseases.

Table C3: Age-corrected impact by income quartile and cause of death of a cold day below 10°C on cumulative 31-day mortality

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile
Infectious diseases	0.018 (0.01)	0.005 (0.008)	0.014 (0.01)	0.01 (0.008)
Neoplasms	0.005 (0.017)	-0.007 (0.015)	0.003 (0.018)	0.018 (0.017)
Endocrine, nutritional and metabolic diseases	0.135 (0.022)	0.147 (0.022)	0.154 (0.023)	0.084 (0.019)
Circulatory system diseases	0.181 (0.03)	0.19 (0.024)	0.212 (0.026)	0.133 (0.037)
Respiratory system diseases	0.171 (0.022)	0.157 (0.018)	0.137 (0.025)	0.10 (0.023)
Violent and accidental deaths	-0.004 (0.019)	-0.003 (0.016)	0.019 (0.02)	0.029 (0.014)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C on mortality, for specific age-corrected quartiles and causes of death. The dependent variable the daily mortality rate in deaths per 100,000 inhabitants, normalised to one according to the average daily mortality rate in each age-corrected quartile. For example, for the first age-corrected quartile of income, a day below 10°C leads to a 17.4% increase in the daily mortality rate because of respiratory system diseases. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with municipality-by-month-by-year fixed effects. Standard errors are in brackets and clustered at municipality level. All regressions are weighted by the municipal population belonging to the relevant age-corrected quartile.

Appendix C4: Effect of temperature on mortality by quartiles defined with a poverty indicator

Instead of using income levels to create quartiles of population, we can use alternative metrics of wellbeing and living conditions. Below, we use a composite indicator inspired from the marginality index of the Mexican Council of Population (CONAPO).

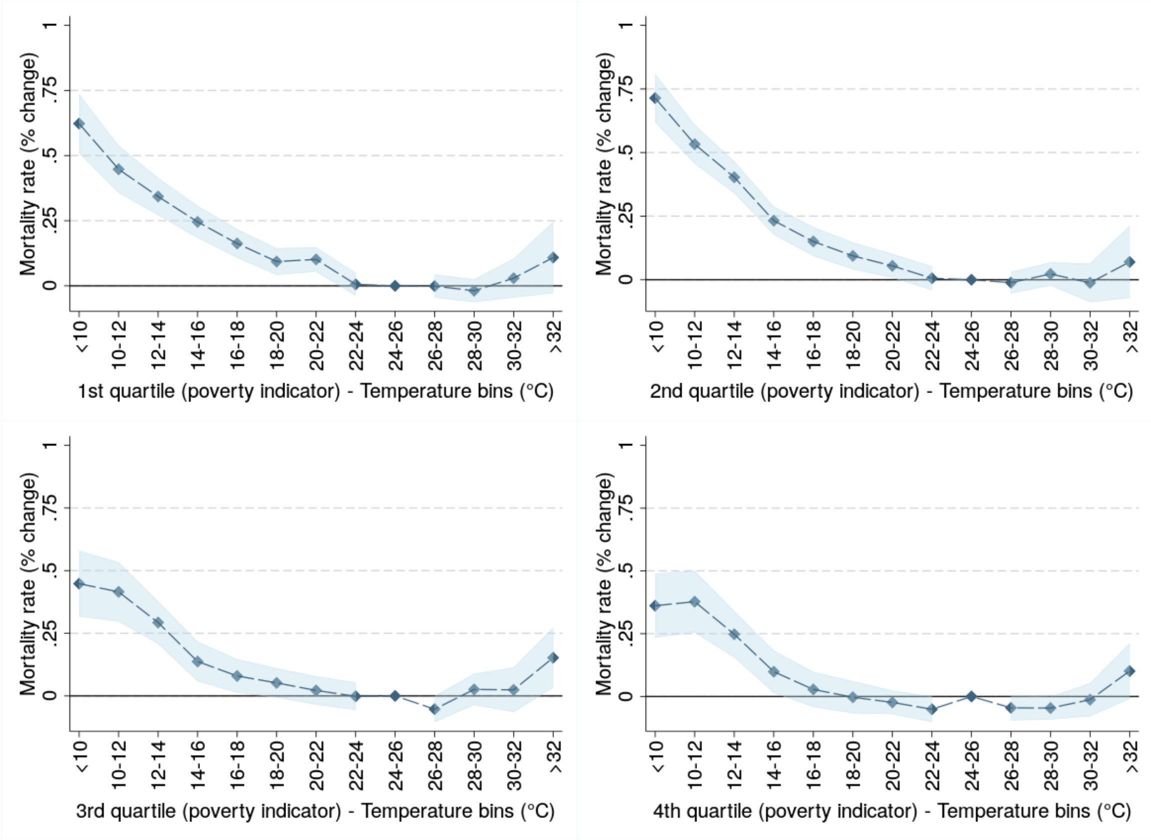
The index of the CONAPO classifies localities according to their degree of marginality (from very low to very high) and has been used by government to design social policies. The indicator of the CONAPO relies on eight variables available from the Mexican censuses. The Council calculates 1) the share of the population of aged 15 or more who is analphabetic; 2) the share of the population of aged 15 or more who did not complete primary education; 3) the average number of occupants per room; 4) the share of households without exclusive toilet; 5) the share of households without electricity; 6) the share of households without current water within their property; 7) the share of houses or flats with earthen floor; and 8) the share of houses or flats with no refrigerator.

We construct an individual-specific poverty indicator based on the features used by CONAPO to classify localities by level of marginality. Since we want an indicator which is equally reflective of poverty for children and adults, we only consider the last five characteristics listed above (4-8): children under a certain age are necessarily analphabetic and cannot have completed primary education. Likewise, a relatively high amount of occupants per room has not exactly the same relevance in terms of living conditions if these include small kids.

We compute an exclusion indicator that range from 0 (no exclusion) to 5 (strong exclusion) for each individual in the Census. If an individual belongs to a household that has exclusive toilets, electricity, current water, a proper floor (not an earthen one) and a refrigerator, then the poverty indicator equals 0. If one of these elements is missing, the indicator is equal to one; if two of these elements are missing, the indicator is equal to two; and so on. The maximum value of 5 is given to households that have no exclusive toilets, no electricity, no current water, an earthen floor in the house and no refrigerator. These are obviously consistent with very precarious living conditions.

Once the indicator has been computed for each person in the 2000 Census, the exact same methodology is applied as for income to create quartiles. In short, we run a linear regression to predict the value taken by the poverty indicator based on a series of observables that are both present in the Census and in the mortality data. We then make out-of-sample predictions of the indicator on the deceased to proxy living conditions at the moment of death. Then we separate the population of the deceased and the living in four groups (from low to high living conditions) and run the econometric model separately for the four groups of people. The results of such process are presented below and confirm higher vulnerability for poorer households.

Figure C4: Impact by quartiles (based on poverty indicator) of temperature on cumulative 31-day mortality



Notes. The results for each quartile are taken from separate regressions. The dependent variable the daily mortality rate in deaths per 100,000 inhabitants, normalised to one according to the average daily mortality rate in each age-corrected quartile. For example, for the first quartile based on the poverty indicator, a day below 10°C leads to a 62% increase in the daily mortality rate. The y-axis corresponds to the cumulative impact after 31 days for each of the 2°C temperature bins in the regressions. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with municipality-by-month-by-year fixed effects. The shaded areas represent the 95 percent confidence interval for each estimated set of coefficients. All regressions are weighted by the municipal population belonging to the relevant quartile.

D – SEGURO POPULAR

Table D1 reproduces all columns of Table 6 with a larger set of 2°C temperature bins. Results are consistent with those obtained with the reduced set used in our baseline specifications.

In complement, the estimated impacts of the *Seguro Popular* by death cause are provided in Table D2 (covered diseases only). Impacts by gender and a few additional age groups are provided in Table D3. Especially, results show no impact for children aged 5-9, consistent with the fact that they are not sensitive to the weather (see Table A5), and negative but statistically not significant effects for people over 45. In Table D3, we do not provide impacts for populations between 10 and 45 for concision: no impact was found.

Table D1: The impact of the *Seguro Popular* on weather mortality when using 2°C bins

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disease type/age	Covered	Cov. & 3 causes	Respir.	0-4	>75	All	Non Cov.	Neopl.
Seguro Popular:								
x days below 10°C	-0.04	-0.014	-0.014	-0.178	-0.503	-0.043	-0.009	0.001
	(0.026)	(0.022)	(0.014)	(0.067)	(0.588)	(0.049)	(0.031)	(0.004)
x days at 10-12°C	-0.065	-0.056	-0.039	-0.109	-0.783	-0.097	-0.02	-0.003
	(0.018)	(0.015)	(0.01)	(0.058)	(0.375)	(0.03)	(0.02)	(0.004)
x days at 12-14°C	-0.023	-0.027	-0.022	-0.01	-0.033	-0.02	0.008	0.0001
	(0.013)	(0.01)	(0.007)	(0.052)	(0.258)	(0.023)	(0.016)	(0.003)
x days at 14-16°C	-0.013	-0.006	-0.003	-0.021	-0.12	-0.018	-0.003	-0.0004
	(0.011)	(0.008)	(0.006)	(0.039)	(0.218)	(0.021)	(0.015)	(0.003)
x days at 16-18°C	-0.029	-0.022	-0.015	-0.018	-0.675	-0.017	0.02	-0.002
	(0.01)	(0.008)	(0.005)	(0.041)	(0.204)	(0.019)	(0.014)	(0.003)
x days at 18-20°C	-0.014	-0.01	-0.005	-0.01	-0.188	-0.01	0.004	0.0003
	(0.012)	(0.008)	(0.005)	(0.05)	(0.202)	(0.022)	(0.014)	(0.004)
x days at 20-22°C	-0.012	-0.008	-0.005	-0.03	-0.262	-0.002	0.016	-0.001
	(0.008)	(0.007)	(0.004)	(0.031)	(0.188)	(0.015)	(0.011)	(0.002)
x days at 22-24°C	-0.033	-0.012	-0.001	-0.072	-0.294	-0.017	0.015	-0.005
	(0.01)	(0.007)	(0.005)	(0.034)	(0.209)	(0.021)	(0.016)	(0.003)
x days at 24-26°C	-	-	-	-	-	-	-	-
x days at 26-28°C	-0.017	-0.006	-0.002	-0.011	-0.229	-0.002	0.008	-0.005
	(0.011)	(0.008)	(0.005)	(0.031)	(0.234)	(0.02)	(0.015)	(0.003)
x days at 28-30°C	0.009	0.013	0.007	-0.007	0.204	0.017	0.021	-0.00004
	(0.008)	(0.006)	(0.004)	(0.026)	(0.19)	(0.018)	(0.013)	(0.002)
x days at 30-32°C	-0.035	-0.026	-0.005	-0.093	-0.431	-0.02	0.001	-0.002
	(0.013)	(0.01)	(0.006)	(0.043)	(0.392)	(0.031)	(0.022)	(0.004)
x days above 32°C	-0.003	-0.005	0.002	0.086	0.024	-0.056	-0.02	-0.001
	(0.029)	(0.024)	(0.013)	(0.058)	(0.701)	(0.057)	(0.05)	(0.008)

Notes: The dependent variable is the all-cause monthly mortality rate per 100,000 inhabitants. All specifications include municipality by month and municipality by year fixed effects, in addition to the interacted fixed effects described in the table. Data is from 1998 to 2015 since information on the number of consultations per capita was unavailable for 2016-2017. Standard errors in brackets clustered at the level of municipalities. Reference day is 24-26 degrees Celsius. The model is estimated using the reghdfe command in Stata based on Guimaraes and Portugal (2010) and Gaure (2010). All regressions are weighted by the municipal population.

Table D2: Specifications to assess the impact of the *Seguro Popular* on weather mortality by disease type

Model	(1)	(2)	(3)	(4)	(5)	(6)
Type of disease	Infectious diseases	Neoplasms	Endocrine, nutritional and metabolic diseases	Circulatory system diseases	Respiratory system diseases	Violent and accidental deaths
Consultations per capita:						
x days below 12°C	-0.004	0.001	-0.007	-0.004	-0.035	0.00006
	(0.003)	(0.003)	(0.005)	(0.003)	(0.008)	(0.00006)
x days at 12-16°C	0.0002	0.002	-0.002	-0.0002	-0.009	-0.000003
	(0.002)	(0.003)	(0.004)	(0.003)	(0.005)	(0.00002)
x days at 16-20°C	-0.001	0.001	-0.003	-0.002	-0.008	0.000004
	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.00002)
x days at 20-24°C	-0.00053	-0.00019	-0.002	-0.002	-0.003	-0.000003
	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.00002)
x days at 24-26°C						
x days at 26-30°C	0.0002	-0.0001	0.003	-0.002	0.002	0.00003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.00003)
x days above 30°C	-0.001	0.001	-0.007	-0.005	-0.003	0.00009
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.00014)

Notes: The dependent variable is the cause-specific monthly mortality rate per 100,000 inhabitants, for covered diseases only. The model includes municipality by month and municipality by year fixed effects, and interacted fixed effects: municipality by temperature bin fixed effects and year by temperature bin fixed effects. The data is from 1998 to 2015 since information on the number of consultations per capita was unavailable for 2016-2017. Standard errors in brackets clustered at the level of municipalities. Reference day is 24-26 degrees Celsius. The model is estimated using the reghdfe command in Stata based on Guimaraes and Portugal (2010) and Gaure (2010). All regressions are weighted by the municipal population.

Table D3: Specifications to assess the impact of the *Seguro Popular* on weather mortality by gender and age group

Model	(1)	(2)	(3)	(4)	(5)	(6)
Demographic group	Men	Women	Aged 5-9	Aged 45-54	Aged 55-64	Aged 65-74
Consultations per capita:						
x days below 12°C	-0.066	-0.044	0.002	-0.046	-0.024	-0.052
	(0.021)	(0.015)	(0.006)	(0.029)	(0.048)	(0.071)
x days at 12-16°C	-0.01	-0.013	-0.001	-0.015	-0.012	-0.036
	(0.014)	(0.011)	(0.006)	(0.022)	(0.037)	(0.055)
x days at 16-20°C	-0.014	-0.016	-0.003	-0.01	-0.044	-0.074
	(0.014)	(0.01)	(0.005)	(0.02)	(0.034)	(0.05)
x days at 20-24°C	-0.018	-0.009	-0.002	-0.007	-0.043	-0.058
	(0.01)	(0.009)	(0.006)	(0.021)	(0.035)	(0.051)
x days at 24-26°C	-	-	-	-	-	-
x days at 26-30°C	0.002	-0.001	-0.009	0.009	-0.017	-0.016
	(0.01)	(0.01)	(0.005)	(0.021)	(0.039)	(0.058)
x days above 30°C	-0.017	-0.013	-0.002	-0.021	-0.07	-0.096
	(0.015)	(0.015)	(0.007)	(0.032)	(0.058)	(0.088)

Notes: The dependent variable is the age- or gender-specific monthly mortality rate per 100,000 inhabitants, for covered diseases only. The model includes municipality by month and municipality by year fixed effects, and interacted fixed effects: municipality by temperature bin fixed effects and year by temperature bin fixed effects. The data is from 1998 to 2015 since information on the number of consultations per capita was unavailable for 2016-2017. Standard errors in brackets clustered at the level of municipalities. Reference day is 24-26 degrees Celsius. The model is estimated using the reghdfe command in Stata based on Guimaraes and Portugal (2010) and Gaure (2010). All regressions are weighted by the municipal population.

In Table D4, we run placebo tests (with non-covered diseases) for all the categories for which we found impacts of covered diseases. Column (1) is for the non-covered diseases within the three causes of death that convey weather-related deaths (respiratory diseases, circulatory system diseases, and metabolic diseases). Column (2) is for non-covered respiratory diseases. Columns (3) and (4) are for all non-covered diseases for infants (aged 0-4) and the elderly (75+) respectively. Columns (5) and (6) are for all non-covered diseases, for men and women separately. We find no statistically significant and negative impact of the *Seguro Popular* on cold related mortality in these placebo tests.

Table D4: Additional placebo tests (with non-covered diseases)

Model	(1)	(2)	(3)	(4)	(5)	(6)
Cause of death or demographic group	Three causes	Respir.	Aged 0-4	Aged 75+	Men	Women
Consultations per capita:						
x days below 12°C	-0.006	-0.001	-0.047	0.696	-0.012	-0.018
	(0.012)	(0.003)	(0.032)	(0.346)	(0.023)	(0.021)
x days at 12-16°C	0.02	0.003	-0.038	0.48	0.008	0.01
	(0.009)	(0.002)	(0.021)	(0.258)	(0.019)	(0.015)
x days at 16-20°C	0.021	0.004	-0.009	0.427	0.006	0.022
	(0.008)	(0.002)	(0.018)	(0.219)	(0.017)	(0.014)
x days at 20-24°C	0.017	0.003	0.011	0.588	0.007	0.027
	(0.007)	(0.002)	(0.021)	(0.239)	(0.016)	(0.013)
x days at 24-26°C	-	-	-	-	-	-
x days at 26-30°C	0.012	0.003	-0.002	0.388	0.011	0.024
	(0.008)	(0.002)	(0.018)	(0.251)	(0.016)	(0.014)
x days above 30°C	0.006	-0.001	-0.019	0.727	-0.029	0.019
	(0.011)	(0.003)	(0.028)	(0.383)	(0.026)	(0.018)

Notes: The dependent variable is the monthly mortality rate (per 100,000 inhabitants) from non-covered diseases among broader types of diseases (e.g. respiratory diseases), or specific demographic groups (e.g. children aged 0-4). The model includes municipality by month and municipality by year fixed effects, and interacted fixed effects: municipality by temperature bin fixed effects and year by temperature bin fixed effects. The data is from 1998 to 2015 since information on the number of consultations per capita was unavailable for 2016-2017. Standard errors in brackets clustered at the level of municipalities. Reference day is 24-26 degrees Celsius. The model is estimated using the reghdfe command in Stata based on Guimaraes and Portugal (2010) and Gaure (2010). All regressions are weighted by the municipal population.

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