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

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Abstract

We examine the impact of temperature on mortality in Mexico using daily data over the period 1998-2017 and find that 3.8 percent of deaths in Mexico are caused by suboptimal temperature (26,000 every year). However, 92 percent of weather-related deaths are induced by cold (<12°C) or mildly cold (12-20°C) days and only 2 percent by outstandingly hot days (>32°C). Furthermore, temperatures are twice 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 at least 1,600 lives per year from cold weather 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 contribute to this literature by investigating the relationship between temperature, mortality, inequality and public health provision in Mexico based on data of unusually high 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-calendar-day, municipality-by-year and day 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. Applying our estimates to the typical daily average temperature distribution in Mexico, we find that around 26,000 deaths annually (3.8 percent of deaths in Mexico) are induced by suboptimal temperature (outside the human body comfort zone). To put things in perspective, this is equivalent to 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 24-28°C. Therefore, while unusually cold days with a mean temperature below 12°C are responsible for the deaths of around 5,700 people each year, we estimate that 71 percent of weather-induced deaths – around 18,700 people per year – occur in the aftermath of days with mean temperatures between 12°C and 20°C.[1] This may be because these days imply low temperatures at night, which favour the development of respiratory pathologies and put the human body at higher cardiovascular risk. 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 500 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 7.5°C below the daily average. Days recording an average temperature of 12°C typically imply a minimum temperature of around 2.5°C at night. Likewise, mildly cold days, e.g. averaging 12-16°C, expose people to fairly cold temperatures (on average 6.6°C) at night. This is well below the comfort zone of the human body which lies between 20 and 25°C.

[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

The second contribution of this study is to show that vulnerability to extreme weather is negatively correlated with personal income. Overall, death following cold and mildly cold days (all days below 24°C compared to 24-28°C) is more than twice as 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 and circulatory system diseases.[3] In contrast, we find no statistically significant differences in vulnerability to heat across income groups. These results may be relevant in the context of the COVID-19 pandemic, since they suggest that poorer communities are usually more exposed to respiratory diseases than other households.

The final 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).[4]

We assess if the rollout of the *Seguro Popular* led to a reduction in the extra mortality triggered by cold and mildly cold temperatures. To do so, we focus on the population eligible to the *Seguro Popular* and interact the availability of the *Seguro Popular* in each municipality with temperature bins. To control for the endogenous enrolment of municipalities into the policy as well as for seasonality, we include a full range of interaction terms between temperature bins and municipality-by-month fixed effects. In addition, we use month-by-year fixed effects interacted with temperature bins to control for the autonomous evolution of weather

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.

[3] This suggests that flu pandemics or coronaviruses may constitute a stronger threat for low-income households.

[4] 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.

vulnerability over time. We find that the *Seguro Popular* saved at least 1,600 lives per year from mildly cold weather, representing around 6.6 percent of weather-induced deaths. While our analysis focuses on weather vulnerability, which is only one specific aspect of the impact of the *Seguro Popular* on mortality, it is in fact one of the few assessments of the impact of the *Seguro Popular* on mortality more generally[5] and thus also contributes to the literature assessing the impact of healthcare extensions in emerging countries, 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

[5] 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). Research by Pfutze (2014, 2015) suggests that the *Seguro Popular* may have reduced infant mortality and miscarriages.

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 nonlinear specifications in panel data analyses (Deschenes and Greenstone, 2011). With temperature bins, the impact between temperature and mortality is 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. They may be also associated with the development of viruses. For example, the transmission of influenza and other respiratory diseases are strongly influenced by ambient air temperature and humidity (Lipsitch and Viboud, 2009; Prel et al., 2009; Shaman and Kohn, 2009; Tamerius et al., 2011; Shaman and Karspeck, 2012; Tamerius et al., 2013; Lowen and Steel, 2014).

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).[6] Recent developments in epidemiology show that the impact of cold weather on human health is in fact seemingly much stronger than the impact of hot weather (Barnett et al., 2012; Guo et

[6] 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.

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 both extreme cold and extreme heat have strong marginal impacts on mortality. However, because cold days are more frequent than hot days, they 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.

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; Guerrero Compeán, 2013; Burgess *et al.*, 2017; Barreca *et al.*, 2016).[7] 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. In Mexico and using annual data, Guerrero Compeán (2013) also finds that hot days are associated with strong increases in mortality rates. The difference with our findings likely comes from the fact that, while our estimates based on daily data focus on the short-term biological response of the human body to unusual weather, those of Guerrero Compeán (2013) should additionally include the effect of weather on mortality through economic channels (such as reduced agricultural productivity and household income), as suggested by the much greater impact found in rural areas compared to urban ones.[8] Similar differences in the estimated temperature-mortality relationship across daily and annual specifications has also been observed in the U.S. (see for example Deschenes and Moretti, 2009, vs Deschenes and Greenstone, 2011).

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

[7] See Basu (2008) and Deschenes (2014) for thorough literature reviews.

[8] Another possibility is that some of our mortality impacts are for people that are weak and would have died anyway within a year. This is however unlikely to explain most of the difference in estimates since we already largely account for displacement effects (at 30 days).

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 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, 1990-2017) and weather data from the National Climatological Database of Mexico (CONAGUA, 2018).

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. However, we are able to construct monthly mortality rates over the full period (1990-2017) and use this information in all monthly analyses.

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.[9] 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.

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; violent and accidental deaths; and other causes. As reported elsewhere, the primary cause of death is circulatory system diseases, which has been shown to be affected by temperature in the epidemiological 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.

[9] 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 (INEGI, 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.

[TABLE 1 ABOUT HERE]

II.B Weather and climate data

The National Climatological Database of Mexico (CONAGUA, 2018) provides daily temperature and precipitation records for around 5,500 operating and formerly operating land-based stations in Mexico, of which around 2,500 were operative in any given year on average between 1998 and 2017. 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.[10] 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[11] and includes over 14 million observations. Figure 1 presents the historical distribution of daily average temperature in Mexico from 1998 to 2017.[12] The temperature data is weighted according to the population of each municipality to reflect the average exposure of Mexican people to low and high temperatures. We use seven temperature bins: "below 12°C", "above 32°C" and five 4°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 20°C, and about 70 percent of days lie in the range 12°C-24°C. At the extremes of the distribution, the average Mexican is exposed to 17 days per year below 12°C (around 54°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

[10] To do so, we use the information on the longitude and latitude of municipalities from the INEGI's National Geostatistical Framework (INEGI, 2020). 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.

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

[12] 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).

days below 12°C and many more days above 32°C.[13] The distribution is also more spread out in the US.

[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 (INEGI, 2000). We use the publicly available sample of the 2000 Census covering 10 percent of the Mexican population. 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 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

We use daily data to estimate the impact of temperature on mortality, allowing us to causally identify the impact of exposure to unusual temperatures on mortality. Daily specifications also allow us to look at short-term dynamics and evaluate how long it takes for pathologies to develop after populations are exposed to particular temperatures. We complement our daily specifications with estimates obtained with data aggregated at monthly level in Appendix A4. The results obtained from these regressions at monthly level are similar in magnitude to the ones found with our daily specifications.

In order to assess the impact of daily temperatures on mortality, we correlate daily temperatures with daily mortality rates using a fixed-effect linear regression. We use three sets of fixed effects. First, the model includes municipality-by-calendar-day (1st January to 31st December) fixed effects to control for differences in mortality rates due to seasonal phenomena at

[13] 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).

municipality level. With these fixed effects, parameters are identified from year-to-year deviations in temperature from the municipality average of a given calendar day. Second, the model includes time fixed effects for every day in the sample (e.g. 1st January 2006, 2nd January 2006, etc), which control for unobserved factors that affect daily mortality across all Mexican municipalities. Third, municipality-by-year fixed effects control for differential trends in mortality rates over time across municipalities.

All these fixed effects strongly improve the comparability of observations across municipalities and time. However, they could absorb some of the effect since our model only compares mortality in the same calendar day across different years. Prior to running such models, we checked that there was enough variance within calendar days and location to estimate differences in effects across temperature bins.[14]

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

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

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, $\mu_{i,d,.m}$ is a vector of municipality-by-calendar-day fixed effects, $\mu_{i,t}$ corresponds to municipality-by-year fixed effects, $\mu_{d,.m,t}$ is a vector of day-by-month-by-year fixed effects and $\varepsilon_{i,d,m,t}$ is the error term.[15] Standard errors are clustered at the municipality level.[16] In addition, the regression coefficients are weighted by the population in each municipality.[17]

[14] Within calendar days (1-365) and municipalities, the standard deviation of the average temperature recorded across different years is about 2°C. There is a 4.5°C difference between the 10 percent highest and lowest temperatures recorded within the same calendar day and municipality, and a 10°C difference between the 1 percent highest and 1 percent lowest. Therefore, the model can generally compare a cold day at 10°C with days in the range of 14-20°C, and days at 33°C with days in the range of 23-29°C.

[15] 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. After weighting for population, around 29 percent of daily death rates have zero mortality. 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. Furthermore, results are similar with a specification using monthly data (see Appendix A4). Monthly data naturally includes less zero values since deaths are aggregated over a month.

[16] 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. In the baseline regressions, we do not use 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.

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

$T_{i,d,m,t}$ includes our climatic variables of interest. One issue of importance is to account for non-linearity (Dell, Jones and Olken, 2014). A 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 4°C temperature bins between 12°C and 32°C (e.g. 12°C-16°C, 16°C-20°C and so on) to construct the vector $T_{i,d,m,t}$. The lowest bin covers days with a temperature below 12°C, and the highest bin covers days with a temperature above 32°C. In Appendix A5, we run the model with 2°C bins. This provides very similar results.

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-mortality relationship and for dynamic effects, Deschenes and Greenstone (2011) mention the possibility of combining temperature bins with a distributed lag model. We consider 7 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:

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

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 24-28°C as the baseline temperature bin. 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.

The fixed-effect models are estimated using the *reghdfe* command in Stata based on Guimaraes and Portugal (2010) and Gaure (2010). The command allows us to flexibly include the three sets of fixed effects mentioned previously.

III.B Main results

We now present the results obtained with the distributed lag model. 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. Regarding heat, we find statistically significant impacts of the two bins above 28°C, suggesting that hot days (28-32°C) and extremely hot days (>32°C) displace death by more than one month and not only by a few days.[18] However, relatively mild days that are unusually cold in the Mexican setting also lead to extra mortality. A day with an average temperature below 12°C kills about 30 percent more than a day with an average temperature above 32°C. 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 "harvesting" for hot days whereas the impact of cold days accumulates after the event (more details can be found in Appendix A6).

[FIGURE 2 ABOUT HERE]

Furthermore, we find statistically significant and strong impacts on mortality for all temperatures bins below 20°C. A day between 12°C-16°C increases mortality by 0.12 deaths per 100,000 inhabitants, while a day below 12°C increases mortality by around 0.26 deaths per 100,000 inhabitants compared with a day falling in the 24-28°C bin. Therefore, two mildly cold days between 12°C and 16°C convey nearly the same mortality impact as one unusually cold day below 12°C.

The comparison between these marginal effects needs to be considered along the fact that the average person in Mexico is exposed to 72 days at 12°C-16°C per year, but to only 17 days per year below 12°C. Table 2 combines the results presented in Figure 2 with the distribution of

[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.

hot and cold days in Mexico shown in Figure 1. Applying our estimates to the typical daily average temperature distribution in Mexico, days under 12°C cause the death of around 5,700 people each year (95 percent confidence interval is 4,548–6,863).[19] This represents 0.8 percent of the number of deaths in Mexico in 2017. However, because mild temperatures between 12°C and 20°C are much more frequent, the total number of additional deaths associated with moderately low temperatures between 12°C and 20°C is around 18,700 per year[20] (95 percent CI: 13,292–24,063), or 2.7 percent of the number of deaths in Mexico in 2017. This suggests that the total impact of mild temperatures on mortality is much larger than the impact of unusually cold days.[21] At the other end of the spectrum, unusually hot days over 28°C trigger a comparably small amount of additional deaths (around 2,300 annually, 95 percent CI: 1,465–3,150), because although the marginal impact of such days is large, extremely hot days, especially above 32°C, have been rare so far.

[TABLE 2 ABOUT HERE]

In Table 3, we 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 spells and heat waves.

Applying our estimates to the typical daily average temperature distribution in Mexico, we find that people over 75 concentrate nearly 58 percent of deaths and are therefore particularly at risk. For example, the marginal impact of days below 12°C on mortality is 22 times higher for this group than for the whole population. However, most age groups are vulnerable to unusually cold days (<12°C), including the very young (<5 years old) and all age groups above 35. In contrast, the vulnerability to mildly cold temperatures only concerns older age groups (above 45). As to heat, extreme heat seems to have an impact on mortality that strongly increases with age, starting with people aged 35. Effects by disease type are provided in panel B of Table 3. Cold appears to have a particularly strong impact on metabolic, circulatory and respiratory diseases. These three causes of death are estimated to concentrate more than 80 percent of the deaths induced by suboptimal weather exposure.[22]

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[19] This is obtained for the 2017 population estimate of 129 million people, a death rate of about 0.26 deaths per 100,000 inhabitants for a day below 12°C compared to a day at 24-28°C and around 17 days below 12°C per year.
[20] This excludes the impact of days below 12°C.
[21] We are comparing days with an average temperature between 12°C and 20°C with days with an average temperature between 24°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).
[22] 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

[TABLE 3 ABOUT HERE]

We provide years of life lost estimates in Appendix A7. Most years of life lost are due to cold weather effects on people over 55. Moreover, we can use our model to simulate the impact that climate change may have on 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 A8. Because the frequency of cold and mildly cold days is expected to decrease, the number of deaths imputable to temperature reduces with the forecasted temperatures implied by climate change as compared to historical ones. Meanwhile, a much larger share of people could die because of heat. Under the very high RCP 8.5 emissions scenario, we calculate that around 70 percent of weather-induced deaths could be due to heat by 2075-2099 under climate change. Ceteris paribus (e.g. with constant population), the change in the number of hot days would increase the number of heat-related deaths per year from around 2,300 to around 15,000.

III.C Robustness

We conduct a series of robustness checks and complementary analyses in Appendix B. We look separately at minimum vs. maximum temperature (Appendix B1). We furthermore separate the dataset in different years, look at the effect on weekdays vs. weekends, and in rural vs. urban areas (Appendix B2). We also show that acclimation may play a role (Appendix B3): cold days have a stronger mortality effect in hot regions, and hot days in cold regions. However, the results are very similar when defining temperature relative to the municipality average. We also reduce the number of fixed effects (Appendix B4). We use temperature leads as a placebo test (Appendix B5), and present the results obtained with a simpler model with no lags, therefore considering only the contemporaneous relationship between temperature and mortality (Appendix B6). We include additional control variables related to precipitation, humidity and pollution (Appendix B7). Finally, we provide a brief comparison of our results with other studies in Appendix B8.

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and Moretti, 2009). Looking at the corresponding estimates for Mexico, we find that cardiovascular diseases account for 38.3 percent of deaths, followed by metabolic ones (27.4 percent, including mostly diabetes), and respiratory diseases (16.8 percent). However, a large share of the 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.

IV. The role of income in weather-related mortality

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 C1. 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 predicted 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 C1. 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=0.44).

Second, we use the predicted income values to construct predicted income quartiles. Based on the sample of 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 predicted income quartile for each municipality *i* at time *t*.[23]

The results of these regressions by predicted income quartile are reported in Figure 3. Impacts between quartiles are statistically different from one another.[24] Results show a strong difference

[23] With this method, we are able to assign an income quartile to 81.6% 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 1/0.816 to account for the deaths for which no income quartile could be attributed.

[24] We ran a joint regression estimating the coefficients for the 1^{st} and 4^{th} quartiles of income in order to determine if the coefficients for the temperature bins were statistically different between both quartiles. The p-value of the F-test is <0.01, with an F-statistic of 2.00, with 180 numerator and 2281 denominator degrees of freedom.

in vulnerability to cold at unusual and mild levels between the first two and last two quartiles. For example, an unusual cold day below 12°C conveys 0.37 deaths per 100,000 inhabitants for the first quartile of income, versus 0.20 for the last quartile. 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 3 ABOUT HERE]

The results of Figure 3 could be driven by differences in baseline mortality rates across quartiles. In Table 4, 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 cold temperatures is still clearly higher for the 1st quartile of income, especially for mildly cold days (12-20°C). We also report the magnitude of the impacts in number of annual deaths by income quartile based on the typical daily average temperature distribution in Mexico of Figure 1. Cold and mildly cold days (below the reference bin of 24-28°C) lead to more than twice as many deaths in the first two quartiles of predicted income compared to the 3rd and 4th quartiles.[25]

Panels B to D of Table 4 provide a series of robustness checks confirming these findings. Firstly, 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 constitutes 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 poorer. The young and the very old are thus overrepresented in the lowest quartiles. To account for this, age-corrected results are provided in Table 4, Panel B (the methodology is presented in Appendix C1). Correcting for age does not affect our conclusion: the first two quartiles of income are about 35% more vulnerable to mildly cold days compared to the last two quartiles. The difference between quartiles is statistically significant.[26] Therefore, a sizeable difference in vulnerability levels correlates with differences in living conditions and social protection.

[25] 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 3, while the estimates of Table 2 are based on our baseline regression (Figure 2). However, differences are small: there are 26.324 deaths in Table 2 and 27,355 in Table 4, panel A.
[26] An F-test between the 1st and 4th quartile of income suggests that the coefficients for the temperature bins are statistically different at 1 percent.

[TABLE 4 ABOUT HERE]

Because we use income declarations from the 2000 Census, results could be sensitive to the fact that respondents may misreport their income. In Table 4, Panels C, we make sure that our findings by quartiles of predicted income are robust to using 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 respondents. 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 methodology is detailed in Appendix C1 but results are summarized in Table 4, Panel C. They corroborate the findings obtained with predicted income levels. Table 4, Panel D also provides age-corrected results using the poverty index to define quartiles and similarly shows that the most deprived groups are more vulnerable to unusual weather.

Finally, we run the quartile-specific econometric models for separate causes of death.[27] Results by cause of death are reported in Appendix C2 and corroborate that low-income households are more vulnerable to cardiovascular and respiratory diseases.

The policy implications of these results are substantial. They suggest that the poor are not only much more vulnerable to unusually cold temperatures, 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. Furthermore, the results obtained for respiratory diseases may have implications for the COVID-19 pandemic: low-income households appear at a much higher risk against respiratory diseases.

These results by income group are not surprising considering that low-income families have insufficient access to quality housing, drinking water and health insurance (as reported in the 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 housing units are equipped with some form of heating equipment.

[27] 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.

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.[28] Considering that financial constraints may prevent developing countries from protecting their citizens against the consequences of cold and heat, targeted 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.

In Mexico, the two major providers of health insurance, the Mexican Social Security Institute (IMSS) and the Institute for Social Security and Services for State Workers (ISSSTE), are directly linked to employment. Before the *Seguro Popular*, this meant that a large share of the population (around 60%) was not covered by these institutions or any other health insurance provider.

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. Another feature of the *Seguro Popular* is that health coverage was restricted to a reduced list of priority diseases. This list mostly included 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 were weather-sensitive, especially respiratory pathologies. In contrast, a long list of varied pathologies and treatments still remained excluded from the program, or were only covered for children and teenagers. To give a few examples, many types of cancers, diseases such as chronic kidney insufficiency, access to blood and

[28] 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).

homoderivatives, or organ transplants were not covered by the *Seguro Popular*. The treatment of leukemias was only offered to minors.

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 chronic, long-term diseases, in particular cancer and HIV.[29] The *Fondo de Protección contra Gastos Catastróficos* is still ongoing, while the *Seguro Popular* has been replaced since 1st January 2020 with a new program called *Instituto para la Salud y el Bienestar* (Insabi).

In 2004, 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.[30] 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 from 2012 onwards.

The evidence so far suggests that there have been clear benefits of the rollout of the *Seguro Popular*. King et al. (2009) and Avila-Burgos et al. (2013) find that out-of-pocket health expenditure and catastrophic health expenditure reduced for the beneficiaries of the program. Sosa-Rubi, Galárraga and Harris (2009) also find that pregnant women strongly preferred being attended in units sponsored by the *Seguro Popular* rather than paying out of pocket for attendance in private centres.

However, the *Seguro Popular* was also criticized for being insufficiently funded (Lakin, 2010). There may also have been a perverse effect of the policy on the job market, since access to universal healthcare has been found to reduce employment in the formal sector (Aterido, Hallward-Driemeier and Pagés, 2011; Bosch and Campos-Vazquez, 2014).

The overall health impacts of the program are difficult to assess. The study by King et al. (2009) finds no discernible effect of the *Seguro Popular* on health outcomes after 10 months of

[29] 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*.

[30] 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.

implementation, possibly because health effects could require more time to materialize. In contrast, other studies have identified health benefits. Knox (2008) find effects of the program on the utilization of healthcare services. Parker, Saenz and Wong (2018) find similar effects of higher healthcare utilization among the elderly. Likewise, Servan-Mori (2015) found that access to prescribed medicine was higher among the beneficiaries of the program. For infant mortality, Pfutze (2014, 2015) provides evidence of a possible reduction in miscarriages and infant mortality from the implementation of the *Seguro Popular*.

Cohen (2020) provides the preliminary results of a staggered difference-in-difference model to assess the impact of the *Seguro Popular* on all-cause mortality. While some of the assumptions underlying this analysis (such as the stable unit value treatment assumption) may not be fully valid, it suggests that the policy led to a reduction in all-cause mortality after 2 years of implementation, of around 7.4 percent on average during the 3rd and 4th years of implementation. We reproduce the relevant figure from Cohen (2020) in Appendix D1. In the rest of this section, we focus on the impact of the *Seguro Popular* on weather-related mortality, as temperature provide an exogenous source of variation enabling us to recover the causal effects of the policy.

V.A Method

We aim to assess if the rollout of the *Seguro Popular* led to a reduction in weather-related vulnerability. We focus the analysis on the population that was targeted by the *Seguro Popular*: people without health insurance suffering from the diseases covered by the *Seguro Popular*. We define a monthly mortality rate for the people eligible to the *Seguro Popular*, i.e. those without a traditional health insurance and dying from the diseases covered by the *Seguro Popular*.[31] We construct this mortality rate with the information present on the death certificates, since death certificates report the cause of death and whether the deceased was affiliated to an insurance scheme. People without a standard health insurance are those that report having either no health insurance, the *Seguro Popular* or a scheme called *IMSS Oportunidades* (destined to vulnerable, low-income households beneficiaries of *Oportunidades*) as a health insurance. To construct mortality rates, we use population estimates

[31] We identify these diseases with the 2016 nomenclature of covered diseases for the *Seguro Popular*, the *Fondo de Protección contra Gastos Catastróficos* and the *Seguro Médico Siglo XXI*, the scheme that complements the *Seguro Popular* for children (Comisión Nacional de Protección en Salud. 2016). The list of covered diseases had been stable after 2010, with only a few additions/subtractions.

that account for the share of people with no affiliation to a standard health insurance in each municipality.[32]

We then use an econometric method similar to Barreca *et al.* (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. We similarly interact temperature bins with the availability of *Seguro Popular*.

An important feature of an interacted model is that it controls for the impact of the *Seguro Popular* on all-cause mortality and only focuses on the impact of the *Seguro Popular* on weather-related vulnerability. This is statistically more robust than looking at the impact of the *Seguro Popular* on all-cause mortality because fluctuations in weather provide an exogenous source of variation to assess the effect of the *Seguro Popular* on mortality when comparing the municipalities that adopted the policy with those that have not adopted it yet.

To assess the impact of the *Seguro Popular* on weather vulnerability, we create a dummy variable that takes the value of 1 if the *Seguro Popular* is available in municipality i in month m and year t, and 0 otherwise. We obtain this information directly from the mortality data: we assume that the *Seguro Popular* is available in municipality i as soon as we record one death from someone covered by the *Seguro Popular* in municipality i.[33] Based on this definition, we observe that the *Seguro Popular* spread very rapidly, with 48 percent of the population having some access to it in 2004, 76 percent in 2005 and 89 percent in 2006. We include this variable in the model and interact it with our temperature bins (below 12°C; 12-16°C; 16-20°C; 20-24°C; 24-28°C (reference bin); 28-32°C; and above 32°C) to look at the impact of the *Seguro Popular* on weather-related mortality.[34]

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[32] The estimates of the general population without health insurance come from the INEGI censuses of population and housing. The information is provided for years 2000, 2005 and 2010. We use a linear extrapolation to estimate the relevant population between two censuses and beyond 2010. For the estimates of the population without health insurance by age group, we estimate the share of population without health insurance by age group using the 2000 census. We then multiply this share by our overall population estimates by municipality and year.

[33] This identifies very precisely the introduction of the *Seguro Popular* in large municipalities, since there are enough deaths per month to ensure that the introduction of the policy coincides with a death from someone receiving the policy. In small municipalities, there may be measurement error since several months could pass between the introduction of the policy and the first death of someone affiliated with the *Seguro Popular*. We check whether this has an impact on the results in the Table D4 of Appendix D2: we simply re-run the model after excluding all municipalities with less than 10,000 inhabitants. Results are very similar.

[34] We are only interested in the interaction terms since the *Seguro Popular* variable in simply provides information on the difference in mortality levels between treated and non-treated observations. We consider it to be exogenous: the exact timing of the policy, e.g. in February versus March, is deemed exogenous after accounting for the municipality by year fixed effects. Furthermore, in Table D3 of Appendix D2, we use a variable that takes the value of 1 in municipality i and year t if, during this year or the previous years, someone has died in this municipality while being covered by the *Seguro Popular*. The variable is then absorbed by the fixed effect, while

We introduce two types of additional interaction variables. The first one is a full set of interaction parameters between the temperature bins and municipality-by-month fixed effects. These parameters allow us to control for differences in weather vulnerability across municipalities and seasons. We also include interactions between each temperature bin and month-by-year fixed effects. This set of interactions controls for the autonomous evolution of weather vulnerability in Mexican municipalities that is unrelated to the deployment of the *Seguro Popular*.

With so many additional control variables, the model with daily data becomes unsolvable. This is because we would need to have municipality interaction terms for each of the 6 x 30 bin-specific lags. 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*, year *t* and for municipality *i*". With the data aggregated at monthly level, the number of temperature-bin-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-calendar-day fixed effects. Alternatively, we include three sets of overlapping fixed effects: municipality-by-year fixed effects, municipality-by-month fixed effects, and month-by-year fixed effects. This allows the monthly model to be as close as possible to the original daily specification. The results for a monthly model without the interactions with the *Seguro Popular* (corresponding to the baseline results presented in Section 3) are reported in Appendix A.4 and are very close to our general results of Figure 2 for the impact of weather on mortality.

V.B Results

In Table 5, we present our estimates for the effect of the *Seguro Popular* on weather vulnerability. In all columns, the sample is composed of people eligible to the *Seguro Popular* because (i) they do not have any standard health insurance such as the IMSS and ISSSTE and (ii) they died from a pathology covered by the *Seguro Popular*. Columns (1) to (4) are for the whole population; columns (5) and (6) focuses on people aged 55 and over who are significantly more at risk of dying following weather shocks, as shown in Table 3. Columns (1) to (3) and column (5) focus on weather-sensitive death causes (excluding infectious and parasitic diseases,

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we can still assess the impact of the interaction terms. Results lose precision but are however similar to our baseline results.

neoplasms, and accidental and violent deaths, which we have found to be only weakly correlated with cold weather – see Table 3) whereas columns (4) and (6) include all causes of death.

The results in Table 5 show a clear reduction in mortality for the 12-16°C bin as well as a likely reduction in mortality for the 16-20°C bin, particularly for people over 55 years old. This result is consistent with the results by income quartile of section IV, which show that the lower sensitivity of higher-income households to temperature shocks is highest for mildly cold days.[35] When applying the baseline estimates from column (1) to the historical distribution of temperatures in Mexico, we can derive that the statistically significant reduction in mortality from the 12-16°C bin implies that the *Seguro Popular* saved around 1,600 lives (95% confidence interval is 334 – 2,850) every year since 2004.[36]

[TABLE 5 ABOUT HERE]

This result is robust to variations in the interaction parameters between the temperature bins and the fixed effects. When using less of these interaction parameters (columns 2 and 3), point estimates remain almost identical while confidence intervals reduce. The 16-20°C becomes statistically significant at 10 percent. The estimates for this bin would correspond to an additional 1,350 lives saved every year.[37]

Furthermore, our baseline model (columns 1-3) excluded infectious and parasitic diseases, neoplasms and violent and accidental deaths. These are included in column (4). Point estimates are very similar, but precision decreases slightly. In columns (5) and (6), we show that the *Seguro Popular* had the strongest impact on the weather-related mortality of people over 55. Additional results for all-cause mortality and detailed results by age group, death cause and income quartiles are presented in Appendix D2.

So far, we used specifications that focus on the population that was eligible to the *Seguro Popular* (those without any other health insurance and dying from diseases covered by the scheme), who could undoubtedly benefit from the policy. However, the *Seguro Popular* may

[35] In Appendix D2, we provide additional evidence that the impact of the *Seguro Popular* is stronger in poorer municipalities (see Tables D5 and D6).

[36] This is using the coefficient for the interaction between the *Seguro Popular* and the 12-16°C temperature bin (-0.035 per 100,000 inhabitants) and applying it to the typical distribution of days at 12-16°C in Mexico (an average of 72.6 per year). Furthermore, in the estimation sample, 92% of the population had access to the *Seguro Popular* between 2004 and 2017. The figure is also for a total population of 129 million people, of which 60% would have no access to any other health insurance: 0.031 / 100,000 x 72.6 x 129,000,000 x 0.92 x 0.60 ≈ 1,600.

[37] This is using the same formula as above, with the coefficient for the interaction between the *Seguro Popular* and the 16-20°C temperature bin (-0.020 per 100,000 inhabitants) and applying it to the typical distribution of days at 16-20°C in Mexico (an average of 112.5 per year): 0.017 / 100,000 x 112.5 x 129,000,000 x 0.92 x 0.60 ≈ 1,350.

have had spill-over effects on other groups. In Table 6, column (1), we focus on people without any other health insurance, whether or not their cause of death was covered by the *Seguro Popular* (all results in Table 6 focus on weather-sensitive death causes). They could have benefited from the policy for pathologies which did not lead to death. Marginal effects for mildly cold days increase substantially, particularly for the 16-20°C bin which becomes statistically significant at 5 percent. They suggest that the policy might have had positive health effects on people without health insurance that died from non-covered diseases. We look at this group separately in Table 6, column (2): impacts are negative and statistically significant at 10 percent for the 16-20°C bin, suggesting the existence of spillovers to non-covered diseases, even if the bulk of the effects are concentrated on covered diseases.

Similarly, the *Seguro Popular* could have had an impact on the health of those who already had a health insurance, for example by reducing the prevalence of transmissible diseases. In Table 6, columns (3) to (5), we look at the population that already had health insurance and check for potential spill-over effects on this group of the population. Column (3) includes all diseases while columns (4) and (5) respectively focus on pathologies covered (col. 4) and not covered (col. 5) by the *Seguro Popular*. Coefficients are mostly insignificant, suggesting that the policy mainly had an effect on people without a traditional health insurance. An exception is days below 12°C for people with a health insurance and dying from diseases covered by the *Seguro Popular* (column 4). This effect could be explained if the policy had reduced the diffusion of contagious diseases covered by the *Seguro Popular*, which would positively impact the health of those with a health insurance.

Finally, we provide estimates for the entire population in column (6). This is the combination of groups in columns (1) and (3). While impacts for cold days remain negative, they unsurprisingly lose statistical significance as we found no statistically significant effect for the people with a health insurance in column (3).

We conclude from Table 6 that our main specification focusing on people without health insurance and covered diseases is likely to provide a lower bound of the impact of the *Seguro Popular* on death through temperature shocks, as we report suggestive evidence that other groups could have also benefited from the policy due to spill-over effects.

[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. When applying our econometric estimates to the historical distribution of temperatures in Mexico, we find that random variation in temperatures is responsible for the death of around 26,000 people every year in Mexico, representing 3.8 percent of annual deaths in the country. However, extreme weather events only account for a small proportion of weather-related deaths: unusually cold days (<12°C average temperature) trigger around 5,700 deaths each year, extremely hot days (>32°C) kill around 500 annually, while 71 percent of weather-related deaths are induced by mildly cold days (average temperature between 12°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 20 percent) 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. Longer-term impacts of climate change on human health through reductions in agricultural output or financial losses are not captured by our econometric specifications based on daily information.

We find that vulnerability to weather shocks is strongly correlated with individual income. The impact of suboptimal temperature exposure is much 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 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* to assess its contribution to reducing weather vulnerability. Applying the historical distribution of temperature in Mexico to our estimates, we find that the scheme saved around 1,600 lives per year since 2004 from exposure to mildly cold temperature (12°-16°C). This represents – a 6.6 percent reduction in weather vulnerability from days below 20°C. This effect is a clear lower bound: we also find evidence of an effect at other temperature levels, particularly for people aged 55 and over, as well as suggestive evidence of spillover effects on non-covered diseases and already insured patients.

The overall welfare implications of weather vulnerability in low- and middle-income countries are very large: in the sole case of Mexico, we estimate that 26,000 deaths each year are triggered by temperatures from which people in low-income households are inadequately protected. 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.

References

Aterido, Reyes, Mary Hallward-Driemeier, and Carmen Pagés. *Does Expanding Health Insurance Beyond Formal-Sector Workers Encourage Informality?: Measuring the Impact of Mexico's Seguro Popular*. The World Bank, 2011.

Ávila-Burgos, Leticia, et al. "Efectos del Seguro Popular sobre el gasto en salud en hogares mexicanos a diez años de su implementación." *Salud pública de méxico* 55 (2013): S91-S99.

Barnett, A. G., Hajat, S., Gasparrini, A., & Rocklöv, J. (2012). Cold and heat waves in the United States. *Environmental research*, *112*, 218-224.

Barreca, Alan, 2012. "Climate change, humidity, and mortality in the United States," *Journal of Environmental Economics and Management*, Vol. 63, Issue 1, Pages 19–34.

Barreca, Alan; Karen Clay; Olivier Deschenes; Michael Greenstone and Joseph S. Shapiro, 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century," *Journal of Political Economy*, Vol. 124, Issue 1, Pages 105–159.

Barros, R., 2008. "Wealthier but not much healthier: effects of a health insurance program for the poor in Mexico". Unpublished working paper.

Basu, Rupa. "High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008." *Environmental health* 8.1 (2009): 40.

Bosch, Mariano, and Raymundo M. Campos-Vazquez. "The trade-offs of welfare policies in labor markets with informal jobs: The case of the" Seguro Popular" program in Mexico." *American Economic Journal: Economic Policy* 6.4 (2014): 71-99.

Braga, Alfésio Luís Ferreira; Antonella Zanobetti and Joel Schwartz, 2001. "*The time course of weather-related deaths*," *Epidemiology*, Vol. 12, Issue 6, Pages 662–667.

Burgess, Robin; Olivier Deschenes; Dave Donaldson and Michael Greenstone, 2017. "Weather, Climate Change and Death in India," unpublished working paper.

Carleton, Tamma A., et al. *Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits*. No. w27599. National Bureau of Economic Research, 2020.

Cohen, Francois (2020) The Impacts of Universal Healthcare Extension in Mexico. Unpublished working paper.

Comisión Nacional de Protección en Salud. 2016. *Catálogo Universal de Servicios de Salud: CAUSES 2016*.

Coordinación General del Servicio Meteorológico Nacional de la Comisión Nacional del Agua *(CONAGUA)*. 2018. *Base de datos climatológica nacional de Mexico: datos diarios*. Data accessed after requesting it from the CONAGUA and downloaded on 14th December 2018.

Curriero, F.C.; K.S. Heiner; J.M. Samet; S.L. Zeger; L. Strug and J.A. Patz, 2002. “Temperature and mortality in 11 cities of the Eastern United States,” *American Journal of Epidemiology*, Vol. 155, Pages 80–87.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, Vol. 4, Issue 3, Pages 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, Vol. 52, Issue 3, Pages 740–98.

Deschênes, Olivier and Enrico Moretti, 2009. “Extreme Weather Event, Mortality and Migration,” *The Review of Economics and Statistics*, Vol. 41, Issue 4, Pages 659–681.

Deschenes, Olivier and Michael Greenstone, 2011. “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US,” A*merican Economic Journal: Applied Economics,* Vol. 3, Pages 152–185.

Deschenes, Olivier, 2014. “Temperature, human health, and adaptation: A review of the empirical literature,” *Energy Economics*, Vol. 46, Pages 606–619.

Dirección de Monitoreo Atmosférico. 1998-2017. Índice de Calidad del Aire. http://www.aire.cdmx.gob.mx/default.php?opc=%27aqBjnmU=%27 (last accessed on 2nd January 2021).

Dupas, P., & Miguel, E. (2017). Impacts and determinants of health levels in low-income countries. In *Handbook of economic field experiments* (Vol. 2, pp. 3-93). North-Holland.

El-Zein, A.; M. Tewtel-Salem and G. Nehme, 2004. “A time-series analysis of mortality and air temperature in Greater Beirut,” *Science of the Total Environment*, Vol. 330, Pages 71–80.

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., ... & Leone, M. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet*, *386*(9991), 369-375.

Gasparrini, A., Guo, Y., Sera, F., Vicedo-Cabrera, A. M., Huber, V., Tong, S., ... & Ortega, N. V. (2017). Projections of temperature-related excess mortality under climate change scenarios. *The Lancet Planetary Health*, *1*(9), e360-e367.

Gaure, Simen. "OLS with Multiple High Dimensional Category Dummies". Memorandum 14/2010, Oslo University, Department of Economics, 2010.

Gouveia, Nelson; Shakoor Hajat and Ben Armstrong, 2003. “Socioeconomic differentials in the temperature–mortality relationship in São Paulo, Brazil,” *International Journal of Epidemiology*, Volume 32, Issue 3, Pages 390–397.

Graff-Zivin, Joshua and Matthew J. Neidell, 2010. "Temperature and the Allocation of Time: Implications for Climate Change," *National Bureau of Economic Research*, Working Paper No. 15717.

Guerrero Compeán, Roberto. "The death effect of severe climate variability." *Procedia Economics and Finance* 5 (2013): 182-191.

Guimaraes, Paulo and Pedro Portugal. "A Simple Feasible Alternative Procedure to Estimate Models with High-Dimensional Fixed Effects". Stata Journal, 10(4), 628-649, 2010.

Guo, Y., Gasparrini, A., Armstrong, B., Li, S., Tawatsupa, B., Tobias, A., ... & Tong, S. (2014). Global variation in the effects of ambient temperature on mortality: a systematic evaluation. *Epidemiology (Cambridge, Mass.)*, *25*(6), 781.

Hajat, S., & Gasparrini, A. (2016). The excess winter deaths measure: why its use is misleading for public health understanding of cold-related health impacts. *Epidemiology (Cambridge, Mass.)*, *27*(4), 486.

Hajat, S.; R.S. Kovats and K. Lachowycz, 2007. "Heat-related and cold-related deaths in England and Wales: who is at risk?" *Occupational and Environmental Medicine*, Vol. 64, Pages 93–100.

Hajat, Shakoor; Ben Armstrong; Michela Baccini; Annibale Biggeri; Luigi Bisanti; Antonio Russo; Anna Paldy; Bettina Menne and Tom Kosatsky, 2006. "Impact of high temperatures on mortality," *Epidemiology*, Vol. 17, Issue 6, Pages 632–638.

Hajat, Shakoor; Ben Armstrong; Nelson Gouveia and Paul Wilkinson, 2005. "Mortality displacement of heat-related deaths," *Epidemiology*, Vol. 16, Issue 5, Pages 613–620.

Harris, J. E., & Sosa-Rubi, S. G., 2009. "Impact of "Seguro Popular" on Prenatal Visits in Mexico, 2002-2005: Latent Class Model of Count Data with a Discrete Endogenous Variable," Workip paper No. 14995. National Bureau of Economic Research.

Heutel, Garth; Nolan H. Miller and David Molitor, 2017. "Adaptation and the Mortality Effects of Temperature Across U.S. Climate Regions," NBER Working Paper No. 23271.

INEGI (Instituto Nacional de Estadística y Geografía). 1990-2017. *Microdatos de mortalidad: defunciones registradas (mortalidad general).* Available at https://www.inegi.org.mx/programas/mortalidad/default.html#Datos_abiertos (last accessed on 2nd February 2020).

INEGI. 1990, 1995, 2000, 2005 and 2010. Censos de Población y Vivienda. Conjunto de datos: Población total (con información hasta localidad). Data available on INEGI website (www.inegi.org.mx) and last accessed on 2nd January 2021.

INEGI. 2000. Censo de Población y vivienda 2000: Microdatos de la muestra (cuestionario ampliado) de las 32 entidades federativas de México. https://www.inegi.org.mx/programas/ccpv/2000/#Microdatos (last accessed 2nd January 2021).

INEGI, 2008. *Mexico y sus municipios*.

INEGI. 2008b. Conjunto de datos vectoriales escala 1:1 000 000. Unidades climáticas. https://www.inegi.org.mx/contenido/productos/prod_serv/contenidos/espanol/bvinegi/productos/geografia/tematicas/CLIMAS/702825267568_s.zip (last accessed 2nd January 2021).

INEGI. 2010. Marco geoestadístico 2010 versión 5.0 (Censo de Población y Vivienda 2010). https://www.inegi.org.mx/contenido/productos/prod_serv/contenidos/espanol/bvinegi/productos/geografia/marc_geo/702825292805_s.zip (last accessed 2nd January 2021).

INEGI. 2020. *Catálogo Único de Claves de Áreas Geoestadísticas Estatales, Municipales y Localidades*. *Marco Geoestadístico National de México*. Fecha de corte de la información: Octubre de 2010. https://www.inegi.org.mx/app/ageeml/ (last accessed 2nd January 2021).

Kahn, Matthew E. "The climate change adaptation literature." *Review of Environmental Economics and Policy* 10.1 (2016): 166-178.

King, G. and others, 2009. "Public policy for the poor? A randomised assessment of the Mexican universal health insurance programme, " *The lancet*, Volume 373, Issue 9673, Pages 1447-1454.

Knox, Melissa. "Health insurance for all: an evaluation of Mexico's Seguro popular program." *Unpublished manuscript, Department of Economics, University of California Berkley* (2008).

Lakin, Jason M. "The end of insurance? Mexico's Seguro Popular, 2001–2007." *Journal of Health Politics, Policy and Law* 35.3 (2010): 313-352.

Lipsitch, Marc, and Cécile Viboud. "Influenza seasonality: lifting the fog." *Proceedings of the National Academy of Sciences* 106.10 (2009): 3645-3646.

Lowen, Anice C., and John Steel. "Roles of humidity and temperature in shaping influenza seasonality." *Journal of virology* 88.14 (2014): 7692-7695.

Ma, W., Chen, R., & Kan, H. (2014). Temperature-related mortality in 17 large Chinese cities: how heat and cold affect mortality in China. *Environmental research*, *134*, 127-133.

McMichael A.J.; P. Wilkinson; R.S. Kovats; S. Pattenden; S. Hajat, B. Armstrong, N. Vajanapoom, E.M. Niciu, H. Mahomed; C. Kingkeow *et al.*, 2008. "International study of temperature, heat and urban mortality: the 'ISOTHURM' project," International Journal of Epidemiology 2008, Vol. 37, Pages 1121–1131.

Parker, Susan W., Joseph Saenz, and Rebeca Wong. "Health insurance and the aging: Evidence from the Seguro Popular program in Mexico." *Demography* 55.1 (2018): 361-386.

Pfutze, Tobias. "Does access to health insurance reduce the risk of miscarriages? Evidence from Mexico's Seguro popular." *Latin American Economic Review* 24.1 (2015): 8.

Pfutze, Tobias. "The effects of Mexico's Seguro Popular health insurance on infant mortality: An estimation with selection on the outcome variable." *World Development* 59 (2014): 475-486.

Prel (du), Jean-Baptist, et al. "Are meteorological parameters associated with acute respiratory tract infections?." *Clinical infectious diseases* 49.6 (2009): 861-868.

Secretaría General del Consejo Nacional de Población – CONAPO, 2010. "Principales causas de mortalidad en México: 1980-2007," Working paper for the 43rd period of sessions of the *Comisión de Población y Desarrollo "Salud, morbilidad, mortalidad y desarrollo"*.

Servan-Mori, Edson, et al. "Access to medicines by Seguro popular beneficiaries: pending tasks towards universal health coverage." *PloS one* 10.9 (2015): e0136823.

Shaman, Jeffrey, and Alicia Karspeck. "Forecasting seasonal outbreaks of influenza." *Proceedings of the National Academy of Sciences* 109.50 (2012): 20425-20430.

Shaman, Jeffrey, and Melvin Kohn. "Absolute humidity modulates influenza survival, transmission, and seasonality." *Proceedings of the National Academy of Sciences* 106.9 (2009): 3243-3248.

Sosa-Rubi, S. G., Galárraga, O., & Harris, J. E., 2009. "Heterogeneous impact of the "Seguro Popular" program on the utilization of obstetrical services in Mexico, 2001–2006: a multinomial probit model with a discrete endogenous variable," *Journal of health economics*, Volume 28, Issue 1, Pages 20-34.

Sosa-Rubi, Sandra G., Omar Galárraga, and Jeffrey E. Harris. "Heterogeneous impact of the "Seguro Popular" program on the utilization of obstetrical services in Mexico, 2001–2006: A multinomial probit model with a discrete endogenous variable." *Journal of health economics* 28.1 (2009): 20-34.

Tamerius, James D., et al. "Environmental predictors of seasonal influenza epidemics across temperate and tropical climates." *PLoS Pathog* 9.3 (2013): e1003194.

Tamerius, James, et al. "Global influenza seasonality: reconciling patterns across temperate and tropical regions." *Environmental health perspectives* 119.4 (2011): 439-445.

Universidad Nacional Autónoma de México. Centro de Ciencias de la Atmósfera. Unidad de Informática para las Ciencias Atmosféricas y Ambientales, 2014. Modelo GFDL-CM3, resolución espacial de 30'' por 30''. Horizonte 2075-2099. Temperatura promedio para RCP 4.5 y temperaturas mínimas y máximas para RCP 8.5. Last downloaded on 6th March 2021: RCP 4.5, average temperature (http://ri.atmosfera.unam.mx:8550/geonetwork/srv/eng/catalog.search#/metadata/b57acb62-785e-4a62-8ee4-fd4578ab27e5), RCP 8.5, minimum temperature (http://ri.atmosfera.unam.mx:8550/geonetwork/srv/eng/catalog.search#/metadata/55e45dd2-12dc-4af7-9361-55b4ee592f09), RCP 8.5, maximum temperature (http://ri.atmosfera.unam.mx:8550/geonetwork/srv/eng/catalog.search#/metadata/acb5564f-416b-4670-9067-0ab31b82a2a2).

WHO. 2010. Mexico Life Table 2010. Global Health Observatory data repository: expectation of life at age x by age group in 2010. https://apps.who.int/gho/data/view.main.61060 (last accessed 19th March 2021).

World Meteorological Organization, 2011. *Guide to Climatological Practices*. WMO-No. 100.

Yang, J., Yin, P., Zhou, M., Ou, C. Q., Guo, Y., Gasparrini, A., ... & Luan, G. (2015). Cardiovascular mortality risk attributable to ambient temperature in China. *Heart*, *101*(24), 1966-1972.

Tables and figures

Table 1: Summary of death statistics

Group	Average pop. per mun.	All causes	Respir. diseases	Circul. Diseases	Metab. Diseases
		Average daily municipal mortality rate (deaths per 100,000 inhabitants)			
Total	44,418	1.36	0.117	0.323	0.221
			(8.6)	(23.8)	(16.3)
Men	21,696	1.54	0.13	0.337	0.215
			(8.4)	(21.9)	(14)
Women	22,722	1.18	0.104	0.309	0.227
			(8.8)	(26.2)	(19.2)
Aged 0-4	4,317	0.96	0.097	0.014	0.03
			(10.1)	(1.5)	(3.2)
Aged 5-9	4,533	0.07	0.005	0.002	0.003
			(6.1)	(3.3)	(4.1)
Aged 10-19	8,861	0.15	0.005	0.007	0.004
			(3.3)	(4.4)	(2.6)
Aged 20-34	10,830	0.39	0.012	0.025	0.015
			(3.2)	(6.5)	(3.9)
Aged 35-44	5,880	0.66	0.025	0.076	0.062
			(3.9)	(11.6)	(9.4)
Aged 45-54	4,140	1.36	0.056	0.233	0.25
			(4.1)	(17.1)	(18.4)
Aged 55-64	2,643	3.07	0.159	0.659	0.755
			(5.2)	(21.5)	(24.6)
Aged 65-74	1,586	5.11	0.265	1.1	1.26
			(5.2)	(21.5)	(24.7)
Aged 75+	1,032	21.31	2.85	7.71	3.49
			(13.4)	(36.2)	(16.4)

Group	Infect. diseases	Neopl.	Violent and accid.	All other
	Average daily municipal mortality rate (deaths per 100,000 inhabitants)			
Total	0.045	0.168	0.151	0.335
	(3.3)	(12.4)	(11.1)	(24.6)
Men	0.056	0.168	0.249	0.385
	(3.6)	(10.9)	(16.2)	(25)
Women	0.034	0.168	0.058	0.28
	(2.9)	(14.2)	(4.9)	(23.7)
Aged 0-4	0.066	0.013	0.075	0.669
	(6.8)	(1.4)	(7.8)	(69.3)
Aged 5-9	0.005	0.013	0.024	0.022
	(7.1)	(17.3)	(32.4)	(29.6)
Aged 10-19	0.005	0.016	0.081	0.033
	(3.4)	(10.5)	(54)	(21.8)
Aged 20-34	0.029	0.03	0.2	0.076
	(7.5)	(7.7)	(51.7)	(19.6)
Aged 35-44	0.046	0.085	0.189	0.175
	(6.9)	(12.9)	(28.8)	(26.6)
Aged 45-54	0.056	0.225	0.185	0.355
	(4.1)	(16.5)	(13.6)	(26.1)
Aged 55-64	0.082	0.529	0.202	0.684
	(2.7)	(17.2)	(6.6)	(22.3)
Aged 65-74	0.136	0.882	0.336	1.131
	(2.7)	(17.3)	(6.6)	(22.1)
Aged 75+	0.373	2.21	0.56	4.117
	(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 from 1998 to 2017. 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
<12°C	5,705
	(591)
12-16°C	11,142
	(1,494)
16-20°C	7,536
	(1,449)
20-24°C	-367
	(718)
24-28°C	-
28-32°C	1,769
	(403)
>30°C	539
	(75)
Total	26,324
	(3,609)

Notes: The standard errors are in brackets. They only take 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 is 24-28 Celsius degrees.

Table 3: Mortality and death estimates by age group and type of disease

Sample	Mortality per 100,000 inhabitants				Deaths per year
	<12°C	12-16°C	16-20°C	>32°C	
A. Age groups					
0-4	0.199	0.015	0.004	-0.004	328
	(0.033)	(0.025)	(0.021)	(0.055)	(602)
5-9	-0.001	-0.008	-0.006	-0.008	-237
	(0.01)	(0.007)	(0.005)	(0.012)	(163)
10-19	0.012	-0.003	-0.008	0.043	-286
	(0.01)	(0.007)	(0.006)	(0.015)	(350)
20-34	0.002	-0.004	-0.01	0.02	-393
	(0.014)	(0.011)	(0.009)	(0.032)	(713)
35-44	0.052	0.016	-0.011	0.063	56
	(0.028)	(0.022)	(0.017)	(0.038)	(832)
45-54	0.243	0.064	0.019	0.255	1,956
	(0.047)	(0.037)	(0.027)	(0.073)	(986)
55-64	0.531	0.325	0.211	0.433	5,536
	(0.092)	(0.059)	(0.046)	(0.151)	(1,121)
65-74	0.872	0.52	0.342	0.698	5,327
	(0.152)	(0.097)	(0.074)	(0.247)	(1,083)
75+	5.70	2.52	1.07	4.53	15,243
	(0.526)	(0.301)	(0.237)	(0.621)	(2,142)
B. Selected disease types					
Infectious and parasitic	0.002	-0.001	-0.001	0.007	-219
	(0.002)	(0.002)	(0.001)	(0.004)	(443)
Neoplasms	0.008	0.002	0.002	-0.003	626
	(0.004)	(0.003)	(0.003)	(0.008)	(825)
Endocrine, nutritional and	0.060	0.032	0.014	0.049	7,216
metabolic	(0.007)	(0.005)	(0.004)	(0.008)	(1,221)
Circulatory	0.080	0.047	0.024	0.044	10,079
	(0.011)	(0.006)	(0.005)	(0.013)	(1,562)
Respiratory	0.056	0.023	0.007	0.015	4,410
	(0.007)	(0.004)	(0.003)	(0.006)	(934)
Violent and accidental	-0.002	-0.006	-0.005	0.033	-1,021
	(0.005)	(0.004)	(0.003)	(0.01)	(1,117)
All other causes	0.052	0.022	0.011	0.054	5,232
	(0.007)	(0.005)	(0.004)	(0.011)	(1,251)

Note: The estimates in each row come from separate regressions by age group (panel A) and selected disease type (panel B). They rely on similar specifications to Figure 2: the dependent variable is the daily mortality rate per 100,000 inhabitants, the regressions control for the daily precipitation level and include day-by-month-by-year fixed effects, municipality-by-calendar-day (1st January to 31st December) fixed effects, and municipality-by-year fixed effects. Standard errors are in brackets and clustered at the municipality level. The first four columns provide mortality estimates due to unusually cold (<12°C), mildly cold (12-16°C and 16-20°C) and unusually hot (>32°C) temperatures, as compared to a day with an average temperature of 24-28°C. The last columns provide estimates of the number of deaths per year, taking into account the frequency of cold, mildly cold and hot days. Population is assumed to be 129 million in total and age-specific population estimates are based on our linear extrapolation of population for 2017. Note that, 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.

Table 4: Impact of cold temperatures by predicted income quartile

Model	% change in average daily mortality			Average deaths per year		
	<12°C	12-16°C	16-20°C	<12°C	12-24°C	>28°C
A. Predicted income quartiles						
1st	0.265	0.136	0.068	2,037	8,313	267
	(0.028)	(0.018)	(0.013)	(212)	(1,335)	(168)
2nd	0.193	0.105	0.031	1,617	5,435	761
	(0.031)	(0.022)	(0.017)	(256)	(2,000)	(243)
3rd	0.154	0.073	0.021	1,089	2,706	861
	(0.031)	(0.023)	(0.017)	(221)	(1,631)	(277)
4th	0.179	0.084	0.014	1,096	2,782	391
	(0.038)	(0.026)	(0.018)	(235)	(1,599)	(239)
B. Age-corrected predicted income quartiles						
1st	0.249	0.133	0.072	1,624	7,193	241
	(0.029)	(0.02)	(0.014)	(191)	(1,234)	(157)
2nd	0.178	0.099	0.029	1,364	4,843	628
	(0.029)	(0.021)	(0.017)	(221)	(1,791)	(210)
3rd	0.177	0.075	0.019	1,335	3,050	632
	(0.028)	(0.023)	(0.016)	(212)	(1,774)	(235)
4th	0.207	0.103	0.031	1,502	4,675	762
	(0.038)	(0.023)	(0.016)	(275)	(1,613)	(283)
C. Predicted quartiles based on poverty indicator						
1st	0.248	0.137	0.068	1,803	7,904	194
	(0.028)	(0.018)	(0.013)	(201)	(1,312)	(175)
2nd	0.2	0.104	0.04	1,522	5,400	600
	(0.028)	(0.021)	(0.017)	(211)	(1,754)	(197)
3rd	0.173	0.088	0.029	1,190	4,282	786
	(0.027)	(0.023)	(0.016)	(185)	(1,586)	(250)
4th	0.18	0.074	0.007	1,395	2,116	689
	(0.037)	(0.023)	(0.017)	(284)	(1,797)	(303)
D. Age-corrected predicted quartiles based on poverty indicator						
1st	0.245	0.138	0.066	1,852	8,224	210
	(0.026)	(0.018)	(0.013)	(200)	(1,332)	(176)
2nd	0.182	0.09	0.029	1,481	4,509	627
	(0.027)	(0.02)	(0.016)	(217)	(1,741)	(198)
3rd	0.207	0.106	0.046	1,648	6,629	953
	(0.032)	(0.025)	(0.018)	(256)	(2,030)	(290)
4th	0.172	0.067	-0.007	971	576	538
	(0.045)	(0.027)	(0.019)	(255)	(1,450)	(240)

Notes: Standard errors in brackets (clustered at the municipality level). Each row refers to the output of a separate regression. The mortality estimates correspond to the 31-day long-run cumulative effect of a day at a given temperature on mortality for all death causes. The dependent variable is 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 12°C leads to a 26.5% increase in the daily mortality rate. Each regression controls for the daily precipitation level and includes day by month by year fixed effects, municipality by calendar day (1-365) fixed effects, and municipality by year fixed effects. Reference day is 24-28 degrees Celsius. The estimates for the average number of deaths are based on the coefficients displayed on the first four columns, and the frequency of cold days provided in Figure 1.

Table 5: Impact of the *Seguro Popular* on the eligible population

	(1)	(2)	(3)	(4)	(5)	(6)
Age group	All age groups				55 and over	
Death cause	Weather-sensitive[a]			All	Weather-sensitive[a]	All
Seguro Popular:						
x days below 12°C	0.013	0.010	0.010	0.012	0.091	0.271
	(0.022)	(0.019)	(0.019)	(0.026)	(0.223)	(0.252)
x days at 12-16°C	-0.031**	-0.032***	-0.034***	-0.043***	-0.433***	-0.538***
	(0.012)	(0.011)	(0.011)	(0.016)	(0.129)	(0.154)
x days at 16-20°C	-0.017	-0.017*	-0.016*	-0.020	-0.186*	-0.129
	(0.011)	(0.009)	(0.009)	(0.014)	(0.106)	(0.127)
x days at 20-24°C	0.001	-0.005	-0.005	-0.003	-0.101	-0.214
	(0.011)	(0.010)	(0.010)	(0.014)	(0.119)	(0.138)
x days at 28-32°C	-0.008	-0.001	-0.001	-0.024	-0.177	-0.170
	(0.014)	(0.012)	(0.012)	(0.018)	(0.152)	(0.181)
x days above 32°C	-0.010	-0.011	-0.017	-0.037	-0.105	-0.853
	(0.078)	(0.052)	(0.054)	(0.097)	(0.712)	(0.799)
Interacted fixed effects						
Temperature bins and precipitations:						
x month by year	X	X	X	X	X	X
x municipality by month	X			X	X	X
x State			X			

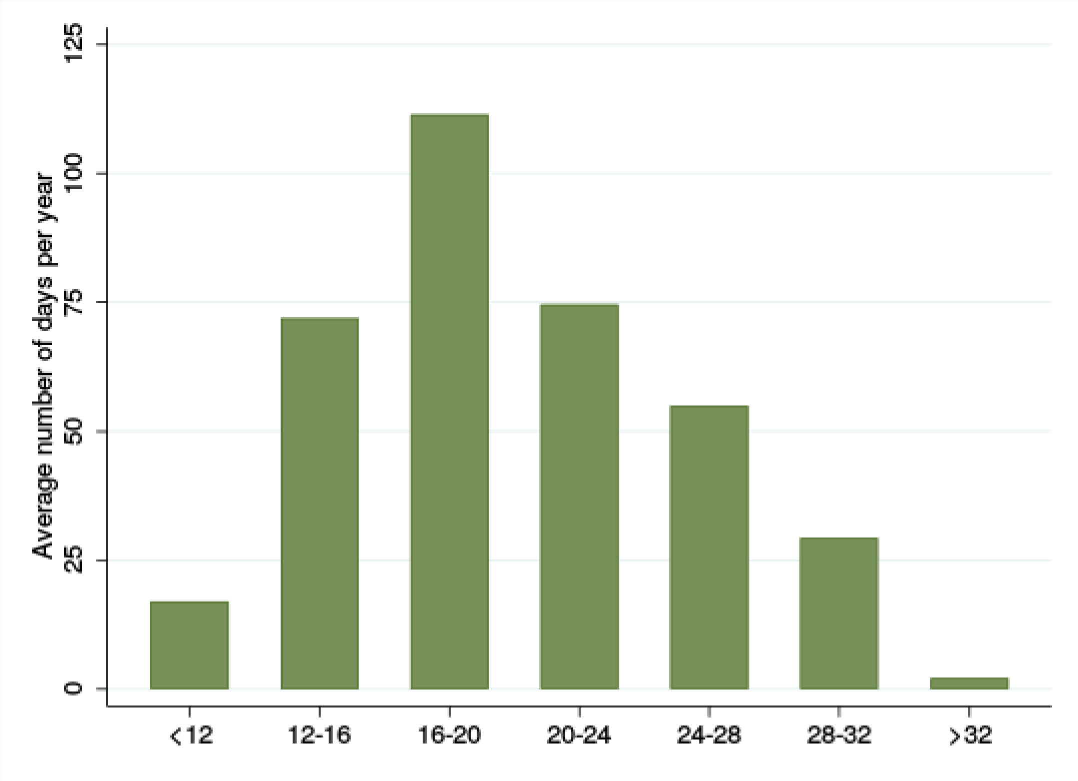
Notes: (a) Weather-sensitive death causes are all death causes excluding infectious and parasitic diseases, neoplasms and violent and accidental deaths. They therefore include endocrine, nutritional, metabolic, circulatory and respiratory diseases as well as all other death causes. *, ** and *** means statistically significant at 10, 5 and 1 percent. The dependent variable is the monthly mortality rate per 100,000 inhabitants for the people without any other health insurance, dying from the diseases covered by the *Seguro Popular*. All specifications include municipality by month, municipality by year and month by year fixed effects, as well as a dummy variable for the presence/absence of the *Seguro Popular*. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We use additional fixed effects that are interacted with the temperature bins. These interactions vary across specifications and are reported directly in the table. Standard errors in brackets are clustered at the level of municipalities and the model is weighted by the population in each municipality with no access to any other health insurance. Reference day is 24-28 degrees Celsius.

Table 6: Effects of the *Seguro Popular* on other groups

	(1)	(2)	(3)	(4)	(5)	(6)
Health insurance status	Without		With			With and without
Death cause (weather-sensitive[a])	Covered and not	Not Covered	Covered and not	Covered	Not Covered	Covered and not
Seguro Popular:						
x days below 12°C	0.007	-0.007	-0.054	-0.064**	0.010	-0.025
	(0.028)	(0.018)	(0.046)	(0.032)	(0.032)	(0.026)
x days at 12-16°C	-0.038**	-0.007	0.020	0.0001	0.020	-0.025
	(0.018)	(0.012)	(0.034)	(0.024)	(0.021)	(0.017)
x days at 16-20°C	-0.035**	-0.018*	-0.010	-0.012	0.002	-0.028*
	(0.016)	(0.010)	(0.031)	(0.022)	(0.019)	(0.016)
x days at 20-24°C	-0.005	-0.005	0.022	0.014	0.008	0.0004
	(0.016)	(0.011)	(0.031)	(0.023)	(0.019)	(0.016)
x days at 28-32°C	-0.024	-0.016	0.027	0.022	0.005	-0.024
	(0.020)	(0.013)	(0.038)	(0.027)	(0.025)	(0.020)
x days above 32°C	0.067	0.077	0.005	-0.146	0.151	0.058
	(0.103)	(0.058)	(0.191)	(0.136)	(0.122)	(0.088)

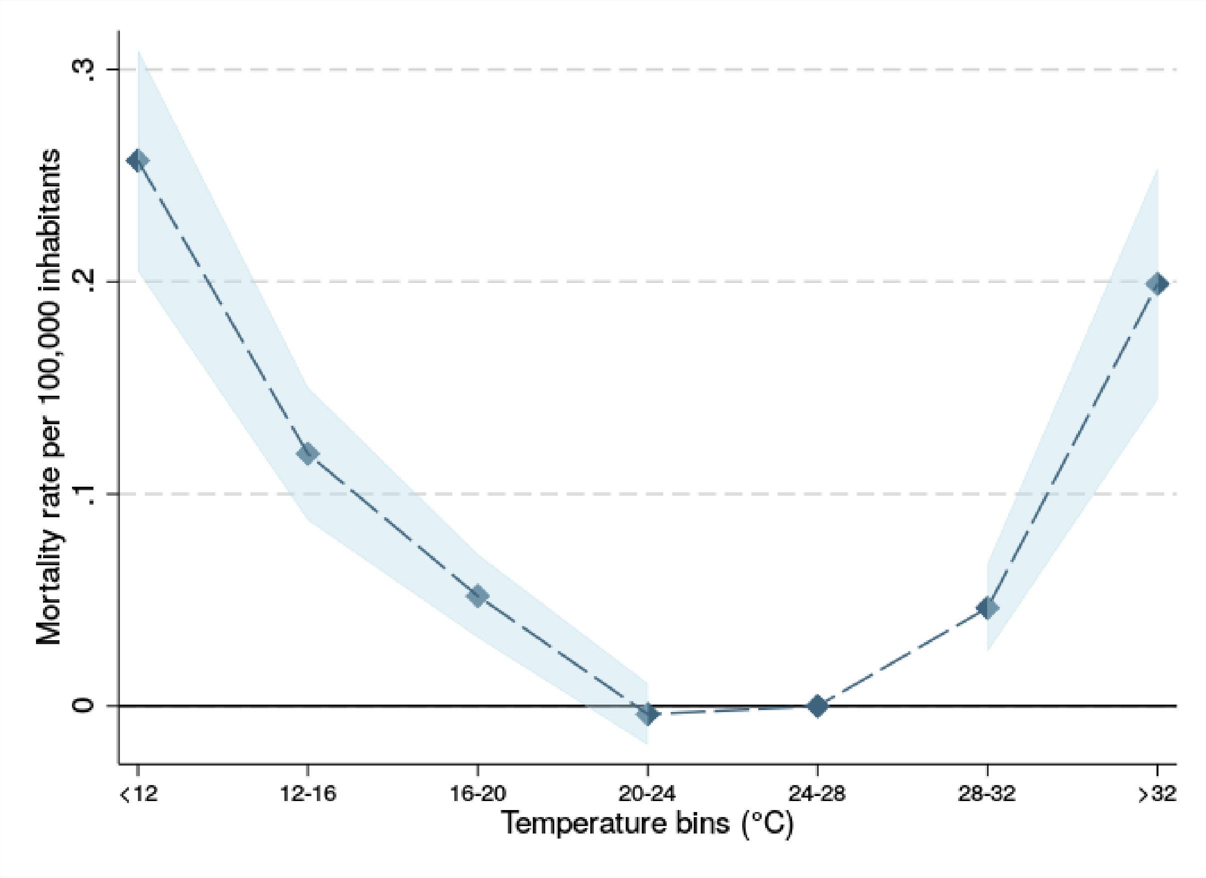
Notes: (a) Weather-sensitive death causes are all death causes excluding infectious and parasitic diseases, neoplasms and violent and accidental deaths. They therefore include endocrine, nutritional, metabolic, circulatory and respiratory diseases as well as all other death causes. *, ** and *** means statistically significant at 10, 5 and 1 percent. The dependent variable is the monthly mortality rate per 100,000 inhabitants from the selected population (with/without access to standard health insurance) and pathologies (covered and/or not by the *Seguro Popular*), for all death causes except infectious and parasitic diseases, neoplasms, and violent and accidental deaths. All specifications include municipality by month, municipality by year and month by year fixed effects, as well as a dummy variable for the presence/absence of the *Seguro Popular*. The specifications also control for the interaction between the Seguro Popular and precipitations. We also interact the temperature bins and the level of precipitations with the month by year fixed effects and the municipality by month fixed effects. Standard errors in brackets are clustered at the level of municipalities. Reference day is 24-28 degrees Celsius.

Figure 1: Population-weighted number of days per year falling within each temperature bin (in °C) for historical data (1998-2017)



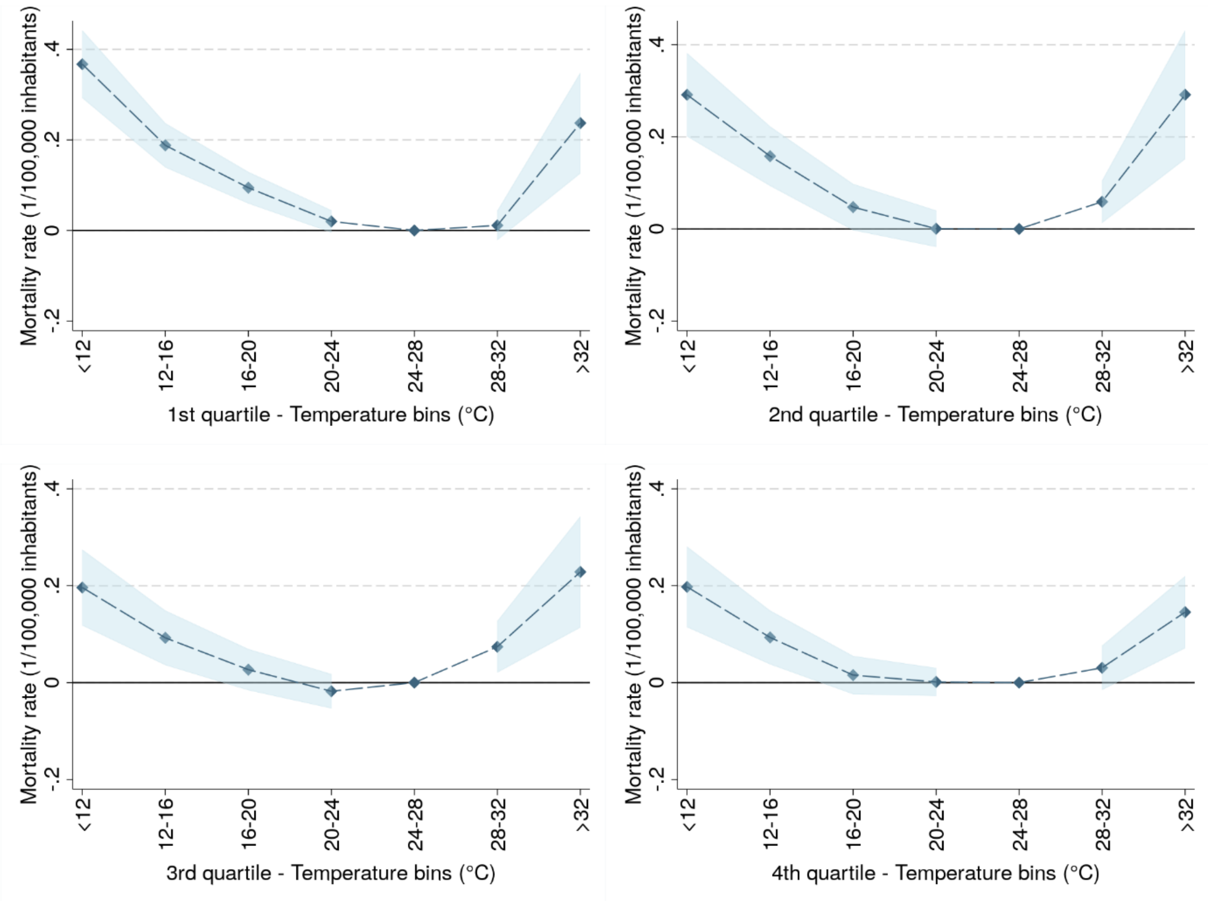
Notes: The figure shows the distribution of daily mean temperatures across 7 temperature-day bins (in °C). Each green bar represents the historical average number of days in each temperature category during a year (calculated over 1998-2017). Municipality averages have been weighted by total population in a municipality.

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-28°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 (clustered at municipality level). The dependent variable is the daily mortality rate at the municipality level. 14,231,164 observations. The regression controls for the daily precipitation level and includes day-by-month-by-year fixed effects, municipality-by-calendar-day (1st January to 31st December) fixed effects, and municipality-by-year fixed effects.

Figure 3: 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 4°C temperature bins in the regressions. The reference bin is 24-28°C. The regressions control for the daily precipitation level and includes day-by-month-by-year fixed effects, municipality-by-calendar day (1-365) fixed effects, and municipality-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/(1-0.184) because 18.4% 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 A8), robustness checks (B1 to B8), impacts by quartile of predicted income (C1 and C2) and *Seguro Popular* (D1 and D2).

A – 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.[38] 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,

[38] 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).

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 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.[39]

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.[40] Like in the case of heat, people with inefficient thermoregulation systems or with preconditions will be

[39] 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 tends 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.

[40] 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).

more vulnerable to cold, and start being at risk for ambient air temperatures between 10°C and 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.[41] 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.

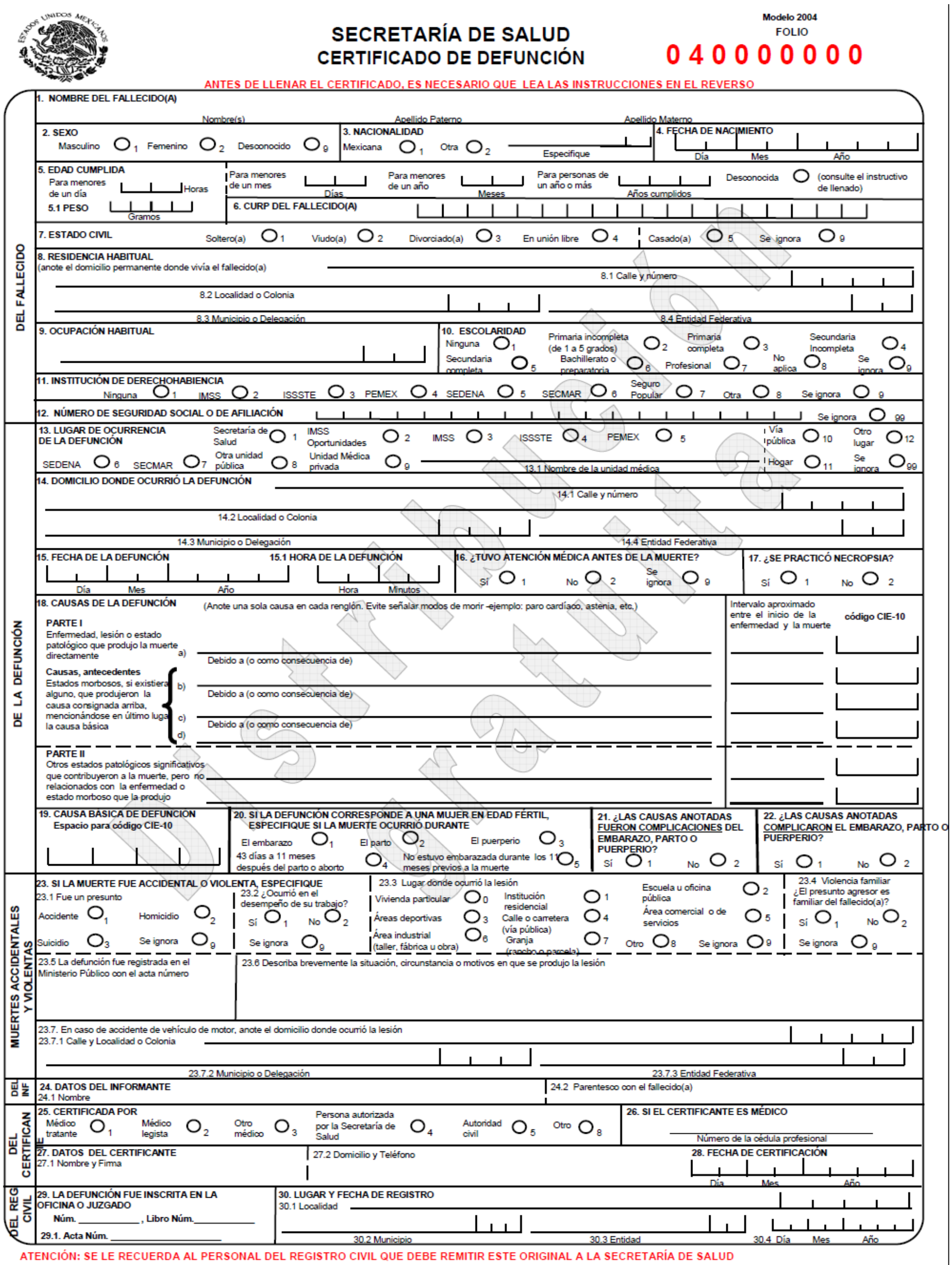
[41] Muscle mass is the essential component of heat production in the body (Horvath, 1981) whereas body fat offers additional protection to cold.

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 A1: 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
Distribución gratuita

Appendix A3: Summary statistics from the 2000 Mexican Census

Table A1: 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. The calculations in this table exclude households declaring zero income. †: includes people that were completing secondary school.

Appendix A4: Estimates using monthly data

We estimate the temperature-mortality model after aggregating the data at the monthly level. We use municipality-by-year fixed effects, municipality-by-month fixed effects, and month-by-year fixed effects. We find similar results to the ones obtained with our base model with daily data. We find an increase in mortality by around 0.2 deaths per 100,000 inhabitants for days below 12°C and above 32°C.

While the daily data only starts in 1998, we have monthly data from 1990. We provide results for 1990-2017 and for 1998-2017.

Table A2: Impact of temperature on mortality using monthly data

Sample	1990-2017	1998-2017
Day below 12°C	0.188	0.191
	(0. 019)	(0.023)
Day at 12-16°C	0. 078	0.081
	(0. 012)	(0.014)
Day at 16-20°C	0. 025	0.024
	(0.008)	(0.009)
Day at 20-24°C	-0.008	-0.010
	(0.006)	(0.007)
Day at 28-32°C	0.049	0. 052
	(0.009)	(0. 011)
Day above 32°C	0.201	0.206
	(0. 022)	(0.027)
Observations	676,635	468,887

Notes: The table shows the effect of a day with an average temperature falling within each bin (relative to the 24°C-28°C category) on the monthly mortality rate per 100,000 inhabitants, using two different samples (1990-2017 and 1998-2017). Standard errors in brackets, clustered at the municipality level. The regressions control for municipality-by-month fixed effects, municipality-by-year fixed effects, and month-by-year fixed effects. The model furthermore controls for precipitations.

We furthermore provide additional results with different fixed effects and monthly data below.

Table A3: Impact of temperature on mortality using monthly data and changing the fixed effects

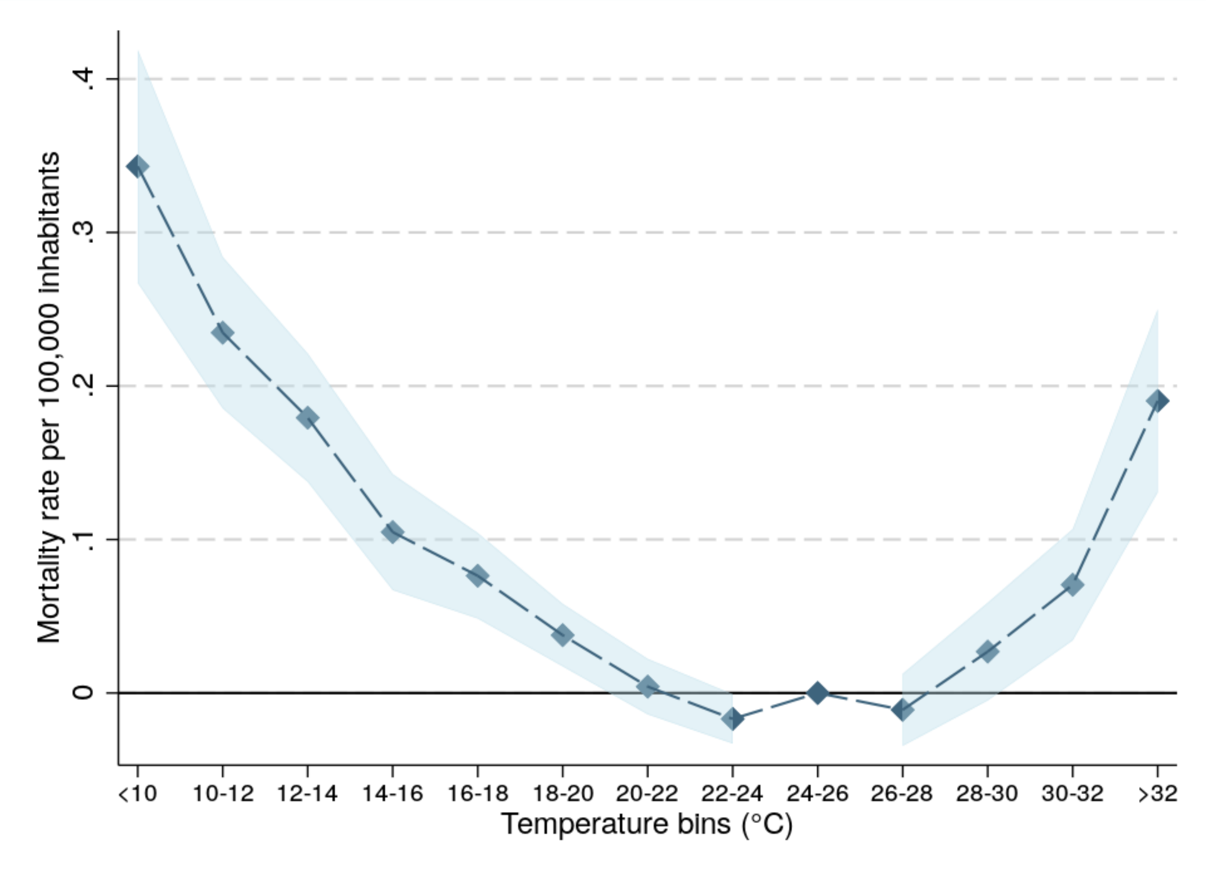
Column	(1)	(2)	(3)	(4)
Day below 12°C	0.188	0.0905	0.387	0.287
	(0.019)	(0.048)	(0.038)	(0.040)
Day at 12-16°C	0.078	0.011	0.220	0.155
	(0.012)	(0.028)	(0.026)	(0.026)
Day at 16-20°C	0.025	-0.010	0.080	0.046
	(0.008)	(0.020)	(0.020)	(0.020)
Day at 20-24°C	-0.008	-0.009	-0.0002	-0.009
	(0.006)	(0.013)	(0.014)	(0.015)
Day at 28-32°C	0.049	0.069	0.050	0.068
	(0.009)	(0.027)	(0.011)	(0.020)
Day above 32°C	0.201	0.190	0.089	0.080
	(0.022)	(0.030)	(0.026)	(0.021)
Fixed effects:				
Municipality	X	X	X	X
Month by year	X	X	X	X
Municipality by month	X	X		
Municipality by year	X		X	
Observations	676,635	676,635	676,635	676,635

Notes: The table shows the effect of a day with an average temperature falling within each bin (relative to the 24°C-28°C category) on the monthly mortality rate per 100,000 inhabitants, using the data for 1990-2017. Standard errors in brackets, clustered at the municipality level. The model furthermore controls for precipitations.

Appendix A5: Estimation with 2°C bins

The figure below is very similar to our baseline model. However, it uses 2°C temperature bins (from <10°C to >32°C) instead of 4°C. Results are very similar to the ones obtained with 4°C bins.

Figure A2: Impact of temperature on mortality using 2°C bins

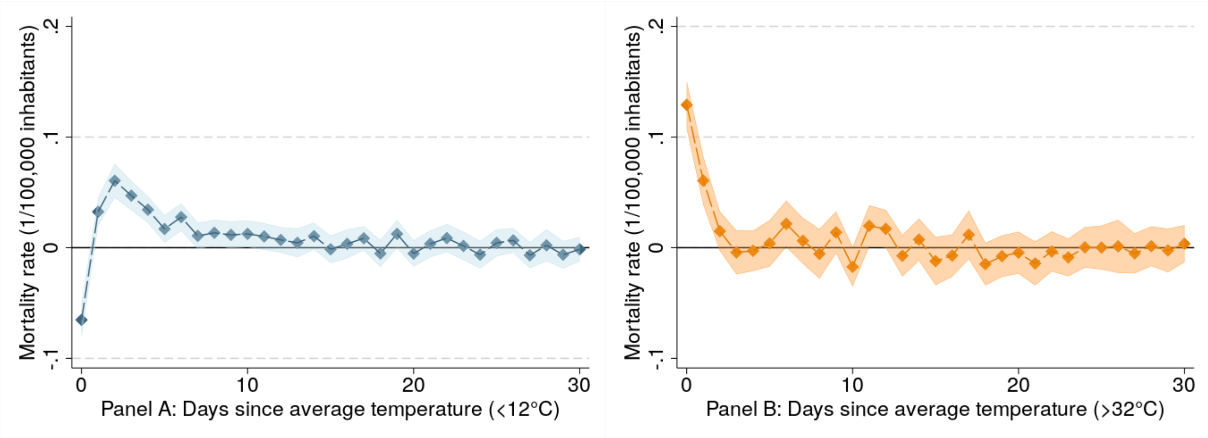


Notes: The graph shows the cumulative effect of a day with a temperature within each 2°C bin (relative to the 24°C-26°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 percent confidence interval (clustered at municipality level). The dependent variable is the daily mortality rate at the municipality level. The regression controls for the daily precipitation level and includes day-by-month-by-year fixed effects, municipality-by-calendar-day (1st January to 31st December) fixed effects, and municipality-by-year fixed effects.

Appendix A6: Short-term dynamics

In Figure 2, we calculated the overall mortality impact of temperature after 30 days. Below, we display the separate effect of unusually cold and hot days on the day of the weather event and for each of the following 30 days. During a cold day, the observed mortality on the day is in general lower, probably because people go out less, and are therefore either less likely to report a death or less likely to expose themselves to health risks on an unusually cold day. However, this effect is small compared to the additional mortality that follows on the next days, probably because people contract weather-sensitive pathogens the health effects of which only become visible after a few days. 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 coefficients tend to become systematically negative although not statistically significantly so.

Figure A3: Impact within 31 days of a cold day (<12°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 12°C (Panel A) or above 32°C (Panel B). Shaded areas correspond to the 95 percent confidence interval obtained for each estimated coefficient. 14,231,164 observations. The regression controls for the daily precipitation level and includes day by month by year fixed effects, municipality by calendar day (1st January to 31st December) fixed effects, and municipality by year fixed effects.

Appendix A7: 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 (WHO, 2010). 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 A4. 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 (compared to 24,724 in Mexico). The impact of cold weather on infant mortality is therefore possibly 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 may have to be different. US policies to reduce weather-related mortality may need to focus on the elderly (>75), whereas emerging countries like Mexico may need to tackle mortality effects across a wider age range.

Note that some values are negative because the reference bin of 24-28°C is not the one that records the lowest mortality for an age group. However, none of the negative values are statistically different from zero.

Table A4: Years of life lost estimates by age group and temperature level

Age group	All years of life lost	<24°C	>28°C
0-4	24,724	23,662	1,061
5-9	-16,925	-16,933	8
10-19	-18,367	-24,650	6,282*
20-34	-20,727	-26,672	5,945
35-44	2,299	-3,056	5,355
45-54	62,882*	52,203*	10,678*
55-64	131,522*	126,320*	5,202
65-74	86,779*	83,328*	3,451
75+	115,371*	103,377*	11,993*

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 A8: 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 (Universidad Nacional Autónoma de México. Centro de Ciencias de la Atmósfera. Unidad de Informática para las Ciencias Atmosféricas y Ambientales, 2014). Annual death estimates under climate change are provided in Table A5. 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 RCP 4.5 scenario (low GHG emissions), temperature-related mortality would be about 27% smaller. The RCP8.5 scenario (high GHG emissions) corresponds to a 20% reduction in the estimated relationship between mortality and temperature. The reduction in weather-related deaths is smaller due to a surge in heat-induced deaths. While cold represents more than 90 percent of deaths today, it could represent less than 30 percent of deaths under RCP 8.5. We show in section IV 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-year fixed effects and time 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 A5: Impact of temperatures on annual deaths in several climate scenarios

Number of deaths	**Total**	**<24°C**	**>28°C**
Historical data	26,324	24,016	2,308
	(19,250-33,398)	(17,037-30,995)	(1,465-3,150)
Climate scenarios:			
RCP 4.5	19,232	11,696	7,536
(GFDL CM3)	(14,168-24,297)	(6,972-16,420)	(5,434-9,639)
RCP 8.5	20,928	5,933	14,995
(GFDL CM3)	(16,080-25,776)	(2,651-9,214)	(11,112-18,879)

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. Estimates are for a population of 129 million inhabitants and, therefore, do not take into account population growth in Mexico.

B – ROBUSTNESS CHECKS FOR THE TEMPERATURE-MORTALITY RELATIONSHIP

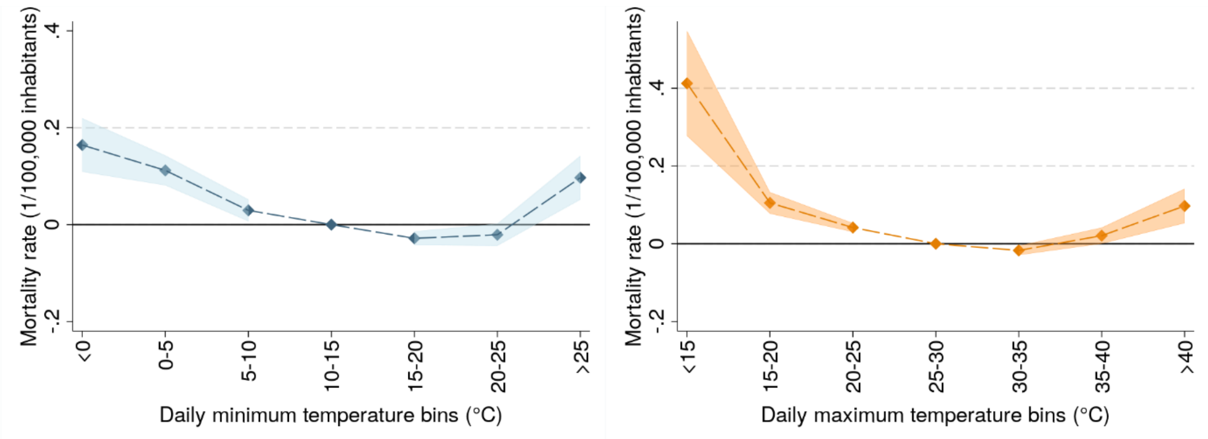
Appendix B1: Minimum and maximum temperatures

Minimum and maximum temperatures. 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 (Figure B1). In both cases, we find the same typical U-shape relationship as when using the daily average 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
<12°C	2.5	3.3	18.0	3.6
12-16°C	6.6	2.7	22.2	2.6
16-20°C	10.4	2.6	25.7	2.5
20-24°C	14.5	2.6	29.4	2.5
24-28°C	19.2	2.5	32.9	2.3
28-32°C	22.4	1.8	36.4	2.2
>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.

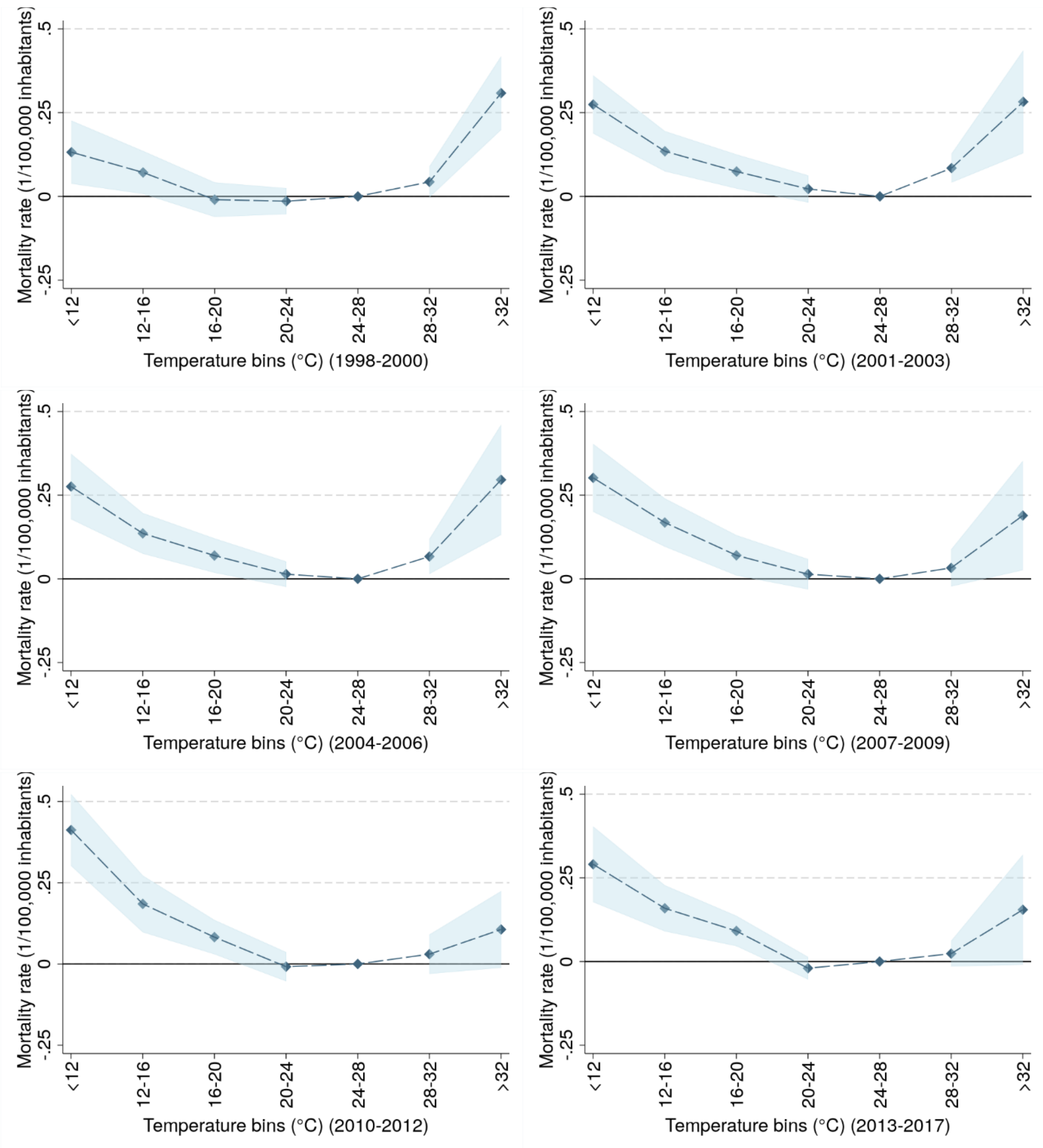


Notes. The dependent variable is the daily mortality rate at the municipality level. The graph shows the cumulative, 31-day effect of a day with a temperature falling within each bin. The diamonds show the 31-day multiplier, and is reported in deaths per 100,000 inhabitants on the y-axis. The estimates 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 municipality-by-calendar-day fixed effects, municipality-by-year fixed effects, and a fixed effect for each specific date (day, month and year). It is weighted by municipal population.

Appendix B2: Heterogeneous effects over time

Effects in different years. We run our model on six periods: 1998-2000, 2001-2003, 2004-2006, 2007-2009, 2010-2012 and 2013-2017. The coefficients vary slightly across periods but no clear pattern emerges.

Figure B2: Impact of temperature bins on 31-day cumulative mortality for 6 periods

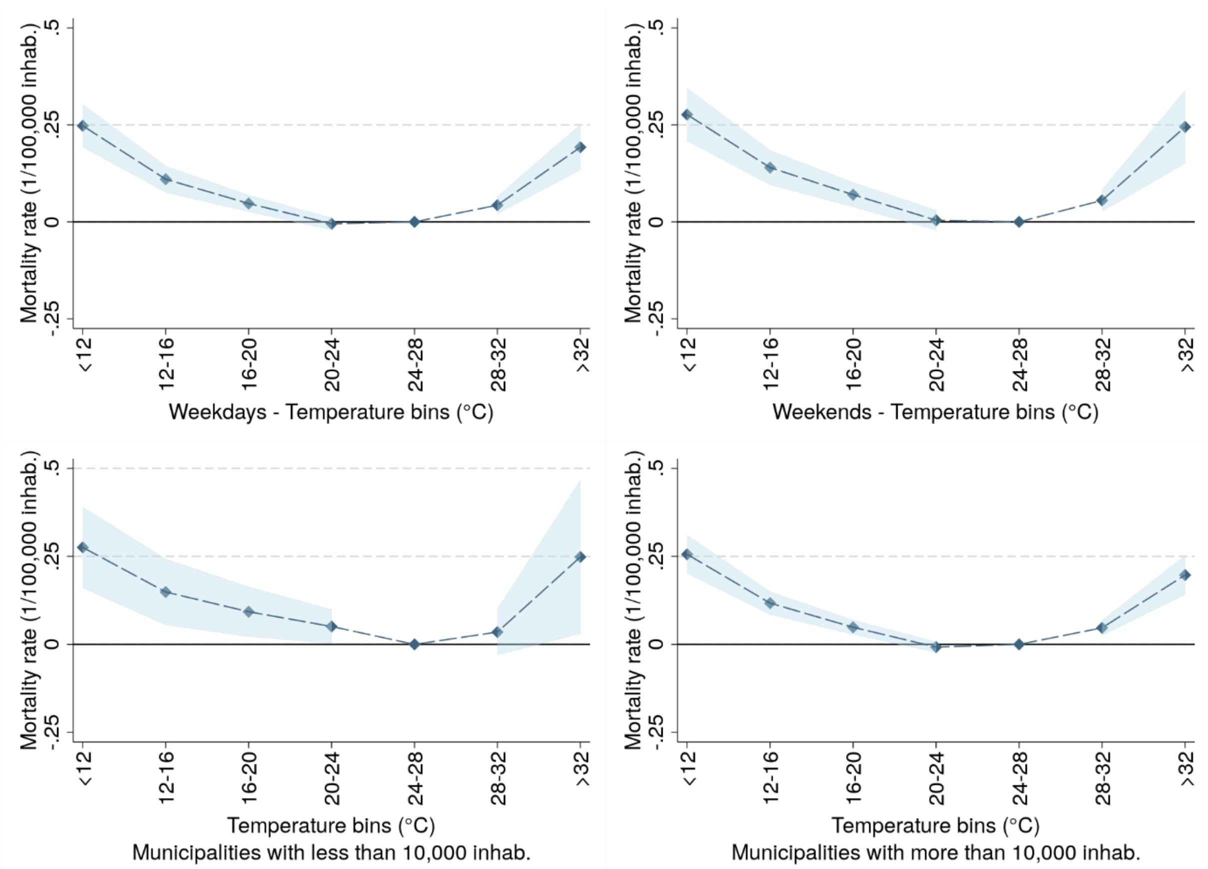


Notes: The graphs are calculated separately for six periods. They show the cumulative effect of a day with a temperature within each bin (relative to the 24°C-28°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. 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 day-month-year fixed effects, municipality-by-calendar-day and municipality-by-year fixed effects. They are weighted by municipal population.

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

Rural versus urban areas. We assess if short-run vulnerability to temperatures differs between people living in large vs. small municipalities. Results are displayed on the lower panels of Figure B3. Impacts suggest similar vulnerability to unusual cold and hot weather for small and large municipalities.

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

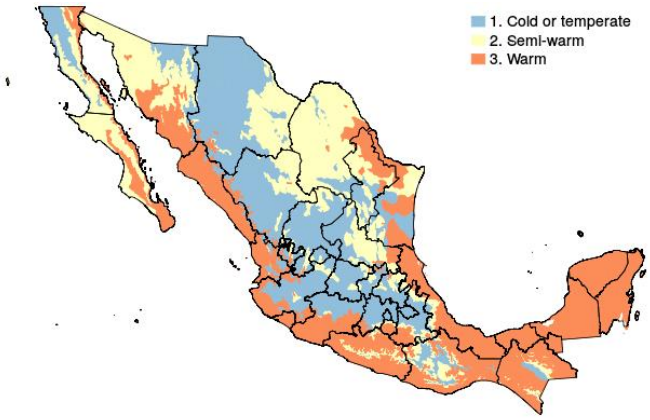


Notes. The graphs have been obtained separately. They show the cumulative effect of a day with a temperature within each bin based (relative to the 24-28°C category) obtained from a dynamic model with 30 lags. Regressions in the upper panels estimate the temperature-mortality relationship separately for weekdays (upper left panel) and weekends (upper right panel). Regressions in the lower panels estimate the temperature-mortality relationship separately for populations living in municipalities with less than 10,000 inhabitants (lower left panel) or more than 10,000 inhabitants (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 day-month-year fixed effects, municipality-by-calendar-day fixed effects, and municipality-by-year fixed effects. All regressions are weighted by municipal population.

Appendix B3: Acclimation

***Effects by climate region*.** The INEGI provides a detailed map of Mexico with a typology of 21 climates (INEGI, 2008b). We have simplified this typology and broken down Mexico into 3 climate categories (see Figure B4): 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).

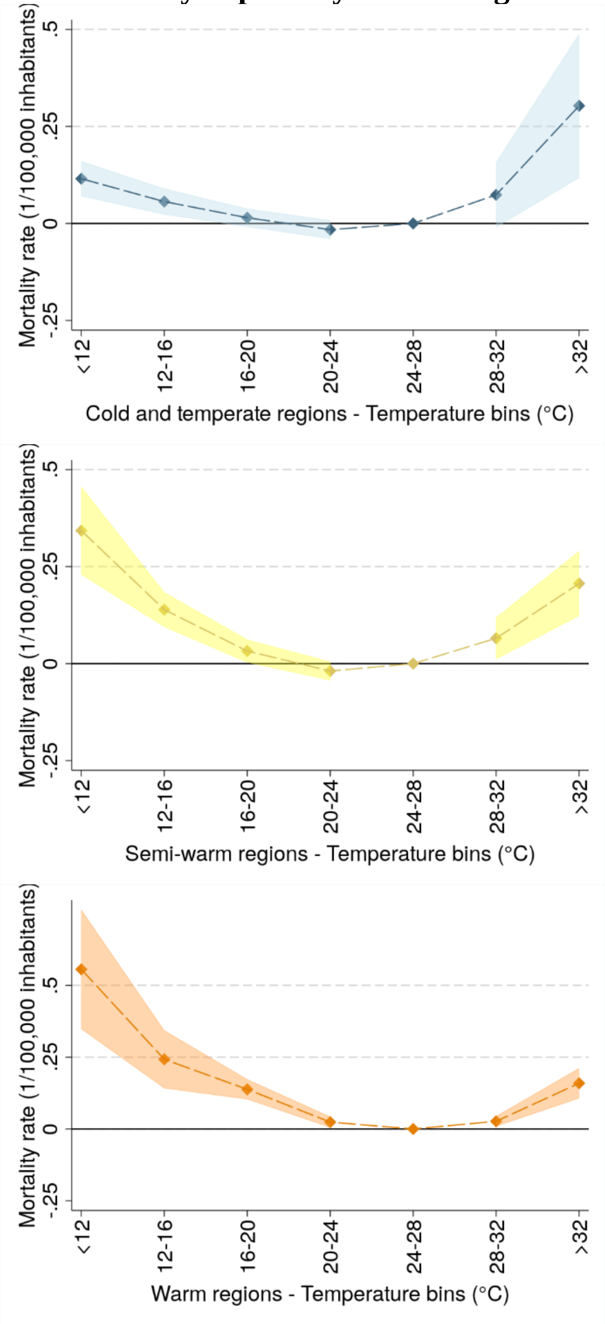
Figure B4: Map of Mexico distinguishing between climates



We have matched the boundaries of the Mexican municipalities (INEGI, 2010) with the boundaries of these three climatic categories by assigning a climate to each point of the polygon that corresponds to the boundaries of a municipality and calculating the share of delimiting data points that fall in a given climate for each municipality. We then run three regressions by weighting observations based on this share.

The output of the separate regressions is provided in Figure B5. There seems to be some form of acclimation: colder regions seem more sensitive to heat and warmer regions more sensitive to cold.

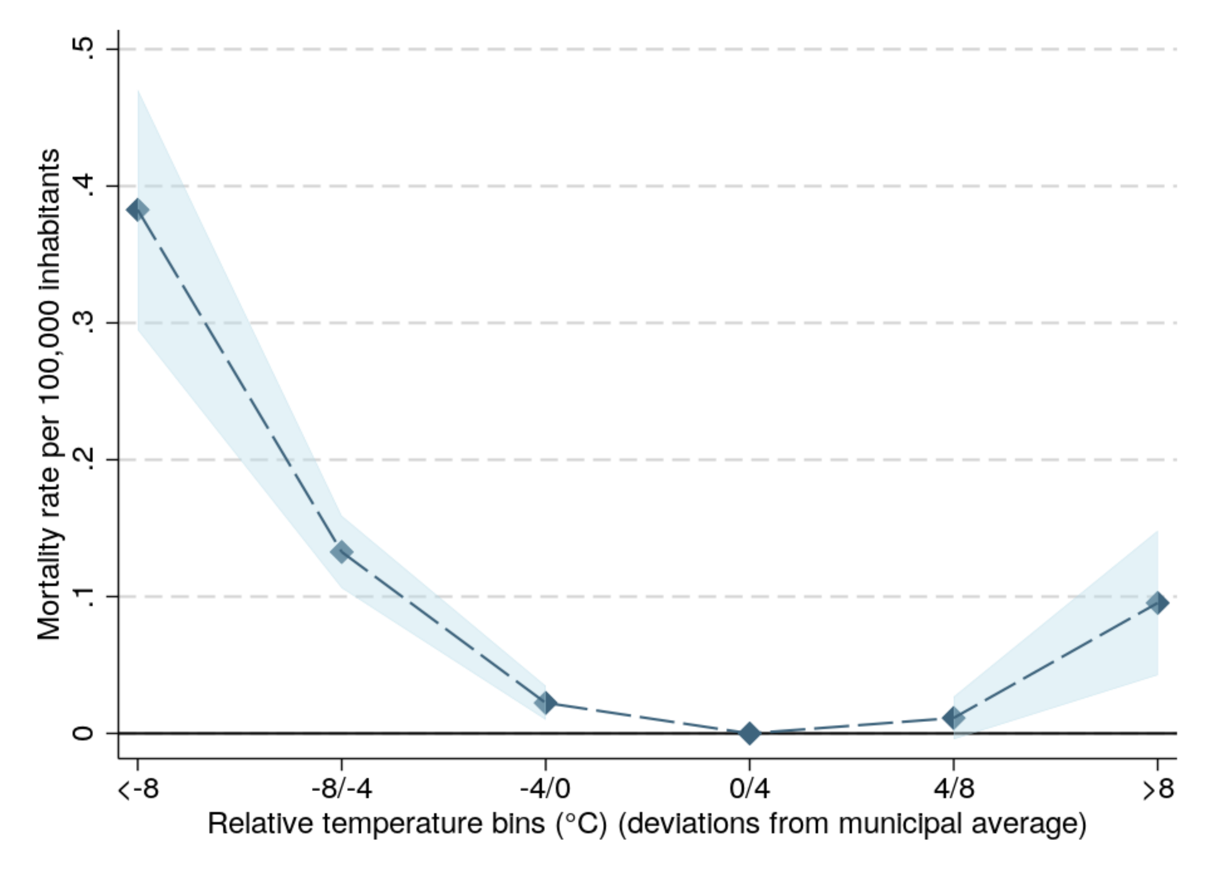
Figure B5: Mortality impacts by climate region in Mexico



Notes: The graphs show the cumulative effect of a day with a temperature within each bin (relative to the 24°C-28°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 day-month-year fixed effects, municipality-by-calendar-day fixed effects and municipality-by-year fixed effects.

Relative temperatures. Instead of using absolute temperature bins, we calculate deviations from the average temperature in each location to construct relative temperature bins with a 4°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 -8°C and below and +8°C and above 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 B6. Results show a strong impact of cold and mildly cold days – relative to average temperature – on mortality.

Figure B6: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, using relative temperature bins

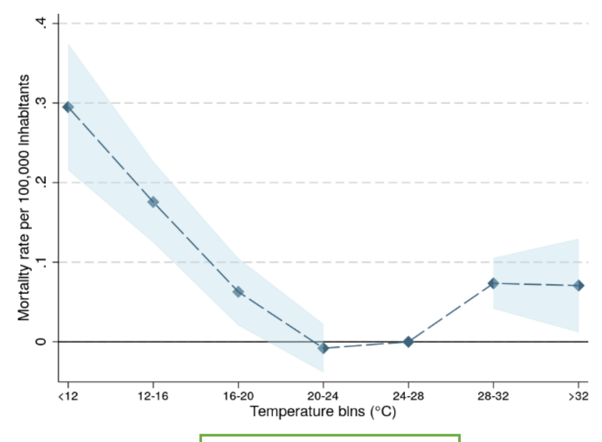


Notes. The graph shows the cumulative effect of a day with a relative temperature within each bin (relative to the 0°C to 4°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 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 day-month-year fixed effects, municipality-by-calendar-day and municipality-by-year fixed effects. It is weighted by municipal population.

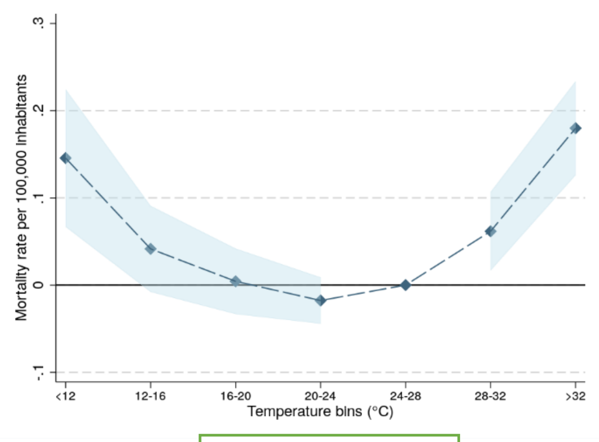
Appendix B4: Relaxing the fixed effects used in the baseline model

In Figure B7, we use fewer fixed effects than in the baseline model. We only use day-month-year fixed effects and municipality fixed effects in specification 1. We complement them with municipality-by-calendar-day fixed effects in specification 2. Specification 3 includes day-month-year fixed effects and municipality-by-year fixed effects. Controlling for seasonality (as in specification 2) seems necessary to properly identify the relative contribution of cold and hot days on mortality.

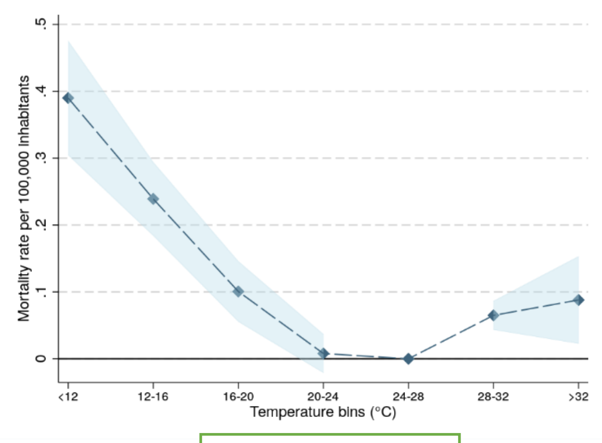
Figure B7: Impact of temperature (in °C) on mortality using different sets of fixed effects



Specification 1



Specification 2



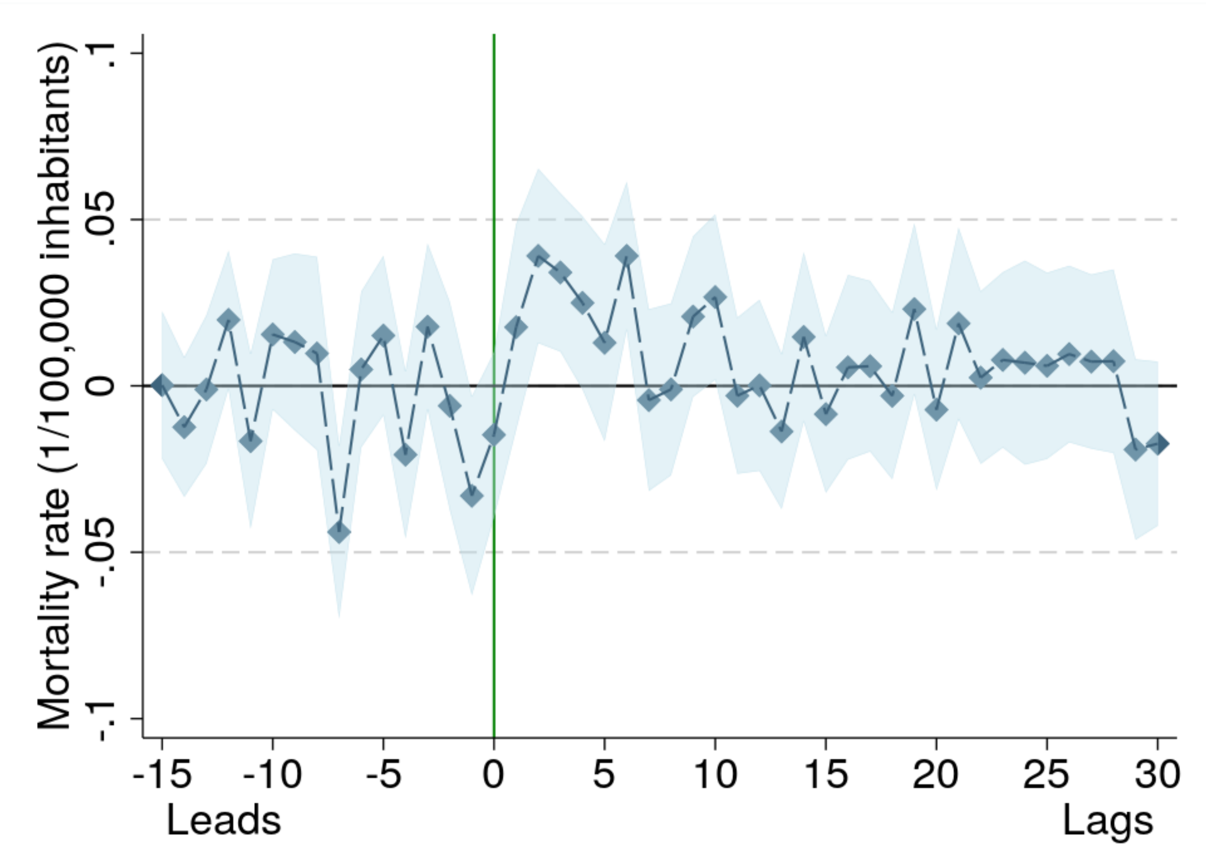
Specification 3

Notes. The graphs show the cumulative effect of temperature bins on mortality (relative to the 24°C-28°C category) obtained from a dynamic model with 30 lags, based on three different specifications. In all specifications, 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 and the regressions are weighted by municipal population. The regressions control for daily precipitation level and include different fixed effects: specification 1 includes day-month-year fixed effects and municipality fixed effects; specification 2 includes day-month-year fixed effects and municipality-by-calendar-day fixed effects; and specification 3 includes day-month-year fixed effects and municipality-by-year fixed effects.

Appendix B5: Temperature leads

We ran a placebo test with the leads of the temperature bins used as explanatory variable. To do so, we added 15 leads for all the temperature bins of our distributed lag model. In Figure B8 below, we report the estimates for each coefficient of the 15 leads, the contemporaneous effect and the 30 lags for the "below 12°C" temperature bin. We observe a clear extra mortality effect for the contemporaneous effect and nearer lags: if a cold day occurred less than 1 week ago, then mortality is impacted. The 31-day cumulative impact is 0.247 deaths per 100,000 inhabitants (standard error of 0.027). We also observe a statistically significant effect of the first temperature lead on mortality (-0.033, standard error of 0.015). This is probably because either people anticipate low temperatures and reduce their exposure to cold, or because the first lead strongly correlates with the on-the-day minimum temperature. We observe no clear pattern for leads after the 1st lead. The cumulative effect for leads 2-15 is close to zero and not statistically significant (0.004, standard error of 0.019).

Figure B8: Impact of the lags and leads of the "below 12°C" bin on mortality, in deaths per 100,000 inhabitants

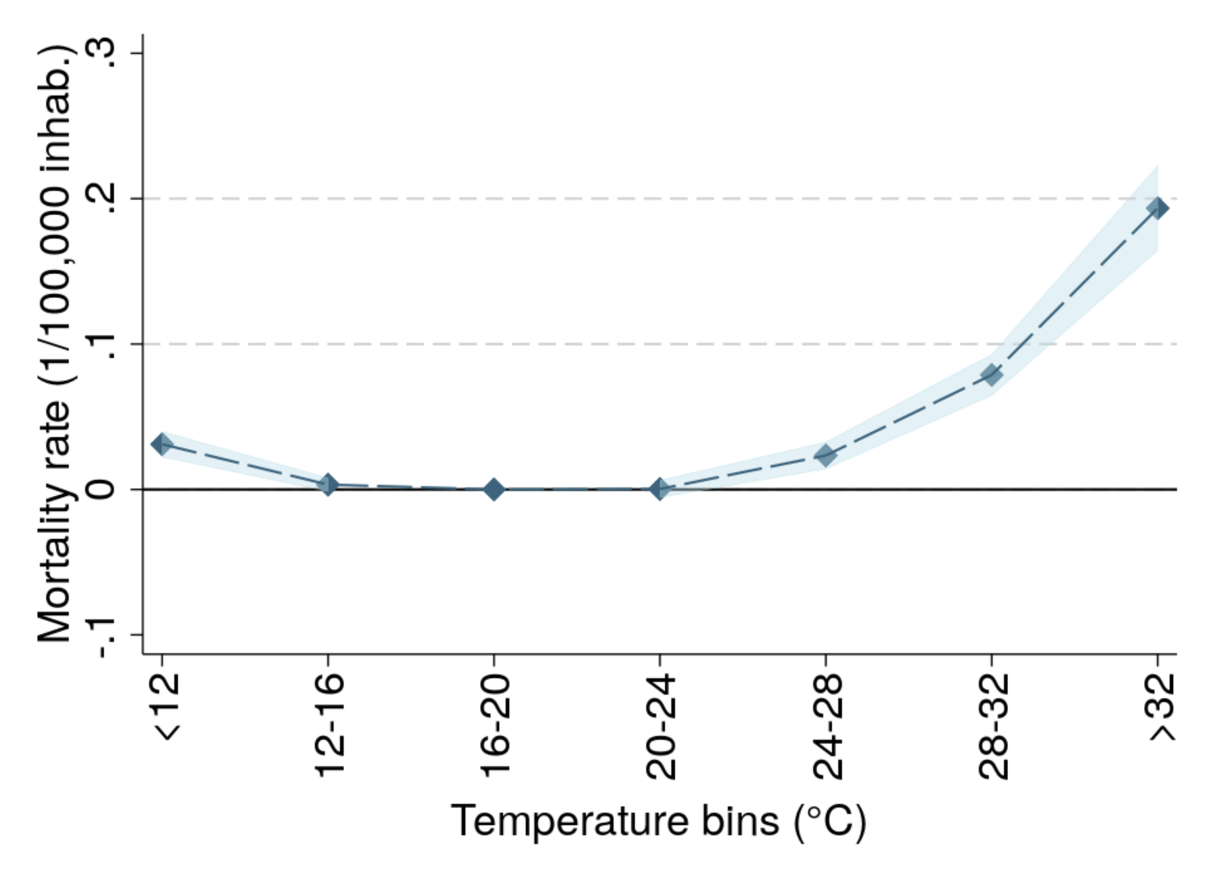


Notes: The graphs show the coefficient value and 95% confidence interval (shaded area) for the below 12°C category (relative to the 24°C-28°C category) obtained from a dynamic model with 15 leads (on the left, from -1 to -15) and 30 lags (on the right, from +1 to +30). The dependent variable is the daily mortality rate at the municipality level. The regression controls for daily precipitation level and includes day-month-year fixed effects, municipality-by-calendar-day fixed effects and municipality-by-year fixed effects. It is weighted by municipal population.

Appendix B6: Contemporaneous model

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 B9 displays the impact of the day's temperature on mortality for the whole Mexican population 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 model with only contemporaneous temperatures underestimates the effect of cold.

Figure B9: Impact of the day's average temperature on daily mortality, in deaths per 100,000 inhabitants

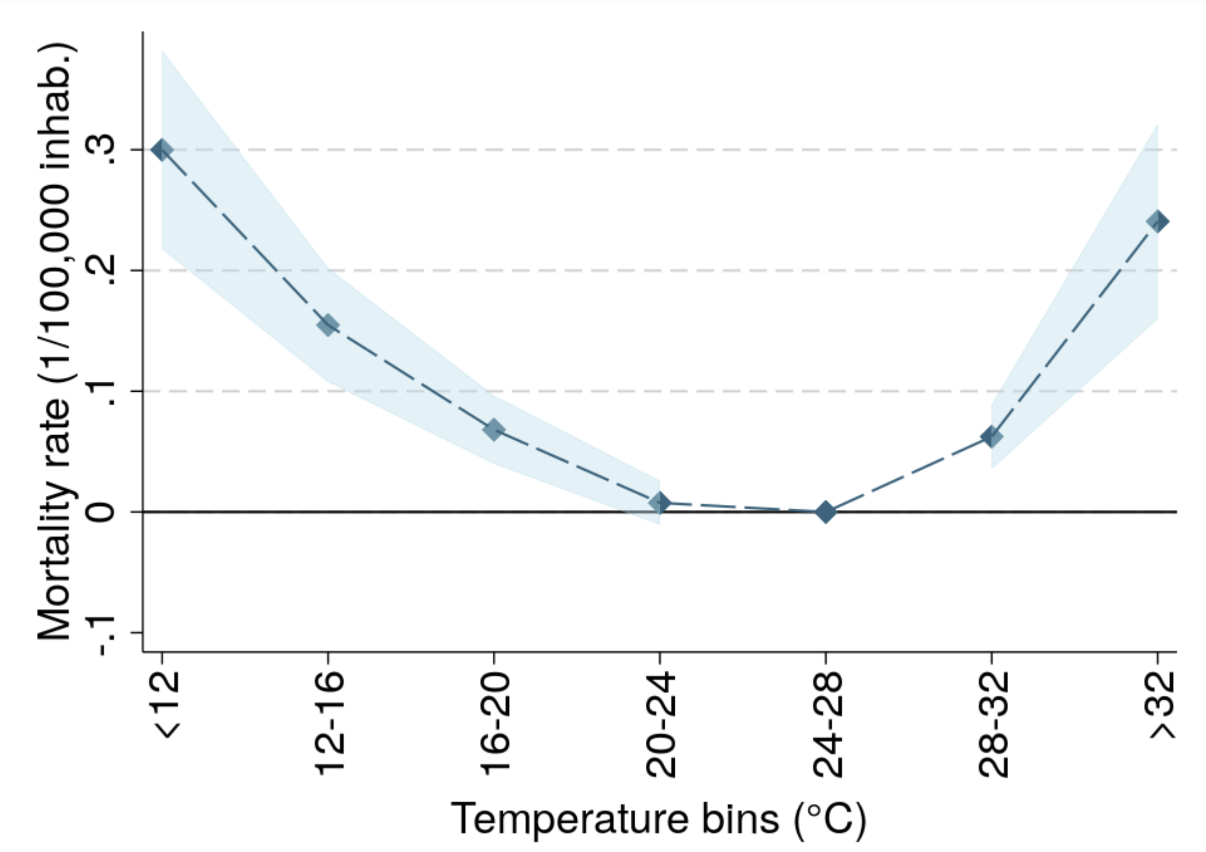


Notes. The dependent variable is the daily mortality rate at the municipality level. The graph shows the contemporaneous effect of a day with a temperature within each bin (relative to the 16°C-20°C category). The diamonds show the average point estimate, reported in deaths per 100,000 inhabitants on the y-axis. The shaded area corresponds to the 95 percent confidence interval. The regression controls for daily precipitation level and includes day-month-year fixed effects, municipality-by-calendar-day fixed effects and municipality-by-year fixed effects. It is weighted by municipal population.

Appendix B7: Considerations regarding omitted variable bias

Controlling for lagged precipitations and evaporation levels. We run an additional model in which we add lagged precipitations and lagged evaporation levels in the model. The results for temperature, displayed below, are very similar.

Figure B10: Cumulative 31-day impact of temperatures when controlling for lagged precipitations and evaporation levels



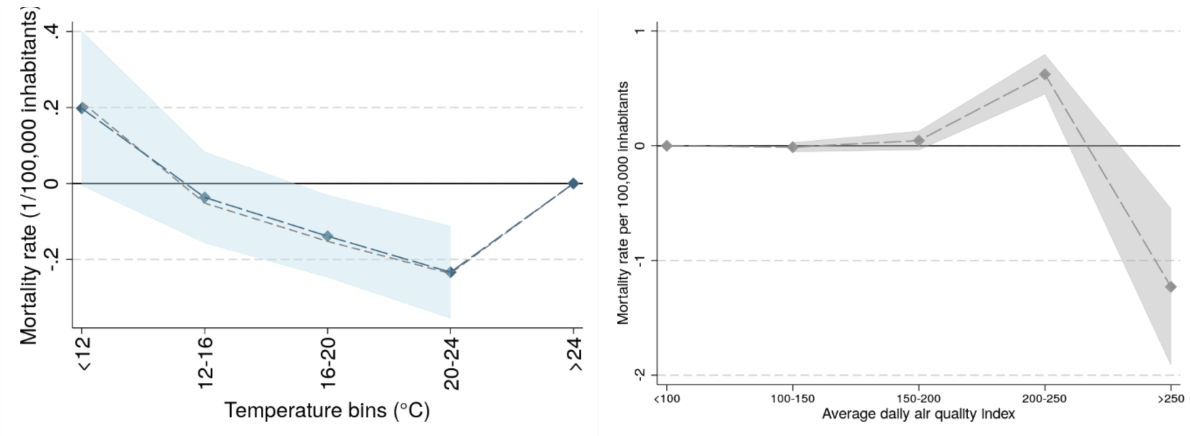
Notes: The graph shows the cumulative effect of a day with a temperature within each bin (relative to the 24°C-28°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regression controls for the daily and lagged precipitation and evaporation levels. It also includes day by month by year fixed effects, municipality by calendar day (1st January to 31st December) fixed effects, and municipality by year fixed effects.

Controlling for pollution (Mexico City only). Another issue could be that our results are driven by air pollution or by 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 Dirección de Monitoreo Atmosférico (1998-2017). 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. The left panel of Figure B11 displays the impact of temperature on mortality for the Federal District. The maximum temperature bin in Figure B11 is "above 24°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 shaded area corresponds 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 mortality.

The right-hand side of Figure B11 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 air quality (IMECA between 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 may adapt to these terribly polluted days (e.g. by not going out), explaining the lower mortality levels recorded in the data.

Figure B11: Impact of temperature and air quality on 31-day cumulative mortality, in deaths per 100,000 inhabitants in the Federal District of Mexico



Notes. The dependent variable is daily mortality rate per 100,000 inhabitants at the municipality level. The regression controls for the daily precipitation level and includes day-by-month-by-year fixed effects, municipality-by-calendar-day (1-365) fixed effects, and municipality-by-year fixed effects, as well as a wide range of controls for pollution on the same day and over the past 30 days. In the left panel, the graph shows the cumulative effect of a day with a temperature within each bin based (relative to the >24°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 blue line show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 percent confidence interval, with municipality-level clusters. For comparison, the average effects obtained for the Federal District without the air pollution controls are represented by the short-dashed line in grey. In the right panel, we provide the impact of the different pollution bins. It shows the cumulative effect of a day with an air quality index falling within each bin (relative to the "<100" category (cleaner air)).

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 (see Figure B3). Since 75 percent of the Mexican population lives in urban areas,[42] our results cannot be primarily driven by the interaction between temperature and indoor pollution through the 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.

[42] Own calculation based on 2000 Census data.

Appendix B8: Comparison of our 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 estimates are close to ours (0.20 deaths per 100,000 inhabitants for days between 40°F and 50°F (4.4-10°C)), but this is for a much older population in the US compared to Mexico. For the 64-75 age group, Deschenes and Moretti (2009) report an increase in mortality by 0.2915 and 0.1839 deaths per 100,000 inhabitants from an exposure to a day at 30°F (-1.1°C) respectively for males and females. For this same age group, we observe an increase in mortality by 0.872 deaths per 100,000 inhabitants for days below 12°C. Therefore, our estimates of weather vulnerability seem larger in Mexico compared to the US.

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 between 40°F and 50°F (4-10°C) increase mortality by 0.27 deaths per 100,000 inhabitants as compared to a day between 50°F and 60°F (10-15.5°C).

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 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 because we look at a different time period.

Outside of the US, evidence has been reported in a large number of studies. We briefly compare ours with the study on Mexico by Guerrero Compeán (2013), the one on India by Burgess et al. (2014), and the multi-country analysis of Gasparrini et al. (2015).

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.

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 0.26 deaths per 100,000 inhabitants caused by a day below 12°C roughly represents a marginal increase of about 0.05% 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 and heat on mortality in Mexico seem much lower than in India.

Finally, the multi-country analysis by Gasparrini et al. (2015) comes up with similar conclusions to ours. These authors find that both unusual heat and unusual cold have an impact on mortality. However, due to the higher frequency of cold days, these represent a much larger share of weather-induced mortality.

C – IMPACTS BY QUARTILES OF PREDICTED INCOME

Appendix C1: Method to predict income quartiles, produce age-corrected quartiles and use an alternative indicator of poverty

Income is not reported on death certificates. We use data from the 2000 Mexican census to estimate income levels at the moment of death in our mortality dataset.[43] 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 fit 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 healthcare registration. 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. The regression coefficients are weighted using the weights provided in the publicly available sample of the 2000 Census, which includes about 10 percent of the Mexican Population. The output of this estimation is presented below.

[43] 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.

Table C1: Regression used to predict income levels

Dependent variable	Log(Personal income)
Age	-0.0089 (0.0008)
Age squared	0.0001 (0.00005)
Female	-0.0037 (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	0.44
Number of observations	8,756,128

Notes. Cluster-robust standard errors at the level of municipalities 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=0.44).

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). To make income predictions, we restricted the independent variables used in the income regression to those that are also present on the death certificates.

We then use predicted income values and predicted standard errors to assign a probability of each observation to belong to an income quartile. We use these probabilities to estimate the proportion of people in each municipality i whose predicted income would have fallen within income quartile κ, and the proportion of deaths in each municipality with a predicted income likely to belong to quartile κ. We then 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 81.6% of deaths. For that reason, we augment all estimated impacts by a factor of 1/0.816.

The daily mortality rates by income quartile can be used to run separate distributed lag models for each income quartile.[44] 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.

We have run separate regressions of Equation 1 for each income quartile. The main results are displayed in Figure 3 in the core of the text.

Age-corrected 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 conditional on 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. Table 4, panel B, presents the 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.

Defining quartiles with a poverty indicator. Instead of using income levels to create quartiles of population, we can use alternative metrics of wellbeing and living conditions. In Table 4, panels C and D, 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

[44] 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.

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 ranges 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 sample of the 2000 Census, the exact same methodology is applied as for income to create quartiles and age-corrected 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 quartiles (from low to high living conditions) and run the econometric model separately by quartile (see Table 4, panels C and D).

Appendix C2: Effects by quartile of predicted income and selected type of diseases

We provide estimates for the number of deaths by income quartile and death causes (without age correction). We find that differences in vulnerability may mostly come circulatory system diseases and respiratory system diseases. Some other less common disease types also seem to play a role and predominantly affect the first quartile of predicted income.

Table C2: Weather-induced deaths by predicted income quartile and cause of death

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile
Infectious diseases	-468*	430	439	-26
Neoplasms	898*	-616	-689	772
Endocrine, nutritional and metabolic diseases	2,273***	3,118***	2,272**	1,594**
Circulatory system diseases	3,691***	3,209***	1,667**	1,970**
Respiratory system diseases	2,435***	2,064***	820	438
Violent and accidental deaths	544	-838	48	-692
All other diseases	2,199***	1,195	562	625

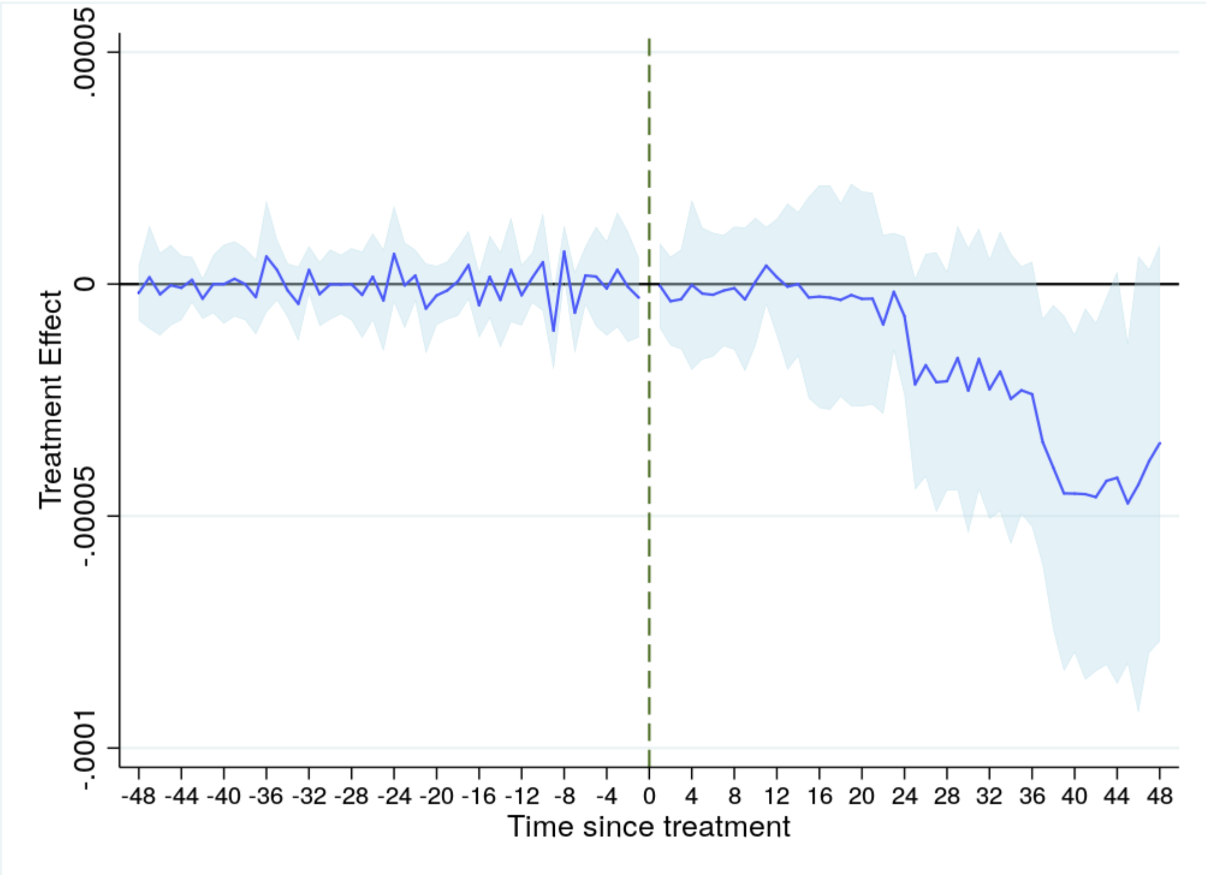
Notes: predictions on the number of deaths caused by all temperature bins, using the distribution of temperatures of Figure 1. Each estimate in the Table come from a different regression. Estimates are multiplied by 1/0.816 since we were only able to assign a quartile to 81.6 percent of deaths. *, ** and *** respectively denote statistical significance at 10, 5 and 1 percent.

D – *SEGURO POPULAR*

Appendix D1: Evidence on the overall mortality impact of the *Seguro Popular*

Preliminary evidence on the overall mortality impact of the *Seguro Popular* is provided in Cohen (2020). Cohen (2020) uses a staggered difference-in-difference model on the monthly mortality data from the INEGI. It estimates 48 coefficients comparing the death rate in control and treatment groups for each month before the implementation of the policy in the treatment group, and 48 coefficients for each month after implementation. Figure D1 provides results for the impact of the *Seguro Popular* on mortality, as extracted from Cohen (2020).

Figure D1: Reproduction of the results from Cohen (2020) for the impact of the *Seguro Popular* on all-cause mortality



Notes: See Cohen (2020) for details on the method. The green line indicates the month when the treatment group enrols into the *Seguro Popular*.

There is no effect of the policy before its implementation. Impacts are slightly negative but not statistically different from zero during the first two years of implementation and become negative and statistically significant at 10 percent during the 3rd year and 5 percent during the

4th year. On average, the reduction in mortality during the 3rd and 4th year is equal to around 3.1 deaths per 100,000 inhabitants per month. It is equivalent to about 7.4 percent of the average mortality rate in the sample used in Cohen (2020) (41.77 deaths per 100,000 inhabitants).

Appendix D2: Additional results for the impact of the *Seguro Popular* on weather-related mortality

Results by age and death cause. In Table D1, the effect of the *Seguro Popular* seems spread out across diseases. We find statistically significant effects for infectious and parasitic diseases, and respiratory system diseases. We also find that older people are more likely to benefit from the reduction in weather-induced mortality associated with the *Seguro Popular* (Table D2).

Table D1: Specifications to assess the impact of the *Seguro Popular* on weather mortality by disease type

Disease type	Infectious and parasitic	Neopl.	End., nutr. and metab.	Circul.	Respir.	Violent and accidental	All other diseases
Seguro Popular:							
x days below 12°C	-0.002	0.007	0.003	0.009	-0.003	-0.006	0.004
	(0.004)	(0.008)	(0.003)	(0.012)	(0.005)	(0.010)	(0.015)
x days at 12-16°C	-0.004*	-0.008	0.002	-0.009	-0.009**	-0.0008	-0.015*
	(0.002)	(0.005)	(0.002)	(0.008)	(0.003)	(0.007)	(0.008)
x days at 16-20°C	-0.004*	0.001	0.002	-0.006	-0.004	0.0002	-0.008
	(0.002)	(0.005)	(0.002)	(0.007)	(0.003)	(0.006)	(0.007)
x days at 20-24°C	-0.004**	-0.001	0.001	0.009	-0.001	0.002	-0.009
	(0.002)	(0.005)	(0.002)	(0.007)	(0.003)	(0.006)	(0.007)
x days at 28-32°C	-0.005*	-0.001	0.001	-0.008	-0.001	-0.011	-0.0001
	(0.003)	(0.007)	(0.002)	(0.009)	(0.003)	(0.008)	(0.009)
x days above 32°C	-0.010	-0.020	-0.006	-0.010	0.001	0.003	0.005
	(0.012)	(0.031)	(0.010)	(0.065)	(0.017)	(0.052)	(0.038)

Notes: ** means statistically significant at 5%. The dependent variable is the monthly mortality rate per 100,000 inhabitants for the people without any other health insurance, dying from the diseases covered by the *Seguro Popular*. Furthermore, each column corresponds to people dying from selected disease types. All specifications include municipality by month, municipality by year and month by year fixed effects, as well as a dummy variable for the presence/absence of the *Seguro Popular*. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We also interact the municipality-by-month and year-by-month fixed effects with the temperature bins and the level of precipitations. Standard errors in brackets are clustered at the level of municipalities and the model is weighted by the population in each municipality with no access to any other health insurance. Reference day is 24-28 degrees Celsius.

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

Age group	0-4	5-9	10-19	20-34	35-44
Seguro Popular:					
x days below 12°C	0.025	0.002	-0.012	-0.014	0.027
	(0.064)	(0.012)	(0.010)	(0.015)	(0.046)
x days at 12-16°C	-0.023	-0.007	0.002	-0.011	0.011
	(0.034)	(0.006)	(0.006)	(0.010)	(0.025)
x days at 16-20°C	0.016	-0.001	-0.004	-0.011	-0.006
	(0.024)	(0.005)	(0.005)	(0.008)	(0.021)
x days at 20-24°C	0.016	-0.004	-0.003	-0.010	0.039*
	(0.027)	(0.005)	(0.005)	(0.009)	(0.022)
x days at 28-32°C	0.028	0.006	-0.002	-0.004	-0.008
	(0.029)	(0.008)	(0.006)	(0.011)	(0.027)
x days above 32°C	-0.006	-0.040*	0.003	0.038	0.054
	(0.133)	(0.024)	(0.025)	(0.048)	(0.105)
Age group	**45-54**	**55-64**	**65-74**	**>75**	
Seguro Popular:					
x days below 12°C	-0.024	0.026	-0.001	0.191	
	(0.084)	(0.160)	(0.262)	(0.751)	
x days at 12-16°C	0.018	-0.168**	-0.303**	-1.330***	
	(0.045)	(0.083)	(0.138)	(0.485)	
x days at 16-20°C	-0.038	-0.136*	-0.243**	-0.232	
	(0.038)	(0.072)	(0.120)	(0.395)	
x days at 20-24°C	0.050	-0.103	-0.184	-0.020	
	(0.035)	(0.082)	(0.134)	(0.403)	
x days at 28-32°C	0.010	-0.183*	-0.327*	0.041	
	(0.050)	(0.103)	(0.176)	(0.530)	
x days above 32°C	-0.116	0.190	0.279	-1.705	
	(0.260)	(0.487)	(0.780)	(2.641)	

Notes: ** means statistically significant at 5%. The dependent variable is the monthly mortality rate per 100,000 inhabitants for the people without any other health insurance, dying from the diseases covered by the *Seguro Popular*, for all deaths except from infectious and parasitic diseases, neoplasms and violent and accidental deaths. Furthermore, each column corresponds to people belonging to a different age group. All specifications include municipality by month, municipality by year and month by year fixed effects, as well as a dummy variable for the presence/absence of the *Seguro Popular*. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We also interact the municipality-by-month and year-by-month fixed effects with the temperature bins and the level of precipitations. Standard errors in brackets are clustered at the level of municipalities and the model is weighted by the population in each municipality with no access to any other health insurance. Reference day is 24-28 degrees Celsius.

Using annual information on the availability of the Seguro Popular (instead of the monthly information). We have assumed that, after using municipality by year fixed effects, the month of introduction of the *Seguro Popular* in municipality i (e.g. February versus March) is exogenous. This allows us to control for the introduction of the policy in the model with interactions. We check that this led to no substantial bias in the estimation of the interaction parameters. Below, to construct the interaction parameters between the *Seguro Popular* and temperature, we use an alternative variable that takes the value of 1 in municipality i and year t if, during this year or the previous years, someone has died in this municipality while being covered by the *Seguro Popular*. The variable is therefore invariant at monthly level and absorbed by the municipality by year fixed effects. However, we can still assess the impact of the interaction terms between this variable and the temperature bins. In Table D3, we reproduce some of the results of Table 5 with this variable. Results lose precision but point estimates are similar to our baseline results: i.e. colder bins, especially days between 12 and 16°C, would lead to a reduction in mortality.

Table D3: The impact of the *Seguro Popular* on eligible people, using information on the year of introduction of the policy

Column	(1)	(2)	(3)
Sample	Weather-sensitive[a]	All	55+ (Weather-sensitive[a])
Seguro Popular:			
x days below 12°C	0.006	-0.012	-0.160
	(0.023)	(0.029)	(0.237)
x days at 12-16°C	-0.012	-0.033*	-0.379**
	(0.016)	(0.020)	(0.160)
x days at 16-20°C	0.003	-0.017	-0.061
	(0.013)	(0.017)	(0.137)
x days at 20-24°C	0.009	0.002	0.015
	(0.013)	(0.016)	(0.129)
x days at 28-32°C	-0.020	-0.036*	-0.304*
	(0.015)	(0.019)	(0.167)
x days above 32°C	0.009	0.064	0.818
	(0.074)	(0.095)	(0.624)

Notes: (a) Weather-sensitive death causes are all death causes excluding infectious and parasitic diseases, neoplasms and violent and accidental deaths. They therefore include endocrine, nutritional, metabolic, circulatory and respiratory diseases as well as all other death causes. *, ** and *** means statistically significant at 10, 5 and 1 percent. The dependent variable is the monthly mortality rate per 100,000 inhabitants for the people without any other health insurance, dying from the diseases covered by the *Seguro Popular*, for the group of diseases or people mentioned in each column. All specifications include municipality by month, municipality by year and month by year fixed effects, as well as a dummy variable for the presence/absence of the *Seguro Popular*. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We also interact the municipality-by-month and year-by-month fixed effects with the temperature bins and the level of precipitations. Standard errors in brackets are clustered at the level of municipalities and the model is weighted by the population in each municipality with no access to any other health insurance. Reference day is 24-28 degrees Celsius.

Results with municipalities with more than 10,000 inhabitants. We provide below the results of our main model when we restrict the sample of municipalities to those with more than 10,000 inhabitants.

Table D4: Impact of the *Seguro Popular* on the eligible population for municipalities with more than 10,000 inhabitants

Seguro Popular:	
x days below 12°C	0.018
	(0.023)
x days at 12-16°C	-0.029**
	(0.013)
x days at 16-20°C	-0.016
	(0.011)
x days at 20-24°C	0.005
	(0.012)
x days at 28-32°C	-0.002
	(0.015)
x days above 32°C	0.022
	(0.084)

Notes: *, ** and *** means statistically significant at 10, 5 and 1 percent. The dependent variable is the monthly mortality rate per 100,000 inhabitants for the people without any other health insurance, dying from the diseases covered by the *Seguro Popular*, and for all deaths excluding infectious and parasitic diseases, neoplasms and violent and accidental deaths. The specification includes municipality by month, municipality by year and month by year fixed effects, as well as a dummy variable for the presence/absence of the *Seguro Popular*. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We also interact the municipality-by-month and year-by-month fixed effects with the temperature bins and the level of precipitations. Standard errors in brackets are clustered at the level of municipalities and the model is weighted by the population in each municipality with no access to any other health insurance. Reference day is 24-28 degrees Celsius. We only use municipalities with a population above 10,000 inhabitants.

Impacts of Seguro Popular according to income. We look at the impact of the *Seguro Popular* by quartiles of predicted income below (see Table D5). Results are imprecisely estimated, even though the point estimates are negative and strong on mildly cold bins for the 2nd quartile.

To increase precision, we interact the average income per capita[45] in each municipality with our policy variable (see Table D6). Results seem to confirm that the effect of the *Seguro Popular* on weather vulnerability has been stronger in poorer municipalities.

[45] The average is based on the 2000 census. It is obtained by dividing household income by the square root of the number of people that compose the household. The 99th percentile of income is excluded from the calculation of the average. The population-weighted average for this variable is 2,046, with a standard deviation of 903.

Table D5: The impact of the *Seguro Popular* on weather vulnerability by quartile of predicted income

Sample	1st quartile of predicted income	2nd quartile	3rd quartile	4th quartile
Seguro Popular:				
x days below 12°C	0.039	0.004	-0.028	0.013
	(0.057)	(0.044)	(0.049)	(0.046)
x days at 12-16°C	0.01	-0.053	0.014	0.02
	(0.032)	(0.032)	(0.033)	(0.037)
x days at 16-20°C	-0.014	-0.048	-0.016	0.007
	(0.026)	(0.03)	(0.031)	(0.031)
x days at 20-24°C	0.008	-0.008	-0.001	0.027
	(0.023)	(0.029)	(0.033)	(0.034)
x days at 28-32°C	0.0003	-0.013	0.023	0.055
	(0.029)	(0.034)	(0.038)	(0.045)
x days above 32°C	0.152	0.145	0.214	0.059
	(0.146)	(0.147)	(0.205)	(0.197)

Notes: *, ** and *** means statistically significant at 10, 5 and 1 percent. The dependent variable is the monthly mortality rate per 100,000 inhabitants from the population belonging to each quartile, for all deaths excluding infectious and parasitic diseases, neoplasms and violent and accidental deaths. The specification includes municipality by month, municipality by year and month by year fixed effects. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We also interact the municipality-by-month and year-by-month fixed effects with the temperature bins and the level of precipitations. Standard errors in brackets are clustered at the level of municipalities. Reference day is 24-28 degrees Celsius.

Table D6: The impact of the *Seguro Popular* on weather vulnerability according to the average income per capita in each municipality

Seguro Popular:	
x days below 12°C	-0.187***
	(0.056)
x days at 12-16°C	-0.041
	(0.028)
x days at 16-20°C	-0.031
	(0.028)
x days at 20-24°C	-0.018
	(0.021)
x days at 28-32°C	-0.005
	(0.031)
x days above 32°C	-0.0002
	(0.105)
Seguro Popular x Average income per capita ('000 pesos):	
x days below 12°C	0.089***
	(0.029)
x days at 12-16°C	0.008
	(0.012)
x days at 16-20°C	0.006
	(0.011)
x days at 20-24°C	0.011
	(0.009)
x days at 28-32°C	-0.010
	(0.012)
x days above 32°C	0.050*
	(0.029)

Notes: *, ** and *** means statistically significant at 10, 5 and 1 percent. The dependent variable is the monthly mortality rate per 100,000 inhabitants from all diseases excluding infectious and parasitic diseases, neoplasms and violent and accidental deaths. The specification includes municipality by month, municipality by year and month by year fixed effects. The specifications also control for the interaction between the *Seguro Popular* and precipitations. We also interact the municipality-by-month and year-by-month fixed effects with the temperature bins and the level of precipitations. Standard errors in brackets are clustered at the level of municipalities. Reference day is 24-28 degrees Celsius.

Additional references cited in the Appendices

▪ Basu, R; F. Dominici and J.M Samet, 2005. “Temperature and mortality among the elderly in the United States: a comparison of epidemiologic methods,” *Epidemiology*, Vol. 16, Pages 58–66.

▪ Chenuel, Bruno, 2012. *La Thermorégulation.* Class material for UE3 PACES. Université de Lorraine.

▪ Colón-González, Felipe J.; Iain R. Lake and Graham Bentham, 2011. “Climate Variability and Dengue Fever in Warm and Humid Mexico,” American Journal of Tropical Medicine and Hygiene, Vol. 84, Issue 5, Pages 757–763.

▪ Horvath, S.M., 1981. “Exercise in a cold environment,” *Exercise and Sports Sciences Reviews*, Vol. 9, Pages 221–263.

▪ Inbar, Omri; Norman Morris; Yoram Epstein and Gregory Gass, 1989. “Comparison of thermoregulatory responses to exercise in dry heat among prepubertal boys, young adults and older males,” *Journal of Experimental Physiology*, Vol. 6, Pages 691–700.

▪ Mallet, M.L. , 2002. “Pathophysiology of accidental hypothermia,” *Quarterly Journal of Medicine*, Vol. 95, Pages 775–785.

▪ Marriott, Bernadette and Sydne Carlson (Eds.), 1996. *Nutritional Needs in Cold and High-Altitude Environments: Applications for Military Personnel in Field Operations*. Committee on Military Nutrition Research, Institute of Medicine.

▪ Morales, C.F. and P.J. Strollo, 1993. “Noncardiogenic Pulmonary Edema Associated with Accidental Hypothermia,” Chest, Vol. 103, Pages 971–973.

▪ Pica, Natalie and Nicole Bouvier, 2014. “Ambient Temperature and Respiratory Virus Infection,” *The Pediatric Infectious Disease Journal*, Vol. 33, Issue 3, Pages 311–313.

▪ Schubert, Armin, 1995. “Side Effects of Mild Hypothermia,” Journa*l of Neurosurgical Anesthesiology*, Vol. 7, Issue 2, Pages 139–147.

▪ Scott, A.R.; T. Bennett and I.A. Macdonald, 1987. “Diabetes mellitus and thermoregulation,” *Canadian Journal of Physiology and Pharmacology*, Vol. 65, Issue 6, Pages 1365–1376.

▪ Secretaría General del Consejo Nacional de Población – CONAPO, 2010. “Principales causas de mortalidad en México: 1980-2007,” Working paper for the 43rd period of sessions of the *Comisión de Población y Desarrollo “Salud, morbilidad, mortalidad y desarrollo”*.

▪ Thonneau, Patrick; Louis Bujan; Luc Multigner and Roger Mieusset, 1998. “Occupational heat exposure and male fertility: a review,” *Human Reproduction*, Vol.13, Issue 8, Pages 2122–2125.

▪ Young, 1991. “Effects of aging on human cold tolerance,” *Experimental Aging Research*, Vol. 17, Pages 205–213.