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

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Abstract

We examine the impact of temperature on mortality across income groups in Mexico using individual death records (1998-2010) and Census data. Random variations in temperature are responsible for 8% of deaths in Mexico (45,000 deaths every year). However, 99% of these weather-related deaths are induced by cold (<10°C) or mildly cold (10-20°C) days rather than by outstandingly hot days (>32°C). Moreover, temperatures only kill people in the bottom half of the income distribution. We show that the *Seguro Popular*, a universal healthcare policy progressively rolled out since 2004, reduced cold-related mortality among eligible people by about 13%.

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

JEL codes: I13, I14, Q54

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1. Introduction

Between 1980 and 2015, life expectancy increased from 61.7 to 71.8 years worldwide (Global Burden of Disease Study, 2016). Despite persistent differences between countries, this significant gain in longevity largely comes from developing countries. However, because these countries are more vulnerable and have low adaptive capacity, climate change in the twenty-first century could slow down the convergence in life expectancy between high and low-income countries.[1] Recent studies looking at the impacts of extreme temperatures in the US (Braga *et al.*, 2001; Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; Barreca, 2012; Heutel, Miller and Molitor, 2017) have found much smaller impacts than those found in rural India by Burgess *et al.* (2014), suggesting the importance that income may play in shaping the impacts of climate change on health both across and within countries.[2]

In this paper, we investigate the relationship between temperature, mortality and socio-economic inequalities in Mexico. Temperature shocks are the most direct way in which climate change can affect mortality. We use a large dataset of over 9 million daily mortality rates from 1998 to 2010 for 2,289 Mexican municipalities, representing around 95% of the country's population, matched with weather data from the closest meteorological stations, to measure the extent to which temperature stress unequally affects individuals depending on their capacity to protect themselves from adverse weather conditions.[3] To this effect, we 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 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 developing country that combines daily mortality data with individual estimates of income level. In the final section of the paper, we exploit the progressive implementation of a universal

[1] Fast-growing emerging economies (e.g. China, Brazil or Mexico) have recently experienced a drastic reduction in the mortality caused by transmissible diseases. Despite these significant gains, developing countries are less prepared to face catastrophic events affecting health, as demonstrated by the recent West Africa Ebola virus epidemic or the HIV/AIDS pandemic. Climate change in the twenty-first century will likely add to this burden by affecting many determinants of health: water, food supply, public infrastructure, housing, economic growth and conflict. By 2030-2050 climate change could trigger 250,000 additional deaths per year globally (http://www.who.int/mediacentre/factsheets/fs266/en/).

[2] Climate change may also widen the differences that exist within countries between the rich and the poor. These differences seem to have increased recently for non-transmissible diseases: in the United States, recent studies have documented a growing life expectancy gap between the affluent and less affluent, which has been associated to widening income inequality (Olshansky et al., 2012).

[3] The relationship between income and health has been studied at least since Preston (1975). The health economics literature (see Deaton, 2003, for a review) has shown that it is difficult to disentangle the impact of income on improving health from the impact of good health on raising revenues. In the context of climate change, income determines the capacity of households to invest in protective measures.

healthcare policy – the *Seguro Popular* – to analyse the impact of extending universal healthcare on reducing weather vulnerability. To our knowledge, this paper is also the first to assess the impact of pro-poor public health policies on resilience to weather shocks.

The use of daily data has two major advantages. First, the inclusion of municipality-by-month-by-year fixed effects allows us to purge the estimates from a large number of confounding factors that might be correlated with both temperatures and mortality. Second, the use of distributed lag models *à la* Deschenes and Moretti (2009) or Braga *et al.* (2001), allows us to report the effect of extreme temperatures on mortality up to a month after an unusually hot or cold day, which accounts for possible mortality displacement effects.[4]

We find that random variation in temperatures is responsible for the death of around 45,000 people every year in Mexico, representing 8% of annual deaths in the country. Consistent with previous epidemiological research, we find that the most vulnerable group to extreme temperatures is the elderly, in particular people over 75 years old, followed by young children. The predominant causes of death from excessive heat and cold are, in order of importance, circulatory, respiratory and metabolic diseases. In terms of magnitudes, our results suggest at least a three-time stronger vulnerability to cold in Mexico than in the US, based on estimates from recent studies (Braga *et al.*, 2001; Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; Barreca, 2012). On the other hand, we find a modest, but statistically significant impact of heat on mortality whereas previous studies in the US did not find any impact (Braga *et al.*, 2001; Deschenes and Moretti, 2009). In contrast, the impact of temperatures on mortality in Mexico appears to be much smaller than the impacts found in India by Burgess *et al.* (2014).

A 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 mean temperature below 20°C (68°F) are associated with statistically significant increases in the daily mortality rate. Therefore, while very cold days with mean temperature below 10°C are responsible for the death of around 4,700 people each year, we estimate that 88% of weather-induced deaths – around 40,000 people per

[4] While the impact of on-the-day temperatures on death has been widely reported in the medical literature, their impact on longevity is debated and depends on the magnitude of mortality displacement effects: extreme temperatures could simply accelerate the death of already weak people by only a few days (e.g. Deschenes and Moretti, 2009; Hajat et al., 2006; Hajat et al., 2005; Braga et al., 2001).

year – occur because of daily mean temperatures between 10°C and 20°C.[5] In contrast, extremely hot days over 32°C trigger a comparably small amount of additional deaths (around 400 annually). We present data on the very low rate of heating equipment across Mexico which may account for this impact of mildly cold temperatures on mortality.

In terms of longevity, we find that the number of years of life lost due to cold days under 10°C is 50% larger for children under 5 than for people aged 75. This is not only because children under 5 have a longer life expectancy, but also because the Mexican population is very young: there are around four times more children under 5 than people over 75. These results are in sharp contrast with the ones found by Deschenes and Moretti (2009) for the US, who found a large effect of cold temperatures on the longevity of people over 75, and a negligible one on children under 5.

Combining our results with long-term climate scenarios, we predict that, by the end of the 21st century, the number of weather-related deaths in Mexico would decrease by 50 to 80% even in the absence of any adaptation. This finding stands in sharp contrast with most recent 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. 2014), and they illustrate the vast heterogeneity in climate change impacts across countries and regions.

The second contribution of this research is to show that vulnerability to extreme weather is negatively correlated with personal income. Controlling for differences in the age structure across income groups, we show that vulnerability to unusual cold (defined as a day with mean temperature below 10°C) is 35% higher for people in the bottom half of the income distribution compared to people in the top half. Death following mildly cold days (10-20°C) appears to concern only people living below the national median personal income. Hence, the great majority of cold-related deaths only affect the poorest income groups. In contrast, we find no statistically significant differences in vulnerability to heat across income groups.

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

[5] Since the daily mean temperature is the average between the minimum and maximum temperature, a daily average of 10°C may hide much lower temperatures at night. On a day with mean temperature of 20°C, the minimum temperature at night may well be below 10°C.

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 be able to 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. It provides protection against a set of diseases which happen to be particularly sensitive to weather conditions (e.g. pneumonias and diabetes).[6]

We use a matching method on a large sample of death certificates to artificially recover the identifying conditions of a randomized experiment.[7] We exploit information on affiliation to the *Seguro Popular* as reported on all death certificates between 2004 and 2010 to compare the vulnerability to extreme weather between two groups of deceased people: the *treated*, who were registered with the *Seguro Popular* at the time of their death, and a control group that did not have any social insurance when they died. To construct the control group, we pair each treated individual with an untreated observation of the exact same age, gender, education, profession and place of residence. We then compare the distribution of deaths throughout the year for the treated and the control groups. If both groups were similar, deaths should be equally distributed within the year. However, we observe a difference in the spread of deaths across cold, temperate and hot days, suggesting that deceased people from the treated and the control group are drawn from different distributions. We find that the scheme reduces weather vulnerability during cold days (<10°C) by around 35%. When including milder days (<16°C), we find that the reduction in weather vulnerability is around 13%. We estimate that the increase in resilience to cold weather provided by the Seguro Popular would save around 3,300 lives every year if extended to all the people in need in Mexico. While our analysis focuses on weather vulnerability, which is only one specific aspect of the impacts of the *Seguro Popular* on mortality, it actually is the first assessment of the impact of the *Seguro Popular* on mortality.[8]

The policy implications from this paper go beyond the frontiers of Mexico. Even in hot countries where the coldest temperatures almost never reach 0°C, cold remains a risk factor with potentially large health impacts. Low-income households, particularly in the developing

[6] 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.

[7] A randomized control trial would likely not be economically feasible because both deaths and unusually cold days are rare events.

[8] 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).

world, are ill-equipped to protect themselves against it. 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 remaining of this paper is structured as follows. Section 2 discusses the previous empirical literature on the impact of weather on mortality. Section 3 describes the data. The general impact of temperatures on mortality is presented in Section 4. Results by quartiles of income are presented in section 5, and the impact assessment of universal healthcare on reducing weather-related mortality is presented in section 6. A concluding section summarises our findings and discusses the implications of our results.

2. Previous empirical literature on temperature and mortality

Appendix A1 presents a review of the epidemiological literature focusing on the physiological impact of cold and heat on human health, but we summarize the most important results 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 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 is heat- or cold-related mortality. This is in line with medical evidence that the human body starts being at risk outside a comfort zone which varies across individuals but is generally believed to lie in the range of 20°C to 25°C. From a methodological perspective, such a nonlinear relationship between mortality and temperature calls for the use of temperature bins in panel data analyses (Deschenes and Greenstone, 2011): the impact between temperature and mortality is then separately evaluated at different levels of temperature stress.

Despite evidence from the medical literature that even mildly cold or hot days can negatively affect human health, the economic literature has primarily focused on the impact of extremely hot and cold days (see for example Deschenes and Moretti, 2009; and Deschenes and Greenstone, 2011), plausibly because these extreme weather events tend to concentrate media attention. However, while the impact of a mildly cold or hot day is definitely less dangerous than that of an extremely hot or cold day, days lying outside the typical human body comfort zone are much more frequent. This misrepresentation of the relative burden of extreme temperatures in the media is particularly striking in the case of very hot days. Whereas unusually hot days receive 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 mortality on hot days was often found to be offset by lower mortality in 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).[9]

However, uncertainty remains on the true mortality impact of hot days because extreme weather events may not only directly affect human physiology, but also reduce agricultural output, potable water availability or family income. These impacts may in turn affect health or access to healthcare and lead to extra mortality. In order to account for these longer-term impacts, a few economic studies have used monthly or annual panel data rather than daily data (Deschenes and Greenstone, 2011; Barreca, 2012; Burgess *et al.*, 2014; Barreca *et al.*, 2016).[10] These studies find a clear correlation between hot temperatures and monthly or annual mortality. Burgess *et al.* (2014) find a strong impact of extreme temperatures on annual mortality in India, plausibly because shocks on temperatures affect agricultural productivity, and therefore the food intake and income of populations located in rural areas.

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

[9] 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.

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

include migration to places with a more indulgent 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. For example, 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%), but this hides significant heterogeneity: mortality would decrease in the coldest states whereas it would significantly increase (by up to 3%) in the warmest and most humid States. In India, Burgess et al. (2014) 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%.

Overall, evidence suggests that weather vulnerability in emerging 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 become the major cause of death in these countries, contrary to many developing countries. Furthermore, elemental protection measures (e.g. proper clothing) are available to all in industrialised countries, and national programs such as Medicare and Medicaid provide universal healthcare coverage in life-threatening cases.

3. Data and summary statistics

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

3.1 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 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 1998-2010. Table 1 displays the average daily mortality rate by cause of death, gender and age, together with the average population within each group for 1998-2010.[11] The average daily mortality rate across all municipalities is 1.3 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 21.2 per 100,000 inhabitants for people aged 75 years and above.

Table 1: Summary of death statistics

		Average daily municipal mortality rate (deaths per 100,000 inhabitants)							
Group	Average population per municipality	All causes	Respiratory system diseases	Circulatory system diseases	Endocrine, nutritional and metabolic diseases	Infectious diseases	Neoplasms	Violent and accidental deaths	All other deaths
Total	44935	1.30	0.114 (8.8%)	0.295 (22.7%)	0.204 (15.7%)	0.049 (3.8%)	0.163 (12.5%)	0.142 (10.9%)	0.333 (25.6%)
Men	21886	1.47	0.127 (8.6%)	0.303 (20.6%)	0.195 (13.3%)	0.061 (4.1%)	0.162 (11%)	0.231 (15.7%)	0.391 (26.6%)
Women	23049	1.13	0.102 (9%)	0.288 (25.5%)	0.212 (18.8%)	0.038 (3.3%)	0.164 (14.5%)	0.057 (5%)	0.27 (23.9%)
Aged 0-4	4543	1.08	0.12 (11.1%)	0.014 (1.3%)	0.037 (3.4%)	0.081 (7.5%)	0.015 (1.3%)	0.081 (7.5%)	0.732 (67.7%)
Aged 4-9	4739	0.08	0.005 (6.2%)	0.002 (3%)	0.003 (4%)	0.006 (7.4%)	0.014 (17%)	0.027 (33.2%)	0.024 (29.2%)
Aged 10-19	9227	0.15	0.005 (3.4%)	0.007 (4.3%)	0.004 (2.6%)	0.006 (3.8%)	0.017 (11.1%)	0.079 (52.4%)	0.033 (22.3%)
Aged 20-34	11042	0.37	0.012 (3.3%)	0.023 (6.3%)	0.015 (4%)	0.032 (8.6%)	0.03 (8.2%)	0.178 (48%)	0.08 (21.7%)
Aged 35-44	5674	0.66	0.025 (3.8%)	0.075 (11.3%)	0.06 (9%)	0.051 (7.7%)	0.089 (13.4%)	0.174 (26.2%)	0.19 (28.6%)
Aged 45-54	3880	1.39	0.056 (4%)	0.232 (16.7%)	0.248 (17.8%)	0.061 (4.4%)	0.235 (16.9%)	0.182 (13.1%)	0.377 (27.1%)
Aged 55-64	2462	3.10	0.16 (5.2%)	0.658 (21.2%)	0.751 (24.2%)	0.091 (2.9%)	0.545 (17.6%)	0.207 (6.7%)	0.688 (22.2%)
Aged 65-74	1482	5.16	0.266 (5.2%)	1.09 (21.1%)	1.25 (24.2%)	0.151 (2.9%)	0.905 (17.5%)	0.343 (6.6%)	1.155 (22.4%)
Aged 75+	963	21.25	2.92 (13.7%)	7.51 (35.3%)	3.41 (16%)	0.425 (2%)	2.28 (10.7%)	0.591 (2.8%)	4.114 (19.4%)

Notes: The table shows cause-specific daily mortality rates in number of deaths per 100,000 inhabitants. The share of average group mortality is presented in brackets. The sample includes 2,289 municipalities over 11.65 years on average. All means are weighted by the relevant population group in municipalities.

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 Organisation (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% of deaths in this category, followed by malnutrition); diseases of the circulatory system; diseases of the respiratory system; and violent and accidental deaths. As it has been reported elsewhere, the primary cause of death is circulatory system diseases, which has been identified as affected by temperatures in the epidemiologic literature. The importance of each cause of death differs

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

by age and gender. For example, the prevalence of violent and accidental death is four times greater among men than among women. It is also the main cause of death for people aged between 10 and 44. The importance of circulatory system diseases rises with age and peaks above 75, when it becomes the primary cause of death.

3.2 Weather and climate data

The National Climatological Database of Mexico provides daily temperature and precipitation records for around 5,500 operating and formerly operating land-based stations in Mexico. Information on the longitude and latitude of the stations is also provided. In order to compute mean temperatures and precipitations at municipal level, we match the municipalities in Mexico with the closest land-based stations.[12] This leads us to exclude a few municipalities which are too far from any weather station, or close to weather stations that did not efficiently record both minimum and maximum temperatures. Our combined daily temperature-mortality dataset covers 2,289 Mexican municipalities over the period 1998-2010[13] and includes over 9 million observations.

Figure 1 below presents the historical distribution of daily average temperature in Mexico from 1998 to 2010.[14] The temperature data is weighted according to the population of each municipality to reflect the average exposure of Mexicans to low and high temperatures. We use 13 temperature bins: “below 10°C”, “above 32°C” and eleven 2°C bins in between. In the empirical models presented hereafter, we use the same temperature bins to estimate the relationship between temperature and mortality. In Figure 1, each bar represents the average number of days in each temperature category for the average person in Mexico. The mode of the distribution is between 16 and 18°C, and 50% of days lie in the range 14-22°C. At the extremes of the distribution, the average Mexican is exposed to 5.6 days per year below 10°C (50°F) and 2.5 days per year above 32°C (90°F). Mexico’s climate is much warmer than that

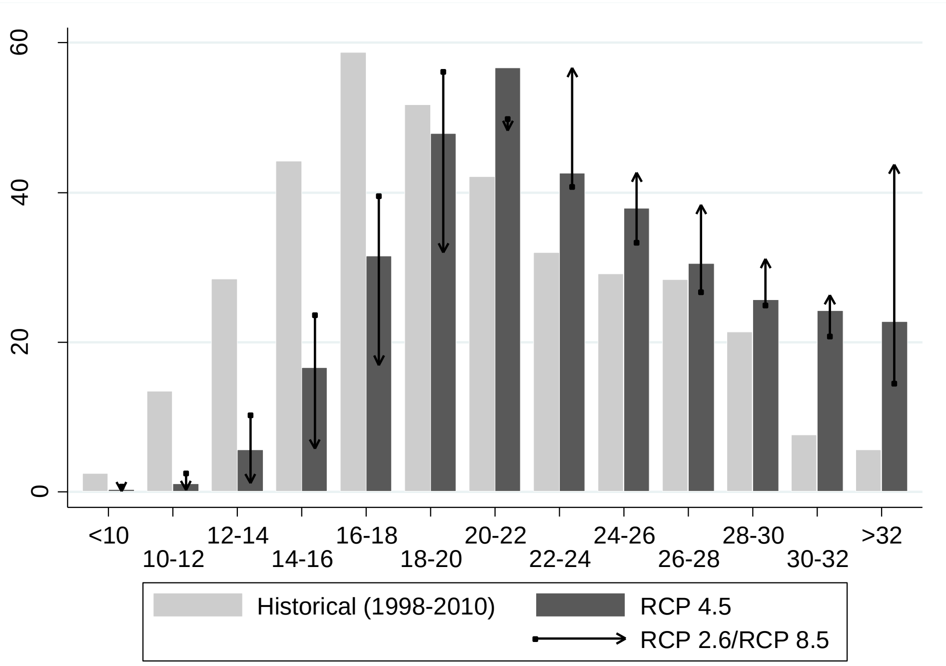
[12] To do so, we use the information on the longitude and latitude of municipalities from the National Geostatistical Framework (marco geoestadístico nacional) of the INEGI. We calculate the longitude and latitude of the centroid of each municipality (averaging the coordinates of all the locations that are part of a municipality), and then the distance between this centroid and all the land-based stations of the climatological data. Based on their distance to 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. For municipalities that are in very isolated zones, we have 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 the stations considered to be relevant to a given municipality.

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

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

of the US, which fewer days below 16°C and many more days above 26°C. [15] The distribution is also more spread out in the US. In addition, Figure 1 also provides estimates of the distribution of cold and hot days under climate change. These estimates are derived from the output of the third version of the Coupled Physical Model of the Geophysical Fluid Dynamics Laboratory (GFDL CM3) of the National Oceanic and Atmospheric Administration (NOAA).[16] We observe that the distribution of daily temperature shifts sharply to the right in all climate change scenarios with much fewer cold days and many more hot days by the end of the century.

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



Notes: The figure shows the distribution of daily mean temperatures across 13 temperature-day bins. Each light grey bar represents the average number of days in each temperature category over 1998-2010, weighted by total population in a municipality-year. The climate change results depend on the scenario chosen. The dark grey bar is for the RCP4.5 scenario whereas the arrows represent the impact of shifting from the RCP2.6 scenario (low emissions) to the RCP8.5 scenario (high emissions).

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[15] 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).

[16] We extract monthly average temperature forecasts for Mexico and 2075-2099 based on three IPCC emissions scenarios (RCP2.6, RCP4.5 and RCP8.5). We obtain the model output from the Atlas Climático Digital de México. This Atlas provides climate model output for Mexico online and is monitored by Centro de Ciencias de la Atmósfera of the Universidad Nacional Autónoma de México (UNAM). We extrapolate the number of days falling within each temperature bin for each climate scenario and municipality. To do so, we calculate the difference between the monthly average temperature as observed in the historical data (1998-2010) and the forecasts of GFDL CM3: this gives estimates of monthly increases in average temperature due to climate change. Assuming that the distribution of daily temperatures around the monthly average temperature in one location and the population distribution across municipalities would remain constant under climate change, we can evaluate the proportion of days falling within each temperature bin under each climate change scenario. The result of this exercise is synthetically provided in Figure 1 for the three climate scenarios.

3.3 Socioeconomic data

In addition, information from the Mexican 2000 census of population and housing is used in this paper to estimate the income of the deceased. In particular, we extract socioeconomic information on income, educational attainment, social insurance coverage, profession, age, etc. We also refer to survey data from the Mexican Survey of Household Income and Expenditure (ENIGH: Encuesta Nacional de Ingreso y Gasto de Hogares) between 1998 and 2010 to assess heating and cooling equipment ownership. These data sources are described in detail in Appendices A3 (census data) and C7 (ENIGH data). In a nutshell, the 2000 Census shows larges differences in the average personal income between the poorest and the richest households. People in the first income quartile have an average personal income which is 18 times lower than people in the top quartile. This large 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 large inequalities translate into low healthcare coverage of the very poor: more than 80% of the people in the 1st quartile of income have no social security.

4. The effect of temperatures on mortality in Mexico

4.1 Method

One of the simplest approaches to assess the impact of daily temperatures on mortality is to correlate daily temperatures with daily mortality rates using a fixed-effect linear regression. To control for differences in mortality rates due to seasonal phenomena and structural differences between municipalities (e.g. in the quality of medical services), the model includes municipality by month by year fixed effects. Thus, in the baseline regressions, identification of the parameters comes from deviations in temperature from the municipality average in a given month and year, but we show robustness to using alternative sets of fixed effects. More precisely, we run regressions of the type:

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

where $Y_{i,d,m,t}$ is the mortality rate of municipality i on day d of month m and year t, θ is a vector of parameters, $T_{i,d,m,t}$ is a vector of climatic variables that we discuss in detail below, $\mu_{i,m,t}$ is a vector of municipality-by-month-by-year fixed effects and $\varepsilon_{i,d,m,t}$ is the error term. Standard errors are clustered at the municipality-month level but we explore the robustness of our results to alternative clusters. [17] In addition, the regression coefficients are weighted by the square root of the population in each municipality.[18]

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

Furthermore, $T_{i,d,m,t}$ cannot only consists 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 during a cold day and die a few days after) 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) suggest combining temperature bins with a distributed lag model. Thus, we consider 12 temperature bins and include 30 lags for each bin. The choice of 30 lags is arbitrary but allows comparison of our results with Deschenes and Moretti (2009). In practice, this choice is rather conservative since all effects seem to fade out after 15-20 days (see Appendix A.5). The expression for the distributed lag model is as follows:

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

The subscript s stands for the various temperature bins, and $B_{s,d-k,i}$ is a dummy variable equal to one if the temperature in day (d-k) of municipality *i* falls within bin *s*. Furthermore, we use

[17] In an alternative specification, we have also used State-level clusters to relax the hypothesis of zero correlation between municipalities, and zero correlation between observations of a same municipality but pertaining to a different month or year. Standard errors increase but the statistical significance of the effects remains for the baseline model covering all causes of death and the entire Mexican population.

[18] This is because, without any weights, coefficients would be representative of municipalities and not of the population. Furthermore, $Y_{i,d,m,t}$ is noisily estimated in small municipalities and the effect of such noise on the estimation is mitigated when population-based weights are used. Note that using total population as a weight instead of the square root such as Deschenes and Moretti (2009) has no significant impact on the results.

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 overcoming the multicollinearity problems arising when many lags and temperature bins are considered simultaneously.

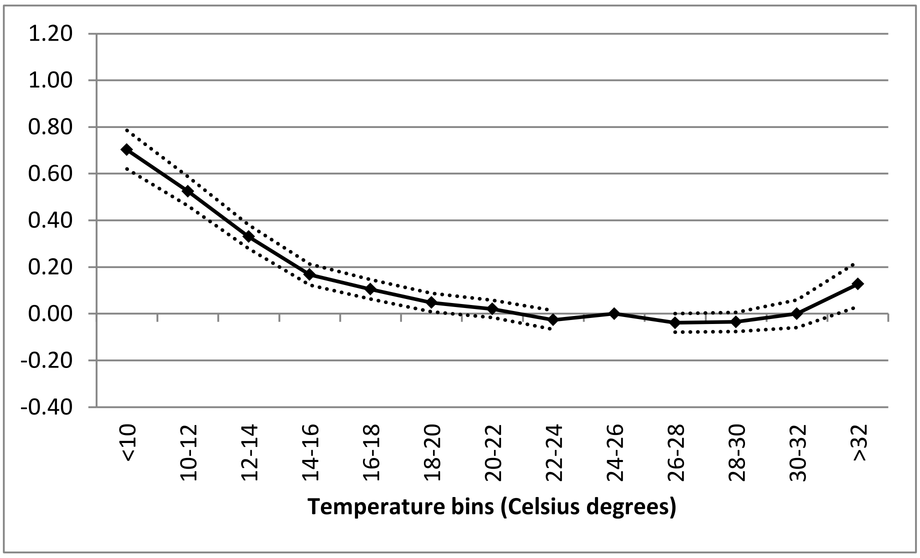
4.2 Main results

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

Figure 2 displays the cumulative impact of temperature on 31-day mortality for the whole population and all causes of death as estimated with our distributed lag model. We find the classical U-shaped relationship between temperatures and mortality identified in previous studies. However, looking at the two extremes of the temperature distribution observed in Mexico, low temperatures appear to lead to much more extra mortality than high temperatures. A day with an average temperature below 10°C kills 6 to 7 times more than a day with an average temperature above 32°C. Interestingly, we find statistically significant impacts of days above 32°C, suggesting that extremely hot days displace death by more than one month and not only a few days, a finding in contrast with that of Deschênes and Moretti (2009) for the US. Furthermore, we find statistically significant and strong impacts on mortality of all temperatures bins below 20°C. In fact, the contrast between a day below 10°C and a day between 10-12°C is not sharp. A day between 10-12°C increases mortality by around 0.5 deaths per 100,000 inhabitants when a day below 10°C increases mortality by 0.7 deaths per inhabitants. Likewise, a day between 16-18°C increases mortality by 0.1 deaths per 100,000 inhabitants: a week of mildly cold days at 16-18°C will have the same mortality impact as one unusually cold day below 10°C. The comparison is interesting when we consider that there are around 51 days at 16-18°C per year in Mexico and only 5.6 days per year below 10°C. In Mexico, the effects of temperatures below 20°C and above 32°C have long-lasting effects that can reduce longevity.

These results are consistent with the dynamic effects of heat and cold days on mortality as reported previously, for example by Deschenes and Moretti (2009). Like these authors, we find evidence of strong harvesting for hot days whereas the impact of cold days accumulates after the event (see all details in Appendix A5). A cold day below 10°C has a statistically significant effect on mortality every day during the first week, and we find statistically significant effects at 5, 14 and even 21 and 22 days after the cold day. By contrast, we find that a hot day above 32°C has a strong and immediate effect on mortality but this effect is statistically significant only for the first two days, after which the coefficients become systematically negative although not statistically significantly so.

Figure 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 based (relative to the 24-26°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. Dashed lines correspond to the 95% confidence interval. The dependent variable is daily mortality rate at the municipality level. 312,140 groups and 30.1 observations per group on average. The regression controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects.

Table 2 combines the results presented in Figure 2 with the distribution of hot and cold days in Mexico shown in Figure 1. Days under 10°C are responsible for the death of around 4,700 people each year (95% confidence interval is 4,177–5,296). This represents 0.8% of the annual number of deaths in Mexico. However, because mild temperatures between 10 and 20 degrees are much more frequent, the total amount of extra mortality associated with moderately low temperatures below 20°C is around 43,700 per year[19] (95% CI: 34,600-52,800), or 7.7% of the annual number of deaths in Mexico, suggesting that the impact of mild temperatures on mortality is much stronger than the impact of unusually cold days.[20] At the other extreme of the spectrum, extremely hot days over 32°C trigger a comparably small amount of additional deaths (around 380 annually, 95% CI = 92–663).

[19] This includes the impact of days below 10°C. The estimate for the impact of mild temperatures alone (10°C-20°C) is slightly below 40,000 deaths.
[20] We are comparing days with an average temperature between 10°C and 20°C with days with an average temperature between 24°C and 26°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).

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

Average daily temperature	Average deaths per year	95% confidence interval
<10°C	4,736*	(4177; 5296)
10-12°C	8,474*	(7457; 9491)
12-14°C	11,259*	(9553; 12965)
14-16°C	8,910*	(6470; 11349)
16-18°C	7,399*	(4468; 10331)
18-20°C	2,968*	(510; 5426)
20-22°C	1,036	(-834; 2907)
22-24°C	- 1,018	(-2561; 526)
24-26°C	-	-
26-28°C	-1,332	(-2665; 0)
28-30°C	-900	(-1944; 144)
30-32°C	2	(-539; 544)
>32°C	378*	(92; 663)

Notes: * denotes statistically significant at 5%. The 95% confidence interval in brackets only takes into account the uncertainty of the impact of temperature bins on mortality. It does not take into account the variability of hot and cold days in Mexico from one year to the other.

These estimates can be compared with the results of recent studies conducted with US panel data (Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; and Barreca, 2012) and Indian data (Burgess *et al.*, 2014). This comparison is presented in detail in Appendix A6, but in short, our results are higher in magnitude than the ones obtained in the US, and are far smaller in magnitude than the ones found by Burgess et al. (2014) for extremely hot days in India. Burgess et al. (2014) find strong effects on rural populations and not on urban populations. This is because unusually hot weather during the growing season sharply depresses agricultural yield and the wages of agricultural laborers in rural areas, which in turns pushes mortality up. For Mexico, we find no statistically significant difference between rural and urban areas (see Appendix B9). This suggests that the impact of heat is smaller in countries in which people in rural areas do not entirely rely on subsistence agriculture.

4.3 Implications for climate change

We can use our model to simulate the impact that climate change may have on mortality in Mexico. This is done in detail in Appendix A7. Because the frequency of cold and mildly cold days is expected to decrease, the number of deaths imputable to temperatures reduces with the forecasted temperatures of GFDL CM3 as compared with the historical ones. With the RCP2.6 scenario (low GHG emissions), temperature-related mortality would be twice as small. The RCP8.5 scenario (high GHG emissions) corresponds to an 80% reduction in the estimated relationship between mortality and temperature. We show later 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. Economic development may furthermore cancel off the remaining impact of cold waves on mortality if Mexico registers steady growth. These results are high in magnitude. However, this analysis comes with serious warnings: because we only look at short run impacts, our analysis restrains weather-related deaths to short term variability in weather. Climate change could also affect mortality through increased frequency of natural catastrophes and not only through temperatures and these deaths are unaccounted for in the present study. Also, our analysis at the daily level does not allow for acclimatization, and we could be underestimating the impact of increased heat waves if the effect of heat grows non-linearly beyond 32°C days. In addition, our model includes municipality-by-month-by-year fixed effects which control for income, technologies, and for the general health of the population, three factors that climate change could influence. All in all, our results simply suggest that extra winter mortality will reduce and that mortality will be more equally spread across seasons.

4.4 Impacts by gender, age and cause of death

We now look at the impact of temperatures on mortality by gender, age and cause of death. This exercise is useful to identify the type of people at risk during cold waves. We focus on the two extremes of the temperature distribution: days with average temperature below 10°C (corresponding to the left-hand side of Figure 2) and days with average temperature above 32°C (corresponding to the right-hand side of Figure 2). The full regression results are presented in Appendix A8; here, we briefly discuss the main results from this analysis.

We find that the 31-day effects of cold are much stronger for people over 75: the coefficient for cold-related mortality is 16 times higher than for the whole population. In addition, the very young (<5 years old) and senior people (>55) are also vulnerable to cold. Cold appears to have a particularly strong impact on metabolic, circulatory and respiratory diseases.[21] These three causes of death are estimated to concentrate 70% of deaths due to unusual cold. Interestingly, cold days induce more accidental and violent deaths, but only among women. As for extreme heat, because of the small number of days above 32°C differences between age groups are not statistically significant. However, the model seems to indicate that days above 32°C primarily kill people between 35 and 54 years old and then again above 75 years old. Most heat-related

[21] There is also an impact of cold on infectious diseases. This could look surprising since diseases like malaria transmit at higher temperatures. However, more than 85% of deaths caused by infectious diseases are triggered by gastroenteritis and colitis; hepatitis B; sepsis and HIV.

deaths seem to be due to circulatory system diseases (affecting men) and accidental and violent deaths (affecting women).

Deschenes and Moretti (2009) similarly find (for the US) that people over 75 are much more vulnerable than the rest of the population. The causes of cold-related deaths seem very different though: in the US, two-thirds of cold-related deaths have a cardiovascular origin and around 20% are caused by respiratory diseases. Diabetes and infectious diseases respectively accounts for only about 3% and 2% of cold related deaths. Looking at the corresponding estimates for Mexico, we find that cardiovascular diseases account for around a third of cold-related deaths only, followed by respiratory diseases (27%) and metabolic ones (17%, including mostly diabetes). Infectious diseases also account for a small share (3%) of cold-related deaths.

The output of the regressions by age groups can be used to compute annual deaths by age groups. These are reported in Table 3 for cold (<10°C), mildly cold (10-20°C) and hot (>32°C) days. The great majority of deaths correspond to people aged 75 and over, mostly during mildly cold day. Children under 5 constitute the second age category in terms of number of deaths. Individuals over 75 are much more vulnerable than children under 5, explaining the large gap in deaths. However, there were only around 700,000 people over 75 in Mexico in 2010, whereas the country comprised around 10 million children under 5 this same year. Results by age group are not statistically significant for days above 32°C.

The estimates by age group are informative about the impact of cold on longevity. We calculate the annual total of years of life lost associated with outdoor temperature exposure for the Mexican population by using the life expectancy estimates of the Mexican life table of 2010 available from the Global Health Observatory data repository. Results are synthesized in Table 4. The number of years of life lost due to cold days under 10°C is 50% larger for children under 5 than for people aged 75. For days between 10°C and 20°C, we find that the number of years of life lost is roughly equivalent between the two groups. Deschenes and Moretti (2009) provide similar calculations of years of life lost for the US. In total, they find that people over 75 suffer from 106,405 years of life lost annually. However, the cumulative number of years of life lost in a year for children under 5 was only 5,410. The impact of cold weather on infant mortality is therefore much higher in the case of Mexico. This result implies that priorities for policy makers in both countries should be different. US policies to reduce weather-related mortality may need to focus on the elderly, whereas emerging countries like Mexico may need to tackle both infant mortality and the vulnerability of the elderly to unusual weather.

Table 3: Death estimates by age group and temperature level

Age group	<10°C	10-20°C	>32°C
0-4	458*	2,706*	-6
5-9	14	-345	-2
10-19	13	754*	31
20-34	225*	-355	19
35-44	203*	356	49
45-54	186*	2,579	26
55-64	378*	2,423	1
65-74	371*	2,297	3
75+	2,536*	24,756*	97

Notes: These are estimates of the annual number of deaths due to cold (<10°C), mildly cold (10-20°C) and hot (>32°C) as compared to a day with average temperature of 24-26°C. Estimates take into account the frequency of cold, mildly cold and got days.

Table 4: Years of life lost estimates by age group and temperature level

Age group	<10°C	10-20°C	>32°C
0-4	35,872*	212,115*	-456
5-9	1,040	-25,734	-144
10-19	898	50,675*	2,073
20-34	12,443*	-19,639	1,050
35-44	8,767*	20,167	2,117
45-54	6,282*	87,130	863
55-64	9,461*	60,652	13
65-74	6,413*	48,452	60
75+	23,766*	232,044*	908

Notes: These are estimates of the total number of years of life lost for each age category. They are obtained from multiplying the estimated number of deaths of table 3 with the remaining life expectancy of each age group, as provided by 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 and for those who did not. This is an approximation with no consequence for the international comparison: the US figures have been obtained with the same assumption (Deschenes and Moretti, 2009). However, we may overestimate the total years of life lost. An asterisk (*) denotes statistically significant results at 5%.

4.5 Robustness

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

First, we have considered specifications in which the definition of the temperature bins is different. We separately estimate the effect of daily minimum and daily maximum temperatures instead of using the daily average temperature (Appendix B1). This allows considering whether intra-day temperature variations has a strong impact on mortality. We find that minimum temperatures below 0°C are associated with an increase in mortality of 0.6 deaths per 100,000 inhabitants. We record no statistically significant effect on mortality for unusually high minimum temperatures above 25°C. We find an extra mortality impact of around 0.36 deaths per 100,000 inhabitants when daily maximum temperatures are below 15°C, and a small effect when they are unusually high (+0.18 deaths per 100,000 inhabitants for maximum temperatures above 40°C). The magnitude of these effects is similar to the one found when using daily averages in our base model. We also study the impact of consecutively hot or cold days on mortality and find no evidence that consecutively hot or cold days induce more mortality than if spread throughout the month (Appendix B2).

We then consider the role of acclimatization (Appendix B3). We assume that the temperature-mortality relationship might depend on the usual temperature faced by households in a given location. Heutel, Miller and Molitor (2017) find radically different results on the health impact of climate change in the US when taking into account differences in regional sensitiveness. Instead of using absolute temperature bins, we calculate deviations from the average temperature in each location to construct relative temperature bins with a 2°C window. The average temperature in each municipality is obtained by averaging all daily temperatures over 1997-2013. Then we rerun our distributed lag model with the newly constructed temperature bins. These include deviations between -10°C and +10°C with respect to the average temperature in each municipality. There are some small differences in magnitudes with the results obtained using absolute temperature bins, but the main messages on the large impact of mild cold and the comparatively small effect of heat remain unaffected. When accounting for the frequency of unusually cold and hot days, we find that days with mean temperature of more than 10°C below the municipality average are responsible for the death of around 2,700 people annually (95% CI is 2,200-3,200). Mild cold (deviations of between -2°C to -10°C) induce the death of 26,700 people (95% CI: 23,600-29,700). On the other hand, unusually hot days – above the average by 10°C or more – would cause around 350 deaths (95% CI: 100-600). We also find statistically significant effects for days with temperatures between 6°C and 10°C above the municipal average: these would be responsible for the death of around 1,500 people (95% CI: 900-2,200). In Appendix B4, we also run the model separately for four different climatic regions in Mexico, and find no statistically different health responses across regions: confidence intervals might be too large for us to effectively assess differences in acclimation, and long run adaptation to historical temperatures, with this method.

We also consider that precipitation levels might have delayed impacts on mortality and correlate with the temperature-mortality relationship. We find no statistically significant impact of lagged precipitations on mortality (Appendix B5). We also look at the confounding effect of humidity (Appendix B6). Results are not substantially modified, but we find that mortality due to heat is higher under dry climates.

We have also tested the sensitivity of the results to different sub-samples and to various alternative specifications. More precisely, we check for coefficient stability by splitting the sample into two periods (1998-2003 and 2004-2010) (see Appendix B7). We find a decrease in the temperature-mortality relationship between the 1998-2003 and the 2004-2010 periods. We also estimate different effects of temperature on mortality for week days and weekends (Appendix B8), and on rural vs. urban populations (Appendix B9). We find that cold-related mortality is higher during weekends, consistent with people spending more time outdoors. We find no statistically significant difference between rural and urban areas. Among other things, this last result pinpoints that pollution is unlikely to be the main contributing factor explaining the temperature-mortality relationship that we observe.

Furthermore, we ensure that our results are fully comparable with the study by Deschenes and Moretti (2009) to draw comparisons between the US and Mexico. We reduce the number of temperature bins in our model to match their baseline specification (Appendix B10).[22] Using the model by Deschenes and Moretti (2009) gives results that are very similar to our baseline model.[23]

Finally, we use different structures for the fixed effects. In the baseline specification, we have used fully interacted, municipality-by-year-by-month fixed effects. This restrains the comparison of mortality effects to days within the same month of the year within a given municipality and disregards the fact that changes in temperature may affect seasonal patterns, and in turn mortality. Above all, we could underestimate the mortality impacts of direct exposure to temperature in very cold or very hot months by comparing very cold days with already cold days, and very hot days with already hot days within a month. To the contrary, we find that relaxing the controls for within-municipality seasonal patterns attenuates estimated impacts (see Appendix B12). This attenuation is likely to be due to an estimation bias. When we allow the comparison of mortality impacts to take place within a municipality and a given month, but across different years, results are similar to the baseline specification, suggesting

[22] Instead of using temperature bins, Deschenes and Moretti (2009) compute two sets of regressions, using as the independent variable either: a) a dummy variable which take the value of 1 on unusually cold days (average temperature <20°F or <30°F, depending on specification); or b) a dummy variable which take the value of 1 on extremely hot days (average temperature >80°F or >90°F, depending on specification). They therefore calculate the impact of unusually cold or hot days on mortality as compared to the impact of any other day in the year.

[23] We also use the specification by Deschenes and Moretti (2009) to check the correctness of the window period of 30 days of our base specification. This is something that cannot be done with a high amount of bins as in our baseline specification because the calculations are far too computationally intensive with our very large dataset. In Appendix B11, we run a distributed lag model with 60 lags instead of 30 using the specification by Deschenes and Moretti (2009). The output confirms the relevance of a model with only 30 lags since results do not vary much: the model provides identical results for cold, but fails to predict any effect of heat due to amplified statistical variability.

that the baseline specification does not underestimate the impact of hot and cold days on mortality (Appendix B12).

5. Impacts by income group

5.1 Method

In this section, we seek to understand if mortality effects are stronger among the poor. We suspect that differences in living conditions and access to healthcare play a central role in the vulnerability to temperature variations, because poorer households will not have the same access to protection measures such as heating or air-conditioning or access to healthcare.

Income is not reported on death certificates, so we started our analysis by running our baseline distributed lag model separately for each profession, which is available on death certificates. These specifications are reported in Appendix C1. However, we do not find clear differences in terms of vulnerability to temperatures across professions, except for workers in agriculture, fisheries and hunting who appear to suffer from cold temperatures. In fact, professional categories are an imperfect depiction of the diversity of living conditions among Mexicans. Whereas the revenues of the 1st quartile are more than 16 times lower than the ones of the 4th quartile of income, the difference between professions is much less contrasted. Therefore, we use data from the 2000 Mexican census to estimate income levels at the moment of death in our mortality dataset.[24] To do so, we run a simple regression with data from the Mexican census where we predict income y_h of each individual h with a series of independent variables also present on death certificates. The regression used to predict income is:

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

Where y_h is personal income for individual h in 2000 Mexican pesos, calculated as total household income divided by the square root of the number of people in the household (to account for economies of scale within households). Because personal income has a skewed distribution, we take the natural log to improve the fitness of the model and the accuracy of predictions. W_h is a vector of independent variables that include gender, age, civil status, occupation, education level and inscription to public or private healthcare. It also includes a quadratic term for age and interaction terms between age (and age squared) and occupation to account for experience at work. $\omega_{i,r}$ is a fixed effect that takes into account that income may

[24] 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 do not report total income, but only income from work. This is a limitation and we have therefore preferred to use the 2000 data only.

vary by municipality. Within a given municipality, we also distinguish between people living in urban areas (e.g. the city centre) from those who live 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[25]. The output of this estimation is presented in Appendix C2. The model includes close to 9 million observations. 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). We can make income predictions by restricting the independent variables used in the income regression to those that are also present on the death certificates.

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

Summary statistics on the daily mortality rate obtained for each income quartile and the proportion of deaths belonging to each quartile by specific cause of death are reported in Appendix C3. As expected, mortality is higher for the first two quartiles. We furthermore find that endocrine, nutritional and metabolic diseases, along with neoplasms, play a smaller role in the mortality of the 1st quartile, while respiratory systems diseases take a higher toll.[26]

The daily mortality rates by income quartile can be used to run separate distributed lag models for each income quartile.[27] The advantage of this approach is its high flexibility since the

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

[26] In Appendix C3, we furthermore provide details on the relative prevalence of the most common diseases for endocrine, nutritional and metabolic diseases; circulatory system diseases; and respiratory diseases. These are of particular interest to this research because they correspond to the main causes of weather-related deaths. Deaths related to malnutrition, heart failures, cerebrovascular diseases and chronic lower respiratory diseases are more common among the first quartile.

[27] 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 error in the dependent variable and this directly affects the statistical power of our regressions.

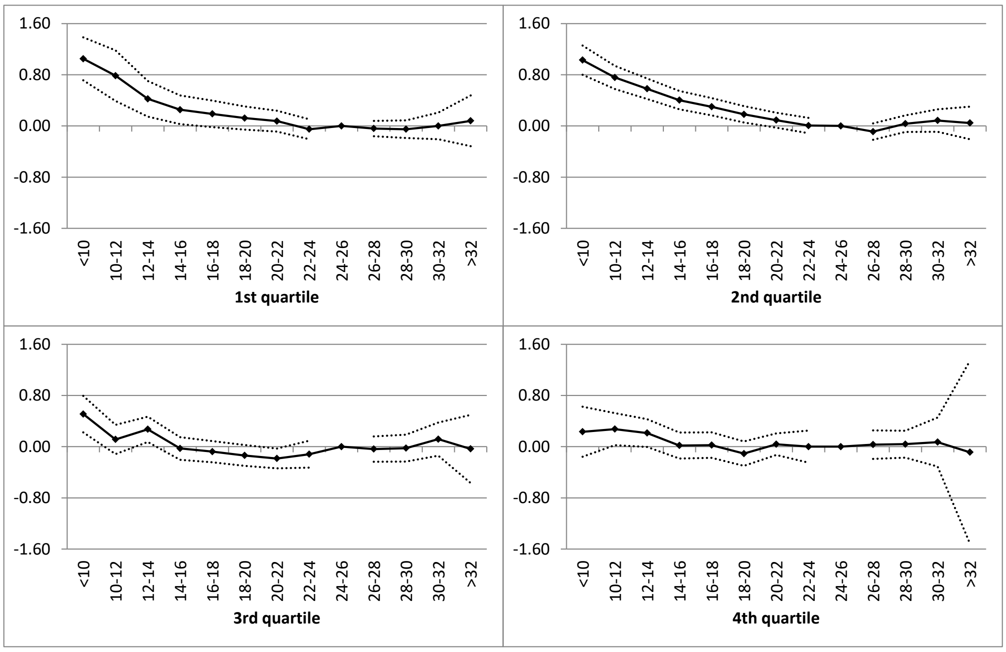
mortality impact of each temperature bin is estimated separately for each income quartile. The results however rely on predicted income values due to the absence of such information on death certificates. The main drawback is a loss of precision in the estimates due to measurement error in the dependent variable.[28]

It is important to keep in mind that income is not randomly allocated across households. It follows that we observe a correlation between income and mortality, and no causal impact. The most accurate interpretation is that our results reflect a situation in equilibrium in which both ill health determines low income, and low income determines ill health.

5.2 Results

We now run separate regressions of Equation 1 for each income quartile. We evaluate the impact of extreme temperatures after up to 31 days on each quartile, using distributed lag models. The results are reported in Figure 3.

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 2°C temperature bins in the regressions. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with municipality-by-month-by-year fixed effects. The dashed lines represent the 95% confidence interval for each estimated set of coefficients.

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

Results show a stronger vulnerability of the first two quartiles compared to the last two, and statistically insignificant impacts of temperatures at all temperature levels for the last quartile. In particular, we find a strong difference in vulnerability to cold between the first and the last quartiles. Vulnerability to unusually cold temperatures is more than 4 times higher for people in the first quartile as compared to people in the fourth quartile and the difference is statistically significant at 1% (see Table 6 – panel A). 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 death are associated with excessive heat.

In addition, Figure 3 clearly depicts an impact of cold temperatures at mild levels but only for the first and second quartiles. In Table 5, we report the magnitude of the impacts in number of annual deaths of both mildly and unusually cold weather (i.e. all temperature bins below 20°C) for each income quartile. For the 1st and 2nd quartiles of income, we find a statistically significant impact of cold below 20°C on mortality whereas no such impact is found for the third and the fourth quartiles. In other words, all the death toll triggered by mildly cold days is borne by the population in the bottom half of the income distribution.

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

To deepen our understanding of the correlation between income and weather-related deaths, we have run the quartile-specific econometric models for separate causes of death for days below 10°C.[29] Results by cause of death tend to corroborate that low-income households are more vulnerable to cardiovascular and respiratory diseases. Interestingly, we find impacts across all quartiles from endocrine, nutritional and metabolic diseases, circulatory system diseases and respiratory system diseases. The magnitude of the impact of cold days remains relatively constant for endocrine, nutritional and metabolic diseases, suggesting little margin for improvement. This can be explained since diabetes has become prevalent across all income groups in Mexico. In contrast, the magnitude of the effect diminishes sharply between the 1st

[29] 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 notice that efficiency is not always very high with the breakdowns by death causes and income groups. For example, we find a higher impact, of circulatory system diseases on the 2nd quartile as compared to the 1st quartile. This impact is likely to be driven by relatively low efficiency: the two point estimates are not statistically different from one another.

and the 4th quartile for circulatory and respiratory system diseases. The results by cause of death are presented in Appendix C4. [30, 31]

Table 5: Estimated deaths per year for temperatures below 20°C by income quartile

	Excess number of deaths per year		
Temperature level	**<10°C**	**10-20°C**	**Total <20°C**
1st quartile	1,813*** (1,232; 2,393)	11,909*** (4,920; 18,899)	13,722*** (6442; 21001)
2nd quartile	1,437*** (1118; 1757)	21,055*** (14,024; 28,087)	22,492*** (15,284; 29,701)
3rd quartile	731*** (321; 1142)	-1,306 (-10,858; 8,246)	-575 (-10,331; 9,182)
4th quartile	404 (-273; 1081)	1,936 (-8,753; 12,626)	2,340 (-8,676; 13,357)
Entire population	4,385*** (3353; 5418)	33,595*** (16,165; 51,025)	37,980*** (20,050; 55,911)

Notes: All estimated coefficients are in reference to a day with an average temperature of 24-26°C. Estimates are made with different distributions for cold days corresponding to population-weighted quartile-specific averages (they can be slightly different from the ones derived from Figure 2), for a total population of 114 million inhabitants equally spread across quartiles. Lower and upper bound of 95% confidence interval in brackets and do not account for the uncertainty in the variability of the weather. One, two and three stars respectively mean statistically significant at 10%, 5% and 1%.

When running separate regressions by income quartiles, demographics are likely to play a role in explaining the differences in vulnerability across income groups. We have shown previously that the elderly is 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. The very young and the very old are thus overrepresented in the lowest quartiles and these people are more vulnerable to the weather independently of their living conditions. Therefore, we also provide results by income quartile while correcting for the differences in the pyramid of ages across quartiles. The methodological details are presented in Appendix C5. We can then interpret the residual difference in vulnerability across the quartiles of income as originating principally from differences in living conditions (and not demographics).

Age-corrected results for cold days below 10°C are provided in Table 6, Panel B, alongside the baseline results shown in Figure 3 (Panel A). Point estimates show that the first two quartiles of income have comparable vulnerability levels. However, these income groups are 35% more vulnerable to unusual cold than the last two quartiles. This difference is statistically different at 5% (t-statistic of 2.04). Therefore, a sizeable difference in vulnerability levels correlates with

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[30] We also find that richer households are statistically more vulnerable to neoplasms than poorer households. However, this information is derived from coefficients for neoplasms that are themselves not statistically different from 0 at the 5% level of significance.

[31] Since we find no statistically different results between rural and urban areas in the core model, we can discard the eventuality that pollution, and not low temperatures, are strongly confounding the effect of cold weather on respiratory diseases.

differences in living conditions and social protection. Results by cause of death also corroborate that low-income households are more vulnerable to cardiovascular and respiratory diseases (see Appendix C5).[32] In addition, age-corrected regressions also corroborate that poor living conditions seem to make households vulnerable to mild cold. Full results for all temperature bins reported in Appendix C5 show statistically significant results for temperatures up to "below 20°C" for the 1st two quartiles, whereas results stop being statistically significant for temperatures above 14°C for the top two quartiles of income.

Table 6: Impact by income quartile and cause of death of a cold day below 10°C on cumulative 31-day mortality

Model	1st quartile	2nd quartile	3rd quartile	4th quartile	1st vs. 4th	First two versus last two
A. Income quartiles	1.05***	1.03***	0.51***	0.23	+0.82***	+0.67***
	(0.17)	(0.12)	(0.15)	(0.2)	(0.26)	(0.16)
B. Age-corrected income	0.31***	0.3***	0.08**	0.09***	+0.22***	+0.22***
quartiles	(0.05)	(0.03)	(0.04)	(0.03)	(0.06)	(0.04)
C.Poverty indicator	1.03***	1.02***	0.62***	0.44***	+0.59***	+0.50***
	(0.13)	(0.11)	(0.15)	(0.17)	(0.21)	(0.14)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C on mortality, for specific quartiles and causes of death. The dependent variable is always the daily mortality rate in deaths per 100,000 inhabitants and all regressions include the daily precipitation level as control. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%. 312,140 groups, 30.1 observations per group. Reference day is 24-26 Celsius degrees.

In addition, to make sure that our findings are robust to a different measure of living conditions, we use a poverty index instead of predicted income. The Mexican Council of Population (CONAPO) defines a marginality index based on a set of questions asked to Mexican households in the 2000 census. The answers to this set of questions are less easy to manipulate by dishonest declarants and are less sensitive than income. We define and predict a poverty index for each deceased person in a way which is very similar to the CONAPO and construct quartiles based on this alternative metric. The detailed results and methodology are in Appendix C6, but are summarized in Table 6, Panel C. They corroborate the findings obtained with predicted income levels.

These results by income groups are not surprising when we consider that low-income families have improper access to housing, drinkable water and health insurance (as reported on Census data – see Appendix A3). Specific protection against cold is also insufficient. Data from the Mexican survey of household income and expenditure shows that about 1% of households in the first income quartile own a heater, versus 7.9% for Mexicans in the fourth quartile (see

[32] We again also find that richer households are statistically more vulnerable to neoplasms than poorer households. However, this information is derived from coefficients for neoplasms that are not statistically significant at 5%.

Appendix C7 – the geographical distribution of heating and cooling appliance ownership is also provided). Similar contrasts are found when looking at air conditioning.

6. Weather-related mortality and universal healthcare

During our study period, Mexico implemented a nationwide policy – the *Seguro Popular* – to increase access to healthcare for low-income households.[33] Considering that developing countries may be financially constrained to protect their citizens from cold, targeted health programmes may offer the possibility to restrict the population of recipients to vulnerable groups. They can also restrict the range of covered diseases to those that are known to arise because of cold weather. Below, we provide evidence that the *Seguro Popular* has reduced weather-related mortality. Our econometric setting greatly attenuates selection bias, which arises from the fact that the weakest people are also the ones most likely to contract a health plan[34], by matching individuals based on observed covariates, and we show evidence that our conservative estimate is likely very close to the true treatment effect.

The *Seguro Popular* was 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 if the family earned enough income. The fee then grew with income. By 2004, the Mexican government decided to progressively extend the programme to the entire population, municipality after municipality. In 2004, the Mexican government also promoted the *Fondo de Protección contra Gastos Catastróficos*, which provides financial support to families affected by a series of chronic, long-term diseases, in particular cancer and HIV.[35] Both programmes are

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[33] Traditionally, low-income families working in the informal sector did not have access to healthcare insurance, and the country suffers from a chronic underfinancing of public hospitals with free attendance. 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).

[34] This section contributes to the literature aiming at assessing the effectiveness of healthcare in reducing the mortality effect of unusual temperatures. Two recent studies have attempted to relate healthcare provision to weather-related mortality. Barreca et al. (2016) uses the number of doctors as a measure for healthcare provision to look at the impact of healthcare on mortality over the last century. They do not find any statistically significant impact. However, this could be because counting the number of doctors does not take into account the significant progress in medicine that occurred over the 20th century. Heutel, Miller and Molitor (2017) look at the impact of temperature on hospitalizations in the US. They find that temperatures are positively correlated with hospitalizations. This pattern differs from the U-shaped association that they find between temperature and mortality. However, they do not analyse the impact of healthcare provision (e.g. access to hospitals) on mortality.

[35] Furthermore, additional protection has been provided to children under 5 born after Dec. 1st 2006 with the implementation of a policy called the *Seguro Médico para una Nueva Generación*. We are not including this policy in the analysis since it has covered only a small minority of young children by 2007.

still ongoing today. The extension of the *Seguro Popular* to the whole Mexican population depended on the enrolment of the existing medical infrastructure into the scheme or on the construction of new infrastructure. The INEGI discloses the number of people that received medical attention under the *Seguro Popular* by municipality and year.[36] At its start in 2004, the *Seguro Popular* provided around 315,000 external consultations. This figure radically increased to 11 million in 2005, 20 million in 2006, 29 million in 2007, 38 million in 2008, 48 million in 2009 and 61 million in 2010.

A particularity of the *Seguro Popular* is that health coverage is restricted to a reduced list of priority diseases. It mostly includes preventive health actions (e.g. vaccines), ambulatory medicine (e.g. measles, tuberculosis), reproductive health, a selection of emergencies (in particular caused by hypertension and diabetes) and surgeries (e.g. appendectomy, treatment of fractures). The list of diseases covered by the *Seguro Popular* and the *Fondo de Protección contra Gastos Catastróficos* is updated every year. We have compiled this information for 2004-2010 using the catalogues published by the Mexican government, and recoded the information to clearly identify which diseases were covered by the scheme, using the ICD-10 nomenclature of diseases. According to our recompilation, in 2004, the *Seguro Popular* covered 734 ICD-10 codes, e.g. “A010 – Typhoid Fever”. In 2010, it covered 1923 ICD-10 codes. For example, the 2010 nomenclature also included code “A02 – Salmonella infections”. Appendix A9 displays the list of diseases covered by the *Seguro Popular* and the *Fondo de Protección contra Gastos Catastróficos* in 2010.

In the remaining of this section, we present a methodology to assess the extent to which affiliation to the *Seguro Popular* correlates with a reduction in weather-related vulnerability. We assume that the affiliates to the *Seguro Popular* could also benefit from the *Fondo de Protección contra Gastos Catastróficos* if their disease fell within the scope of the fund.

6.1 Method

Our method is based on individual death records and assesses the vulnerability to unusual weather for two groups of deceased people: the ones that enrolled in the *Seguro Popular* and the ones that did not have any sort of social insurance before they died.

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[36] The implementation of the *Fondo de Protección contra Gastos Catastróficos* was done through specialised institutions that needed to receive accreditation. The rollout of the programme was therefore very similar to the one of the *Seguro Popular*. We make the simplifying assumption that the municipalities who benefitted from the *Seguro Popular* were also the ones that benefitted from the *Fondo de Protección contra Gastos Catastróficos* since we unfortunately do not have this exact information.

Ideally, we would have liked to study the impact of the extension of universal healthcare in the context of a natural experiment or with a randomised control trial (RCT). However, mortality is a very rare event, and so are unusually cold and hot days. Because of this, RCTs would likely not be economically feasible since they would need to cover a very large share of the population for several years to observe a large enough amount of death counts across the entire temperature spectrum. Likewise, natural experiments are, to our knowledge, unavailable. We use a matching method on a large sample of death certificates to artificially reproduce the conditions of an experiment.

Several methodological threats are pervasive to the evaluation of the impact of a national insurance programme such as the *Seguro Popular* on mortality. The first one is that enrolment to the *Seguro Popular* was voluntary, and higher income groups were asked to pay for it. Hence, among the people that did not have any sort of social insurance, both the weaker and the poorer were more likely to enrol. The second issue is that the rollout of the *Seguro Popular* depended on political will and required infrastructure and staff to run properly. Municipalities that adopted the *Seguro Popular* at time *t* were likely to present structural differences with non-covered municipalities. Likewise, the timing of adoption may have depended on unobservable characteristics also correlated with municipality-level mortality rates. Therefore, covered and non-covered municipalities are unlikely to have common trends. A third difficulty is that we only observe the people that were affiliated to the *Seguro Popular* and died. We do not have access to the micro-data on the affiliates of the *Seguro Popular* at each period, and cannot construct mortality rates specific to subgroups of the Mexican population, e.g. controlling for demographic characteristics such as age, gender, education, profession, etc.

Accounting for these difficulties, our methodology consists in matching deceased people affiliated to the *Seguro Popular* with deceased people with similar characteristics but with no social security before they died *within the same municipalities and year of death*, relying exclusively on the data from death certificates. This method sorts out the problem of non-random enrolment of municipalities, and significantly reduces selection biases by eliminating selection bias due to observed covariates.

However, there may still be systematic differences between affiliates' and non-affiliates' outcomes in the absence of the program, even conditional on observables. This would lead to a violation of the identification conditions required for matching. Importantly, however, this would imply that our estimates will provide a *lower bound* for the effect of the *Seguro Popular* on weather-related mortality. Indeed, voluntary enrolment into the programme should encourage the most vulnerable people to enrol. Therefore, we can expect that the decision to enrol into the *Seguro Popular* will be correlated with higher vulnerability, and not lower vulnerability, biasing our probability estimates of the effect of the policy towards zero. While our strategy deals with selection bias due to observables, selection due to unobservables should attenuate the estimated treatment effect. Hence, our matching strategy should provide a conservative estimate of the reduction in weather vulnerability brought about by the implementation of the policy.

We proceed as follows. For each archetype a with observable characteristics X_a, we identify whether a person belongs to the group of the treated (*Seguro Popular*) or the control group (no social insurance). We also compute the quantity $q_{T,a}$ of treated people with characteristics X_a, and the quantity $q_{0,a}$ of people with the same characteristics but no social security. Then, we delineate a common support between the treated and control groups according to their archetypes. We exclude from the analysis all observations for which $q_{T,a}$ or $q_{0,a}$ are equal to zero, for which we do not have any common support. We also compute the ratio $q_{T,a}/q_{0,a}$ and exclude the observations for which this ratio is either below the 5^{th} percentile or above the 95^{th} percentile. In our baseline specification, this leads us to exclude archetypes when either less than 2.4% or more than 66% of observations have the *Seguro Popular* within a given archetype. This ensures that we do not draw comparisons within archetypes for which either being treated or not being treated is highly unlikely. We suspect that for these excluded observations, the role played by unobservable factors to explain selection is likely to be greater. In section 6.3, we explore the robustness of our results to alternative exclusion criteria.

Our method can only properly identify the effect of the *Seguro Popular* on weather vulnerability if mortality risks are homogeneous within archetypes, except for the difference brought by the *Seguro Popular* between the treatment and control groups. We therefore need the characteristics included in X_a to be good predictors of the underlying probability of dying. We use as much granularity as we have in the data to construct the archetypes and make sure that mortality risks are homogeneous within archetypes. We construct mutually exclusive archetypes based on the exact age at time of death, gender, education level (7 categories), profession (20 categories), municipality of residence, year of death and a dummy that codes whether, within a municipality, the deceased person lived in a rural area or not. Our matching is therefore, by construction, perfectly balanced between treatment and control observations, since we match *exactly* on all these characteristics. In particular, we match exactly on age, cancelling out the very strong effect of age on vulnerability. Such a stringent matching strategy allows us to ensure that observations are perfectly comparable. As we restrict ourselves to closely comparable individual, there will inevitably be a number of individuals for which no control can be found. Out of the 241,089 observations that were affiliated to the Seguro Popular before death in our data, our exact matching method allows us to match 47,047 treated observations with similar but unaffiliated deceased people. What is lost in sample size, however, is regained in terms of accuracy and robustness (see, e.g., Dehejia & Wahba, 1999). In Section 6.3, we explore the validity of our result beyond the matched sample.

At this stage, we have identified, within each archetype defined by a vector of characteristics X_a, a number of people that are treated and a number of people that are not. Let's assume that, across each archetype, we have the same number of treated people and control observations. In this case, and if both treatment and control groups were statistically similar, deaths should be equally distributed within the year: as many people in the control and treatment groups should die during cold and hot days. Put differently, the probability that an individual in our sample has access to the *Seguro Popular* should be the same (50%) on every day of the year, irrespective of the temperature on that day.

However, we know that the *Seguro Popular* provides protection against some diseases that are sensitive to cold and/or the weather (e.g. pneumonia, diabetes). Therefore, the two groups should not be equally vulnerable to weather shocks. Hence, even if we have the exact same proportion of people in the control and treatment groups, we should be observing a difference in the spread of observed deaths across cold, temperate and hot days, because the fixed quantity of deceased people that we have selected have been drawn from different distributions. In the present case, we should observe a higher proportion of people from the control group dying during unusual weather, since people from the treatment group should have received medical support that reduces weather vulnerability. Put differently, on a cold day, the probability that a deceased individual had access to the *Seguro Popular* should be below 50%.

It is straightforward to artificially create two groups (treated and control) of the same size. We simply give a weight $W_{T,a}$ equal to 1 for each observation in the treatment group, and a weight $W_{0,a}$ equal to $q_{T,a}/q_{0,a}$ for each observation in the control group. With these weights, the probability that a randomly selected observation has access to the *Seguro Popular* is set at 50%. With this, we run a linear probability model of having access to the *Seguro Popular* before death with frequency weights $W_{0,a}$ and $W_{T,a}$. The dependent variable is a dummy equal to 1 if the observation belongs to the treatment group. The independent variables of interest are the temperature bins that we have used throughout this paper, for the day of death and the previous days. We furthermore increase efficiency by using the variables included in X_a as control variables.[37] Standard errors are clustered at municipality level.

6.2 Results

As expected, our model predicts probabilities that are statistically significantly below 50% for days below 10°C (see Figure 4). We also find statistically significant results for days between 12°C and 16°C. The shape of the predictions suggests that alleviation must have been higher for stronger weather shocks (<10°C) than milder shocks (e.g. 10-16°C). Even though inefficiently captured for high temperatures, the *Seguro Popular* might have reduced vulnerability to weather shocks for extremely hot temperatures as well (>32°C).

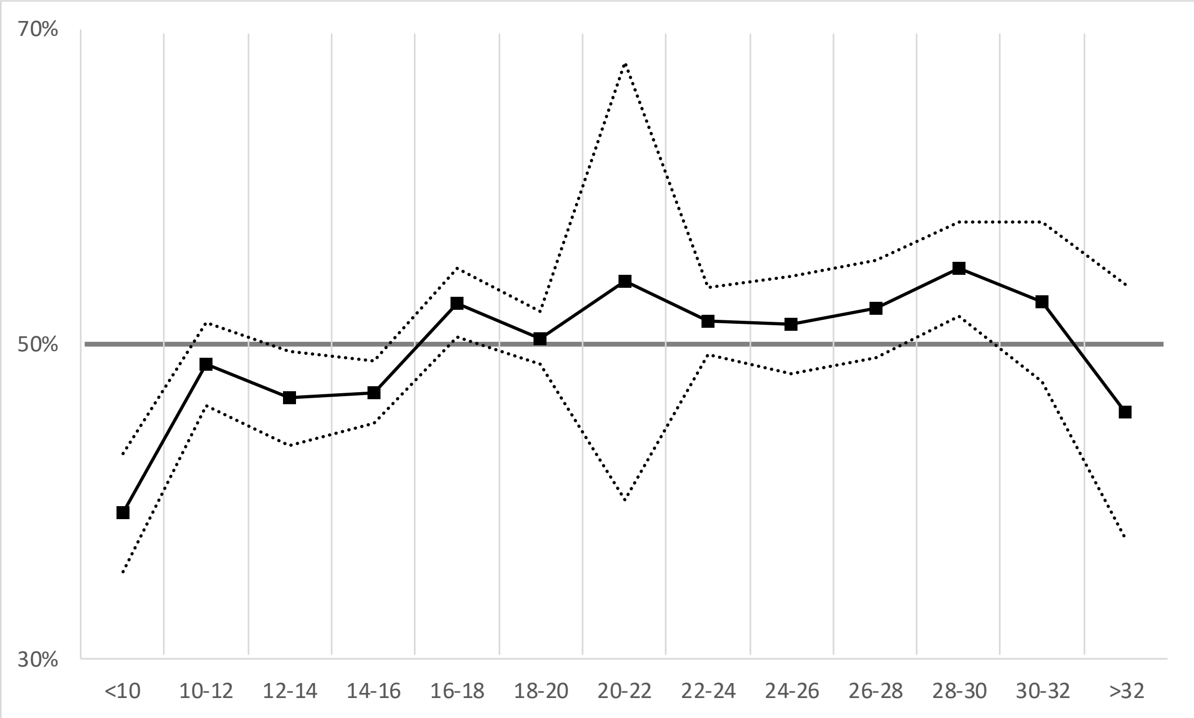
In the model used to draw Figure 4, the reference bin is 20-22°C. We observe higher variance for this temperature bin since the predicted probability depends on the variability of all the other temperature categories. In the regression used to produce Figure 4, the difference between a mild day at 20-22°C and a cold day below 10°C is statistically significant at 5%. We are therefore confident that there is a difference in the probabilities between a cold day below 10°C and a temperate day at 20-22°C.

In terms of magnitude, we find that, in the aftermaths of a cold day, only 39.3% (95% CI: 35.6-43.1%) of the deceased people have the *Seguro Popular*. This translates into a 35% reduction in vulnerability to unusually cold weather $(39.3\%/(1-39.3\%))$ thanks to the *Seguro Popular*. When we look at the average across all days below 16°C, the reduction in weather vulnerability is around 13%. We know that only the people from the first two deciles die from cold, and around 70% of the people in these two income quartiles have no social security. If we take into account these elements and the mortality estimates of Table 2, our results suggest that the extension of the *Seguro Popular* to the entire population in need would save around 3,300 lives per year thanks to a reduction in weather vulnerability.[38]

[37] Even though not displayed for the sake of concision, results are very similar when we do not control for X_a. There is a slight loss of precision though.

[38] To get to this number, we multiply the mortality estimates of table 2 with the estimates in the reduction in vulnerability from Figure 4. The result of this multiplication is 4,579. Then, we make the simplifying assumption that all deaths from table 2 come from the 1st two income quartiles. We know that, in the first quartiles, 71.9% of people do not have social insurance. The number of saved lives is then 71.9% x 4579.

Figure 4: 31-day cumulative impact of temperature on the probability that the deceased had the *Seguro Popular* in the matched sample



Notes: The y-axis represent the predicted probability that the deceased has the *Seguro Popular* in the matched sample, according to temperature. Effects are cumulative: we have added up the effect of each temperature bin over 31 days. The reference bin is 20-22°C: the coefficient displayed is computed as a residual from the effect of the other days on a probability that needs to add up to 50%. The plain line represents the best prediction and the dotted lines the 95% confidence interval. Observations are weighted using $W_{T,a}$ and $W_{0,a}$. The only independent variables in the model are the temperature bins and their 30 lags. Standard errors are clustered at municipality level. 47,047 treated observations have been used. Displayed probability are for a representative observation with average values for X_a.

6.3 Robustness

We performed a number of robustness checks to corroborate the validity of our identification strategy.

Splitting the sample. First, we know that the *Seguro Popular* targeted mothers and young children in priority. We therefore should find impacts on children. We also know that the elderly are the most impacted by cold-related mortality. We expect to find a reduction for this age group as well. We ran the matching process separately for three age groups (<10; 10-65 and >65) (see Table 7, panel A). Even though less precisely estimated due to smaller sample size, probabilities following unusually cold days are lower than 50% for the three age groups. The difference with a 20-22°C day is statistically significant at 10% for children. Excluding infants from the dataset leads to a probability which is close to the baseline, at 41.1%.

We also know that the *Seguro Popular* targeted a specific set of diseases. We can split our sample and run the matching process separately on people that died from covered diseases and people that died from diseases that are not covered by the *Seguro Popular*. The results in are shown in Table 7, panel B. We find probabilities lower than 50% for both types of diseases, but the probability is lower for covered diseases. Even though the difference between the two groups is not statistically significant, the difference in the estimates between a day below 10°C and a day between 20°C and 22°C is small and not statistically significant for non-covered diseases, while it is strong and statistically significant in the case of covered diseases.[39]

SUTVA. Since we match observations within municipalities, the stable unit treatment value assumption that there is no interference between treated and control groups may not be fully valid: providing healthcare to one part of the population (e.g. through vaccines) may reduce exposure for the other part of the population. This issue may bias our estimates downwards. We think this risk is reduced for two reasons. First, many diseases that are sensitive to weather are non-transmissible, in particular diabetes and heart attacks. In addition, we compare people within a municipality, but also on the same year. Therefore, the long-term impacts of the policy (due to the previous years of implementation) in reducing the prevalence of infectious diseases for the entire population is controlled for. Nevertheless, we perform a robustness check in which we relax the requirement that treated and controlled observations belong to the same municipality, reducing the risk of interferences. The results are provided in Table 7, panel C. They are attenuated, even though we still find a probability of having the *Seguro Popular* below 50% on unusually cold days. However, we find no statistically significant difference with days between 20-22°C. We think the attenuation of results comes from the fact that controlling for municipality of origin is important to avoid selection biases.

Selection bias. The main threat to our identification strategy is that individuals self-select themselves into the Seguro Popular and matching can only deal with selection on observables. If we run a naïve estimator without matching, the estimated probability that a person who died following a day below 10°C was registered with the *Seguro Popular* is 51.5%. In other words, despite benefitting from the *Seguro Popular*, enrolled individuals were still more likely than not to die, suggesting that people who self-selected themselves into the SP are indeed more vulnerable. When we start matching individuals with each other based on observed characteristics that are likely to be correlated with vulnerability, however, the treatment effect quickly converges toward our baseline estimate. For example, matching only on municipalities,

[39] We caution against inferring too much from these results. For covered diseases, we suspect that some people may try to get access to the policy by declaring they have a specific condition, decreasing the number of people in the treated group with non-covered cases, making treatment and control groups not really comparable. In addition, people can die from more than one cause of death even though only one is reported.

rurality and year already gives a point estimate of 43.3%, additionally matching on age and gender leads to 42.4% (see Table 7, Panel C), and adding educational level, marital status and profession explains the remaining of the difference in the point estimate. This suggests that adding further matching variables might not dramatically reduce the baseline result of 39.3%.

Table 7: Robustness checks for the probability of having the *Seguro Popular* in the matched sample

Specification	Probability below 10°C	Difference with 20-22°C	Treated observations
Panel A: Age groups			
All age groups (base model)	39.3% [35.6-43.1%]	-0.147** (0.075)	47,407
<10 years old	39.4% [31.7-47.0%]	-0.196* (0.114)	19,272
10-65 years old	41.5% [34.0-48.1%]	-0.186 (0.187)	10,060
>65 years old	39.3% [29.0-49.5%]	-0.138 (0.111)	15,953
Excluding infants (<1 year old)	41.1% [34.1-48.1%]	-0.126 (0.118)	26,733
Panel B: Main cause of death			
Disease included in the list of the Seguro Popular	41.9% [35.4-48.4%]	-0.354** (0.153)	11,904
Disease excluded from the list of the Seguro Popular	43.8% [39.6-48.0%]	-0.077 (0.095)	22,877
Panel C: estimation choices			
Naive estimator†	51.5% [46.9-56.1%]	-0.030 (0.027)	241,089
Matching across all municipalities	46.0% [43.4-48.6%]	-0.006 (-0.025)	180,753
Matching only on municipality, rurality and year of death	43.3% [40.3-46.4%]	0.0.21 (0.035)	169,287
Matching only on municipality, rurality, year of death, sex and age	42.4% [38.8-45.9%]	-0.002 (0.048)	102,322
Excluding beyond the 1st and 99th percentiles of archetypes	38.1% [34.5-41.8%]	-0.155** (0.075)	52,410
Excluding beyond the 25th and 75th percentiles of archetypes	38.9% [33.9-44.0%]	-0.861 (-0.092)	36,160
Archetype size equal or above 10	33.5% [24.3-42.6%]	-0.24.5** (-0.119)	22,685
Reweighting archetypes based on inverse probability of being matched	39.2% [31.3-47.0%]	-0.142 (0.116)	47,231

Notes: Results come from different regressions that are variations of our base specification, using different samples but the same dependent and independent variables. The second column provides the predicted probability for each specification when accounting for the 31-day cumulative impact of a cold day below 10°C, with the 95% confidence interval in brackets. The third column provides the estimate for the difference between an unusual cold day below 10°C and a temperate day at 20-22°C, with the standard error in parentheses. * and ** respectively denote statistically significant results at 10% and 5%. The final column provide the number of observations with the *Seguro Popular* used and matched with observations with similar values for X_a.
†: The naïve estimator simply consists of a regression of the treatment variable on the temperature bins, including only time dummies as controls.

We run an additional set of tests to explore this self-selection issue further. In the baseline specification, we excluded all observations for which the $q_{T,a}/q_{0,a}$ ratio is either below the 5th percentile or above the 95th percentile, because we suspect that for these groups, the role played by unobservable factors to explain selection is likely to be greater than for groups where the proportion of treated and control individuals is more evenly distributed. In Table 7, Panel C, we alternatively exclude observations below the 1st and above the 99th percentile; or below the 25th and above the 75th percentile. Results are robust to this change. For the same reason, we also tried excluding small archetypes with less than 10 observations. This does not affect our conclusions (see also Table 7, Panel C), and in fact the treatment effect increases, suggesting that our baseline results might be a lower bound of the true effect.

Complementary policies. A concern is that the affiliation to the *Seguro Popular* could have been done concomitantly to the provision of other social policies. Therefore, we would be estimating the global effect of a series of policies and wrongly attributing it to the *Seguro Popular* alone. This is unlikely for two reasons. The first one is that we observe individual-level affiliation. There is no reason to think that the people in the control group, who have the same observed characteristics, live in the same municipality and died in the same year might not have benefitted to a large extent from this exact same set of additional policies. An exception might be the policies that would target low-income families since the *Seguro Popular* also target these and we cannot control for income differences within archetypes. However, the rollout of the *Seguro Popular* had to deal with the constraint that both trained staff and health infrastructure should be available. This strong requirement of medical infrastructure is specific to the *Seguro Popular* and does not exist in the case of other social policies, e.g. conditional cash transfers, reducing the risk that the rollout of the programme was paired with the rollout of income-based policies.

External validity. Finally, we ask whether our results are valid beyond our matched sample. Table 8 summarizes the difference between matched and unmatched treated observations over age and gender. It is clear that our marching technique did not randomly selected observations. In particular, matched observations include a much larger population of infants. People living in urban areas are also over-represented, since the likelihood of finding a control group is higher within a larger pool of observations.

Table 8: Differences between recipients of the *Seguro Popular* in the matched and unmatched samples

Variable	Matched sample	Unmatched	T-test difference in means
Proportion of female	54.5%	44.8%	-36.8
Proportion of infants (<1 year old)	35.8%	5.6%	-200
Age (only if >1 year old)	63.3	61.7	11.2
Proportion rural	11.9%	29.8%	80.6

The matched sample includes 47,407 observations and the unmatched sample includes 193,682 observations.

We use a probit model to estimate the probability that a treated observation is matched and weight observations based on the inverse probability that they are matched. Excluding archetypes where the probability of being matched was lower than 0.5%, we ran again our econometric model. The results obtained with this method are very similar to the base results, probably since the impact on vulnerability seems to have been even across all ages groups (see Table 7, Panel C).

7. Conclusion

Because investments in protective measures are determined by income, climate change is predicted to affect the poorest people in developing countries the most. This study analyses the heterogeneous impact of temperature shocks on mortality across income groups in Mexico using individual death records and Census data for the period 1998-2010. We find that random variation in temperatures is responsible for the death of around 45,000 people every year in Mexico, representing 8% of annual deaths in the country. However, extreme weather events only account for a small proportion of weather-related deaths: unusually cold days (<10°C) trigger around 4,700 deaths each year, extremely hot days (>32°C) kill less than 400 annually while 88% of weather-related deaths are induced by mildly cold days (10-20°C). The large effect of mildly cold days on mortality that we document has never been reported before, and we suspect this phenomenon to be specific to developing countries.

A consequence of our findings is that climate change should significantly reduce the number of weather-related deaths in Mexico by 50% to 80% 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 careful that only the short-term impact of weather shocks is considered in this paper.

We find that vulnerability to weather shocks is strongly correlated with individual income, and that only people in the bottom half of the income distribution are vulnerable to mildly cold temperatures. The impact of unusually cold days (<10°C) is 35% greater for those living below the median average income. This suggests that not only are poorer households more vulnerable to cold, they also start being vulnerable at temperatures for which richer households are almost fully resilient. Differences in living conditions could explain these findings. For example, we find that only 1% of people in the bottom quarter of the income distribution are equipped with a heater.

Under these circumstances, there is a role for public policies to reduce the mortality inequalities caused by inclement weather. Healthcare systems can be used to reduce the mortality of vulnerable groups while targeting diseases that are known to respond to weather shocks. We exploit variation in universal healthcare coverage caused by the deployment of the *Seguro Popular* and the *Fondo de Protección contra Gastos Catastróficos* to assess their contribution to reducing weather vulnerability. We find that the schemes induced a 35% reduction in the vulnerability induced by days with mean temperature below 10°C and a 13% reduction in mortality during all cold days with mean temperature below 16°C.

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

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

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APPENDICES – FOR ONLINE PUBLICATION ONLY

Appendices are divided into 3 sections: main appendices (A1 to A9), robustness checks (B1 to B12), and impacts by socioeconomic status (C1 to C7).

MAIN APPENDICES

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

Medical evidence

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.[40] 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.

[40] 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).

High ambient air temperatures can cause increases in core body temperature that are associated with dehydration and the development of pathologies. In a review, Basu and Samet (2005) pinpoint that hot temperatures are associated with excess mortality due to cardiovascular, respiratory, and cerebrovascular diseases. In fact, these pathologies develop much before the body enters severe hyperthermia: mild stress caused by ambient air temperatures above 25°C 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.[41]

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.[42] Like in the

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

[42] 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

case of heat, people with inefficient thermoregulation systems or with preconditions will be more vulnerable to cold, and start being at risk for ambient air temperatures between 10°C and 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.[43] 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.

°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).

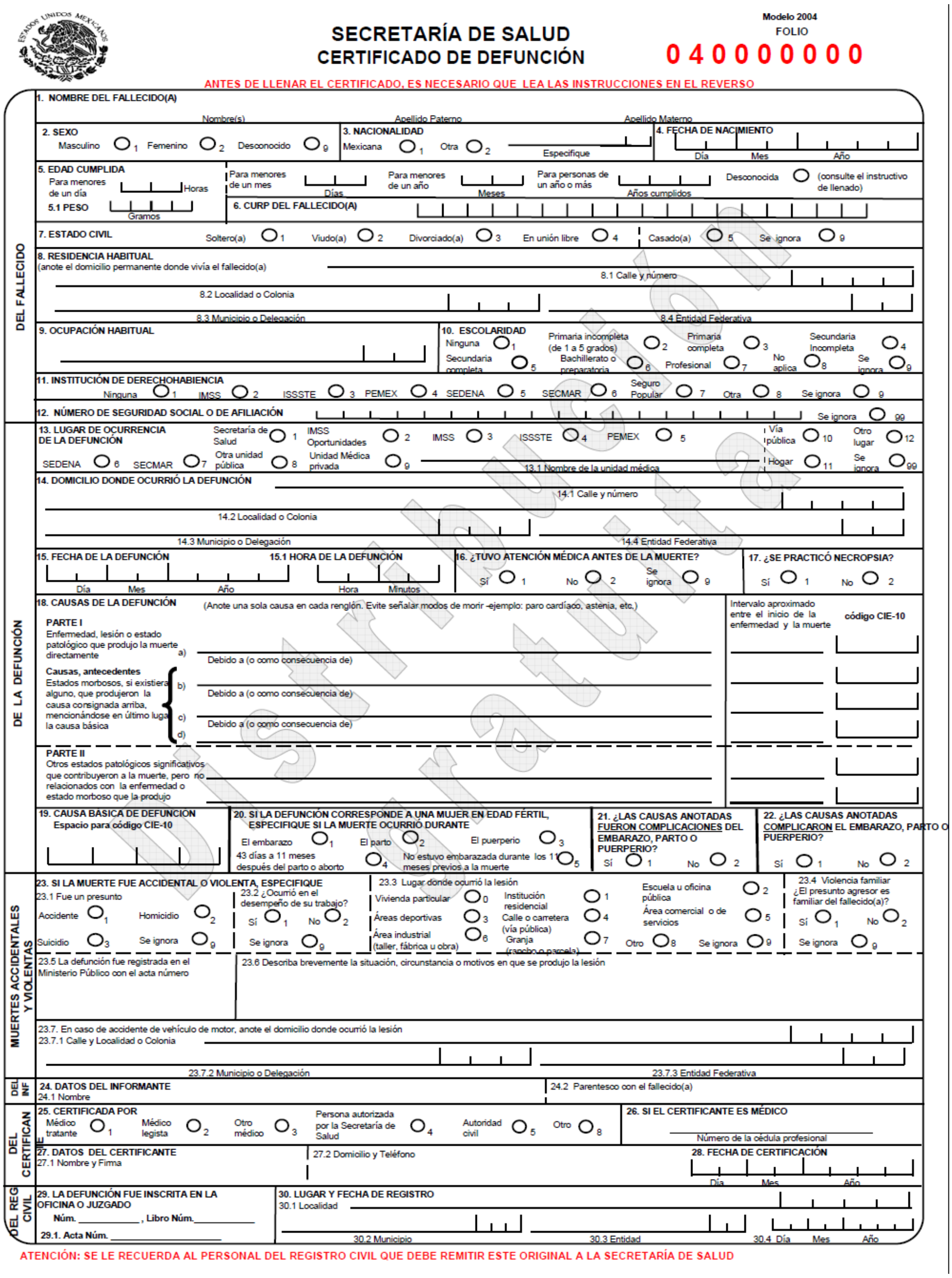
[43] Muscle mass is the essential component of heat production in the body (Horvath, 1981) whereas body fat offers additional protection to cold.

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 B.1: 2004 Template of a death certificate (source: INEGI)



Appendix A3: Summary statistics from the 2000 Mexican Census

Table A3.1 presents some general socioeconomic information on the Mexican population based on the 2000 national Census. The information is split by income quartile, rural vs. urban populations and by type of profession (using the Mexican nomenclature of activities). Not surprisingly, rural populations are less educated, less likely to have access to social security and in general have an average income level about half that of people living in urban areas.

The difference in the average personal income between the poorer profession (agriculture) and the richer one (public servants and directors) is 1 to 6. Economic differences by quartiles are much sharper though since there is high heterogeneity within each profession. People in the first income quartile have an average personal income which is 18 times lower than people in the top quartile. This large inequality is a feature of the Mexican economy which we will use in the next sections to investigate differences in the weather-mortality relationship across income groups.

Table A3.1: Socioeconomic characteristics of the Mexican population based on 2000 Census

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

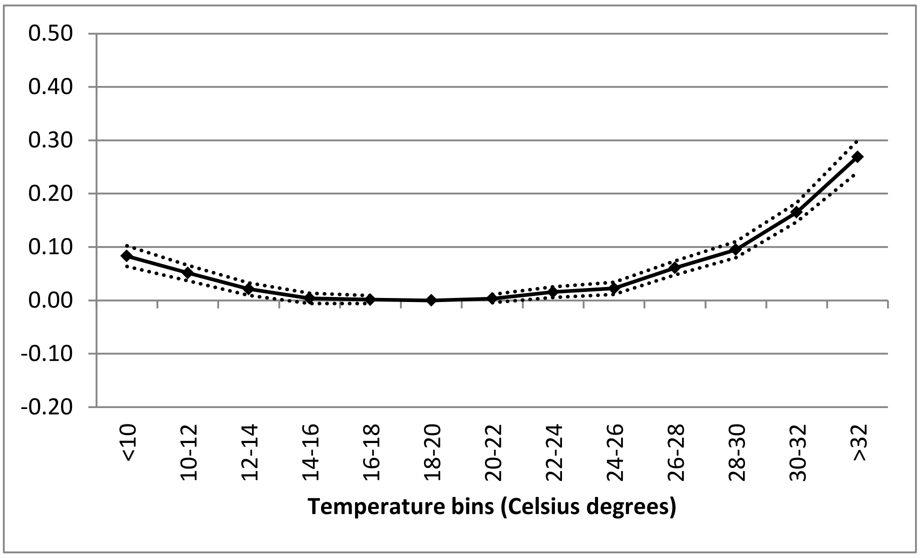
Notes. The table shows average values of socioeconomic characteristics of the Mexican population based on the 2000 Census. Statistics are calculated using the sample weights provided by INEGI. *: Personal income (in 2000 Mexican pesos) is calculated as family income divided by the square root of the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

Appendix A4: Contemporaneous effect

Due to an omitted variable bias, correlating today's temperatures with today's mortality will lead to biased estimates of the impact of temperature on mortality if no account of the temperatures of the previous days is made. Figure A4.1 displays the impact of the day's temperature on mortality for all Mexicans and all causes of death when no lagged temperature bins are included in the model. This can help the reader assess the magnitude and the direction of the bias produced in this case.

The Mexican population appears to be very sensitive to high temperatures above 28°C. A statistically significant impact of temperatures below 14°C is also detected. However, an extremely hot day above 32°C is three times more lethal than an unusually cold day below 10°C. The temperature bin with the lowest mortality is 18-20°C.

Figure A4.1: Impact of the day's average temperature on daily mortality, in deaths per 100,000 inhabitants



Notes. Lines in dash correspond to the 95% confidence interval values obtained for each estimated coefficient. 312,140 groups and 30.1 observations per group. The regression results control for the day's precipitation level.

Therefore, the model with contemporaneous temperatures underestimates the effect of cold and over-estimates the impact of heat. Biases also appear when the contemporaneous model is run with a breakdown by gender, age and type of disease leading to death (see Table A4.1 and Table A4.2). In particular, men appear to be three to four times more strongly impacted by unusual cold – this result is not confirmed with a distributed lag model.

Table A4.1: Impact of a day under 10 Celsius degree on mortality as compared to a reference day of 18-20 degrees

	Cause of death						
Group	All causes	Infectious diseases	Neoplasms	Endocrine, nutritional and metabolic diseases	Circulatory system diseases	Respiratory system diseases	Violent and accidental
Total	0.0831*** (0.0099)	0.0006 (0.0016)	0.0014 (0.0029)	0.0154*** (0.0036)	0.0265*** (0.0047)	0.0217*** (0.0033)	-0.0107*** (0.0037)
Men	0.13*** (0.0149)	0.0016 (0.0024)	0.0042 (0.0044)	0.0244*** (0.0049)	0.0489*** (0.0069)	0.0268*** (0.0048)	-0.025*** (0.0063)
Women	0.0387*** (0.0126)	-0.00037 (0.002)	-0.0013 (0.0039)	0.0071 (0.0052)	0.005 (0.0064)	0.0167*** (0.0044)	0.0033 (0.0033)
Aged 0-4	0.179*** (0.024)	0.0099 (0.0068)	-0.0013 (0.0018)	0.0081 (0.0052)	0.0018 (0.0021)	0.128*** (0.0123)	0.0187** (0.0083)
Aged 4-9	0.0018 (0.0065)	0.0015 (0.0015)	-0.0019 (0.0017)	-0.0001 (0.0014)	-0.001 (0.0007)	0.0019 (0.002)	-0.0013 (0.0041)
Aged 10-19	-0.0088 (0.0066)	-0.0013 (0.0013)	0.0009 (0.0017)	0.0012 (0.0009)	0.0008 (0.0011)	0.00006 (0.0012)	-0.0165*** (0.0052)
Aged 20-34	-0.0054 (0.0107)	0.0001 (0.002)	0.0022 (0.0025)	-0.0002 (0.002)	0.0022 (0.0022)	0.0026 (0.0019)	-0.0271*** (0.008)
Aged 35-44	0.0285 (0.0194)	0.0022 (0.0036)	0.0038 (0.0061)	0.0189*** (0.0063)	-0.0019 (0.0062)	-0.0012 (0.0031)	-0.027** (0.0108)
Aged 45-54	0.0678** (0.033)	0.0053 (0.0072)	-0.0073 (0.011)	0.03** (0.0127)	0.0067 (0.0123)	-0.0025 (0.0071)	-0.0144 (0.014)
Aged 55-64	0.233*** (0.0559)	0.0118 (0.0088)	-0.0153 (0.0206)	0.0621** (0.0254)	0.0844*** (0.0249)	0.0369*** (0.0137)	0.0053 (0.0171)
Aged 65-74	0.372*** (0.0861)	0.019 (0.0135)	-0.0224 (0.0318)	0.102*** (0.0389)	0.131*** (0.0383)	0.0591*** (0.0213)	0.0065 (0.026)
Aged 75+	1.03*** (0.238)	-0.0601** (0.0289)	0.0049 (0.0683)	0.0597 (0.0875)	0.522*** (0.141)	0.168* (0.0946)	0.0359 (0.0397)

Notes: Standard errors in brackets. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level. Unit is deaths in a day per 100,000 inhabitants (in subgroup). 312,140 groups and 30.1 observations per group.

Table A4.2: Impact of a day over 32 Celsius degree on mortality as compared to a reference day of 18-20 degrees

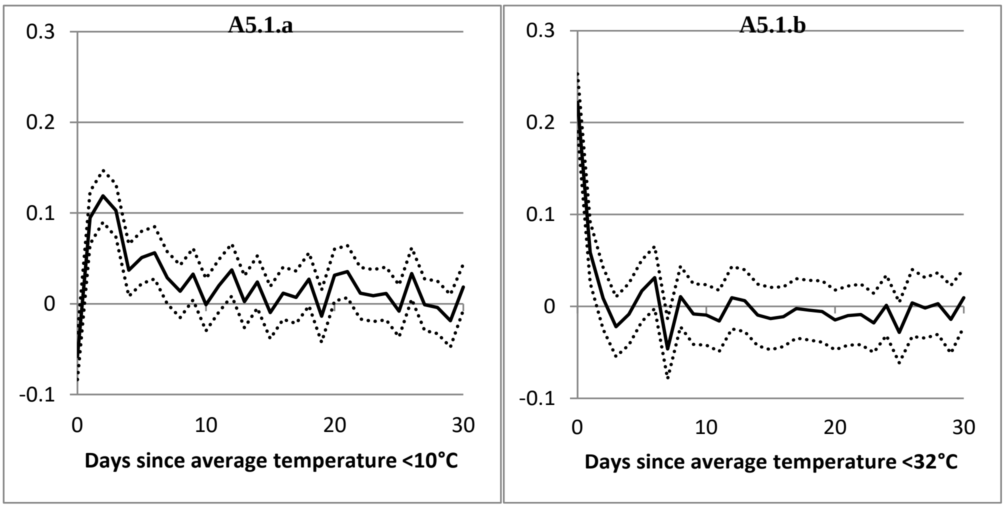
	Cause of death						
Group	All causes	Infectious diseases	Neoplasms	Endocrine, nutritional and metabolic diseases	Circulatory system diseases	Respiratory system diseases	Violent and accidental
Total	0.269*** (0.0152)	0.0072*** (0.0023)	0.0213*** (0.005)	0.0374*** (0.0051)	0.0837*** (0.0073)	0.0227*** (0.0039)	0.057*** (0.0077)
Men	0.29*** (0.0233)	0.008** (0.0035)	0.0144** (0.0071)	0.0334*** (0.007)	0.0907*** (0.011)	0.018*** (0.0058)	0.0952*** (0.0137)
Women	0.249*** (0.0184)	0.0065** (0.003)	0.0283*** (0.007)	0.041*** (0.0073)	0.0766*** (0.0095)	0.0274*** (0.0052)	0.0191*** (0.0058)
Aged 0-4	0.138*** (0.0278)	0.0337*** (0.0102)	0.0029 (0.0024)	0.0271*** (0.0078)	0.0022 (0.0027)	0.0129 (0.0086)	-0.0042 (0.0103)
Aged 4-9	0.0145 (0.0091)	0.0026 (0.0021)	0.0009 (0.0024)	-0.0025 (0.0017)	0.0003 (0.0009)	-0.0002 (0.0018)	0.0117 (0.0072)
Aged 10-19	0.0415*** (0.0112)	-0.0013 (0.0014)	-0.00005 (0.0023)	0.001 (0.0016)	0.001 (0.0015)	-0.0007 (0.0014)	0.0359*** (0.0101)
Aged 20-34	0.0843*** (0.0219)	-0.004 (0.0037)	0.0012 (0.0033)	0.01*** (0.0033)	0.0053 (0.0033)	0.0044 (0.0036)	0.0641*** (0.0195)
Aged 35-44	0.155*** (0.0321)	0.0004 (0.0057)	0.0091 (0.0093)	0.0069 (0.0063)	0.0173* (0.0096)	0.0036 (0.004)	0.105*** (0.0244)
Aged 45-54	0.157*** (0.0441)	0.007 (0.0086)	0.0335* (0.0176)	-0.019 (0.0152)	0.0437** (0.0181)	0.0076 (0.0072)	0.082*** (0.0239)
Aged 55-64	0.206*** (0.0774)	-0.0057 (0.0112)	0.0171 (0.0314)	0.0225 (0.0338)	0.131*** (0.0379)	-0.0002 (0.0153)	0.0322 (0.0279)
Aged 65-74	0.338*** (0.122)	-0.0078 (0.018)	0.0287 (0.0496)	0.0347 (0.0531)	0.212*** (0.0595)	-0.0019 (0.0233)	0.0539 (0.0437)
Aged 75+	5.75*** (0.355)	0.147*** (0.0474)	0.35*** (0.116)	1*** (0.129)	2.46*** (0.214)	0.705*** (0.118)	0.23*** (0.0656)

Notes: Standard errors in brackets. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level. Unit is deaths in a day per 100,000 inhabitants (in subgroup). 312,140 groups and 30.1 observations per group.

Appendix A5: Short-term dynamics of impacts in distributed lag model

Our results are consistent with the dynamic effects of heat and cold days on mortality as reported previously, for example by Deschenes and Moretti (2009). Like these authors, we find evidence of strong harvesting for hot days whereas the impact of cold days accumulates after the event. These short-term dynamics can be observed on Figure A5.1.a and A5.1.b, which present the impact on mortality of extremely hot/cold days on the day of the weather event and for each of the following 30 days. A cold day below 10°C has a statistically significant effect on mortality every day during the first week, and we find statistically significant effects at 5, 14 and even 21 and 22 days after the cold day. By contrast, we find that a hot day above 32°C has a strong and immediate effect on mortality but this effect is statistically significant only for the first two days, after which the coefficients become systematically negative although not statistically significantly so.

Figure A5.1: Impact within 31 days of a cold day (<10°C – panel a) or a hot day (>32°C – panel b) on daily mortality rate per 100,000 inhabitants



Note: These two graphs are obtained from the same regression, considering all Mexican people and all causes of death (1998-2010). Unit is deaths per 100,000 inhabitants. Each point corresponds to an estimated coefficient from the distributed lag model for days below 10°C (Panel a) or above 32°C (Panel b). Dashed lines correspond to the 95% confidence interval obtained for each estimated coefficient. 312,140 groups and 30.1 observations per group. All regressions control for the day’s precipitation level.

Appendix A6: Comparison of main results with related studies

The methodology and data used in this paper are very close to Deschenes and Moretti (2009). These authors use a 30-day distributed lag model and estimate that one day below 30°F (-1.1°C) increases the mortality rate by 0.23 deaths per 100,000 inhabitants as compared to any other day in the year. On the other hand, we find that 31-day cumulated mortality is increased by 0.70 deaths per 100,000 inhabitants for an additional day below 10°C: their estimate is three times lower than ours while we look at hotter days since days below 50°F (10°C) correspond to the lower limit for unusually cold days in our data. If we use the exact same methodology as Deschenes and Moretti (2009) (as in Online Appendix B10), we then find an estimate of 0.60 deaths per 100,000 inhabitants and the lower bound of our 95% confidence interval is 0.53. This figure does not overlap with the upper bound of Deschenes and Moretti (2009)'s 95% confidence interval at around 0.28. Therefore, both estimates are statistically different from each other suggesting that Mexican residents are more vulnerable to cold than US residents.

Table A6.1: Comparison of the main results of similar panel data studies

Study	Country and period	Frequency of data	Day below minus 1.1°C (10°F)	Day between 4.4-10°C (40-50°F)	Day below 10°C (50°F)	Days between 10-14°C (50°F-	Day above 32°C (or 90°F)
This study	Mexico (1998-2010)	Daily			+0.70 deaths per 100,000 inhabitants Annual mortality rate increases by about 0.15%		+0.13 deaths per 100,000 inhabitants Annual mortality rate increases by about 0.03%
Deschenes and Moretti (2009)	USA (1972-1988)	Daily	+0.23 deaths per 100,000 inhabitants				Statistically insignificant
Barreca (2012)	USA (1973-2002)	Monthly		+0.15 deaths per 100,000 inhabitants			+0.17 deaths per 100,000 inhabitants
Deschenes and Greenstone (2011)	USA (1968-2002)	Annual	+0.69 deaths per 100,000 inhabitants				+0.92 deaths per 100,000 inhabitants
Burgess et al. (2014)	India (1957-2000)	Annual				Annual mortality rate increases by about 0.4-0.7%	Annual mortality rate increases by about 0.5-1%

The estimates by Deschenes and Moretti (2009) are in line with those obtained in other studies for the US. Barreca (2012) finds that a day between 40°F and 50°F (4.4-10°C) increases the monthly mortality rate by 4.5 people per 100,000 inhabitants. This corresponds to a daily mortality rate of 0.15 people per 100,000 inhabitants (95% confidence interval = 0.09-0.22). Using annual data, Deschenes and Greenstone (2011) find that a day below 10°F (-12°C) increases mortality by 0.69 people per 100,000 inhabitants and a day between 40°F and 50°F

(4-10°C) by 0.27 people per 100,000 inhabitants as compared to a day between 50°F and 60°F (10-15.5°C). The upper bound of the 95% confidence interval for this last estimate is around 0.49 and therefore statistically below ours.

One reason why Mexicans could be more vulnerable to cold than Americans could be acclimation: since they live in a hot country, Mexicans may be less prepared to face low temperatures. However, our results suggest that Mexicans could also be more vulnerable to high temperatures. For a day above 90°F (32.2°C), Deschenes and Moretti (2009) find no evidence of an impact of heat on mortality after 30 days. They find a highly positive impact of temperatures on mortality on the first days of heat waves but the latter is compensated for in the short run due to a harvesting effect. For the same level of temperatures, we find a statistically significant and positive impact of hot days on 31-day cumulative mortality: with temperatures above 32°C, the mortality rate is, in average, higher by 0.13 deaths by 100,000 inhabitants in Mexico.

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

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

We may compare these figures with ours, taking into considerations that our study uses daily data and therefore is not fully comparable. The average daily mortality rate is around 1.3 deaths per 100,000 inhabitants in Mexico. Converted to an annual rate, this corresponds to about 475 deaths per 100,000 inhabitants. In this context, our estimate of an extra 0.7 deaths per 100,000 inhabitants caused by a day below 10°C roughly represents a marginal increase of 0.15% in the annual death rate. Likewise, the estimate of 0.13 deaths per 100,000 due to a day above 32°C corresponds to a marginal increase in the annual death rate by less than 0.03%. The relative impact of cold on mortality in Mexico seems at least 2-3 times lower than in India whereas the estimated impact for heat is incomparably lower.

Appendix A7: Impacts of Climate Change

We calculate the number of weather-related deaths under climate change based on the output of the climate model GFDL CM3 for 2075-2099. Annual death estimates under climate change are provided in Table A7.1.[44] Because the frequency of cold and mildly cold days is expected to decrease, the number of deaths imputable to temperatures reduces with the forecasted temperatures of GFDL CM3 as compared with the historical ones. With the RCP2.6 scenario (low GHG emissions), temperature-related mortality would be twice as small. The RCP8.5 scenario (high GHG emissions) corresponds to an 80% reduction in the estimated relationship between mortality and temperature. We show later that weather-related mortality affects mostly people in the first two quartiles of the income distribution, suggesting that the reduction in the exposure to cold weather associated by climate change could lead to a reduction in mortality inequality. Therefore, in Mexico, we predict that climate change will reduce the impact of short-term weather variability on mortality, with significant health benefits. However, this analysis comes with serious warnings: climate change could also affect mortality through increased frequency of natural catastrophes and not only through temperatures; our analysis at the daily level does not allow for acclimatization; and we could be underestimating the impact of increased heat waves if the effect of heat grows non-linearly beyond 32°C days. In addition, our model includes municipality-by-month-by-year fixed effects which control for income and for the general health of the population. Climate change may impact income, or the general health of the population, and these factors may in turn impact mortality. Our econometric specification cannot assess the magnitude of such indirect economic effects on mortality. Yet in section 5, we show that these factors can significantly modify the health response to temperature shocks, even when looking at short run impacts.

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

Table A7.1: Impact of temperatures on annual deaths in several climate scenarios

Number of deaths	Estimates	Compared to historical temperatures
Historical	41,335* (27,299; 55,370)	
GFDL CM3:		
RCP2.6	18,152* (5,898; 30,405)	-23,183* (-26,410; -19,956)
RCP4.5	12,842* (1,177; 24,506)	-28,493* (-33,196; -23,790)
RCP8.5	7,513 (-4,000; 19,026)	-33,821* (-41,629; -26,014)

Note: * denotes statistically significant at 5%. The 95% confidence interval in brackets only take into account the uncertainty of the impact of temperature bins on mortality. It does not take into account the uncertainty of climate models in the distribution of daily temperatures.

Appendix A8: Impacts by gender, age and cause of death

Table A8.1 displays the 31-day cumulative impact of a day with average temperature below 10°C whereas Table A8.2 displays the 31-day cumulative impact of a day with average temperature above 32°C.

Table A8.1: Impact of a day under 10 Celsius degree on cumulative mortality

	Cause of death						
Group	All causes	Respiratory system diseases	Circulatory system diseases	Endocrine, nutritional and metabolic diseases	Infectious diseases	Neoplasms	Accidents and violent deaths
Total	0.703*** (0.042)	0.19*** (0.014)	0.21*** (0.02)	0.131*** (0.015)	0.02*** (0.006)	0.004 (0.012)	0.025 (0.016)
Men	0.774*** (0.063)	0.209*** (0.02)	0.248*** (0.029)	0.129*** (0.02)	0.025** (0.01)	0.016 (0.018)	0.008 (0.028)
Women	0.635*** (0.052)	0.171*** (0.018)	0.174*** (0.028)	0.133*** (0.021)	0.015** (0.007)	-0.007 (0.017)	0.044*** (0.014)
Aged 0-4	0.774*** (0.103)	0.37*** (0.052)	0.003 (0.009)	0.045** (0.022)	0.116*** (0.029)	0.004 (0.007)	0.139*** (0.034)
Aged 4-9	0.022 (0.029)	-0.009 (0.012)	-0.001 (0.003)	-0.004 (0.006)	-0.002 (0.006)	-0.004 (0.006)	0.029 (0.018)
Aged 10-19	0.011 (0.027)	0.012** (0.006)	-0.004 (0.004)	0.013** (0.005)	0.001 (0.004)	-0.013** (0.007)	-0.014 (0.021)
Aged 20-34	0.148*** (0.047)	0.009 (0.008)	0.014 (0.01)	0.007 (0.008)	-0.002 (0.008)	0.027*** (0.01)	0.067* (0.037)
Aged 35-44	0.236*** (0.086)	-0.006 (0.013)	0.044* (0.024)	0.075*** (0.023)	-0.012 (0.016)	0.04 (0.025)	0.005 (0.052)
Aged 45-54	0.301** (0.133)	0.063** (0.028)	0.025 (0.053)	0.173*** (0.05)	0.033 (0.021)	-0.066 (0.046)	-0.051 (0.057)
Aged 55-64	0.96*** (0.234)	0.206*** (0.055)	0.404*** (0.104)	0.361*** (0.103)	0.067** (0.033)	-0.046 (0.089)	-0.063 (0.069)
Aged 65-74	1.576*** (0.362)	0.336*** (0.085)	0.633*** (0.161)	0.591*** (0.16)	0.113** (0.053)	-0.072 (0.138)	-0.09 (0.105)
Aged 75+	16.436*** (1.028)	4.574*** (0.403)	6.103*** (0.594)	2.229*** (0.38)	0.183 (0.132)	0.26 (0.281)	0.116 (0.167)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C on mortality, for specific age groups or causes of death. The dependent variable is always the daily mortality rate in deaths per 100,000 inhabitants and all regressions include the daily precipitation level as control. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%. 312,140 groups, 30.1 observations per group. Reference day is 24-26 Celsius degrees.

Table A8.2: Impact of a day over 32 Celsius degree on cumulative mortality

	Cause of death						
Group	All causes	Respiratory system diseases	Circulatory system diseases	Endocrine, nutritional and metabolic diseases	Infectious diseases	Neoplasms	Accidents and violent deaths
Total	0.127*** (0.049)	0.003 (0.013)	0.061** (0.025)	0.006 (0.016)	-0.002 (0.008)	0.014 (0.016)	0.041* (0.025)
Men	0.146* (0.076)	-0.016 (0.021)	0.099*** (0.037)	-0.004 (0.022)	0.003 (0.012)	0.034 (0.023)	0.042 (0.045)
Women	0.108* (0.057)	0.022 (0.014)	0.022 (0.032)	0.015 (0.022)	-0.006 (0.009)	-0.005 (0.022)	0.04** (0.018)
Aged 0-4	-0.022 (0.085)	-0.001 (0.025)	0.004 (0.009)	-0.014 (0.018)	-0.011 (0.023)	-0.016 (0.014)	0.034 (0.032)
Aged 4-9	-0.007 (0.031)	0.007 (0.006)	-0.0003 (0.003)	-0.009 (0.005)	-0.006 (0.007)	0.004 (0.007)	-0.028 (0.026)
Aged 10-19	0.057 (0.041)	0.003 (0.004)	-0.0003 (0.005)	0.003 (0.004)	-0.002 (0.004)	0.003 (0.008)	0.047 (0.038)
Aged 20-34	0.028 (0.073)	0.016* (0.008)	-0.002 (0.011)	0.022** (0.01)	-0.023 (0.014)	0.001 (0.012)	0.033 (0.066)
Aged 35-44	0.129 (0.1)	0.009 (0.016)	0.047 (0.032)	-0.007 (0.022)	0.009 (0.02)	0.006 (0.029)	0.092 (0.072)
Aged 45-54	0.094 (0.157)	0.006 (0.022)	0.006 (0.074)	0.067 (0.053)	0.02 (0.03)	0.033 (0.058)	0.072 (0.082)
Aged 55-64	0.003 (0.249)	0.018 (0.046)	0.04 (0.121)	-0.159 (0.105)	-0.057 (0.043)	0.196* (0.108)	-0.018 (0.102)
Aged 65-74	0.033 (0.389)	0.028 (0.071)	0.078 (0.189)	-0.257 (0.166)	-0.093 (0.068)	0.3* (0.171)	-0.01 (0.152)
Aged 75+	1.423 (1.152)	-0.334 (0.369)	1.156* (0.689)	0.75* (0.399)	0.175 (0.153)	-0.712* (0.379)	-0.079 (0.21)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day over 32°C on mortality, for specific age groups or causes of death. The dependent variable is always the daily mortality rate in deaths per 100,000 inhabitants and all regressions include the daily precipitation level as control. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%. 312,140 groups, 30.1 observations per group. Reference day is 24-26 Celsius degrees.

Appendix A9: List of diseases covered by the Seguro Popular and Fondo de Protección contra Gastos Catastróficos in 2010

We are providing the full lists as per 2010. For a small list of diseases covered under the *Seguro Popular* or the *Fondo de Protección contra Gastos Catastróficos*, conditions of age had to be filled to receive treatment. For some others, only diagnosis and prevention measures are covered (e.g. some cancers). For the robustness check of Table 7, we considered that a disease was covered by the scheme independently of these age conditions, and also as soon as its diagnosis (or some preventive action) was part of the scheme.

Diseases and treatments covered by the Seguro Popular in 2010

PUBLIC HEALTH
Newborn and children under 5 years of age
1 BCG Vaccine
2 Hepatitis B vaccine
3 Pentavalent vaccine with acellular pertussis component (DpaT + VIP + Hib)
4 SRP triple viral vaccine
5 Rotavirus vaccine
6 Influenza vaccine
7 DPT vaccine
8 Sabin trivalent oral polio vaccine
9 Preventive actions for newborn
10 Preventive actions for children under 5 years
Girls and boys from 5 to 9 years old
11 Preventive actions for children between the ages of 5 and 9
Teenagers 10 to 19 years old
12 Early detection of eating disorders
13 Preventive actions for adolescents aged 10 to 19
14 Hepatitis B vaccine
Adults 20 to 59 years old
15 SR double viral vaccine
16 Tetanus and diphtheria toxoid (Td)
17 Preventive actions for women aged 20-59

18 Preventive actions for men aged 20-59
19 Complete medical examination for women aged 40-59
20 Complete medical examination for men aged 40-59
21 Prevention and care of family and sexual violence in women
Adults over 60 years and over
22 Pneumococcal vaccine for the elderly
23 Influenza vaccine for the elderly
24 Preventive actions for adults over 60 and older
General / family consultation
25 Diagnosis and treatment of iron deficiency anemia and vitamin B12 deficiency
26 Diagnosis and treatment of vitamin A deficiency
27 Diagnosis and treatment of rubella
28 Diagnosis and treatment of measles
29 Diagnosis and treatment of chickenpox
30 Diagnosis and treatment of acute pharyngotonsillitis
31 Diagnosis and treatment of whooping cough
32 Diagnosis and treatment of non-suppurative otitis media
33 Diagnosis and treatment of acute rhinopharyngitis (common cold)
34 Diagnosis and treatment of conjunctivitis
35 Diagnosis and treatment of allergic rhinitis
36 Diagnosis and treatment of classical dengue fever
37 Diagnosis and outpatient treatment of acute diarrhea
38 Diagnosis and treatment of paratyphoid fever and other salmonellosis
39 Diagnosis and treatment of typhoid fever
40 Diagnosis and treatment of herpes zoster
41 Diagnosis and treatment of candidiasis
42 Diagnosis and treatment of gonorrhea
43 Diagnosis and treatment of chlamydia infections - including trachoma-
44 Diagnosis and treatment of Trichomonas infections
45 Diagnosis and treatment of syphilis
46 Diagnosis and treatment of cystitis
47 Diagnosis and treatment of acute vaginitis
48 Diagnosis and treatment of acute vulvitis
49 Diagnosis and pharmacological treatment of intestinal amebiasis
50 Diagnosis and pharmacological treatment of hookworm and necatorisis
51 Diagnosis and pharmacological treatment of ascariasis
52 Diagnosis and pharmacological treatment of enterobiasis
53 Diagnosis and pharmacological treatment of echinococcosis
54 Diagnosis and pharmacological treatment of equistosomiasis (bilharziasis)
55 Diagnosis and pharmacological treatment of strongyloidiasis
Pharmacological diagnosis and treatment of filariasis
57 Diagnosis and pharmacological treatment of giardiasis
58 Diagnosis and pharmacological treatment of tapeworms
59 Diagnosis and pharmacological treatment of trichuriasis
60 Diagnosis and pharmacological treatment of trichinosis
61 Diagnosis and treatment of scabies
62 Diagnosis and treatment of pediculosis and phthiriasis
63 Diagnosis and treatment of superficial mycoses
64 Diagnosis and treatment of onychomycosis
65 Diagnosis and treatment of infectious cellulitis
66 Diagnosis and treatment of allergic contact dermatitis
67 Diagnosis and treatment of atopic dermatitis
68 Diagnosis and treatment of irritant contact dermatitis
69 Diagnosis and treatment of diaper dermatitis
70 Diagnosis and treatment of exfoliative dermatitis
71 Diagnosis and treatment of seborrheic dermatitis
72 Diagnosis and treatment of common warts
73 Diagnosis and treatment of acne
74 Diagnosis and treatment of hepatitis A
75 Diagnosis and treatment of acute gastritis
76 Diagnosis and treatment of irritable bowel syndrome
77 Diagnosis and pharmacological treatment of diabetes mellitus 2
78 Diagnosis and pharmacological treatment of hypertension
79 Diagnosis and treatment of osteoarthritis
80 Diagnosis and treatment of low back pain
81 Other general medical care
82 Temporary Family Planning Methods: Hormonal Contraceptives (AH)
83 Temporary family planning methods: condoms
84 Temporary family planning methods: intrauterine device
85 Prenatal care in pregnancy

SPECIALTY CONSULTATION

86 Diagnosis and treatment of attention deficit hyperactivity disorder
87 Diagnosis and treatment of generalized developmental disorders (Autism)
88 Diagnosis and treatment of dysmenorrhea
89 Menopause and climacteric care
90 Diagnosis and treatment of fibrocystic mastopathy
91 Diagnosis and treatment of endometrial hyperplasia
92 Diagnosis and treatment of subacute and chronic vaginitis
93 Diagnosis and treatment of endometriosis
94 Diagnosis and treatment of urethritis and urethral syndrome
95 Diagnosis and treatment of low grade intraepithelial squamous lesions
96 Diagnosis and treatment of high-grade intraepithelial squamous lesions
97 Diagnosis and treatment of malnutrition and obesity in children and adolescents
98 Diagnosis and treatment of Kwashiorkor
99 Diagnosis and treatment of nutritional marasmus
100 Diagnosis and treatment of malnutrition sequelae
101 Diagnosis and treatment of acute laryngotracheitis
102 Diagnosis and treatment of suppurative otitis media
103 Diagnosis and treatment of acute sinusitis
104 Diagnosis and treatment of asthma in adults
105 Diagnosis and treatment of asthma in children
106 Diagnosis and treatment of tuberculosis (TAES)
107 Diagnosis and treatment of drug-resistant tuberculosis
108 Prevention, diagnosis and treatment of psoriasis
109 Diagnosis and treatment of reflux esophagitis
110 Diagnosis and treatment of peptic ulcer
111 Diagnosis and treatment of dyslipidemia
112 Diagnosis and treatment of hyperthyroidism
113 Diagnosis and treatment of congenital and adult hypothyroidism
114 Diagnosis and pharmacological treatment of diabetes mellitus 1
115 Diagnosis and treatment of chronic heart failure
116 Diagnosis and treatment of osteoporosis
117 Diagnosis and treatment of gout
118 Diagnosis and treatment of rheumatoid arthritis
119 Diagnosis and treatment of affective disorders

(Dysthymia, depression and bipolar affective disorder)
120 Diagnosis and treatment of anxiety disorders (generalized anxiety, distress and panic attacks and reactions to severe stress and adaptation disorders [posttraumatic stress disorder and adaptive disorder])
121 Diagnosis and treatment of psychotic disorders (Schizophrenia, delusions, psychotic and schizotypal)
122 Diagnosis and pharmacological treatment of epilepsy
123 Diagnosis and treatment of Parkinson's disease
124 Diagnosis and treatment of congenital dislocation of the hip
125 Rehabilitation of fractures
126 Rehabilitation of facial paralysis
127 Selective and indicated prevention of addictions (Counseling)
128 Diagnosis and treatment of addictions

ODONTOLOGY

129 Prevention of caries and periodontal disease
130 Sealing of dentures and fissures
131 Removal of caries and restoration of teeth with amalgam, resin or glass ionomer
132 Elimination of outbreaks of infection, abscesses (including drainage and pharmacotherapy)
133 Removal of teeth, including erupted and root rests (does not include third molar not erupted)
134 Diagnosis and treatment of pulpitis and pulp necrosis
135 Diagnosis and treatment of maxillary abscess
136 Third molar extraction

EMERGENCIES

137 Stabilization in emergencies due to hypertensive crisis
138 Emergency Stabilization of the Diabetic Patient
139 Urgent management of non-ketotic hyperglycemic syndrome
140 Stabilization in the emergency room for angina pectoris
141 Diagnosis and treatment of acute phenothiazine intoxication
142 Diagnosis and treatment of acute alkali intoxication
143 Diagnosis and treatment of acute food poisoning
144 Diagnosis and treatment of acute salicylate poisoning
145 Diagnosis and treatment of acute methyl alcohol intoxication
146 Diagnosis and treatment of acute organophosphate poisoning
147 Diagnosis and treatment of acute carbon monoxide poisoning
148 Diagnosis and treatment of snake bite
149 Diagnosis and treatment of alacranismo
150 Diagnosis and treatment of bee, spider and other arthropod stings
151 Management of biting and prevention of rabies in humans
152 Extraction of foreign bodies
153 Management of traumatic soft tissue injuries (healing and suturing)
154 Diagnosis and treatment of mild traumatic brain injury (Glasgow 14-15)
155 Emergency management of first-degree burns
156 Diagnosis and treatment of cervical sprain
157 Diagnosis and treatment of shoulder sprain
158 Diagnosis and Treatment of Elbow Sprain
159 Diagnosis and treatment of wrist and hand sprain
160 Diagnosis and treatment of sprained knee
161 Diagnosis and treatment of ankle and foot sprains

HOSPITALIZATION

162 Diagnosis and treatment of pyelonephritis
163 Diagnosis and treatment of bronchiolitis
164 Diagnosis and treatment of acute bronchitis
165 Diagnosis and treatment of meningitis
166 Diagnosis and treatment of mastoiditis
167 Diagnosis and treatment of osteomyelitis
168 Diagnosis and treatment of pneumonia in children
169 Diagnosis and treatment of pneumonia in adults and older adults
170 Diagnosis and treatment of amebic liver abscess
171 Diagnosis and treatment of pelvic inflammatory disease
172 Diagnosis and treatment of threatened abortion
173 Diagnosis and treatment of preterm delivery
174 Care of childbirth and physiological puerperium
175 Pelviperitonitis
176 Puerperal endometritis
177 Diagnosis and treatment of puerperal septic shock
178 Care of the newborn
179 Neonatal jaundice
180 Diagnosis and treatment of uncomplicated prematurity
181 Diagnosis and treatment of prematurity with hypothermia
182 Diagnosis and treatment of the newborn with low birth weight
183 Diagnosis and treatment of preeclampsia
184 Diagnosis and treatment of severe preeclampsia
185 Diagnosis and treatment of eclampsia
186 Puerperal obstetric haemorrhage
187 Bleeding from placenta previa or premature detachment of placenta normoinserta
188 Infection of episiotomy or obstetric surgical wound
189 Diagnosis and treatment of renal and ureteral lithiasis
190 Diagnosis and treatment of lower urinary lithiasis
191 Diagnosis and treatment of hemorrhagic dengue
192 Diagnosis and Treatment of Moderate Head Injury (Glasgow 9-13)
193 Diagnosis and conservative management of acute pancreatitis
194 Hospital management of seizures
195 Hospital management of hypertension
196 Diagnosis and treatment of acute heart failure (pulmonary edema)
197 Chronic Obstructive Pulmonary Disease
198 Diagnosis and treatment of peripheral neuropathy secondary to diabetes
199 Hospital management of second degree burns
200 Diagnosis and treatment of digestive haemorrhage
201 Diagnosis and treatment of HELLP syndrome
202 Diagnosis and treatment of chorioamniositis
203 Diagnosis and treatment of obstetric embolisms
204 Diagnosis and treatment of gestational diabetes
205 Diagnosis and treatment of functional heart disease in the pregnant woman
206 Diagnosis and treatment of deep venous thrombosis in the pregnant woman

GENERAL SURGERY

207 Exploratory laparotomy
208 Appendectomy
209 Splenectomy
210 Surgical treatment of diverticular disease
211 Surgical treatment of ischemia and intestinal infarction
212 Surgical treatment of intestinal obstruction
213 Surgical treatment of gastric and intestinal perforation

214 Surgical treatment of colonic volvulus
215 Surgical treatment of the rectal abscess
216 Surgical treatment of fistula and anal fissure
217 Hemorrhoidectomy
218 Surgical treatment of hiatal hernia
219 Surgical treatment of congenital pylorus hypertrophy
220 Crural Hernioplasty
221 Inguinal Hernioplasty
222 Umbilical Hernioplasty
223 Ventral Hernioplasty
224 Open cholecystectomy
225 Laparoscopic cholecystectomy
226 Surgical treatment of condylomata
227 Surgical Treatment of Breast Fibroadenoma
228 Surgical treatment of ovarian cysts
229 Surgical treatment of torsion of attachments
230 Salpingoclasia (Definitive method of family planning)
231 Surgical care of trophoblastic disease
232 Surgical treatment of ectopic pregnancy
233 Uterine therapeutic uterine by incomplete abortion
234 C-section and surgical puerperium care
235 Uterine repair
236 Endometrial ablation
237 Endometriosis Laparoscopy
238 Myomectomy
239 Abdominal hysterectomy
240 Vaginal hysterectomy
241 Colpoperineoplasty
242 Vasectomy (Definitive method of family planning)
243 Circumcision
244 Orchidopexy
245 Open Prostatectomy
246 Transurethral resection of prostate
247 Removal of cancerous skin lesion (melanoma not included)
248 Removal of benign tumor in soft tissues
Tonsillectomy with or without adenoidectomy
250 Excision of juvenile pharyngeal papilloma
251 Palateplasty
252 Cleft Lip Repair
253 Muscular shortening surgery for strabismus
254 Muscular lengthening surgery for strabismus
255 Surgical treatment of glaucoma
256 Pterygium excision
257 Surgical treatment of hydrocephalus
258 Placement and removal of various catheters
259 Radical neck dissection
260 Thoracotomy, pleurotomy and chest drainage
261 Surgical treatment of congenital dislocation of the hip
262 Surgical treatment of the equine foot in children
263 Safenectomy
264 Surgical reduction by dislocations
265 Surgical reduction of clavicle fracture
266 Surgical reduction of hum fracture

List of diseases and treatments covered by the Fondo de Protección contra Gastos Catastróficos in 2010

Cervical Cancer
Uterine Cancer
Antiretroviral HIV / AIDS Treatment
Cataract in Adults
Congenital cataract
Malignant Breast Tumor

Neonatal Intensive Care
Prematureness
Respiratory insufficiency
Sepsis

Cancer of children
Astrocytoma
Medulloblastoma
Neuroblastoma
Ependymoma
Other Tumors of the Central Nervous System
Wilms tumor
Other kidney tumors
Acute lymphoblastic leukemia
Acute Myeloblastic Leukemia
Chronic Leukemias
Preleukemic Syndromes
Hepatoblastoma
Hepatocarcinoma
Osteosarcoma
Ewing's sarcoma
Non-Hodgkin's Lymphoma
Retinoblastoma
Soft Tissue Sarcoma

Sarcomas Gonadales
Estragonadales Germinal Tumors
Various germinal tumors
Carcinomas
Histiositosis

Extension of coverage of pediatric pathology
Cardiac Congenital Malformations
Esophageal atresia
Omphalocele
Gastrochisis
Atresia / Duodenal Stenosis
Atresia Intestinal
Atresia Anal
Hypoplasia / Renal Dysplasia
Ureter Retrocavo
Ectopic Meatoses
Ureteral Stenosis
Ureterocele
Vesical Extrophy
Hypospadias
Epispadias
Ureteral Stenosis
Ureteral Meat Stenosis
Spina Bifida

ROBUSTNESS CHECKS

Appendix B1: Separating the impact of minimum and maximum temperatures

We have correlated mortality with the average temperature in a day. We have therefore averaged minimum and maximum daily temperatures: the same effect at a given average temperature level is assumed and no consideration is made for within-day variation. To investigate this issue, we can run a specification of the distributed lag model where we calculate separate effects for minimum and maximum temperatures. No additional insight seems to be brought by such an exercise.

Figure B1.1: Impact of minimum daily temperature on 31-day cumulative mortality, in deaths per 100,000 inhabitants.

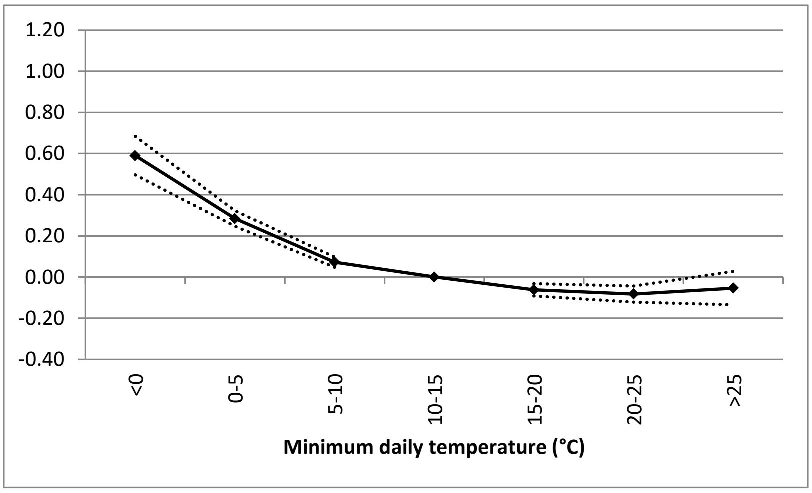
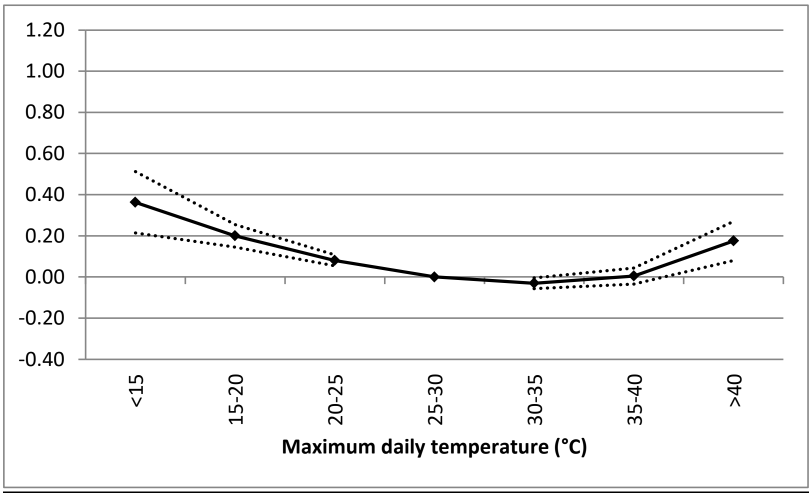


Figure B1.2: Impact of maximum daily temperature on 31-day cumulative mortality, in deaths per 100,000 inhabitants.

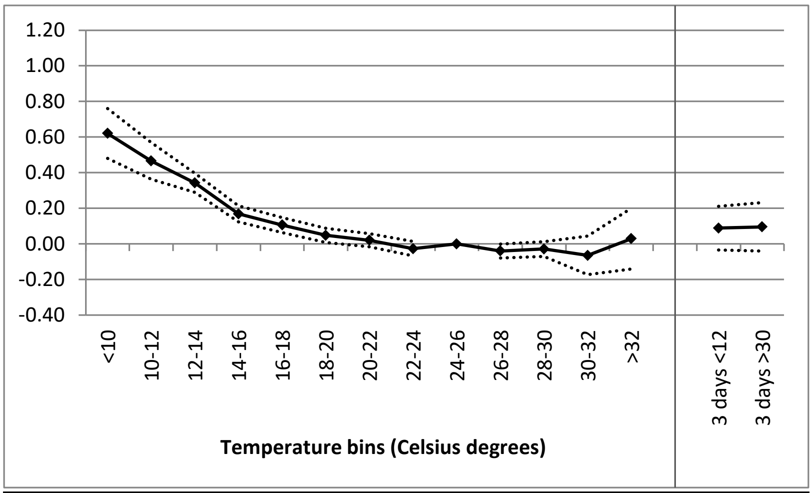


Notes. Lines in dash correspond to the 95% confidence interval values obtained for each sum of estimated coefficients. The regression results control for the day's precipitation level. The coefficients displayed Figure B1.1 and Figure B1.2 have been estimated jointly and come from the same fixed effect regression.

Appendix B2: Consecutive hot and cold days

One might fear that mortality might increase if extremely high or low temperatures remain for more than a day. We have tested this by adding two additional bins to the base specification: the first bin is equal to 1 if the last three days have undergone an average temperature below 12°C. The second bin is equal to 1 if the last three days have suffered from an average temperature above 30°C. The model then includes all the remaining temperature bins and 28 lags. The cumulative effect of the two new bins is positive but not statistically significant, suggesting that the base model with no such bins is a sufficient depiction of the relationship between mortality and temperatures.

Figure B2.1: Impact of consecutive hot and cold days on 28-day cumulative mortality, in deaths per 100,000 inhabitants.

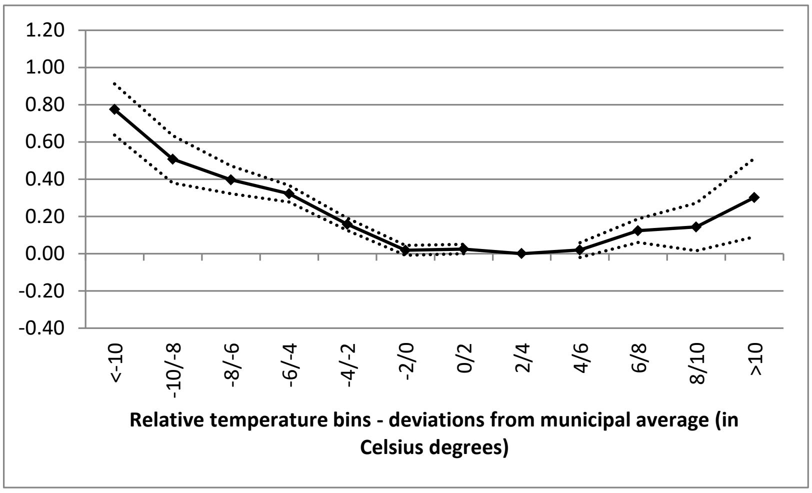


Appendix B3: Using relative temperature bins

Due to acclimatization, the mortality effect of the same cold or a hot day may differ from one location to another. As a robustness check for our mail model, we run a series of specifications where we assume that the impact of temperature on mortality depends on the difference between the temperatures faced during a given day and the ones that are usually experienced: instead of using absolute temperature bins, we calculate deviations from the average temperature in each location to construct relative temperature bins with a 2°C window. The average temperature in each municipality is obtained by averaging all daily temperatures over 1997-2013. Then we rerun our distributed lag model with the newly constructed temperature bins. These include deviations between -10°C and +10°C with respect to the average of each municipality.

The 31-day cumulative results for all the population and causes of deaths are displayed in Figure B3.1.

Figure B3.1: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, using temperature bins relative to the average temperature in each municipality



Notes. Lines in dash correspond to the 95% confidence interval values obtained for each sum of estimated coefficients. 312,140 groups and 30.1 observations per group. The regression results control for the day's precipitation level.

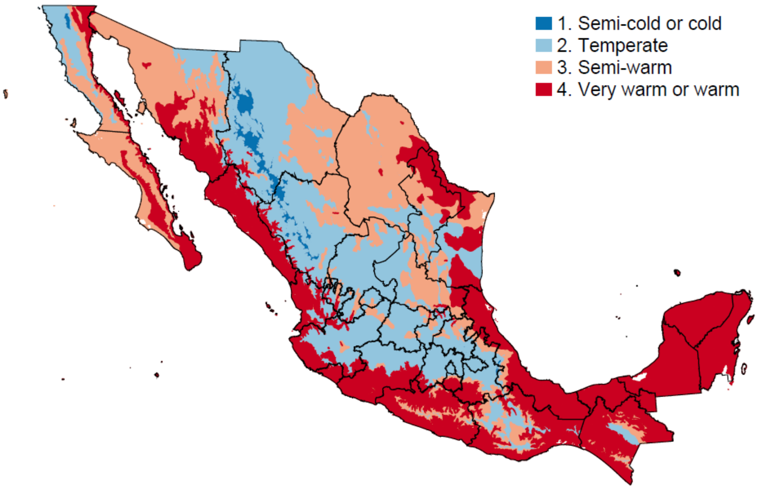
They show little difference with the results obtained using absolute temperature bins, even though the effect of cold is smaller whereas the effect of heat is bigger. When accounting for the frequency of unusually cold and hot days, we find that days with temperatures below the average by 10°C or more would be responsible for the death of around 2,700 people annually (95% confidence interval is 2,200-3,200). Mild cold (deviations between -2°C to -10°C) are imputed the death of 26,700 people (95% confidence interval is 23,600-29,700). On the other hand, unusually hot days – above the average by 10°C or more – would cause around 350 deaths (95% confidence interval is 100-600). We also find statistically significant effects for days with temperatures between 6°C and 10°C above the municipal average: they would be responsible for the death of around 1,500 people (95% confidence interval is 900-2,200).

In addition, we have run the distributive lag model for every subgroup and type of disease covered in this analysis and found results very similar to the ones uncovered with the distributive lag model.

Appendix B4: The temperature-mortality relationship by climate region

Mexico is a large country with very diverse climates. Due to adaptation and acclimation, it is likely that the temperature-mortality relationship is different in the hottest regions are compared to the coldest ones. The INEGI provides a detailed map of Mexico with a typology of 21 climates. We have simplified this typology and broken down Mexico into 4 climate categories (see Figure B4.1): very warm and warm (covering very dry, dry, semi-dry, humid and semi-humid regions that are also very warm and warm); semi-warm; temperate; and semi-cold or cold (covering respectively all semi-warm, temperate, semi-cold or cold regions independently of humidity).

Figure B4.1: Map of Mexico distinguishing between warm, semi-warm, temperate and cold climates

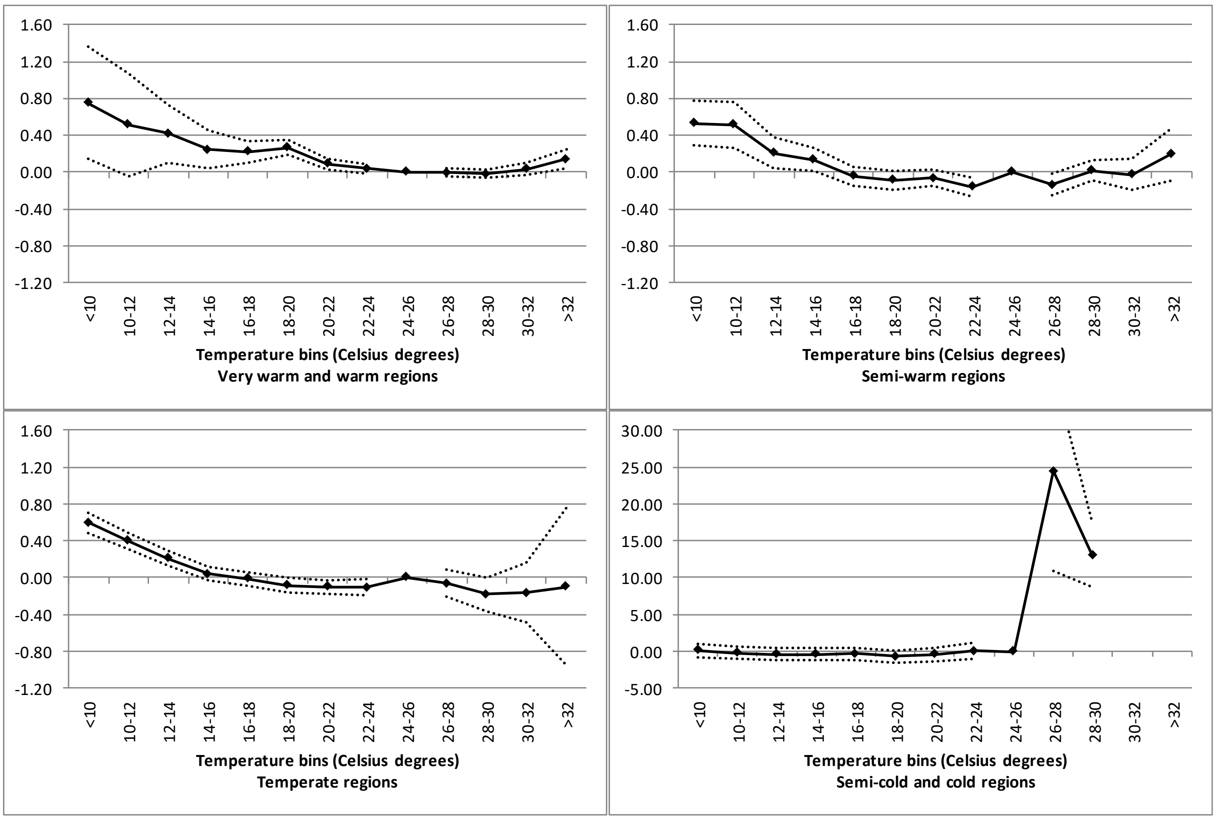


By overlapping the map of Mexican climates with the map of Mexican municipalities, we have matched the boundaries of the 2,456 Mexican municipalities with the boundaries of our four climatic categories. The map of INEGI defines municipalities as a set of data points that produce a polygon.

Our matching strategy assigns a climate to each point of the polygon that corresponds to the boundaries of a municipality. For each municipality, we calculate the number of delimiting data points that fall in a given climate. If this number exceeds half the total number of data points that constitute the boundary of the municipality, we consider that this municipality belongs to this climate.

This approximation allows us to classify municipalities into four main climate categories, for which we run the distributed lag model separately. The output of the separate regressions is provided below. In cold regions, we find very strong mortality impacts of hot days. However, the sample is of limited scope since it includes only 11 municipalities. On the other hand, we find no striking difference between warm, semi-warm and temperate regions. However, the confidence interval for the impact of cold days on mortality is large in hot regions. This is likely to be due to the lack of cold events in hot regions.

Figure B4.2: Mortality impacts by climate region in Mexico



Appendix B5: Polynomial model and interactions with precipitations

We have found a J-shaped temperature-mortality relationship in this paper, in which cold days have a stronger effect than hot days on mortality. Instead of using temperature bins, we can proxy this relationship using a polynomial form to describe the relationship between mortality and average temperatures:

$$Y_{i,d,m,t} = \sum_{k=0}^{K=30} \sum_{a=1}^{A} \theta_{-k}^{a} . T_{i,d-k,m,t}^{a} + \sigma . P_{i,d,m,t} + \mu_{i,m,t} + \varepsilon_{i,d,m,t}$$

In the equation above, we have replaced the temperature bins by the average temperature for municipality i in day d minus k of month m in year t, denoted $T_{i,d-k,m,t}$. We can then consider a nonlinear relationship by including $T_{i,d-k,m,t}^{2}$, $T_{i,d-k,m,t}^{3}$ and so on in the equation. We restrict ourselves to the case where $\mathrm{A} = 3$.

Using a polynomial function instead of temperature bins reduces the amount of coefficients to be estimated by the model and therefore its computational intensity. We take advantage of this fact to better control for the confounding effect of precipitations, and interact precipitations with temperatures. To do so, we also include lagged precipitations over 30 days and assume a polynomial relationship between precipitations and temperatures. We also interact precipitations with temperatures.

Estimated coefficients are provided in the table below for three different specifications. They show very little difference in the estimated impacts and the cumulative effects of precipitations are not statistically significant. A polynomial form for the relationship between temperatures and mortality is preferred to a linear form.

Table B5.1: Cumulative 31-day impact of temperatures and precipitations using polynomials as functional forms in the fixed effect linear model

31-day effects	Dependent variable: daily mortality rate		
Temperature	-0.18*** (0.02)	-0.32*** (0.02)	-0.17*** (0.02)
Squared	0.0048*** (0.0012)		0.0041*** (0.0012)
To the cube	-0.000035** (0.000019)		-0.000022 (0.00002)
Precipitations		0.02 (0.03)	0.0007 (0.0041)
Squared			-0.000001 (0.000001)
To the cube			0.0000000001 (0.0000000001)
Interaction: Temperature x precipitation		-0.001 (-0.001)	(0.0003) 0.0002

Notes. Unit is deaths per 100,000 inhabitants. The first specification only controls for on-the-day precipitation levels.

Appendix B6: Confounding effect of humidity

Barreca (2012) shows that humidity interacts with temperatures in a way that can slightly alter mortality estimates, along with and their geographical distribution. In the regressions below, we use a specification similar to Deschenes and Moretti (2009) and introduce evaporation levels as an additional control variable with 30 lags. We also interact it with temperature bins. Table B6.1 displays the results obtained.

We find that mortality due to heat is higher under dry climates. Our results therefore do not match those of Barreca (2012) who find that higher humidity lead to higher mortality in hot and humid regions.

Table B6.1: Impact of humidity on mortality using a specification similar to Deschenes and Moretti (2009)

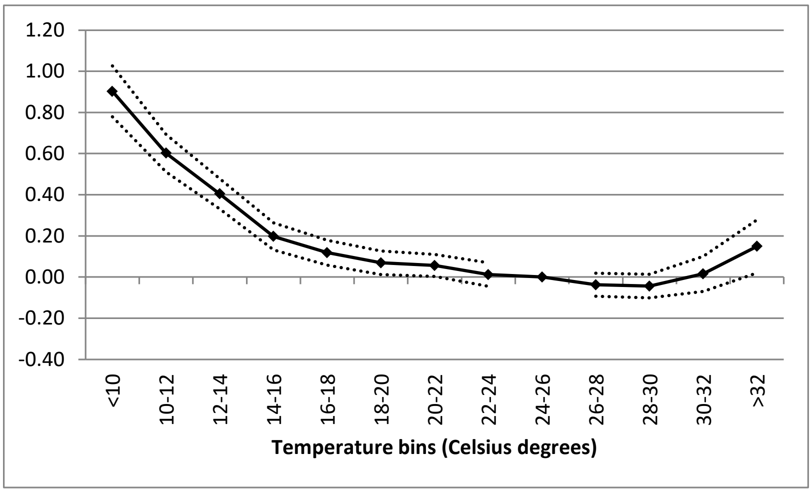
Independent variables	(1)	(2)	(3)	(4)
Temperature <10° C	0.56*** (0.039)		0.97*** (0.106)	
Temperature >32° C		0.22*** (0.049)		-0.11 (0.216)
24h evaporation (in mm):	-0.02*** (0.003)	-0.03*** (0.003)	-0.02*** (0.003)	-0.03*** (0.003)
x Temperature <10° C			-0.13*** (0.031)	
x Temperature >32° C				0.04 (0.024)

Notes. Dependent variable is mortality per 100,000 inhabitants. All population and causes of death are considered. Reported effects are cumulated effects over 31 days. Standard errors in brackets. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix B7: Splitting the sample into two periods

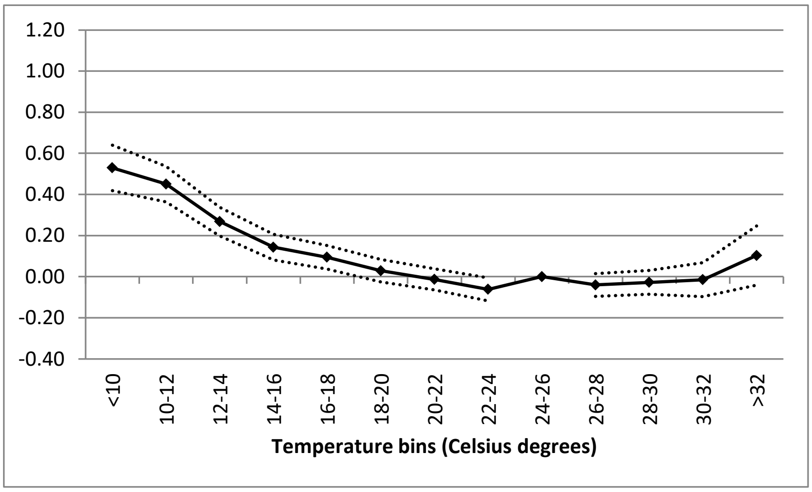
We report below the results of the distributed lag model for all the population and all causes of death, splitting the sample into two periods: 1998-2003 and 2004-2010. As one could expect, the temperature-mortality relationship seems less strong in the later period, probably due to an improvement of living conditions. The two coefficients for temperatures below 12°C are statistically different between both periods.

Figure B7.1: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, during the 1998-2003 period



Notes: Lines in dash correspond to the 95% confidence interval values obtained for each sum of estimated coefficients. The regression results control for the day's precipitation level.

Figure B7.2: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, during the 2004-2010 period



Notes: Lines in dash correspond to the 95% confidence interval values obtained for each sum of estimated coefficients. The regression results control for the day's precipitation level.

Appendix B8: Separate effects for week days and weekends

The figures below provide the 31-day cumulative mortality estimates for hot and cold days, depending on whether they fell during a week day or the weekend.

Figure B8.1: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, for events occurring during week days

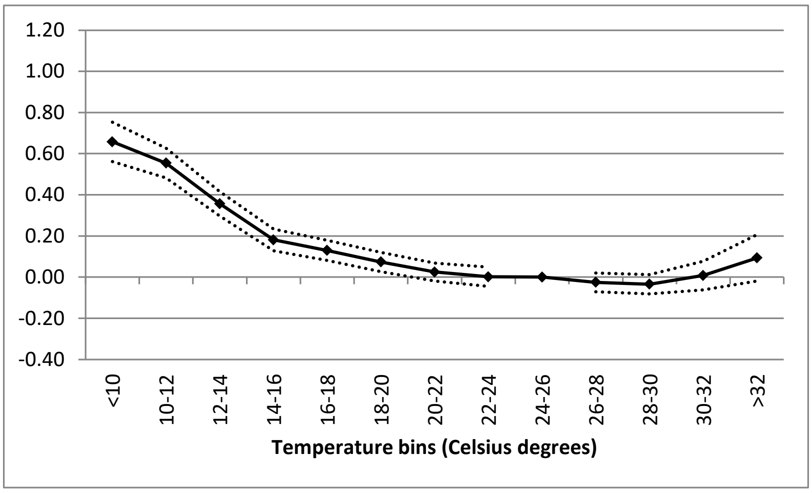
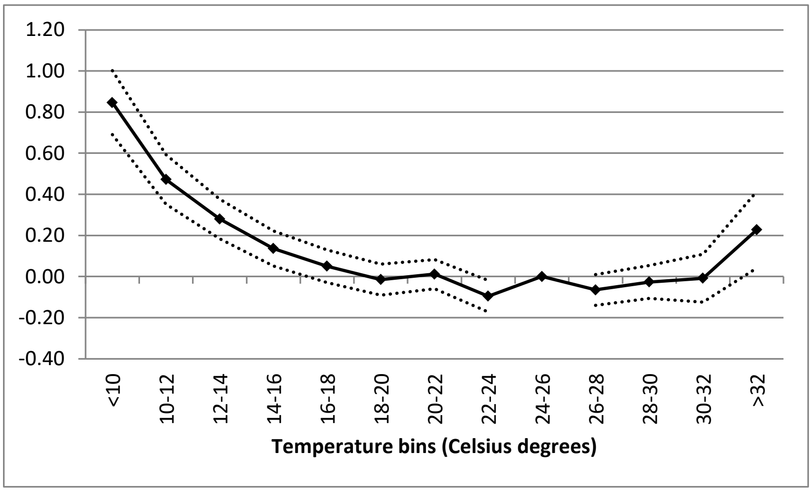


Figure B8.2: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants, for events occurring during the weekend

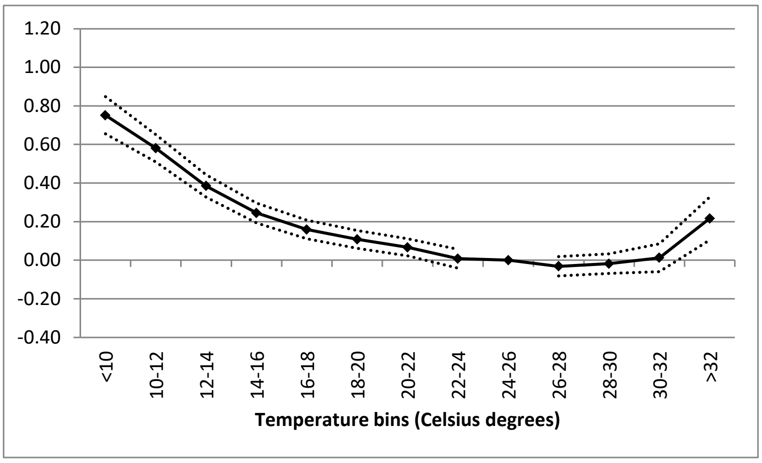


The estimates are roughly the same (no statistical difference for any temperature bin). This is consistent with the fact that most temperature-related deaths concentrate on the elderly.

Appendix B9: Effects in rural versus urban areas

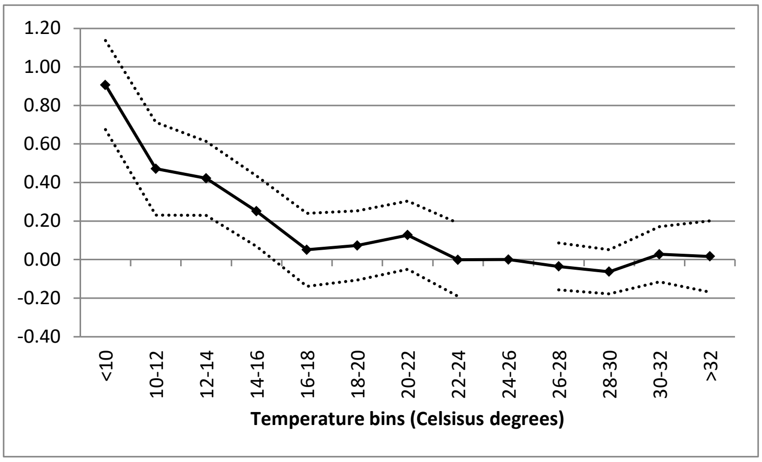
We look here if short-run vulnerability to temperatures may differ between people living in urban areas vs. people living in rural areas. Results are displayed on Figure B9.1 and Figure B9.2. Even though the coefficient associated with day below 10°C in rural areas is above the one for urban areas, the curves are not statistically different from one another. This suggests that distance to city centres might have no strong implications for short-term weather-related mortality in the case of Mexico.

Figure B9.1: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants in urban areas



Notes. The graph shows the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags run for populations living in urban areas only. The diamonds show the sum of the coefficients on these thirty lags in each category. Dashed lines correspond to the 95% confidence interval. The dependent variable is daily mortality rate at the municipality level. The regression controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects.

Figure B9.2: Impact of temperature bins on 31-day cumulative mortality, in deaths per 100,000 inhabitants in rural areas



Notes. The graph shows the cumulative effect of a day with a temperature within each bin based (relative to the 24-26°C category) obtained from a dynamic model with 30 lags run for populations living in rural areas only. The diamonds show the sum of the coefficients on these thirty lags in each category. Dashed lines correspond to the 95% confidence interval. The dependent variable is daily mortality rate at the municipality level. The regression controls for daily precipitation level and includes a range of municipality-by-year-by-month fixed effects.

Appendix B10: Results with the exact same method as in Deschenes and Moretti (2009)

There are two differences between the distributed lag model used in this paper and the one by Deschenes and Moretti (2009). First, these authors use total population as a weight and not the square root. This is because they put more emphasis on the results to be representative of the total population whereas we do not want them to be too much dependent on estimates for only a few big cities. In fact, either using total population or the square root has not significant impact on the results.

Second, instead of using temperature bins, Deschenes and Moretti (2009) use as independent variables: a) either a dummy variable which take the value of 1 on unusually cold days (average temperature <20°F or <30°F, depending on specification) and its lags; or b) a dummy variable which take the value of 1 on extremely hot days (average temperature >80°F or >90°F, depending on specification) and its lags. They therefore calculate the impact of unusually cold or hot days on mortality separately and as compared to the impact of any other day in the year. We chose not to do so because epidemiological studies (as cited previously) show that the temperature-mortality relationship very often is a U- or V-shaped function. At the bottom, there is a threshold (e.g. 20°C) with very low mortality. The more temperatures depart from this threshold, the more mortality increases. Therefore, evaluating the impact of extremely hot or cold temperatures as compared to the impact of any other day in the year is not ideal because not only extremely hot/cold days lead to extra mortality with respect to the bottom threshold. This method is likely to systematically underestimate the impact of temperatures on mortality, because it does not take the days with least temperature stress as a reference for calculating extra mortality.

We reproduce here the results obtained with the method of Deschenes and Moretti (2009), limiting ourselves to the ones for all causes of death. Using such a methodology leads to the same persistent effects of cold and heat on mortality using our dataset. The magnitude of the effects is also similar.

Table B10.1: Cumulative 31-day impact of extraordinarily cold and hot days on daily mortality, deaths for 100,000 inhabitants by subgroup

	Daily average temperature	
Group	<10° C	>32° C
Total	0.6*** (0.036)	0.13*** (0.037)
Men	0.6*** (0.05)	0.18*** (0.056)
Women	0.59*** (0.04)	0.08* (0.045)
Aged 0-4	0.63*** (0.091)	-0.04 (0.077)
Aged 4-9	0.05** (0.02)	0.01 (0.023)
Aged 10-19	-0.01 (0.02)	0.04 (0.028)
Aged 20-34	0.09*** (0.031)	0.06 (0.045)
Aged 35-44	0.22*** (0.059)	0.08 (0.074)
Aged 45-54	0.42*** (0.098)	0.32*** (0.117)
Aged 55-64	1.02*** (0.208)	0.32 (0.218)
Aged 65-74	1.71*** (0.35)	0.53 (0.362)
Aged 75+	14.5*** (0.989)	0.88 (1.036)

Notes. Standard errors in brackets. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level. Unit is deaths in a day per 100,000 inhabitants (in subgroup). All causes of death are considered.

Appendix B11: Distributed lag model with 60 lags

The results after 60 lags are consistent with the results at 30 days: the estimated coefficient for unusual cold with 60 lags is not statistically different from the estimated coefficients with 30 lags. The impact of hot days is however no longer statistically significant. If any, the impact of hot days is therefore expected to be rather small as already predicted with the model with 30 lags.

Table B11.1: Cumulative 61-day impact of extraordinarily cold and hot days on daily mortality, deaths for 100,000 inhabitants

	Daily average temperature	
Group	<10° C	>32° C
Total population	0.56*** (0.055)	-0.02 (0.057)

Notes. Standard errors in brackets. *** indicates statistically significant at the 1% level, ** at the 5% level, and * at the 10% level. Unit is deaths in a day per 100,000 inhabitants (in subgroup). All causes of death are considered.

Appendix B12: Changing the structure of the fixed effects

In this Appendix, we use different structures for the fixed effects. In the base specification, we have used fully interacted, municipality-by-year-by-month fixed effects. This restrains the comparison of mortality effects to days within the same month of the year within a given municipality and disregards the fact that changes in temperature may affect seasonal patterns, and in turn mortality. Above all, we could underestimate the mortality impacts of direct exposure to temperature in very cold or very hot months by comparing very cold days with already cold days, and very hot days with already hot days within a month. To the contrary, we find that relaxing the controls for within-municipality seasonal patterns attenuates estimated impacts (Table B12.1, columns 1-3). This attenuation is likely to be due to an estimation bias. When we allow the comparison of mortality impacts to take place within a municipality and a given month, but across different years, results are similar to the base specification, suggesting that the base specification does not underestimate the impact of hot and cold days on mortality (Table B12.1, column 4).

Table B12.1: Impact of days below 10°C and above 32°C using different sets of fixed effects

Fixed effects	Base specification	(1)	(2)	(3)	(4)
Municipality x Year x Month	X				
Municipality		X	X		
Year		X	X		X
Month		X			
Municipality x year				X	
Municipality x month					X
Climatic region x month			X	X	
Day with temperature <10° C	0.70*** (0.04)	0.38*** (0.03)	0.32*** (0.03)	0.43*** (0.02)	0.71*** (0.04)
Day with temperature >32° C	0.13** (0.05)	0.10*** (0.03)	0.09*** (0.02)	0.11*** (0.02)	0.12** (0.05)

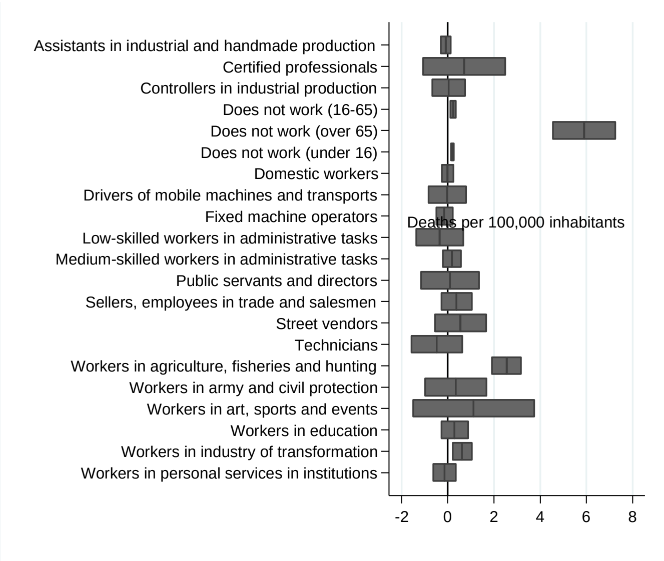
Note: Dependent variable is mortality per 100,000 inhabitants. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%. Reference day is 24-26 Celsius degrees. The impact of hot and cold days are estimated using different regressions.

SOCIOECONOMIC STATUS

Appendix C1: Impact of temperatures by profession

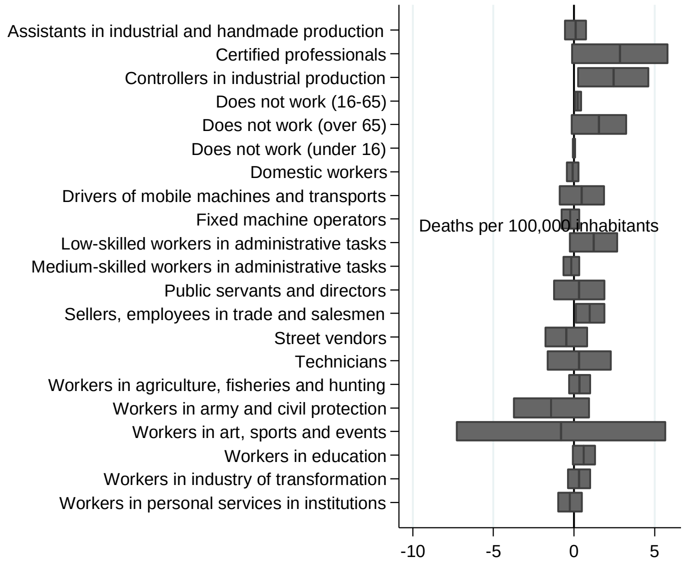
The distributed lag model has been run separately according to the profession of the deceased to assess differences in vulnerability by profession. We suspect that the type of profession is correlated with differences in vulnerability to extreme weather events since professions are correlated with a series of relevant socioeconomic factors, such as wages or access to healthcare (some categories benefit from specific healthcare regimes, e.g. the military and civil servants, whereas informal workers are excluded from any regime). Furthermore, exposure to heat/cold during the day will be different from workers in offices and workers that spend most of their time outdoors. However, as shown on the figures below, running separate regressions by occupation does not show clear differences in terms of vulnerability to temperatures, except for workers in agriculture, fisheries and hunting who appear to suffer from cold temperatures.

Figure C1.1: Impacts of 31-day cumulative mortality for a cold day below 10°C



Notes. The grey areas represent the 95% confidence interval for each estimated coefficient.

Figure C1.2: Impacts of 31-day cumulative mortality for a cold day above 32°C



Notes. The grey areas represent the 95% confidence interval for each estimated coefficient.

Appendix C2: Regression output to predict income with 2000 Census

The regression run to predict personal income with a sample of 2000 Mexican Census is a panel data regression which includes a long list of fixed effects, in particular municipality fixed effects separately estimated for people living in the rural/urban part of a municipality. Table C2.1 provides a brief description of the regression used and just a couple of coefficients (as examples) for age and gender.

Table C2.1: Regression used to predict income levels

Dependent variable	Log(Personal income)
Age	-0.0089*** (0.0002)
Age squared	0.0001*** (0.00001)
Female	0.0033** (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. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%.

Appendix C3: Income quartiles and death causes

Table C3.1: Mortality rates and causes of death by quartile

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile	All quartiles
Daily mortality rate	1.4	1.54	1.25	1.05	1.3
Mortality of each income quartile by cause of death (as % of all deaths in quartile)					
Respiratory system diseases	10%	9%	8%	7%	9%
Circulatory system diseases	24%	24%	24%	25%	24%
Endocrine, nutritional and metabolic diseases	14%	18%	18%	16%	16%
Infectious diseases	4%	3%	3%	4%	4%
Neoplasms	11%	12%	14%	17%	13%
Accidents and violent deaths	13%	10%	11%	12%	11%
All other deaths	24%	23%	22%	19%	22%

Note: The daily mortality rates are in deaths per 100,000 inhabitants.

Table C3.2: Importance of specific diseases within the three categories of weather-sensitive causes of deaths

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile	All quartiles
Endocrine, nutritional and metabolic diseases:					
Diabetes mellitus	73%	84%	88%	88%	83%
Malnutrition	21%	10%	6%	5%	10%
Circulatory system diseases:					
Hypertensive diseases	12%	12%	12%	10%	11%
Ischaemic heart diseases	41%	46%	49%	52%	47%
Heart failure	11%	7%	5%	4%	7%
Cerebrovascular diseases	27%	25%	24%	23%	25%
Respiratory system diseases:					
Pneumonia, (organism unspecified)	29%	28%	28%	28%	28%
Other acute lower respiratory infections	4%	4%	4%	3%	4%
Chronic lower respiratory diseases	52%	51%	49%	47%	50%
Other respiratory diseases principally affecting the interstitium	4%	6%	7%	9%	6%

Note: Percentages correspond to the share of deaths entailed by a specific disease within its category, e.g. 73% of deaths from endocrine, nutritional and metabolic diseases are due to diabetes mellitus for the 1st quartile of income.

Appendix C4: Effect of temperature on mortality by income quartiles and cause of death

Table C4.1: Impact by income quartile and cause of death of a cold day below 10°C on cumulative 31-day mortality

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile	1st vs. 4th	First two versus last two
All causes	1.05*** (0.17)	1.03*** (0.12)	0.51*** (0.15)	0.23 (0.2)	+0.82*** (0.26)	+0.67*** (0.16)
Respiratory system diseases	0.31*** (0.05)	0.3*** (0.03)	0.08** (0.04)	0.09*** (0.03)	+0.22*** (0.06)	+0.22*** (0.04)
Circulatory system diseases	0.31*** (0.08)	0.39*** (0.06)	0.16*** (0.06)	0.08* (0.05)	+0.23*** (0.1)	+0.23*** (0.06)
Endocrine, nutritional and metabolic diseases	0.21*** (0.07)	0.2*** (0.05)	0.17*** (0.05)	0.19*** (0.06)	+0.03 (0.09)	+0.02 (0.05)
Infectious diseases	0.05 (0.03)	0.01 (0.02)	0.004 (0.02)	0.01 (0.01)	+0.03 (0.03)	+0.02 (0.02)
Neoplasms	-0.01 (0.06)	-0.04 (0.04)	0.08* (0.04)	0.06 (0.05)	-0.08 (0.08)	-0.10** (2.08)
Accidents and violent deaths	0.04 (0.07)	0.02 (0.05)	-0.04 (0.09)	-0.2 (0.17)	+0.24 (0.18)	+0.15 (0.11)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C on mortality, for specific quartiles and causes of death. The dependent variable is always the daily mortality rate in deaths per 100,000 inhabitants and all regressions include the daily precipitation level as control. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%. 312,140 groups, 30.1 observations per group. Reference day is 24-26 Celsius degrees.

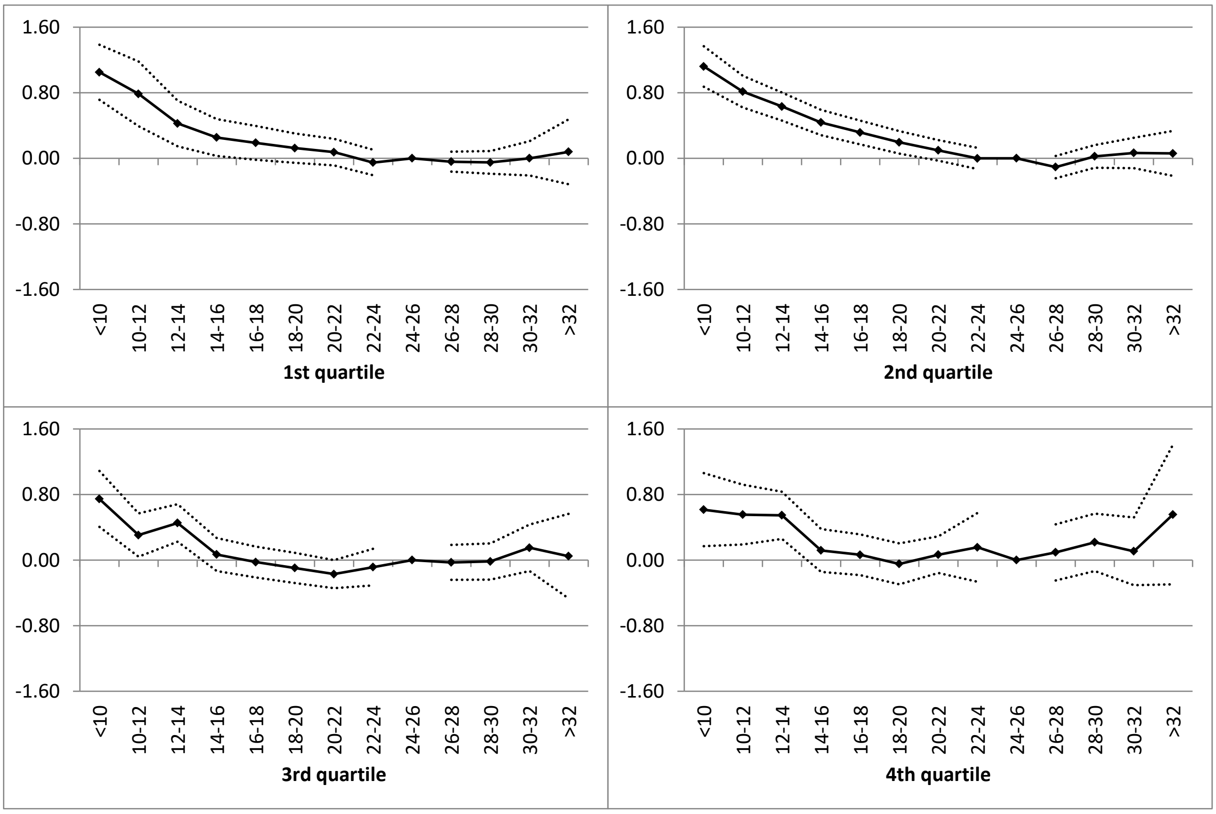
Appendix C5: Age-corrected regressions by income quartiles

For each quartile, we compute the total number of people with a given age in the Mexican population. We then create weights based on the relative age composition of the quartiles of income. We take the 1st quartile as a reference. For example, if there are twice as many people aged 63 in the 1st quartile as in the 4th quartile, we create a weight equal to 2 for the people aged 63 in the 4th quartile. We use these weights to produce age-corrected death counts for the 2nd, 3rd and 4th quartiles. In our example, one death of a person aged 63 in the 4th quartile would count as 2 deaths. This is because there are twice as fewer people aged 63 in the 4th quartile as in the 1st quartile of income. Therefore, if the age composition of the 4th quartiles was similar to the one of the 1st quartile, we could have expected the death of two people instead of one. We run regressions by quartile based on this correction. Note that, for people aged 100 or more, we have created one single age category since we had very few observations by quartile.

Figure C5.1 below presents the full results of the age-corrected regressions by income quartiles for all causes of death. Statistically significant impacts are found for all temperature bins below

16°C for the 1st income quartile, and below 20°C for the 2nd income quartile. Results stop being statistically significant after 14°C in the case of the 3rd and 4th income quartiles.

Figure C5.1: Impact of temperature bins on cumulative 31-day mortality, by income quartile after correcting for differences in age structure across quartiles



Notes. The results for each quartile are taken from separate regressions. Deaths have been weighted to account for differences in the pyramid of ages across quartiles, taking the first quartile of income as a reference. The dependent variable is the mortality per 100,000 inhabitants belonging to the quartile. The y-axis is mortality per 100,000 inhabitants and the x-axis corresponds to the cumulative impact after 31 days for each of the 2°C temperature bins in the regressions. The reference bin is 24-26°C. On-the-day precipitations are used as controls, along with by-month-by year-by municipality fixed effects. The dashed lines represent the 95% confidence interval for each estimated set of coefficients.

Table C5.1: Impact by income quartile and cause of death of a cold day below 10°C on cumulative 31-day mortality correcting for differences in the pyramid of ages across quartiles

Cause of death	1st quartile	2nd quartile	3rd quartile	4th quartile	1st vs. 4th	First two versus last two
All causes	1.05*** (0.17)	1.12*** (0.13)	0.75*** (0.17)	0.61*** (0.23)	+0.43 (0.28)	+0.36** (0.18)
Respiratory system diseases	0.31*** (0.05)	0.34*** (0.04)	0.10** (0.05)	0.21*** (0.06)	+0.10 (0.08)	+0.17*** (0.05)
Circulatory system diseases	0.31*** (0.08)	0.43*** (0.06)	0.26*** (0.08)	0.18* (0.10)	+0.13 (0.13)	+0.15* (0.08)
Endocrine, nutritional and metabolic diseases	0.21*** (0.07)	0.22*** (0.05)	0.22*** (0.06)	0.19** (0.10)	+0.02 (0.11)	+0.01 (0.07)
Infectious diseases	0.05 (0.03)	0.01 (0.02)	0.01 (0.02	-0.002 (0.02)	0.05 (0.03)	+0.02 (0.02)
Neoplasms	-0.01 (0.06)	-0.05 (0.04)	0.10* (0.06)	0.12 (0.08)	-0.13 (0.09)	-0.14** (0.06)
Accidents and violent deaths	0.04 (0.07)	0.02 (0.06)	-0.01 (0.09)	-0.11 (0.14)	+0.15 (0.15)	+0.09 (0.09)

Notes: All the coefficients come from a different regression and correspond to the 31-day long run cumulative effect of a day below 10°C on mortality, for specific quartiles and causes of death. The dependent variable is always the daily mortality rate in deaths per 100,000 inhabitants and all regressions include the daily precipitation level as control. Death counts and population levels have been weighted such that the pyramid of ages are comparable across age groups, taking the 1st quartile of income as a reference. Standard errors in brackets. *, **, ***: statistically significant at 10%, 5% and 1%. Reference day is 24-26 Celsius degrees.

Appendix C6: Effect of temperature on mortality by quartiles defined with a poverty indicator

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

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

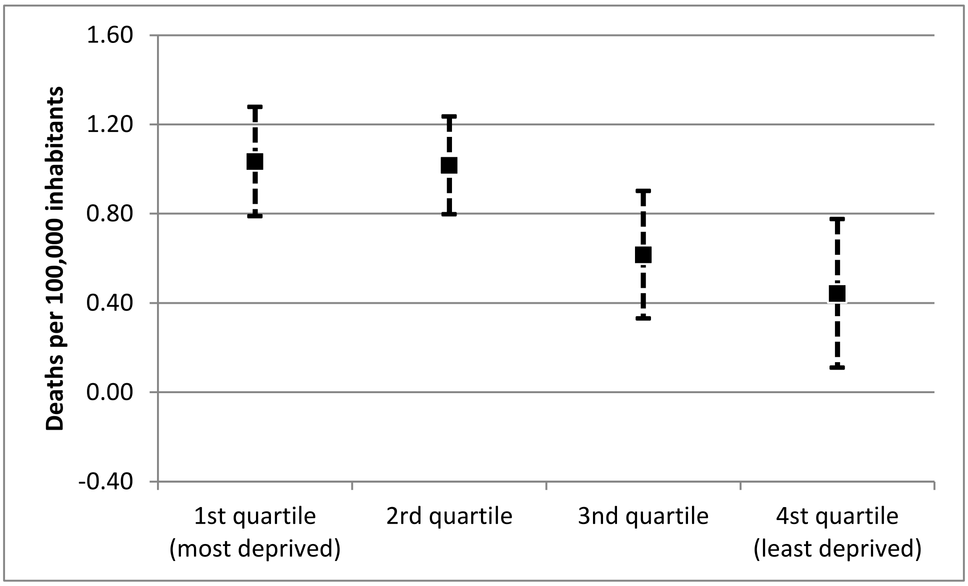
We construct an individual-specific poverty indicator based on the features used by CONAPO to classify localities by level of marginality. Since we want an indicator which is equally reflective of poverty for children and adults, we only consider the last five characteristics listed above (4-8): children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

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

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

The results of such process are presented below and confirm higher vulnerability for poorer households.

Figure C6.1: Impact by quartiles (based on poverty indicator) of a cold day below 10°C on cumulative 31-day mortality



Notes. The grey areas represent the 95% confidence interval for each estimated set of coefficients.

Appendix C7: Heating and cooling appliance ownership in the Mexican income and family expenditure surveys

We have gathered ownership data from the Mexican income and family expenditure surveys (*Encuestas Nacionales de Ingresos y Gastos de los Hogares*) for the following waves of the survey: 1998, 2000, 2002, 2004, 2005, 2006, 2008 and 2010. Questions are slightly different from one year to the other. In 1998 and 2000, the questions were:

- Do you have heaters in your home? If so, how many heaters do you have?
- Do you have air conditioning in your home? If so, how many air conditioners do you have?

In 2002, the questions were changed to distinguish central systems from individual appliances:

- Do you have central heating in your home?
- Do you have room heaters in your home? If so, how many?
- Do you have central air conditioning in your home?
- Do you have room air conditioners in your home? If so, how many?

For central heating and central air conditioning, respondents could answer “yes, of exclusive use”, “yes, shared” or “no”.

In 2004, 2005 and 2006, the same questions were asked but respondents could no longer precise if central heating or air conditioning was of exclusive use or shared. Answers were restricted to “yes” or “no”.

In 2008 and 2010, only two questions were asked:

- Does this house/flat have heating?
- Does this house/flat have air conditioning?

Respondents could respond either “yes” or “no”.

We provide summary statistics on appliance ownership at national level in Table C6.1. A further breakdown by Mexican State is provided hereafter.

Table C7.1: Ownership rates of heating and cooling appliances by income quartile

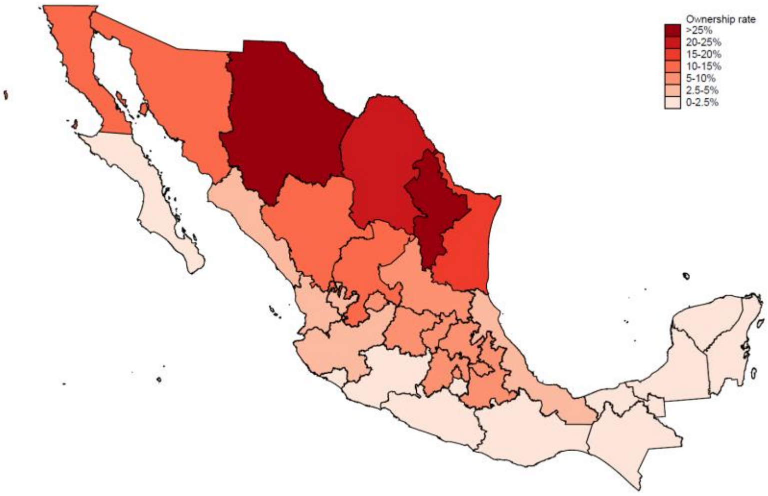
	Heaters and/or heating systems				Air conditioners and/or air conditioning systems			
Quartile	**1st**	**2nd**	**3rd**	**4th**	**1st**	**2nd**	**3rd**	**4th**
1998	0.6%	1.2%	2.0%	6.4%	2.3%	4.2%	8.5%	18.0%
2000	0.9%	1.5%	2.6%	8.6%	3.9%	7.8%	9.4%	22.0%
2002	4.0%	3.2%	3.9%	8.6%	4.8%	6.4%	10.4%	21.3%
2004	0.7%	1.2%	2.7%	9.7%	4.1%	7.9%	14.1%	27.1%
2005	0.6%	1.3%	3.0%	9.7%	3.8%	8.5%	14.3%	28.3%
2006	0.9%	1.7%	3.2%	10.7%	4.2%	8.9%	14.4%	29.2%
2008	0.1%	0.6%	1.1%	4.5%	4.9%	8.7%	13.7%	25.7%
2010	0.2%	0.5%	1.5%	5.1%	5.8%	9.6%	14.9%	28.1%
All years	1.0%	1.4%	2.5%	7.9%	4.2%	7.8%	12.5%	25.0%

Note: the left hand-side panel reports the ownership rate of heaters and/or heating systems by income quartile as reported in the Mexican national income and expenditure survey; the right hand-side panel reports the ownership rate of air conditioners and/or air conditioning systems. The questions vary from year to year, explaining differences in average level between years. For example 2002-2006 surveys distinguish between central and room appliances, others do not. See Appendix V for the exact questions. Consequently, it is unfortunately not possible to interpret the evolution across time by income quartile. Source: Encuesta Nacional de Ingreso y Gasto de Hogares, various years.

Figure C7.1: Share of households from 1st income quartile declaring that they have at least one heater in their house (2004-2006 survey)

Source: Encuesta Nacional de Ingreso y Gasto de Hogares (2004, 2005, 2006).

Figure C7.2: Share of households from 4th income quartile declaring that they have at least one heater in their house (2004-2006 survey)



Source: Encuesta Nacional de Ingreso y Gasto de Hogares (2004, 2005, 2006).

Figure C7.3: Share of households from 1st income quartile declaring that they have at least one air conditioner in their house (2004-2006 survey)

Source: Encuesta Nacional de Ingreso y Gasto de Hogares (2004, 2005, 2006).

Figure C7.4: Share of households from 4th income quartile declaring that they have at least one air conditioner in their house (2004-2006 survey)

Source: Encuesta Nacional de Ingreso y Gasto de Hogares (2004, 2005, 2006).

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