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

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<u>APPENDICES – FOR ONLINE PUBLICATION ONLY</u>

Appendices are divided into 4 sections: main appendices (A1 to A8), robustness checks (B1 to B8), impacts by quartile of predicted income (C1 and C2) and *Seguro Popular* (D1 and D2).

A – MAIN APPENDICES

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

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

High ambient air temperatures can cause increases in core body temperature that are associated with dehydration and the development of pathologies. In a review, Basu and Samet (2005)

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

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.²

As much as high temperatures can overwhelm thermoregulation, cold days can also prevent core body temperature from being maintained at 37°C. Very serious cases of hypothermia (<32°C) impair cardiac, cerebrovascular and respiratory functions, which can lead to loss of consciousness and death (Colon *et al.*, 2011). However, strong hypothermia is uncommon whereas mild cold below the comfort zone is a very common situation which affects several functions of the organism, in particular the circulatory and respiratory functions.³ Like in the

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

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

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.⁴ Likewise, malnourished people are vulnerable to cold due to lack of body mass and because core body heating requires the consumption of calories beyond the scope of what they may have in stock (Marriott and Carlson, 1996). In addition, some transmissible diseases develop more easily in cold environments. It is well-known that the transmission of air-borne viruses can be facilitated by low temperatures. Cold environments may also provide increased stability to enveloped viruses, such as influenza. This is why we observe waves of influenza throughout fall and winter. Colder temperatures may also encourage people to spend more time indoors, in closer proximity to one another and in poorly ventilated environments (Pica and Bouvier, 2014).

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

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

Appendix A2: Template of death certificate used in Mexico

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

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

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Figure A1: 2004 Template of a death certificate (source: INEGI)

Appendix A3: Summary statistics from the 2000 Mexican Census

Table A1: Socioeconomic characteristics of the Mexican population based on 2000 Census

Population	Personal income*	No social security	Completed secondary school [†]	Age	Male	Share of population
Total	2,876	58.6%	37.1%	26.2	48.7%	100.0%
Rural	1,433	83.7%	17.3%	25.0	49.6%	25.4%
Urban	3,330	50.1%	43.8%	26.5	48.4%	74.6%
By quartile of income:						
1st quartile	437	82.9%	18.6%	24.7	48.2%	25.0%
2nd quartile	1,155	60.8%	31.5%	24.5	48.7%	25.0%
3rd quartile	2,119	47.4%	42.3%	26.0	49.2%	25.0%
4th quartile	7,816	36.2%	59.7%	28.6	49.3%	25.0%
By type of profession						
Workers in agriculture, fisheries and hunting activities	1,552	87.1%	18.1%	38.2	92.7%	5.2%
Do not work (under 16)	2,371	62.5%	14.4%	7.7	50.0%	37.3%
Assistants in industrial and handmade production	2,397	62.1%	44.9%	28.5	85.3%	1.5%
Do not work (over 65)	2,647	49.4%	10.9%	74.4	36.5%	4.1%
Do not work (16-65)	2,648	62.4%	47.5%	34.3	21.2%	25.9%
Street vendors	2,679	81.4%	41.5%	38.6	68.8%	0.7%
Workers in industry of transformation	2,784	64.0%	46.9%	34.9	85.7%	5.5%
Workers in army and civil protection	3,059	21.4%	66.3%	36.5	94.3%	0.8%
Drivers of mobile machines and transports	3,061	54.6%	59.5%	35.8	99.3%	1.6%
Workers in personal services in institutions	3,116	47.0%	53.2%	34.2	60.4%	1.9%
Fixed machine operators	3,323	15.6%	61.3%	28.7	61.9%	1.9%
Domestic workers	3,753	78.2%	27.4%	34.0	12.2%	1.4%
Sellers, employees in trade and salesmen	3,817	57.9%	67.5%	35.0	60.6%	3.8%
Low-skilled workers in administrative tasks	4,124	24.1%	91.3%	31.0	38.4%	2.3%
Technicians	4,641	26.4%	91.4%	33.8	56.0%	1.0%
Overseers in industrial	5,045	16.4%	84.0%	34.4	79.7%	0.6%
production Workers in education		15.00/	00.00/	36.8	20.00/	1 40/
	5,662	15.0%	98.9%	36.8	39.8%	1.4%
Medium-skilled workers in administrative tasks	5,973	18.3%	93.5%	35.8	67.6%	0.8%
Workers in art, sports and events	6,176	58.0%	81.3%	34.7	74.9%	0.3%
Certified professionals	7,758	32.0%	99.8%	36.5	63.2%	1.3%
Public servants and directors	10,453	29.0%	95.8%	39.7	74.0%	0.7%

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

Appendix A4: Estimates using monthly data

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

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

Table A2: Impact of temperature on mortality using monthly data

Sample	1990-2017	1998-2017
Day below 12°C	0.188	0.191
	(0.019)	(0.023)
Day at 12-16°C	0.078	0.081
	(0.012)	(0.014)
Day at 16-20°C	0. 025	0.024
	(0.008)	(0.009)
Day at 20-24°C	-0.008	-0.010
	(0.006)	(0.007)
Day at 28-32°C	0.049	0. 052
	(0.009)	(0.011)
Day above 32°C	0.201	0.206
	(0.022)	(0.027)
Observations	676,635	468,887

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

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

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

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

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

Appendix A5: Estimation with 2°C bins

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

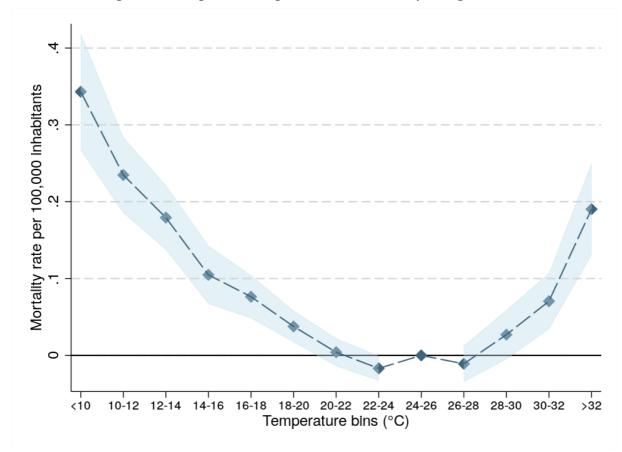


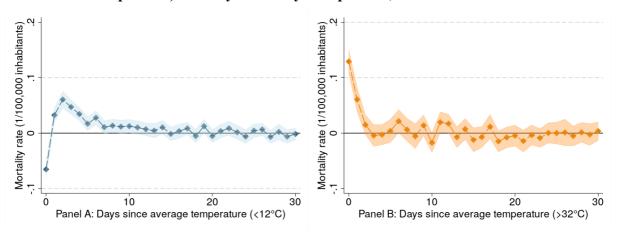
Figure A2: Impact of temperature on mortality using 2°C bins

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

Appendix A6: Short-term dynamics

In Figure 2, we calculated the overall mortality impact of temperature after 30 days. Below, we display the separate effect of unusually cold and hot days on the day of the weather event and for each of the following 30 days. During a cold day, the observed mortality on the day is in general lower, probably because people go out less, and are therefore either less likely to report a death or less likely to expose themselves to health risks on an unusually cold day. However, this effect is small compared to the additional mortality that follows on the next days, probably because people contract weather-sensitive pathogens the health effects of which only become visible after a few days. By contrast, we find that a hot day above 32°C has a strong and immediate effect on mortality but this effect is statistically significant only for the first two days, after which coefficients tend to become systematically negative although not statistically significantly so.

Figure A3: Impact within 31 days of a cold day (<12°C – panel A) or a hot day (>32°C – panel B) on daily mortality rate per 100,000 inhabitants



Note: These two graphs are obtained from the same regression, considering all Mexican people and all causes of death (1998-2017). Unit is deaths per 100,000 inhabitants. Each diamond corresponds to an estimated coefficient from the distributed lag model for days below 12°C (Panel A) or above 32°C (Panel B). Shaded areas correspond to the 95 percent confidence interval obtained for each estimated coefficient. 14,231,164 observations. The regression controls for the daily precipitation level and includes day by month by year fixed effects, municipality by calendar day (1st January to 31st December) fixed effects, and municipality by year fixed effects.

Appendix A7: Years of life lost estimates

The estimates by age group are informative about the impact of cold on longevity. We calculate the annual total of years of life lost associated with outdoor temperature exposure for the Mexican population by using the life expectancy estimates of the Mexican life table of 2010 available from the Global Health Observatory data repository (WHO, 2010). Results are calibrated based on the death estimates of Table 3, which assume a population of 129 million (2017 estimate). Results are synthesized in Table A4. Deschenes and Moretti (2009) provide similar calculations of years of life lost for the US. In total, they find that people over 75 lose 106,405 years of life annually. However, the cumulative number of years of life lost in a year for children under 5 is only 5,410 (compared to 24,724 in Mexico). The impact of cold weather on infant mortality is therefore possibly higher in the case of Mexico. We also find high impacts for people above 55. This result implies that priorities for policy makers in both countries may have to be different. US policies to reduce weather-related mortality may need to focus on the elderly (>75), whereas emerging countries like Mexico may need to tackle mortality effects across a wider age range.

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

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

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

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

Appendix A8: Impacts of Climate Change

We calculate the number of weather-related deaths under climate change based on the output of the climate model GFDL CM3 for 2075-2099 (Universidad Nacional Autónoma de México. Centro de Ciencias de la Atmósfera. Unidad de Informática para las Ciencias Atmosféricas y Ambientales, 2014a, 2014b, 2014c). Annual death estimates under climate change are provided in Table A5. Because the frequency of cold and mildly cold days is expected to decrease, the number of deaths imputable to temperatures reduces with the forecasted temperatures of GFDL CM3 as compared with the historical ones. With the RCP 4.5 scenario (low GHG emissions), temperature-related mortality would be about 27% smaller. The RCP8.5 scenario (high GHG emissions) corresponds to a 20% reduction in the estimated relationship between mortality and temperature. The reduction in weather-related deaths is smaller due to a surge in heat-induced deaths. While cold represents more than 90 percent of deaths today, it could represent less than 30 percent of deaths under RCP 8.5. We show in section IV that weather-related mortality affects mostly people in the first two quartiles of the income distribution, suggesting that the reduction in the exposure to cold weather associated by climate change could lead to a reduction in mortality inequality. Therefore, in Mexico, we predict that climate change will reduce the impact of short-term weather variability on mortality, with significant health benefits. However, this analysis comes with serious warnings: climate change could also affect mortality through increased frequency of natural catastrophes and not only through temperatures; our analysis at the daily level does not allow for acclimatization; and we could be underestimating the impact of increased heat waves if the effect of heat grows non-linearly beyond 32°C days. In addition, our model includes municipality-by-year fixed effects and time fixed effects which control for income and for the general health of the population. Climate change may impact income, or the general health of the population, and these factors may in turn impact mortality.

Table A5: Impact of temperatures on annual deaths in several climate scenarios

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

Note: The 95% confidence intervals only take into account the uncertainty of the impact of temperature bins on mortality. They do not take into account the uncertainty of climate models in the distribution of daily temperatures. Estimates are for a population of 129 million inhabitants and, therefore, do not take into account population growth in Mexico.

B – ROBUSTNESS CHECKS FOR THE TEMPERATURE-MORTALITY RELATIONSHIP

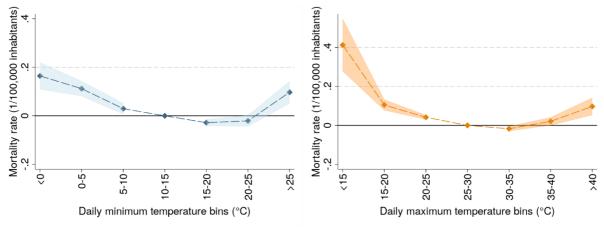
Appendix B1: Minimum and maximum temperatures

Minimum and maximum temperatures. In the baseline model, we correlate mortality with the average temperature in a day. No consideration is made for within-day variation. Yet, intra-day variation is large (see Table B1). To investigate this issue, we run a specification of the distributed lag model where we calculate separate effects for minimum and maximum temperatures (Figure B1). In both cases, we find the same typical U-shape relationship as when using the daily average temperature.

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

	Daily minir	num temperature	Daily maxir	num temperature
Temperature bin	Average	Standard deviation	Average	Standard deviation
<12°C	2.5	3.3	18.0	3.6
12-16°C	6.6	2.7	22.2	2.6
16-20°C	10.4	2.6	25.7	2.5
20-24°C	14.5	2.6	29.4	2.5
24-28°C	19.2	2.5	32.9	2.3
28-32°C	22.4	1.8	36.4	2.2
>32°C	24.9	1.9	41.3	2.0
Total	12.8	6.0	27.7	5.4

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



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

Appendix B2: Heterogeneous effects over time

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

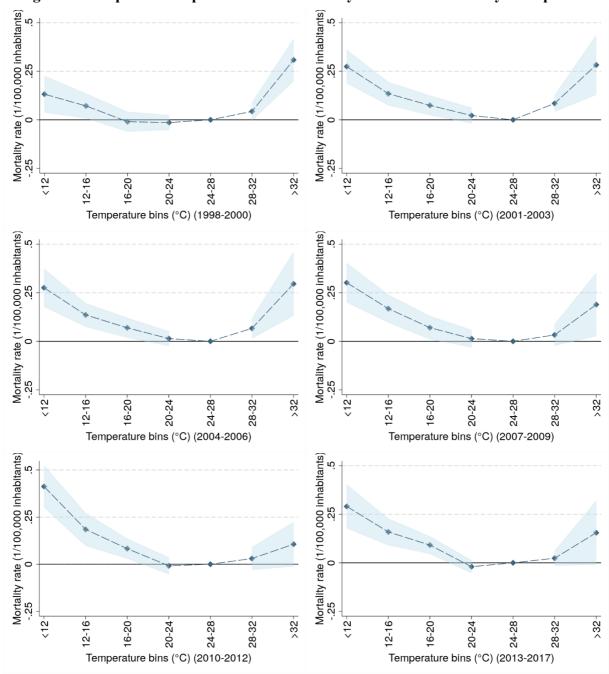


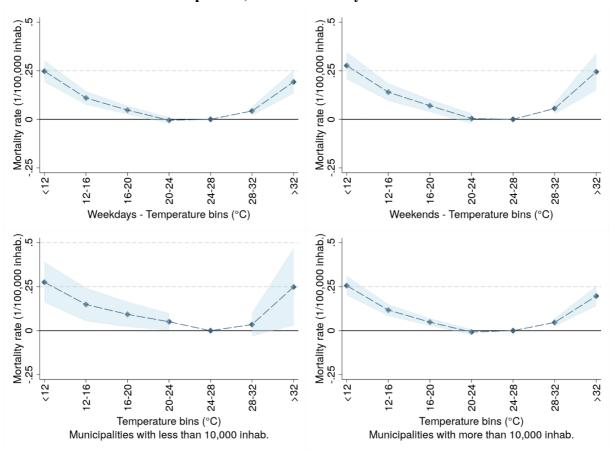
Figure B2: Impact of temperature bins on 31-day cumulative mortality for 6 periods

Notes: The graphs are calculated separately for six periods. They show the cumulative effect of a day with a temperature within each bin (relative to the 24°C-28°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. Shaded areas correspond to the 95% confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regressions controls for daily precipitation level and includes day-month-year fixed effects, municipality-by-calendar-day and municipality-by-year fixed effects. They are weighted by municipal population.

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

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

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



Notes. The graphs have been obtained separately. They show the cumulative effect of a day with a temperature within each bin based (relative to the 24-28°C category) obtained from a dynamic model with 30 lags. Regressions in the upper panels estimate the temperature-mortality relationship separately for weekdays (upper left panel) and weekends (upper right panel). Regressions in the lower panels estimate the temperature-mortality relationship separately for populations living in municipalities with less than 10,000 inhabitants (lower left panel) or more than 10,000 inhabitants (lower right panel). The diamonds show the sum of the coefficients on these thirty lags in each category. Shaded areas correspond to the 95% confidence interval. The dependent variable is daily mortality rate at the municipality level. The regressions control for daily precipitation level and include a range of day-month-year fixed effects, municipality-by-calendar-day fixed effects, and municipality-by-year fixed effects. All regressions are weighted by municipal population.

Appendix B3: Acclimation

Effects by climate region. The INEGI provides a detailed map of Mexico with a typology of 21 climates (INEGI, 2008b). We have simplified this typology and broken down Mexico into 3 climate categories (see Figure B4): very warm and warm (covering very dry, dry, semi-dry, humid and semi-humid regions that are also very warm and warm); semi-warm; cold and temperate (covering cold, semi-cold and temperate regions).

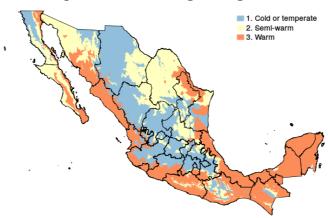


Figure B4: Map of Mexico distinguishing between climates

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

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

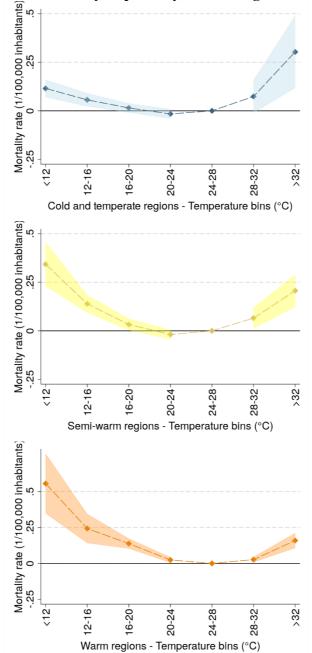


Figure B5: Mortality impacts by climate region in Mexico

Notes: The graphs show the cumulative effect of a day with a temperature within each bin (relative to the 24°C-28°C category) obtained from a dynamic model with 30 lags, for three different types of regions, sorted according to their climate: cold and temperate regions (upper panel), semi-warm regions (central panel), and warm regions (lower panel). The diamonds show the sum of the coefficients on these thirty lags in each temperature bin. Shaded areas correspond to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regressions control for daily precipitation level and include a range of day-month-year fixed effects, municipality-by-calendar-day fixed effects and municipality-by-year fixed effects.

Relative temperatures. Instead of using absolute temperature bins, we calculate deviations from the average temperature in each location to construct relative temperature bins with a 4°C window. The average temperature in each municipality is obtained by averaging all daily temperatures over 1961-2018. We then rerun our distributed lag model with the newly constructed temperature bins. These include deviations between -8°C and below and +8°C and above with respect to the average of each municipality. The 31-day cumulative results for all the population and causes of deaths are displayed in Figure B6. Results show a strong impact of cold and mildly cold days – relative to average temperature – on mortality.

Nortality rate per 100,000 inhabitants

Relative temperature bins (°C) (deviations from municipal average)

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

Notes. The graph shows the cumulative effect of a day with a relative temperature within each bin (relative to the 0°C to 4°C category) obtained from a dynamic model with 30 lags. The diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level. The regression controls for daily precipitation level and includes a range of day-month-year fixed effects, municipality-by-calendar-day and municipality-by-year fixed effects. It is weighted by municipal population.

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

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

Specification 1

Specification 2

Specification 2

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

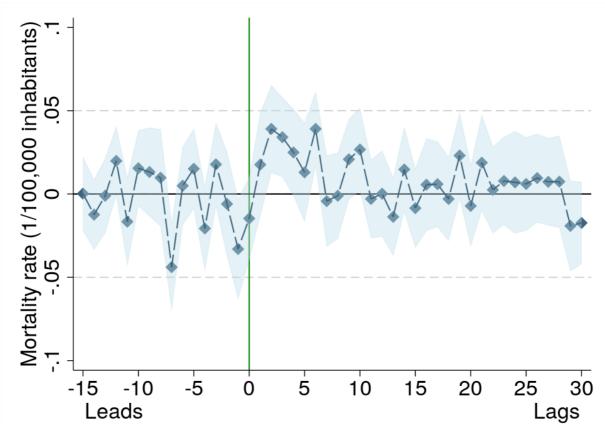
Notes. The graphs show the cumulative effect of temperature bins on mortality (relative to the 24°C-28°C category) obtained from a dynamic model with 30 lags, based on three different specifications. In all specifications, the diamonds show the sum of the coefficients on these thirty lags in each category. The shaded area corresponds to the 95 percent confidence interval. The dependent variable is the daily mortality rate at the municipality level and the regressions are weighted by municipal population. The regressions control for daily precipitation level and include different fixed effects: specification 1 includes day-month-year fixed effects and municipality fixed effects; specification 2 includes day-month-year fixed effects and municipality-by-calendar-day fixed effects; and specification 3 includes day-month-year fixed effects and municipality-by-year fixed effects.

Specification 3

Appendix B5: Temperature leads

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

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



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

Appendix B6: Contemporaneous model

Due to an omitted variable bias, correlating today's temperatures with today's mortality will lead to biased estimates of the impact of temperature on mortality if no account of the temperatures of the previous days is made. Figure B9 displays the impact of the day's temperature on mortality for the whole Mexican population and all causes of death when no lagged temperature bins are included in the model. This can help the reader assess the magnitude and the direction of the bias produced in this case. The model with only contemporaneous temperatures underestimates the effect of cold.

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

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

Appendix B7: Considerations regarding omitted variable bias

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

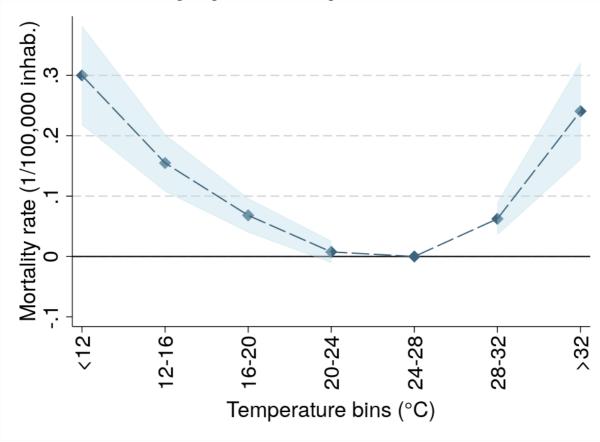


Figure B10: Cumulative 31-day impact of temperatures when controlling for lagged precipitations and evaporation levels

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

Controlling for pollution (Mexico City only). Another issue could be that our results are driven by air pollution or by the interaction between air pollution and temperature. We collected data for outdoor air pollution for Mexico City, where pollution is monitored for several pollutants and daily information on air quality is directly accessible from the Dirección de Monitoreo Atmosférico (1998-2017). The Mexican air quality index data (IMECA) has been downloaded from their website for the period 1998-2017 and we use the data for Central Mexico City as a control variable in our distributed lag model. For this purpose, we produced 4 air quality bins and 30 daily lags for each. We then run the model on all the municipalities located in the

Mexican Federal District. The left panel of Figure B11 displays the impact of temperature on mortality for the Federal District. The maximum temperature bin in Figure B11 is "above 24°C" because Mexico is in the mountains and temperatures rarely go beyond that point. The solid line is the effect obtained after controlling for pollution. The shaded area corresponds to the 95 percent confidence interval. For comparison, we also report the average effect of temperature for the Federal District when we do not control for pollution (dashed line). Results are very similar, suggesting that temperature and pollution convey two separate effects on mortality.

The right-hand side of Figure B11 reports the results obtained for the effect of pollution in Mexico City, using the Mexican air quality index data (IMECA). We have added 4 air quality bins and 30 daily lags for each to our baseline distributed lag model. We find significant mortality effects after 31 days caused by poor air quality (IMECA between 200-250). However, days with extremely poor air quality (IMECA over 250) are correlated with less mortality. These days are extremely rare (around 1 every 400 days), suggesting that people may adapt to these terribly polluted days (e.g. by not going out), explaining the lower mortality levels recorded in the data.

Mortality rate (1/100,000 inhabitants)

-2 . 4

-2 . 4

12-16

Nortality rate per 100,000 inhabitants

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

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

Temperature bins (°C)

Indoor air pollution could also be a confounding factor explaining our results. As already mentioned, there is no clear difference in estimates between rural areas (where wood might be sourced and used for heating) and urban areas (see Figure B3). Since 75 percent of the Mexican

population lives in urban areas,⁵ our results cannot be primarily driven by the interaction between temperature and indoor pollution through the use of solid fuels for heating (or cooking). However, the use of solid fuels could still be a contributing factor explaining high vulnerability in Mexico. In the national Income and Household Expenditure Surveys, 15.5 percent of Mexicans used wood (15.24 percent) or coal (0.21 percent) as the main cooking fuel in 1998. This proportion is stable over time: in the 2010 survey, 14.4 percent of households were using either wood or coal, and 14.5 percent in 2016.

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⁵ Own calculation based on 2000 Census data.

Appendix B8: Comparison of our main results with related studies

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

The estimates by Deschenes and Moretti (2009) are in line with those obtained in other studies for the US. Barreca (2012) finds that a day between 40°F and 50°F (4.4-10°C) increases the monthly mortality rate by 4.5 people per 100,000 inhabitants. This corresponds to a daily mortality rate of 0.15 people per 100,000 inhabitants (95% confidence interval = 0.09-0.22). Using annual data, Deschenes and Greenstone (2011) find that a day between 40°F and 50°F (4-10°C) increase mortality by 0.27 deaths per 100,000 inhabitants as compared to a day between 50°F and 60°F (10-15.5°C).

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

However, Barreca (2012) and Deschenes and Greenstone (2011) do find a mortality impact of hot days: respectively 0.17 and 0.92 deaths per 100,000 inhabitants for temperatures above 90°F (32°C). The impact found by Barreca (2012) using mortality data is therefore comparable to ours in magnitude. As for Deschenes and Greenstone (2011), they use annual data over a long time period (1968-2002) so as to capture indirect effects of temperatures on mortality through other channels (e.g. agricultural and industrial output, and therefore income, employment,

access to healthcare, etc.). Their estimates would indicate stronger vulnerability in the US but are not as easily comparable to our results, not only because we use with daily data but also because we look at a different time period.

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

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

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

We may compare these figures with ours, taking into considerations that our study uses daily data and therefore is not fully comparable. The average daily mortality rate is around 1.36 deaths per 100,000 inhabitants in Mexico. Converted to an annual rate, this corresponds to about 496 deaths per 100,000 inhabitants. In this context, our estimate of an extra 0.26 deaths per 100,000 inhabitants caused by a day below 12°C roughly represents a marginal increase of about 0.05% in the annual death rate. Likewise, the estimate of 0.20 deaths per 100,000 due to a day above 32°C corresponds to a marginal increase in the annual death rate by 0.04%. The relative impact of cold and heat on mortality in Mexico seem much lower than in India.

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

C – IMPACTS BY QUARTILES OF PREDICTED INCOME

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

Income is not reported on death certificates. We use data from the 2000 Mexican census to estimate income levels at the moment of death in our mortality dataset.⁶ To do so, we run a simple regression with data from the Mexican census where we predict income y_h of each individual h with a series of independent variables also present on death certificates. The regression used to predict income is:

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

Where y_h is personal income for individual h in 2000 Mexican pesos, calculated as total household income divided by the square root of the number of people in the household (to account for economies of scale within households). Because personal income has a skewed distribution, we take the natural log to improve the fit of the model and the accuracy of predictions. W_h is a vector of independent variables that include gender, age, civil status, occupation, education level and healthcare registration. It also includes a quadratic term for age and interaction terms between age (and age squared) and occupation to account for experience at work. $\omega_{i,r}$ is a fixed effect that takes into account that income may vary by municipality. Because professions are recorded with a different, non-comparable nomenclature from 2013 onwards, we performed the analysis with data from 1998 to 2012 only. Within a given municipality, we also distinguish between people living in urban areas (e.g. the city centre) and those living in rural areas. Thus, $\omega_{i,r}$ is a municipality i by-urban/rural area r fixed effect $(r \in \{rural, urban\})$. Finally, ω_h is an idiosyncratic error term and ψ is a vector of coefficients estimated from the regression. The regression coefficients are weighted using the weights provided in the publicly available sample of the 2000 Census, which includes about 10 percent of the Mexican Population. The output of this estimation is presented below.

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

Table C1: Regression used to predict income levels

Dependent variable	Log(Personal income)
Age	-0.0089
Age	(0.0008)
Age squared	0.0001
rige squared	(0.00005)
Female	-0.0037
	(0.0014)
Fixed effects:	
Civil status	Yes
Occupation	Yes
Social security affiliation	Yes
Educational level	Yes
Municipality and rural/urban area	Yes
Interactions:	
Civil status x gender	Yes
Occupation x age	Yes
Occupation x age squared	Yes
R2	0.44
Number of observations	8,756,128

Notes. Cluster-robust standard errors at the level of municipalities in brackets.

The regression results are consistent with economic theory (higher experience or education is correlated with higher income) and the model captures a large share of the variation in revenues (R2=0.44).

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

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

The daily mortality rates by income quartile can be used to run separate distributed lag models for each income quartile.⁷ The advantage of this approach is its high flexibility since the mortality impact of each temperature bin is estimated separately for each income quartile. The results however rely on predicted income values due to the absence of such information on death certificates. The main drawback is a loss of precision in the estimates due to measurement errors in the dependent variable.

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

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

Defining quartiles with a poverty indicator. Instead of using income levels to create quartiles of population, we can use alternative metrics of wellbeing and living conditions. In Table 4, panels C and D, we use a composite indicator inspired from the marginality index of the Mexican Council of Population (CONAPO).

The index of the CONAPO classifies localities according to their degree of marginality (from very low to very high) and has been used by government to design social policies. The indicator of the CONAPO relies on eight variables available from the Mexican censuses. The Council calculates (1) the share of the population of aged 15 or more who is analphabetic; (2) the share of the population of aged 15 or more who did not complete primary education; (3) the average number of occupants per room; (4) the share of households without exclusive toilet; (5) the share of households without current water

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⁷ Even though we are using predicted mortality rates, standard errors using clustering are valid and there is no need for bootstrapping: this is because these predicted rates are used as the dependent variable. Using predicted instead of actual values therefore increases measurement errors in the dependent variable and this directly affects the statistical power of our regressions.

within their property; (7) the share of houses or flats with earthen floor; and (8) the share of houses or flats with no refrigerator.

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

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

Once the indicator has been computed for each person in the sample of the 2000 Census, the exact same methodology is applied as for income to create quartiles and age-corrected quartiles. In short, we run a linear regression to predict the value taken by the poverty indicator based on a series of observables that are both present in the Census and in the mortality data. We then make out-of-sample predictions of the indicator on the deceased to proxy living conditions at the moment of death. Then, we separate the population of the deceased and the living in quartiles (from low to high living conditions) and run the econometric model separately by quartile (see Table 4, panels C and D).

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

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

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

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

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

D – SEGURO POPULAR

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Using annual information on the availability of the Seguro Popular (instead of the monthly information). We have assumed that, after using municipality by year fixed effects, the month of introduction of the Seguro Popular in municipality i (e.g. February versus March) is exogenous. This allows us to control for the introduction of the policy in the model with interactions. We check that this led to no substantial bias in the estimation of the interaction parameters. Below, to construct the interaction parameters between the Seguro Popular and temperature, we use an alternative variable that takes the value of 1 in municipality i and year t if, during this year or the previous years, someone has died in this municipality while being

covered by the *Seguro Popular*. The variable is therefore invariant at monthly level and absorbed by the municipality by year fixed effects. However, we can still assess the impact of the interaction terms between this variable and the temperature bins. In Table D3, we reproduce some of the results of Table 5 with this variable. Results lose precision but point estimates are similar to our baseline results: i.e. colder bins, especially days between 12 and 16°C, would lead to a reduction in mortality.

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

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

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

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

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

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

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

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

To increase precision, we interact the average income per capita⁸ in each municipality with our policy variable (see Table D6). Results seem to confirm that the effect of the *Seguro Popular* on weather vulnerability has been stronger in poorer municipalities.

⁸ The average is based on the 2000 census. It is obtained by dividing household income by the square root of the number of people that compose the household. The 99th percentile of income is excluded from the calculation of the average. The population-weighted average for this variable is 2,046, with a

standard deviation of 903.

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

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

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

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

-0.187***	
(0.056)	
-0.041	
(0.028)	
-0.031	
(0.028)	
-0.018	
(0.021)	
-0.005	
(0.031)	
-0.0002	
(0.105)	
0.089***	
(0.029)	
0.008	
(0.012)	
0.006	
(0.011)	
0.011	
(0.009)	
-0.010	
(0.012)	
0.050^{*}	
(0.029)	

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

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