Figures

LATIN AMERICA
AND CARIBBEAN

BACKGROUND NOTE 2. VALUING MORTALITY ATTRIBUTABLE TO CLIMATE CHANGE IN ARGENTINA

World Bank Group

COUNTRY CLIMATE AND DEVELOPMENT REPORT

November 3, 2022

Table of Contents

1. Introduction 3
2. Empirical strategy 8
   - 2.1. Benchmark model 8
   - 2.2. Climate change estimation 9
   - 2.3. Number of deaths due to extreme temperature and its change 9
   - 2.4. Mortality damages attributable to temperature extremes and their change 10
3. Data 11
   - 3.1. Mortality rate 11
   - 3.2. Meteorological records 11
   - 3.3. Climate change 12
   - 3.4. Valuation 13
4. Results 15
   - 4.1. Mortality rates 15
   - 4.2. Extreme temperatures: deaths and economic damages 17
   - 4.3. Robustness checks 18
5. Conclusions 20
6. References 22

Appendix 25

Background Note 2. Valuing mortality attributable to climate change in Argentina

Prepared by Christian García-Witulski (UCA), Mariano Rabassa (UCA), Mariana Conte Grand (WBG), and Julie Rozenberg (WBG)

This manuscript analyzes the effect temperature on human mortality rates in Argentina. The study rests on nonparametric techniques applied to data with a panel structure to estimate the causal effect of temperature extremes on mortality. Monthly mortality rates for municipalities, constructed from the universe of deaths between 2010 and 2019 were regressed on monthly temperatures, precipitation, and municipality-by-month and month fixed effects. Separate regressions were carried out to examine the heterogeneous impacts by age and gender. We also explore alternative specifications as well as differences by aggregate death causes. Results show that extreme temperatures increase mortality rates relative to mean temperatures, and the impact of colder-than-average temperatures in slightly greater in magnitude than that of hotter ones. There exists substantial heterogeneity between age groups, with older people facing greater risks while results for gender and proxied income level is inconclusive. All days of extreme cold cause associated death damages equivalent to 0.5% of GDP, while heat damages correspond to 0.1% of 2019 GDP. On the other side, when climate change impacts are valued, damages total 0.2% of GDP in scenario 8.5 since saving due to less mortality occurring in cold day compensate only partially the increase in the number of hot days.

Keywords: temperature; climate change; mortality; value of a statistical life; Argentina

JEL codes: I18, Q51, Q54

1. Introduction

Climate change represents a major threat to human beings and other forms of life on our planet. The potential impact of climate change on the social and environmental determinants of health outcomes is at the heart of both scientific and policy making efforts. The World Health Organization (WHO) reports that climate change is expected to cause approximately a quarter million additional deaths per year worldwide between 2030 and 2050 due to climate-sensitive diseases as, malnutrition, diarrhoea, malaria and heat stress (WHO 2022).

Presently, the global mean temperature is approximately 1.1 degree Celsius above the pre-industrial (1850-1900) era (WMO 2021). There is strong agreement among scientists in the research community regarding the human influence on the observed and predicted changes in temperature and precipitation patterns. Compared to 1850–1900, global surface temperature averaged over 2081–2100 is very likely to be higher by 2.1°C to 3.5°C in the intermediate GHG emissions scenario (SSP2-4.5) and by 3.3°C to 5.7°C under the very high GHG emissions scenario (SSP5-8.5) (Zhongming et al. 2021). Understanding the effects that extreme temperatures could have on human health is key to promote both effective adaptation policies to rising temperatures from climatic change, and mitigation policies around the planet.

The potential impacts of weather changes on mortality are usually divided in two categories: direct effects (i.e., those produced by temperature increases) and indirect effects arising mainly from changes in vector-borne diseases and food security or increases in weather-related natural disasters. There are in fact other indirect impacts: it is known that weather tends to affect economic growth, energy consumption, agricultural production, labor productivity and pollution levels and all those impacts would likely produce a feedback effect towards worse health (Deschênes & Greenstone 2011).

Across the literature, some articles limit themselves to study the present sensitivity of mortality at different temperature levels (e.g. Otrachshenko et al. 2017, for Russia) and others study also temperature mortality aspects due to climate change (e.g., Deschênes & Greenstone 2011 or A. I. Barreca 2012for the US; Burgess et al. 2017 for India; or Yu et al. 2019 for China). The few articles that study climate change impacts on mortality use some of IPCC greenhouse gases emissions' scenarios projections (Representative Concentration Pathways: RCP2.6, RCP4.5, RCP6.0 or RCP8.5[1]) o alternative scenarios. For example, Yu et al. (2019) consider two extreme pathways, RCP2.6 and RCP8.5, whereas Burgess et al. (2017) take the Hadley CM3 A1F1 scenario that authors affirm corresponds to a business-as-usual trajectory, and Deschenes (2018) follow the CCSME3 A2 scenario.

A U-relationship between thermal ambient levels and mortality has been extensively documented in the literature. The causal effect of temperature on mortality rates is usually non-linear. That is the reason why nonparametric models estimated by ordinary least squares have been widely applied (Basu 2009). There are several alternatives to account for nonlinearity: log linear functions (e.g., Curriero et al. 2002); polynomial functions (Basu & Samet 2002); splines, which are piecewise polynomial functions (e.g., Kaiser et al. 2007; Doyon et al. 2008; A. I. Barreca 2012; A. I. Barreca & Shimshack 2012); or, bins (Deschênes & Greenstone 2011; Otrachshenko et al. 2017; Deschenes 2018; Yu et al. 2019, among others).

Bins are among the alternatives more widely used in the literature to capture the non-linear relationship between temperature and mortality rates. They arise from discretizing the temperature in parts. The binned result is in terms of the time unit selected. For example, if daily temperatures in a month within a year are used, then the marginal effect for a given bin is the additional effect of "one more day" for

[1] For a more detailed description of scenarios characteristics, see Meinshausen et al. (2011).

which the temperature falls into that bin. The main advantage of bins over the other ways of capturing non-linearity is that they offer a very flexible functional form that allow each temperature bin to have a different impact on mortality. In addition, since most of the recent papers in economics use bins, we follow that same approach to ease the comparison.[2]

As highlighted by several authors as Deschenes (2014) or Son et al. (2019), even when we restrict our review to those articles that use bins, it is not easy to compare the results because of several reasons. There are many differences among studies related to: the units of measurement of mortality rates and weather conditions as well as on valuation methodologies.

First, in general with respect to deaths, since heat or cold related illnesses are not coded separately under the International Classification of Diseases, studies typically relate all-causes mortality to ambient measures of weather. In addition, some articles use monthly mortality (A. I. Barreca 2012, for example), while others use yearly mortality rates (Deschênes & Greenstone 2011; Otrachshenko et al. 2017; Yu et al. 2019, among others), and only a few use daily mortality (Cohen & Dechezleprêtre 2019).

Second, in what concerns meteorological conditions, temperature and precipitations are the most usual control variables included in the empirical studies. For temperatures, there is no homogeneous definition of what “cold day” or “hot day” is and so each of the studies divides temperature bins differently.[3] Since the mortality risk is expected to change with the level of temperature, comparisons loose precision. Another aspect is that most articles use mean temperature (e.g., A. I. Barreca 2012; Deschênes & Greenstone 2011, among others), and only in few cases, minimum or maximum temperatures are also considered for the regressions (e.g., Yu et al. 2019 or Cohen & Dechezleprêtre 2019).

Another variable that is something included in mortality-weather regressions is humidity (A. I. Barreca 2012). Other authors combine temperature and humidity in a “heat index” to capture “Apparent temperature” (Yu et al. 2019) and the results only change slightly. According to the review performed by Deschenes (2014, p. 609), adding precipitation or humidity “do not lead to meaningful changes in model estimates compared to models that only control for temperatures”. Yu et al. (2019) also find that the change in mortality estimates after including humidity in the model are “almost negligible”.

Third, once mortality impacts are calculated, a few articles estimate the annual total of years of life lost (Deschenes & Moretti 2009; Burgess et al. 2017; Cohen & Dechezleprêtre 2019). To do that implies leaving aside monetary valuation,[4] and differentiate life years lost depending on each age group life expectancy. To avoid valuation is not free of problems. As Deschênes & Greenstone 2011, p.183) explicitly state, people dying from extreme weather may not be the median citizen and so his/her life expectancy will like likely be lower than that of the average citizen. Another thing that may happen is that life expectancies may vary along time and that shift is not considered in this type of calculation.

Moving beyond life-years impacts requires an economic assessment. There are articles that use the present value of foregone earnings of a death among working population, which requires to know deaths by age group, income by age as well as labour force participation (Otrachshenko et al. 2017). This perspective is what is known as the human capital approach, and as such constitutes a lower bound, since productivity lost is only a component of the value of a statistical life, there are also utility

[2] Deschenes (2014, p. 609) states that “The temperature-bins approach is used in most economic papers in the literature, whereas in public health the spline approach is more common.” Another difference is that public health literature often uses time-series econometrics instead of individual level regression or panel data. Instead of a time series approach, we use repeated cross-sectional data (i.e., a panel) because we believe this approach might help overcome the problem of relatively short time series usually observed in Argentinian data.

[3] Moreover, some studies use statistical indicators to define a reference temperature to which all the days should be compared, whereas other opt for a definition based on “comfortable temperature”. As discussed in Otrachshenko et al. (2017, p. 291), “A typical range of the comfortable temperature limits for a human body is from 68 °F to 74 °F (20–23.3 °C) during the winter and from 73 °F to 78 °F (22.3–25.6 °C) during the summer”.

[4] Burgess et al. (2017) mentions product and wages losses, but do not combine economic analysis with life years lost.

losses when a life ends. Hence, present value of lost income neglects the value of leisure time and important subjective aspects and focuses only on pecuniary impacts of death. The full willingness derives from what is known as the Value of a Statistical Life (VSL) estimates.[5,6] In this case, an option could be to assign the same value of a statistical life -VSL- for all age groups, another would be to calculate the value of a statistical life per year (VSLY), which allow a differentiation of the value of life for people in different age groups since expected remaining years up to life expectancy varies by age group. Deschênes & Greenstone (2011) lead these types of estimations since it uses two alternatives: one is to assign a fixed value of a statistical life-year of $100,000 for the different years lost due to deaths in each age group and the other allows for the value of statistical life-year to be adjusted over time by a real per capita income growth of 2% per year and an elasticity of the value of the statistical life-year to income of 1.6. In any of those cases, as we will show in the next Section, the value can come from local data or from a transfer valuation adjusted by relative income and by the elasticity of VSL to income or both.

Although the existing studies use a variety of periods, models, mortality indicators, meteorological variables, the number and size of the weather bins, the reference bins, and ways to value, the great majority of publications find that temperature extremes lead to significant reductions in mortality. This assessment can be made more precise if we illustrate that with a few of those articles that use temperature bins with panel data and so are clearly related to our work.

Deschênes & Greenstone (2011) is representative of numerous studies for the US on mortality-temperature links. The authors find, for the 1968 to 2002 period, that an additional day with a mean temperature exceeding 90 °F leads to an increase in annual age-adjusted mortality rate of 0.11% per cent with respect to the one within the 50-60 °F interval. Similarly, a day with temperatures below 20 °F is associated with an increase in annual mortality between 0.07 and 0.08 per cent. When they take account for climate change, they estimate that mortality will increase 3 per cent by the end of the century.

Otrachshenko et al. (2017) analyze the case of Russia in the 1989-2014 period and find that one extra day with temperatures above 25 °C with respect to the 20-25 °C range increase yearly mortality by 0.06%, whereas an additional day with low temperature (below -30 °C) only decreases annual mortality by 0.01% and is not significant.[7] Using the present value of foregone income of working population, the authors estimate that an extra day of heat (cold) implies damages equivalent to 0.28% (0.22%) of daily Russian GDP.

Burgess et al. (2017) study the case of India for the 1957-2000 period and compare it to same results for the US. They find that 1 additional day over 95 °F with respect to the 70-74 °F bin in India increases annual mortality by 0.74% when that increase for the US is of 0.03% for the same years.

Yu et al. (2019) find for China between 2014-2012, that an extra day of heat (over 90 °F) over the 50-60 °F level increases annual mortality rate by 0.6%, whereas an extra day of cold (less than 10 °F) increases that mortality rate by 0.3%. The authors also show that climate change raises yearly mortality rates in 2.4% and 14.2% in scenarios RCP2.6 and 8.5 respectively. Using the VSL for China, the authors

[5] Schelling (1968) introduced the idea that valuing risk to life requires capturing individuals' willingness to pay for life-risk reductions (usually referred as the value of a statistical life or VSL). The concept of subjective value of the risk to life is defined as the marginal rate of substitution between risk and consumption: how much consumption the individual is willing to give up reducing his or her risk of dying.

[6] Two categories of methods are typically employed to capture VSL: indirect methods (based on revealed preferences) and direct methods (based on stated preferences). The former generally deal with hedonic estimations, relating wages to labor risks (see Viscusi & Aldy 2003) for a review). The VSL was more often assessed using hedonic pricing for the labor market (Viscusi 1978; Blomquist 2004). The latter method exposes the individuals to hypothetical scenarios of varying risk and cost in which they have to make choices. The idea of capturing the value of life based on directly approaching individuals appeared previously in the work of (Mishan, 1971). The most usual techniques are contingent valuation (CV) and choice experiments (CE). As is the case for hedonic pricing, CV has been extensively applied to health impacts valuation (Cropper et al. 2011).

[7] The authors believe that the result for cold days has to do with a decrease in accidents and diseases' interpersonal transmissions because people, under that type of weather, avoid going outdoors.

estimate climate change damages that account for 0.21% and 1.19% depending on two climate scenario projection.

In addition to the overall mortality result, the literature also discusses factors affecting vulnerability to temperature levels (Hajat & Kosatky 2010; Deschenes 2014; Benmarhnia et al. 2015; Son et al. 2019). One of the clearer ones is age. Elderly are known to face higher risks from cold and heat, which may be due to physiological conditions, housing or health access conditions as well as behavioral characteristics.[8] Findings suggest higher mortality impact from temperature levels in less qualified employees, among black population and unmarried persons (Son et al. 2019). Other individual-level modifiers as gender or education do not yield conclusive results, whereas lower income individuals tend to be more affected by temperature extremes.[9]

The literature analyses other determinants that have to do with community characteristics rather than individual ones. In that sense, there is weak evidence for higher heat related mortality associated with higher population density, poor housing facilities, and higher pollution levels. Additional factors, but also with unsubstantial evidence, are higher risks for heat: in urban areas; in communities with warmer climate; places with less proportion of green areas; etc. Some few studies also report higher vulnerability to cold weather: in regions with warmer climate, in places located in lower latitudes and in rural areas (Burgess et al. 2017). In an attempt to take into account those community factors, it is usual to find studies within this literature that test for regional subsamples (A. I. Barreca 2012 and Deschênes & Greenstone 2011) for different regions in the US; Yu et al. (2019) for different regions in China). From the available literature reviews, it is possible to conclude that, except for the age factor, the rest of the determinants of temperature-mortality sensitivity are location and population sensitive, from where the importance of performing local studies.

This study makes two novel contributions. Firstly, it adds to the limited existing literature on climatic determinants of mortality in developing countries and in Argentina. A literature review on temperature-related mortality between 1980 and 2017, Son et al. (2019) show that most of the studies focus on North America, Europe and Asia, and "many nations, including most in Latin America and Asia, had no studies". Argentina is an interesting case in its own right because it has a vast territory with diverse weather. The wide range of altitudes, that go from high mountains along the Andes plains on the Atlantic coast, contribute to that diversity.[10] The weather is mild in the Pampas, cold in the western Patagonia, subtropical in the Mesopotamia region, and warm in the Northeast. Along the Andes (located in the West), are the coldest areas, with dry and snowy weather.

A few studies have documented the influence of weather on human mortality in Argentina. Of those, the ones that are closers to our work are Almeira et al. (2016), which reports a U-shaped relationship between temperature and mortality for the cities of Buenos Aires and Rosario, and de Garín & Bejarán (2003), that examines the effect of thermal stress during summertime (characterized by the relative strain index) on mortality rates in Buenos Aires city. [11,12] Although very informative, none of the existing

[8] Despite of that apparent clarity in the results, middle age groups are more affected than the elderly in some cases (this seems to happen for Russia according to Otrachshenko et al. 2017, p. 295).

[9] In addition to gender and education, Cohen & Dechezleprêtre (2019) also assess how the effect of temperature on mortality changes with income. They find for Mexico that 11% of annual deaths are associated to climate and that temperatures are more likely to kill people in the bottom half of the income distribution. Barreca et al. (2015) also studies the differences of mortality-temperature impacts across income deciles in the US. They find that cold and hot days impact the most in lowest deciles and the mortality influence of temperature is almost null in the top income deciles.

[10] Under the Köppen climate classification, Argentina has 11 different climate types (Rubio 2018): Humid Subtropical (Cfa, Cwa), moderate oceanic (Cfb), warm semi-arid (BSh), subtropical highland oceanic (Cwb), warm desert (BWh), cold semi–arid (BSk), cold desert (BWk), moderate Mediterranean (Csb), cold oceanic (Cfc), and tundra (ET).

[11] Other studies, are Chesini, Abrutzky, Herrera, et al. (2019) for the mortality associated to extreme cold in Argentina, Chesini et al. (2018) and Chesini, Abrutzky, & Titto (2019) for heat, but they use very different methods, based on time series instead of on panel data.

[12] Other studies for Argentina focus on the impact of meteorological variables on morbility. Using data from emergency room visits at a hospital in central Buenos Aires, Rusticucci et al. (2002) report the association between weather conditions and several pathologies for both winter and summer times during the 1996–97 season. Yet other studies have turned their focus to specific pathologies. Alexander (2013) studies the association between meteorological variables and diverse diseases in the calls to the public ambulance emergency service of the city of Buenos Aires during the years 1999–

work relating weather conditions and health in Argentina perform any economic valuation and this is our first contribution.

Secondly, we provide estimates of the incidence of climate change on mortality (and not only for the link between temperature and death rates). We do for the whole country (i.e., a sizable portion of the population), breaking the analysis by age and gender groups and using state-of-the-art panel data econometrics.

Third, we value mortality damages. In a context of climatic change, where resources must be allocated to promote adaptation to the new climate, comparable countrywide estimates of health impacts and the corresponding damages are indeed needed to develop a rational and sustainable adaptation policy.

The rest of the paper is organized as follows. Section II describes the empirical strategy implemented to value mortality impacts due to temperature variations. Section III describes the data. Section IV shows the estimation results in terms of mortality rate changes, consequent deaths and valuation of those impacts, as well as the robustness checks we perform. The last section V summarizes our findings, the policy consequences they have and discusses the limitations of our results.

2004. Piccolo et al. (2015) documented the relationship between asthma-related hospitalizations and meteorological variables in the city of Bahia Blanca. More recently, two studies for the city of Córdoba found that a higher daily mean temperature and a wider daily temperature range are important determinants of infectious diseases in both the upper and lower respiratory tracts, particularly among the elderly population and in low-income households enduring housing deprivation (Amarillo and Carreras 2012; Carreras et al. 2015).

2. Empirical strategy

The empirical strategy involves four different steps for the case of Argentina. First, estimate a model that relates daily temperature in a recent period with the corresponding mortality rates. Second, calculate the change in temperature according to climate change projections. Third, estimate deaths attributable to extreme temperatures in the benchmark period as well as the ones resulting from climate change. Fourth, value deaths using the value of a statistical life.

2.1. Benchmark model

Our benchmark model is described by the following equation:

$$MR_{dmta} = \beta_0 + \sum_{j=1}^{6} \theta_{aj} \cdot TEM_{dmtj} + \sum_{z=1}^{4} \lambda_{az} \cdot PRE_{dmtz} + \mu_m + \omega_{dm} + \varepsilon_{dmta} \quad [1]$$

where MR_{dmta} is the mortality rate per 100,000 inhabitants in municipality or district *d* (which belong to a given state or province) in month *m* in year *t* for a give age-group *a*. TEM_{dmtj} is the number of days in each district *d* per month *m* per year *t* that fall in each temperature bin *j*, and PRE_{dmtz} is the number of days in each district *d* per month *m* per year *t* that fall in each precipitation bin *j*. As in several articles in this literature (Deschênes & Greenstone 2011; Deschenes 2018), the temperature range was divided in 10 degrees Fahrenheit (°F) bins.[13] The temperature bin taken as the reference is the one of 70-80 °F (≈21.1-26.6 °C), that corresponds to the mode of the frequency distribution of days in a month that fall into each of the bins. Then, μ_m stands for month time effects that allow controlling for potentially confounding effects common to all municipalities that vary overtime, for example macroeconomic shocks affecting the countrywide economic performance, which might affect health outcomes. Finally, ω_{dm} is an interaction term, which captures temporal variations between municipalities due to differences in air quality, income levels, educational attainment, and population density. Thus, these fixed effects could be interpreted as a baseline estimate of mortality rates in each municipality (Barreca & Shimshack 2012). Finally, ε_{dmta} is an error term. Note that we use the monthly mortality to avoid the so-called "harvesting effect": i.e., we try to avoid the temporal displacement of deaths that occur that after a period of more deaths than expected because of the heat, follows a period of mortality deficit because it is likely that heat wave especially affected those whose health weak and so would have died in the short-term anyway. If less than a month was considered, we would likely overestimate the impact of temperature on mortality.

Our main estimate for the calculation of damages is in θ_{aj}, which can be read as the change in *MR* with respect to the *MR* in the temperature bin of reference, when the number of days in each of the other temperature bins varies by 1:

$$\Delta MR_{dmtaj} = \widehat{\theta_{aj}} \cdot \Delta TEM_{dmtj} \text{ , with } \Delta TEM_{dmtj} = 1 \quad [2]$$
$$\text{Hence, } \Delta MR_{dmtaj} = \widehat{\theta_{aj}}$$

Since the final unit of analysis is municipality (*d*) by month (*m*) in a given year (*t*), there will be a $\hat{\theta}$ for each age-group (*a*) for each temperature bin (*j*): $\widehat{\theta_{aj}}$. More specifically, we ran a model for all age groups and both genders, then, we estimate four regressions, one for each age group. In addition, we run alternative specifications. Finally, we perform some robustness check with the model including temperature and precipitation interactions; using the logarithm of the mortality rate; and, using monthly lagged bins.

[13] The precipitation range was partitioned in five bins of 4 millimeters (mm) of rain.

2.2. Climate change estimation

With the different values for $\widehat{\theta_{aj}}$ obtained from equation [1], we estimate how climate change modifies in each district *d* the number of days in a given month *m* of a certain year *t* that fall within each bin *j* (ΔTEM_{dmtj}), using climate scenarios for temperature change predictions for the future as compared to the present period. With those two inputs in hand, the change in the mortality rates due to the modification in the number of days that fit within each bin results from:

$$\Delta MR_{dmtaj} = \widehat{\theta_{aj}} \cdot \Delta TEM_{dmtj} \qquad [3]$$

More specifically, what is calculated to fulfil the objective of this work is the change in the mortality rates due to the shift in the number of extreme cold (*c*), heat (*h*) days, and both extreme types of weather (e), as:

$$\begin{aligned} \Delta MR_{dmtac} &= \widehat{\theta_{ac}} \cdot \Delta TEM_{dmtc} \\ \Delta MR_{dmtah} &= \widehat{\theta_{ah}} \cdot \Delta TEM_{dmth} \\ \Delta MR_{dmtae} &= \widehat{\theta_{ac}} \cdot \Delta TEM_{dmtc} + \widehat{\theta_{ah}} \cdot \Delta TEM_{dmth} \end{aligned} \qquad [3']$$

Note that *c* (for "cold") corresponds to *j* = bin <40 °F ($\approx$<4.4 °C), whereas *h* (for "hot") is *j* = bin > 90 °F ($\approx$> 32.2 °C).

2.3. Number of deaths due to extreme temperature and its change

Based on the changes in mortality rate from [2] and [3], we calculate the number of deaths that result from each of three circumstances (changes in cold days, heat days, and both extreme temperature days).

First, we calculate the number of deaths for the whole country resulting from an extra day within each of the bins with respect to the deaths occurring at the reference temperature bin based on equation [2],

$$\Delta Deaths_{aj} = \underbrace{\widehat{\theta_{aj}} \cdot}_{\Delta MR_{dmtaj}} \; 12 \cdot \frac{Pop_a^{2010}}{100\ 000} \cdot n_d \qquad [4]$$

Where $\Delta Deaths_{aj}$ is the change in the number of deaths in age-group *a* for each additional day of temperature within each bin *j*, $\hat{\theta}_{aj}$ are the estimated coefficients for average monthly mortality rate from equation [1], 12 are the number of months in a year (this converts monthly mortality to annual mortality), Pop_a^{2010} is the population of group *a* in 2010 (it is divided by 100 000 because $\widehat{\theta_{aj}}$ is the ΔMR_{dmtaj} in 100 000), and n_d is the number of districts in Argentina (because $\widehat{\theta_{aj}}$ is an average per district that has to be converted to a national estimate, $n_d = 511$.[14]

Second, to get the change in the number of deaths attributable to each bin temperature per year, we multiply [4] by the average number days in each bin per month during the period used for the estimation of the benchmark model (and then by 12, the number of months in a year):

[14] This is an underestimation that may be adjusted in the next version. As of 2020, there is the capital, 135 *partidos* y the Province of Buenos Aires, 380 *departamentos* in the rest of the country. The city Buenos Aires is not included in the results reported here. It will be added in the new version of this document.

$$\Delta Deaths_{aj} = \underbrace{\widehat{\theta_{aj}}}_{\Delta MR_{dmtaj}} \cdot TEM_{dmtj} \cdot 12 \cdot \frac{Pop_a^{2010}}{100\,000} \cdot n_d \qquad [5]$$

Third, we estimate the number of deaths attributable to the change in the number of days within each bin following equation [3] as:

$$\Delta Deaths_{aj} = \underbrace{\widehat{\theta_{aj}} \cdot \Delta TEM_{dmtj}}_{\Delta MR_{dmtaj}} \cdot 12 \cdot \frac{Pop_a^{2010}}{100\,000} \cdot n_d \qquad [6]$$

As it is clear from equations [4]- [6], overall, the total effect of climate change on deaths varies by the population within each age-group in the whole country and depends on the sensitivity of mortality to colder and hotter periods, on the number of cold and hot days in a year, and on how this changes when the distribution of temperature shift as the result of climate change. The economic valuation of such effects is the only step that remains.

2.4. Mortality damages attributable to temperature extremes and their change

Finally, the $\Delta Deaths_{aj}$ calculated in equations [4]- [6] are valued here using the value of a statistical life.

Even when there are non-market methods to assess the VSL as we mentioned above, they involve detailed data and sophisticated techniques, which require resources and knowledge. This may explain why there are relatively few estimates of VSL for low and middle- income countries, as this is widely acknowledged in the literature (see Robinson 2017, among others). However, there is an estimation of the VSL in Argentina (Picassso and Conte Grand 2019). The estimation is not in the context of health but of crime. However, we use it as an alternative because it is obtained with local data. To cover the uncertainty surrounding that applicability of that VSL for this case, we opt for an alternative: transfer values from studies in other countries. Based on them, we adjust VSL from other places (policy site: denoted by p) to Argentina, which is location of the study (s) relative per capita income (I_p/I_s) and the VSL income elasticity (η), as it is usual in the literature (Brouwer 2000) following:

$$VSL_p = (I_p/I_s)^{\eta} \cdot VSL_s \qquad [7]$$

Then, damages are obtained in each case as the product of $\Delta Deaths_{aj}$ and VSL_p.

3. Data

The first part of our estimation strategy outlined above relies on data for the 2010-2019 period:[15] death counts by administrative subdivision and weather records from meteorological stations Argentinean data. Then, for the second part of our empirical methodology, climate change is captured through the difference between 2010 (the year within the interval that corresponds to the last census done in Argentina) and 2085 distributions of temperature for Argentina as described in the *NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)*.

3.1. Mortality rate

The mortality data correspond to the universe of over 4 million deaths across the country in the period, as compiled by the *Dirección de Estadísticas e Información Pública*, the agency in charge of the *National System of Health Statistics*. The dataset reports each death along with the date of death, the gender and age, and the municipality of residence of the deceased. Thus, death counts were aggregated at the municipal level, the smallest administrative subdivision in the dataset.

Death counts were supplemented with annual population estimates to construct monthly municipal mortality rates per 100,000 inhabitants, by gender and age-groups. Specifically, following Deschênes and Greenstone (2011) and Barreca et al. (2016), the population was stratified into four age groups (0-4, 5-44, 45-64, >64-year-olds).[16] Annual population numbers by municipality had to be interpolated from the 2010 national population census.

Average mortality rates are (per 100,000) approximately 21 inhabitants for children under 5 years of age, 8 for people between 5 and 44 years of age, 58 for adults between 44 and 65, and 413 for older adults. One should expect to observe the greatest impacts of extreme temperatures in the last group, given that it generally includes the most vulnerable people.

3.2. Meteorological records

Weather records were obtained from the *Servicio Meteorológico Nacional*, the official national weather and climatological agency. Daily maximum and minimum temperatures in degree Celsius (°C) as well as total precipitation in millimeters (mm) are reported for the 71 weather stations that comprise the *National Weather Station Network*. The monitoring network might seem to be sparse given the surface area and the degree of development of a country such as Argentina. However, according to the 2010 national census, the Argentinian population is mostly urban, with 91% living in towns bigger than 2,000 inhabitants, and half of the total population living in just 8 cities. Therefore, the 61 weather stations finally included in the analysis provide coverage to approximately 82% of the country's population.[17]

Daily station data had to be spatially interpolated at the municipal level to construct monthly weather exposure variables. Following a common approach in the literature, square inverse distance weights were calculated from each municipal geographical centroid to each station within a 100 kilometers radius (Hanigan et al. 2006). Thus, the interpolated weather variables are simply the weighted average of the stations' records within that radius (i.e., the closest monitoring station to a particular district is given more weight). Limiting the cut-off distance to 100 km was necessary to balance the number of municipalities included in the study while minimizing the potential measurement error that would otherwise be introduced by including distant stations. Despite districts were not included because of those reasons, they cover 84.9 per cent of Argentina's population. In general, monitoring stations are

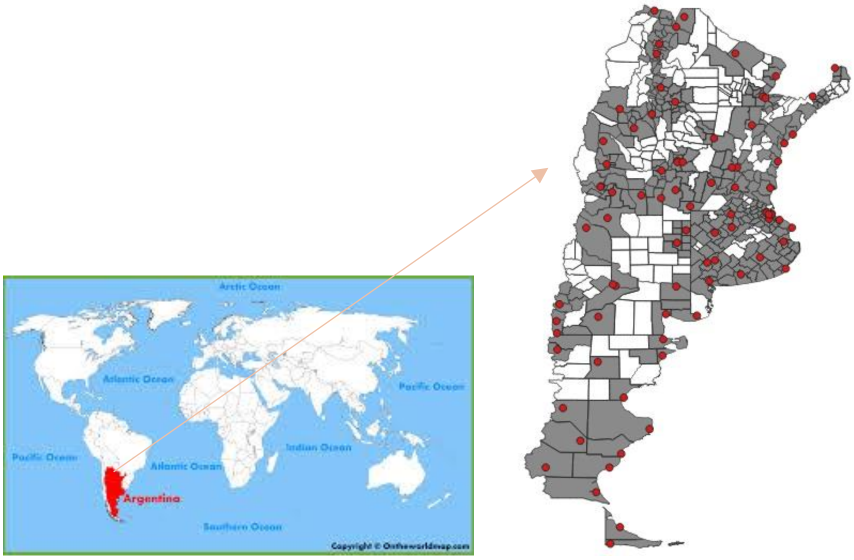
[15] This information was provided to the World Bank Team by the *Dirección de Estadísticas e Información en Salud* of the Argentina's Ministry of Health.

[16] Unfortunately, available information did not allow for the construction of separate mortality rates for infants, i.e., younger than one year old, who are known to be far more susceptible to thermal stress than other young children (Keim et al. 2002).

[17] This is consider enough given that the paper for China refers to 6% of the population and that for Russia covers 92% of the inhabitants.

not located where population is scarce. Similar cut-off levels have been used in empirical estimates for the United States (Deschênes and Greenstone 2011; Barreca 2012; Barreca and Shimshack 2012; Ranson 2014; Barreca et al. 2016). Figure 1 show the municipalities included in the study along with the location of the 71 weather stations.

Figure 1. Municipalities included in the study



Source: Own elaboration

Notes: The departments in white do not have a meteorological station close at less than 100 km from its center. However, those are places with few inhabitants, and that may be in fact the reason why they do not have a meteorological station close by.

3.3. Climate change

Climate change temperature data comes from the *NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)*. That database has daily minimum and maximum temperature as well as precipitation for the whole planet. The temporal coverage is from 1950 to 2014 historical data and 2015 to 2100 projected Shared Socioeconomic Pathways: RCP-4.5 and RCP-8.5. The RCP 4.5 is a moderate scenario where some effort to curb climate change is made but temperatures rise 2.7C globally by the end of the century, whereas RCP-8.5 projects that the global economy grows fueled by exploiting fossil fuels and energy-intensive lifestyles and by 2100 the average global temperature is 4.4C higher. Note that the temperature by 2050 under the 8.5 scenarios would be similar to that of the 4.5 projection to the end of the century.

The spatial resolution of *NEX-GDDP* is approximately 25 degrees x 25 degrees. We took the daily information for temperature available within the geographical limits of Argentina and average it for both 2010 and 2085.[18]

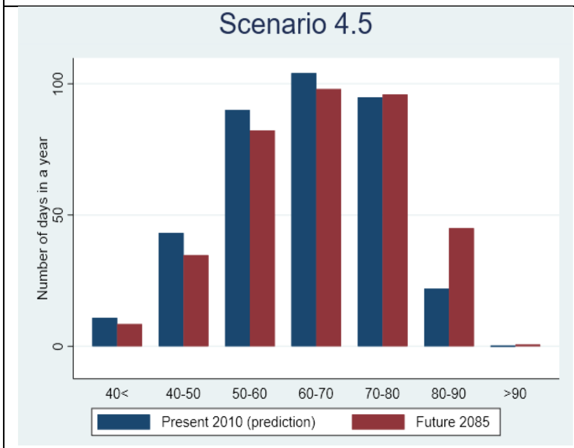
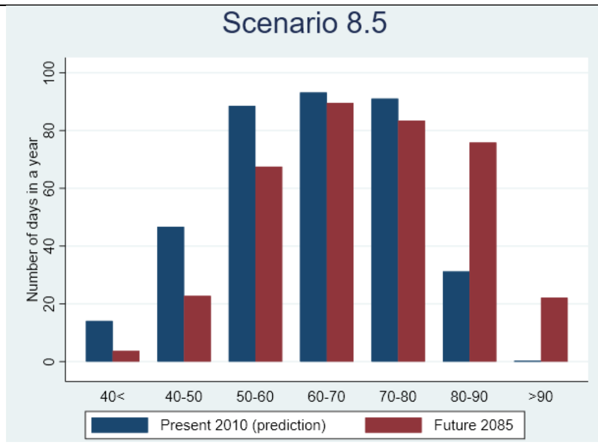
Then, as previously, the temperatures are assigned to each municipality. Figure 2 shows the shift in days within each temperature bin if the projected climate change takes place. What happens in that case is that, as expected, the average temperature increases and the number of cold days decreases while the number of hot days increases.[19] Scenario 8.5, since it projects more climate change, shows

[18] The geographical references for Argentina are as follows. North: Latitude 21o 46’ 52’’ S, Longitude 66o 13’ 17” O; South: Latitude 55o 03’ 21” S, Longitude 66o 31’ 25” O; East: Latitude 26o 15’ 59” S, Longitude 53o 38’ 15” O; West: Latitude 50o 01’ S, Longitude 73o 34’ O.

[19] Note that because NASA data are historical only up to 2014, there is a gap between the base 2010–2019 meteorological information used to estimate the temperature-mortality rate sensitivity and the temperature data from *NEX-GDDP*. This is a usual matter in this type of estimations (Yu et al. 2019). Figure A.1.in Appendix shows the gap between our local data and the *NEX-GDDP* model. For example, NASA data does not show days within the > 90 °F while local data does. Other studies correct that gap (Burgess et al. 2017), which we leave for future work.

a higher number of hot days than the 4.5 one. Those changes are not uniform across the whole country (Figure A. 2 in Appendix).

Figure 2. Change in the distribution of days within a year that fit into each temperature bin in 2010 and 2085 as projected by NASA

a) Scenario 8.5	b) Scenario 4.5
	

Source: Own elaboration

Note: Average temperature increase 2.2 F in RCP 4.5 and 6.8 F in RCP 8.5. RCP 4.5 at 2085 is approximately RCP 8.5 at 2050. Prediction in 2010 is NASA information, which differs from the national information used to estimate the coefficients of our model. Figure A.1 in Appendix shows that discrepancy.

3.4. Valuation

Finally, for the Value of a Statistical Life, we use an estimation for Argentina from Picasso and Conte Grand (2019) that to our knowledge is the only one derived from local data. In addition, for robustness check, we transfer the VSL from estimates in the US (Viscusi and Masterman 2017) and from a global study by the World Bank in association with the Institute of Health Metric and Evaluation (World Bank and IHME 2016).

The local VSL is $1,5 million corresponding to 2014 (Table 1). The original US estimate is $9.6 million 2014 dollars, which transferred using the Argentina to US relative GDP per capita yields a value of $2.4 million.[20] Similarly, the World Bank estimate for OECD countries is $3.8 million, which transferred to Argentina becomes $1.98 million.

We update the estimates to 2019 dollars, which is the last year of our mortality data, and transfer them to Argentina's case adjusting by the relative GDP ratio among countries. Because of the uncertainty surrounding what is the best VSL, we perform a Montecarlo simulation. To do so, we assume a triangular distribution for VSL, with a minimum value, a maximum value and a mode of 1.2, 1.72 and 1.59 respectively.[21]

[20] For simplicity, in both transfers, we assume that the elasticity of value of a statistical to income is 1. *We will also assume uncertainty in last version.*

[21] Note that the values for 2019 are lower than the original studies because Argentina's per capita GDP has decreased from 2014 to 2019.

Table 1. Value of a statistical life used in our calculations

Reference Country, Year Units	Picasso and Conte Grand (2019) Argentina, 2014 *current million US$, 2014*	Viscusi and Masterman (2017) US, 2014 *Atlas method current million US$, 2014*	World Bank and IHME (2016) OECD, 2014 *PPP constant 2011 international $US*
Source, previous to any adjustment	1.5	*9.6*	*3.8*
Argentina per capita Atlas current million $US GDP 2014		12,460	
United States per capita Atlas current $US GDP 2014		55,980	
Argentina GNI per capita, PPP constant 2011 international $			19,101
GDP per capita Reference for the World Bank results (World Development Report, World Bank)	12,335		*37,000*
Argentina GDP per capita current $US 2019	10,006		
VSL adjusted	***1.5***	***2.14***	***1.98***
VSL en millones de dólares corrientes de 2019	***1.20***	***1.72***	***1.59***

Source: Own elaboration based on references

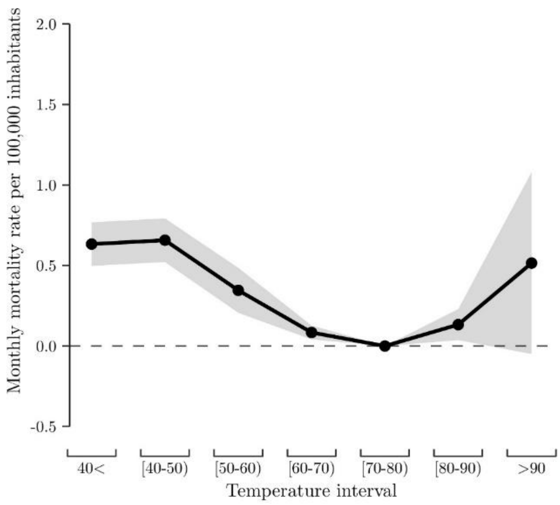
4. Results

This section is divided in two subsections. The first shows the estimates for the mortality rate temperature impacts for the whole population, by age-groups in the 2010-2019 period. The second subsection uses the estimated relationships to predict the impacts on annual deaths due to temperature extremes, its variation due to climate changes, and their valuation.

4.1. Mortality rates

The changes in mortality rates attributable to the 2010-2019 temperature profile are summarized in Figure 3. That figure presents the estimated exposure impacts computed by nonparametric regressions between mortality rates and temperature at the municipal level, controlling for precipitation levels and fixed effects by month and municipality-by-month (i.e., equation [1]) for all age-groups, genders, and regions. The results must be interpreted as the relative impact of daily mean temperature over annual mortality due to an additional day in a given month with temperature above or below the observed mode temperature bin during the 2010-2019 period (i.e., the 70-80 °F or 21.1-26.6 °C bin). Any day with a mean daily temperature above the reference temperature positively and significantly affects mortality rates. Days in the extreme cold temperatures (<40 °F bin) also shows a significant excess mortality with respect to the reference temperature.

Figure 3 Impact of temperature on average monthly mortality rates by district



Source: Own elaboration.
Note: The broader 95 confidence intervals are likely due to the fact that there are less observations, so less precision, in the extremes.

The U shape is usual in the literature (Deschenes and Greenstone 2011, for example). But, the U is not always perfectly symmetric. As Figure 3 suggests, for Argentina, the estimated impacts of colder-than-average temperatures are slightly higher than the computed estimates for hotter than average temperatures. In other countries as Mexico, the higher impacts are also associated to cold and slightly below mean temperature days rather than to heat (Cohen and Dechezlepretre 2020).[22] More precisely, a cold day (average temperature below 10 °C) cause 3.5 fives more excess mortality than a heat day

[22] The authors explain that result by the fact that in Mexico just below average mean temperature occur with cold nights and that induces high pathology risks.

(average temperature above 32 °C).[23] There are also few studies for which the U shape does not appear clearly (this is the case of Otraschsenko et al. 2017 for Russia, for example).

The last row of Panel A in Table 2 shows the same result as Figure 3 in a more detailed way. On average, an additional day with a relative cold day, one with a countrywide mean temperature between 30 and 40 °F (<-4.4 °C) increases the population-weighted average monthly mortality rate in 0.633 each 100,000 inhabitants with respect to the mortality for a day with the reference temperature, and that increase is significant. On the other side, an extra relatively hot day (> 90 °F or 32.2 °C) significantly increases that mortality rate by 0.515 in 100,000. If we were to calculate the difference between the curve in Figure 3 and the x axis, excess mortality due to a temperature different from the ideal everyday would be such that the annual mortality rate goes from 586 to 660 per 100,000 in a year.

Table 2. Impact of extreme temperatures on monthly mortality rate per 100,000 inhabitants (2010-2019)

Panel A. Estimates by age group °F	bin 40<	bin 40_50	bin 50_60	bin 60_70	bin 80_90	bin > 90
1. 0-4	0.197***	0.161***	0.088***	0.001	0.042	0.112
	(0.040)	(0.029)	(0.018)	(0.021)	(0.035)	0.238
2. 5-44	0.008	0.010	0.001	-0.005	0.040***	0.068*
	(0.010)	(0.006)*	(0.004)	(0.004)	(0.007)	(0.041)
3. 45-64	0.220***	0.367***	0.191***	0.005	0.069*	0.304
	(0.052)	(0.040)	(0.037)	(0.024)	(0.041)	(0.263)
4. >64	5.566***	5.542***	2.942***	0.841***	0.892***	3.958**
	(0.484)	(0.534)	(0.584)	(0.124)	(0.332)	(1.877)
5. Population-weighted aggregate estimate	0.633***	0.657***	0.346***	0.084***	0.133***	0.515*
	(0.069)	(0.069)	(0.071)	(0.022)	(0.049)	(0.288)
Panel B. Alternative specifications						
6. Women	0.645***	0.723***	0.343***	0.068**	0.103*	0.598
	(0.108)	(0.085)	(0.086)	(0.030)	(0.061)	(0.404)
7. Men	0.617***	0.665***	0.384***	0.098***	0.170***	0.492*
	(0.079)	(0.084)	(0.079)	(0.027)	(0.059)	(0.299)
8. Model with temperature interactions and precipitation	0.687***	0.756***	0.340***	0.107***	0.165***	0.400
	(0.103)	(0.072)	(0.071)	(0.023)	(0.049)	(0.271)
9. Model with the logarithm of the mortality rate	0.613***	0.649***	0.427***	0.104***	0.169***	0.542**
	(0.061)	(0.055)	(0.029)	(0.026)	(0.059)	(0.236)
10. Model with bin lags	0.511***	0.664***	0.365***	0.038	0.002	0.386
	(0.072)	(0.073)	(0.091)	0.035	0.067	0.423
11. Model with interaction bin 40< × percentil 10	0.743***†	0.653***	0.347***	0.083***	0.133***	0.515*
	(0.094)	(0.070)	(0.071)	(0.022)	(0.049)	(0.288)
12. Model with interaction bin >90 × percentil 90	0.631***	0.655***	0.343***	0.081***	0.124***	0.807**††
	(0.069)	(0.069)	(0.071)	(0.022)	(0.049)	(0.316)

Source: Own calculation

*Notes: * p<0.05, ** p<0.01. *** p<0.001. The estimate 5 in panel A corresponds to averages weighted by the population of each age group for the year 2010. The reference BIN is 70-80 °F. All specifications include precipitation bins, municipality and month fixed effects, and province by year fixed effects.*

Given that several factors can affect the sensitivity of mortality to temperature levels, regressions were stratified by age-group (Table 2, Panel A), income and gender (Table 2, Panel B) in order to examine potential heterogeneity in the temperature-mortality relationship. The elderly is clearly the age-group most affected by temperature since all coefficients are significant in all bins and are much larger than those corresponding to the rest of the age-groups and the population weighted average, as in the literature.[24] That impact for elderly is also larger for colder temperatures than for hotter ones. There does not seem to be a pattern regarding gender, which is in line with existing literature. Robustness checks do not show results very different from those for the whole population.

[23] Note that the change in the U shape for extremely cold days may indicate some adaptive behavior: people may stay home or wear warmer clothes when weather is the coldest and so mortality differentials may be less high than under slightly less cold days (see Figure F.3).

[24] A similar result relation between elderly and overall mortality impact of heat is found by Yu et al. (2019) for China.

4.2. Extreme temperatures: deaths and economic damages

Once obtained the impact on mortality rates of extreme temperatures in a period and climate change, deaths can be calculated following equations [4]-[6]. The results of those calculations for extreme temperatures are summarized in Table 3.

The last two columns of Panel A in Table 3 show the number of deaths per age group when an additional day of extreme cold and extreme heat occur. They are the result of replacing in equation [4] the coefficients from the first column of Table 1. Overall, the annual countrywide number of deaths due to an extra day of cold is 283 and 229 are the deaths due to an extra day of heat. Those deaths represent 0.072 and 0.070% respectively of Argentina's deaths in 2010 (i.e., 318,477). There are six extreme cold days (less than 4.4. degree Celsius average for the day) and two extreme heat days (over 32.2 degree Celsius as the average for a day) in a year. Hence, annual deaths attributable to extreme temperature represent 0.53% and 0.12% of total all cause deaths in Argentina (see 1,767 and 412 deaths in the first two columns of Panel A in Table 3). The latter derive from equation [5]. Note that we are only accounting for excess deaths in the extremes.

Deaths related to changes in extreme temperatures because of climate change are reported on Panel B in Table 3 for the 8.5 and 4.5 scenarios respectively. In the most aggressive scenario in terms of climate change (RCP-8.5), there would be approximately 22 more days of heat and 10 less days of extreme cold per year. Because of the change expected in lower temperature days, mortality decreases in 2,942 deaths, whereas variations in heat days increase mortality by 5,019 cases. Hence, the net effect of temperature changes attributable to climate change accounts for 0.63% of Argentina's yearly average deaths 2010-2019 (i.e., 2,078 per year).

Table 3. Yearly deaths due to extreme cold and heat in Argentina

Panel A. Period 2010-2019

2010-2019 period	Total excess deaths per year			Deaths extra day within bins	
Age range	Due to extreme cold (BIN < 40 ◦F)	Due to extreme heat (BIN > 90 ◦F)	Deaths due to both extremes	BIN 30 to 40 ◦F	BIN > 90 ˚F
0 to 4	46	7	53	7	4
5 to 44	13	32	45	2	18
45 to 64	113	45	158	18	25
> 64	1,595	327	1,922	256	182
Total deaths	**1,767**	**412**	**2,179**	**283**	**229**
Number of days per year within bins	*6*	*2*	*8*		
% of average 2010-2019 deaths	*0.53%*	*0.12%*	*0.66%*	*0.09%*	*0.07%*

Source: Own elaboration.

Panel B. With climate change

	Change in total deaths per year		
Age range	**Due to extreme cold (BIN < 40 ◦F)**	**Due to extreme heat (BIN > 90 ◦F)**	**Due to both extremes**
Scenario RCP-8.5			
0 to 4	-76	91	16
5 to 44	-22	392	370
45 to 64	-189	550	361
> 64	-2,655	3,986	1,331
Total deaths	**-2,942**	**5,019**	**2,078**
Change in the number of days per year within bins	*-10*	*22*	
% of average 2010-2019 deaths	*-0.89%*	*1.51%*	*0.63%*
Scenario RCP-4.5			
0 to 4	*-17*	*3*	*-15*
5 to 44	*-1*	*2*	*1*
45 to 64	*-20*	*7*	*-12*
> 64	*-497*	*95*	*-402*
Total deaths	**-535**	**107**	**-428**
Change in the number of days per year within bins	*-2*	*1*	
% of average 2010-2019 deaths	*-0.16%*	*0.03%*	*-0.13%*

Source: Own elaboration

Note: It has to be remembered that the change in temperature as in NASA does not match exactly the estimated model.

In the less extreme climate change scenario, there would be around 2 days less of extreme cold and 1 day extra (at the maximum) of heat. As a result, mortality would decrease, so there would be gains from climate change.

Once deaths are accounted for, the economic valuation is straightforward. Table 4 shows the estimated damages. All days of extreme cold cause damages equivalent to 0.5% of GDP, while heat damages correspond to 0.1% of 2019 GDP. On the other side, when climate change impacts are valued, damages total 0.7% of GDP in scenario 8.5 since saving due to less mortality occurring in cold day compensate only partially the increase in the number of hot days (a similar finding was made for China by Yu et al. 2019). In the scenario 4.5 climate change is indeed beneficial. Argentina seems to fit in the middle when compared to those for China (Yu et al. 2017): 0.21% for the RCP2.6 "strict" scenario and 1.19% for the "soft" RCP8.5 emissions' projection path.

Table 4. Damages due to yearly extreme temperature and to expected climate change

	Extreme cold	Extreme heat	Net effect in extremes
Deaths per year			
2010-2019 (local data)	1,767	412	2,179
% total deaths 2010-2019	*0.5%*	*0.1%*	*0.7%*
Number of days per year within bins	*6*	*2*	*8*
Change scenario 8.5 (NASA data)	-2,942	5,019	2,078
Change in the number of days per year	*-10*	*22*	
Change scenario 4.5 (NASA data)	-535	107	-428
Change in the number of days per year	*-2*	*1*	
Total deaths 2010-2019			**331,557**
Damages (as % of GDP)			
2010-2019 (local data)	0.6%	0.1%	0.8%
Change scenario 8.5 (NASA data)	-1.0%	1.8%	0.7%
Change scenario 4.5 (NASA data)	-0.19%	0.04%	-0.15%
Argentina GDP million current USD 2019			**449,663**

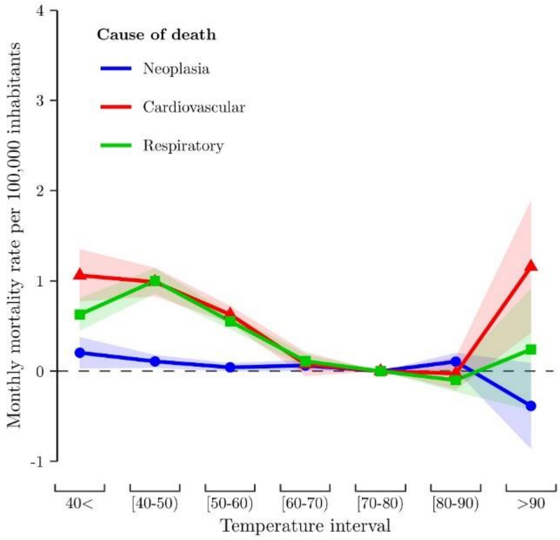
Source: Own calculation

4.3. Robustness checks

We perform several robustness checks: first, we separate mortality by cause to confirm that cardiovascular and respiratory mortality are the ones that are more closely related to temperature variation; second, we estimate the mortality-temperature relationship by region to assess if people living in regions with low frequencies of cold (hot) days have higher impacts when it is cold (hot) than those which are used to cold (hot) days; third we do try other specifications for the model.

First, since the mortality database registers the main cause of death, we compare the mortality-temperature sensitivity for cardiovascular episodes, those associated to respiratory illnesses and malignant neoplasms. As can be seen in Figure 4 cardiovascular related mortality is more responsive to temperatures higher than the reference, and this is particularly the case for high temperatures. Respiratory causes are also sensitive to temperature, but less than cardiovascular-related deaths. This is a usual result in the literature (Otrachshenko et al. 2017; Yu et al. 2019). Finally, and as expected for the robustness of the results, malignants neoplasm are almost unrelated to the profile of temperatures.[25]

Figure 4. Excess mortality per cause of death



Source: Own elaboration

25 This same result is found by other authors (see Deschenes 2014, p. 614). However, almost not related is not cero related. As shown in Barreca (2012, Panel B Figure 3) cold is somehow positively related to cancer. As discussed in Yu et al. (2019), there is evidence that cancer cells may grow faster in cold environments.

5. Conclusions

It is believed that environmental factors are important determinants of human health outcomes. Recently, due to global warming and the recurrence of heatwaves, attention has been placed on how weather affects health outcomes. Of those outcomes it is mortality that has captured the most attention in part because there are some results that show that most of damages of climate change are linked to mortality. According to Hsiang et al. (2017) approximately 66% of expected damages have to do with mortality in the US: for an increase of average temperature 8 degree Celsius, the cost attributable to mortality is 7% of GDP (when temperature rises around 3 degrees, expected costs are around 1% of GDP).

The existing literature, mainly for developed countries, has pointed to a generally U-shaped type of relationship between temperature and mortality risks. Using flexible regression models over longitudinal monthly weather and mortality data for most municipalities in Argentina spanning seven years, from January 2010 to December 2019, our study has confirmed this relationship from a countrywide perspective since it encompasses 85 per cent of the country's population. This was achieved using weather data from 71 closest meteorological stations.

Temperature extremes impact Argentina's population already (estimated average yearly damages related to mortality are approximately 08% of 2019 GDP), and climate change will cause a net increase in excess deaths due to extreme of 0.7% of GDP under a pessimistic scenario, and a gain of 0.15% of GDP if climate changes is mild.

Our study does have limitations. First, some have to do with impacts that we do not account for. Climate change not only affects mortality through temperature changes but it also induces indirect effects as a higher frequency of natural catastrophes that indirectly imply more deaths. Indirect additional deaths are not accounted for in the present study.

Second, there are several limitations in the data we were able to obtain that are not easy to solve. The available population data did not allow us to construct separate mortality rates for infants, i.e. younger than one year old, which are far more susceptible to thermal stress than other young children, as previously mentioned (Deschenes et al. 2009). Therefore, the fact that our results show no statistically significant influence of extreme temperatures on children's mortality rates has to be taken with caution. However, even if it were possible to separate a 0-1 years old, a significant result would nor necessarily occur. Yu et al. (2009) did not find it for China, Otrachsenko et al. (2017) did not see that outcome for Russia, and the same happens in Deschenes and Greenstone (2011). The reason may be that, where possible, infants are well protected from extreme temperatures by their parents.

Mortality is obviously an extreme outcome, and thus underestimates the overall effect of extreme temperatures on human health because there are many milder outcomes that may be related to temperature. Unfortunately, there is no detailed countrywide medical database available to estimate both mortality and morbidity impacts.[26]

Third, and somehow related to the previous one, we omit to explicitly account for individual and policy induced averting behaviour. A possible source of underestimation comes from the adoption of precautionary measures, particularly air conditioning, which have a protective effect in extreme temperatures (Barreca et al. 2016). Adaptation is possible through changes in outdoor activities, geographical mobility, heating and air conditioning adoption or more energy consumption due to a more intensive use of existing cooling and heating appliances. Adaptation may vary income since it changes access to better healthcare and to heating and air conditioning appliances (Cohen and Decheleptretre

[26] Morbidity data was requested from the authorities but not submitted apparently because of problems in data quality.

2020). Some articles make an effort to consider adaptation using data for defensive investments as residential energy consumption or air-conditioning adquisition (Deschenes and Greenstone 2011; Barreca et al. 2016; Carleton et al. 2018), but we do not have that type of data at the county level (to match with our database). Hence, considering explicitly adaptation is out of the scope of our paper. Hence, in that sense, our results can be read as an upper bound of mortality but not of costs since adaptation involves expenditures.

Fourth, we made some assumptions that could be changed. Mortality changes as a result of climate change depends on population changes in level and in terms of its composition as an aging population implies higher costs since older people are more sensitive to temperature extremes. This was not considered here. The 2010 population is taken as the base for calculations and so the age composition of that population across time is assumed to be fixed. Another implicit assumption is that population distribution across municipalities would remain constant under climate change.

Given the sparse distribution of the station network, interpolation of weather parameters from distant stations might have introduced measurement error. To limit the chance of this type of error happening, we follow the convention of excluding weather stations further than 100 kilometers away from each municipal geographical centre. Satellites might provide better weather information, at least in terms of spatial coverage (Kloog et al. 2014), but we leave this to future research. As pointed out before, there is also an error in the merge between local and international temperature data.

Finally, while the impact of climate change on mortality through extreme temperature might be manageable in Argentina or other countries like the United States, the situation will be very different in countries like Pakistan, Bangladesh, countries in Sub-Saharan Africa and in all regions where heat prevails. As Carleton et al. (2022) illustrate, climate change will imply very large increases in mortality in Ghana, and save lives in Germany. The issue is that the most deadly tolls from the greenhouse effect will occur in several of the poorest countries of the world, which would be even more damaging. Something similar occurs at the subnational level because, even if in Argentina as a whole mild climate change would be beneficial, the Northern provinces would indeed suffer because temperatures will become higher and, there, poverty is more prevalent.

Having pointed out the potential shortcomings of this research, we believe this study provides valuable information on weather determinants of mortality in Argentina. The estimation approach employed in this paper helps to disentangle the causal effect of temperatures on mortality risk while controlling for possible confounders, thus reducing the chance that the observed temperature-mortality link could have been driven by omitted factors associated both with weather and mortality.

Finally, the results indicate that temperature is important in terms of mortality, but is also relevant in terms of the implied monetary damages. Having that information is key for both adaptation and mitigation policies' decisions based on benefit-cost analysis.

6. References

Alexander P. 2013. Association of monthly frequencies of diverse diseases in the calls to the public emergency service of the city of Buenos Aires during 1999-2004 with meteorological variables and seasons. International Journal of Biometeorology. 57(1):83-90.

Almeira G, Rusticucci M, Suaya M. 2016. Relationship between mortality and extreme temperatures in Buenos Aires and Rosario. Meteorologica. 41(2):65–79.

Amarillo AC, Carreras HA. 2012. The effect of airborne particles and weather conditions on pediatric respiratory infections in Cordoba, Argentina. Environ Pollut. 170:217–221.

Baccini M, Biggeri A, Accetta G, Kosatsky T, Katsouyanni K, Analitis A, et al. 2008. Heat effects on mortality in 15 European cities. Epidemiology. 19(5):711–719.

Barreca A, Clay K, Deschênes O, Greenstone M, Shapiro JS. 2016. Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the 20th Century. J Polit Econ. 124(1):105–159.

Barreca A. 2012. Climate change, humidity, and mortality in the United States. J Environ Econ Manage. 63(1):19–34.

Barreca AI, Shimshack JP. 2012. Absolute humidity, temperature, and influenza mortality: 30 years of county-level evidence from the United States. Am J Epidemiol. 176(7):114–122.

Basu R. 2009. High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. Environmental Health: A Global Access Science Source.

Basu R, Dominici F, Samet JM. 2005. Temperature and mortality among the elderly in the United States: a comparison of epidemiologic methods. Epidemiology. 16(1):58–66.

Basu R, Samet JM. 2002a. An exposure assessment study of ambient heat exposure in an elderly population in Baltimore, Maryland. Environ Health Perspect. 110(12):1219–1224.

Basu R, Samet JM. 2002b. Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. Epidemiologic Reviews. 24(2):190-202.

Bell ML, O'Neill MS, Ranjit N, Borja-Aburto VH, Cifuentes L, Gouveia NC. 2008. Vulnerability to heat-related mortality in Latin America: a case-crossover study in Sao Paulo, Brazil, Santiago, Chile and Mexico City, Mexico. Int J Epidemiol. 37(4):796–804.

Benmarhnia T, Deguen S, Kaufman J S and Smargiassia A. 2015. Vulnerability to heat-related mortality a systematic review, meta-analysis, and meta-regression analysis. Epidemiology 26: 781–93.

Braga ALF, Zanobetti A, Schwartz J. 2002. The effect of weather on respiratory and cardiovascular deaths in 12 U.S. cities. Environ Health Perspect. 110(9):859–863.

Carmona R, Linares C, Ortiz C, Mirón IJ, Luna MY, Díaz J. 2017. Spatial variability in threshold temperatures of heat wave mortality: impact assessment on prevention plans. Int J Environ Health Research. 27(6):463–475.

Carreras H, Zanobetti A, Koutrakis P. 2015. Effect of daily temperature range on respiratory health in Argentina and its modification by impaired socio-economic conditions and PM10 exposures. Environ Pollut. 206:175–182.

Curriero FC, Heiner KS, Samet JM, Zeger SL, Strug L, Patz JA. 2002. Temperature and Mortality in 11 cities of the Eastern United States. Am J Epidemiol. 155(1):80–87.

De Garín A, Bejarán R. 2003. Mortality rate and relative strain index in Buenos Aires city. Int J Biometeorol. 48(1):31–36.

Deschenes O. 2014. Temperature, human health, and adaptation: A review of the empirical literature. Energy Economics, 46: 606-619.

Deschenes, Olivier, Michael Greenstone, and Jonathan Guryan. 2009. "Climate Change and Birth Weight." American Economic Review, 99 (2): 211-17.

Deschênes O, Greenstone M. 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. Am Econ J Appl Econ. 3(4):152–185.

Doyon B, Bélanger D, Gosselin P. 2008. The potential impact of climate change on annual and seasonal mortality for three cities in Québec, Canada. Int J Health Geogr. 7(23):1–12.

Hajat S and Kosatky T 2010 Heat-related mortality: a review and exploration of heterogeneity J. Epidemiol. Community Health. 64: 753–60.

Hanigan I, Hall G, Dear KBG. 2006. A comparison of methods for calculating population exposure estimates of daily weather for health research. Int J Health Geogr. 13(5):1–16.

Harrell FE. 2001. Regression modeling strategies. With applications to linear models, logistic regression, and survival analysis. Springer Series in Statistics.

[IPCC] Intergovernmental Panel on Climate Change. 2014. Climate Change 2014 Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Available from: http://www.ipcc.ch/pdf/assessment-report/ar5/syr/AR5_SYR_FINAL_SPM.pdf. Accessed on 9 August 2018.

Kaiser R, Le Tertre A, Schwartz J, Gotway CA, Daley WR, Rubin CH. 2007. The effect of the 1995 heat wave in Chicago on all-cause and cause-specific mortality. Am J Public Health. 97(Suppl 1):S158:162.

Keim SM, Guisto JA, Sullivan JB. 2002. Environmental thermal stress. Annals of Agricultural and Environmental Medicine. 9(1):1–15.

Kloog I, Nordio F, Coull BA, Schwartz J. 2014. Predicting spatiotemporal mean air temperature using MODIS satellite surface temperature measurements across the Northeastern USA. Remote Sens Environ. 150:132–139.

Medina-Ramón M, Schwartz J. 2007. Temperature, Temperature Extremes, and Mortality: A Study of Acclimatization and Effect Modification in 50 United States Cities. Occup Environ Med. 64(12):827–834.

Meinshausen, M., Smith, S.J., Calvin, K. et al. 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Climatic Change 109: 213-241.

Piccolo MC, Perillo GM, Ramon CG, DiDio V. 1988. Outbreaks of asthma attacks and meteorologic parameters in Bahia Blanca, Argentina. Ann Allergy. 60(2015):107–110.

Ranson M. 2014. Crime, weather, and climate change. J Environ Econ Manage. 67(3):274–302.

Roldán E, Gómez M, Pino MR, Díaz J. 2015. The impact of extremely high temperatures on mortality and mortality cost. Int J Environ Health Research. 25(3):277–287.

Romero-Lankao P, Qin H, Borbor-Cordova M. 2013. Exploration of health risks related to air pollution and temperature in three Latin American cities. Soc Sci Med. 83:110–118.

Rosenberg PS, Katki H, Swanson CA, Brown LM, Wacholder S, Hoover RN. 2003. Quantifying epidemiologic risk factors using non-parametric regression: Model selection remains the greatest challenge. Stat Med. 22(21):3369–3381.

Rubio, Gerardo; Lavado, Raul; Pereyra, Fernando (2018). The Soils of Argentina. Springer, 268 pages.

Rusticucci M, Bettolli ML, De Los Angeles Harris M. 2002. Association between weather conditions and the number of patients at the emergency room in an Argentine hospital. Int J Biometeorol. 46(1):42–51.

Stata Corp L. 2017. Stata Base Reference Manual Release 15. Stata Press.

Son Ji-Young Jia, Coco Liu y Michelle L Bell. 2019. Temperature-related mortality: a systematic review and investigation of effect modifiers. Environmental Research Letters. 14 073004.

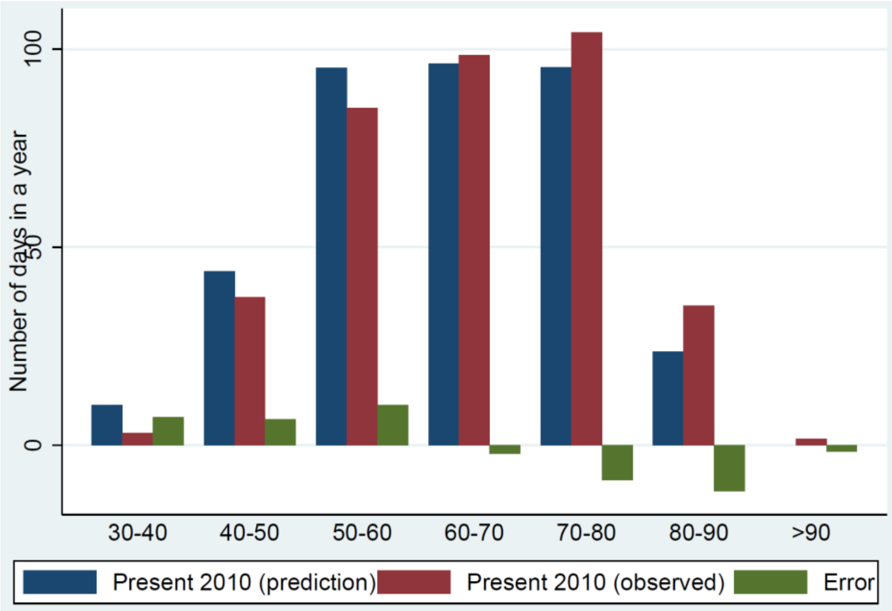
[WHO] World Health Organization. 2022. Climate change and health. Available from: https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health. Accessed on 17 February 2022.

[WMO] World Meteorological Organization. 2021. The State of the global climate 2021. World Meteorological Organization. Available from: https://public.wmo.int/en/media/press-release/state-of-climate-2021-extreme-events-and-major-impacts. Accessed on 17 February 2022.

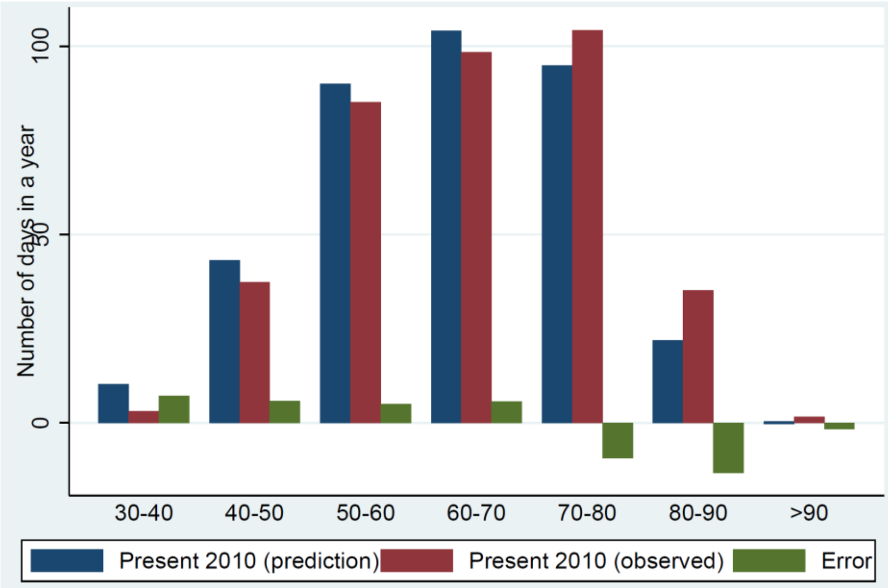
Appendix

Figure A.1. Gap between Argentina's meteorological system temperature and NEX-GDDP data

Panel A. Error in Scenario 8.5

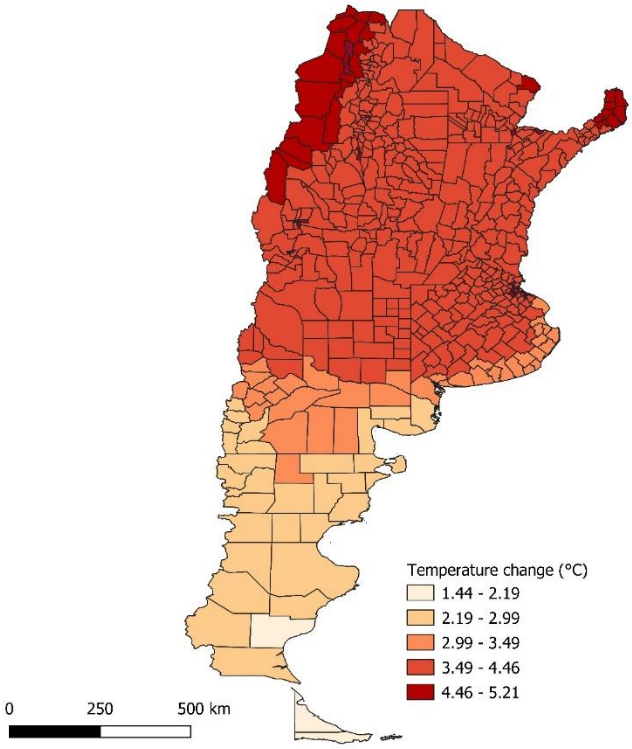


Panel B. Error in Scenario 8.5



Note: Present (observed) is the information from the Argentina' meteorological system whereas Present (prediction) is the NEX-GDDP data.

Figure A.2. Changes in temperature per district: RCP 8.5



Source: Own elaboration
Note: We include here only the changes in temperature and not in deaths and damages because the number of observations does not allow calculating coefficients per bin per district, and we were to use the national estimates to each district, estimates would not do a good job when compared with actual mortality data.