Emergency department visits and temperature:
Evidence from Mexico*

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We estimate the impact of temperatures on emergency department visits using daily data from the universe of public hospitals in Mexico from 2008 to 2021. We find that cold temperatures decrease visits by up to 9.1 percent on the same day, and warm temperatures increase visits by as much as 3.7 percent. Using distributed lag models, we then show that cold temperatures can reduce visits for the next 30 days by up to 16 percent. For warm temperatures, contemporaneous and cumulative effects are similar (limited harvesting). These findings suggest that, unlike mortality, temperatures affect the demand for emergency services linearly. Leveraging the granularity of our dataset, we also document significant heterogeneities (e.g., higher sensitivity for children and teenagers) and provide suggestive evidence about mechanisms, such as ecosystem dynamics and behavioral changes. Finally, we project that—absent adaptation—temperature-driven annual emergency department visits might increase by 0.35 percent by midcentury, resulting in an estimated increase of 8.5 million USD in annual medical expenditures in Mexico.

Keywords: Temperature, Morbidity, Mexico, Climate Change
JEL: I12, O13, Q54

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1. Introduction

In the context of global warming, the impact of adverse temperature conditions on health is a significant public health concern worldwide. Although extensive research has documented the effect of temperature on mortality, its influence on subfatal health conditions largely remains overlooked. A primary reason for this gap is the lack of comprehensive morbidity data, which hinders large-scale assessments and leads to an incomplete estimate of the health costs associated with temperature changes (White, 2017; Gould et al., 2024). This issue is especially pronounced in developing countries, where climate change is likely to have more severe effects due to warmer climates and lower adaptive capacities (Davis et al., 2021).

We estimate the relationship between temperature and morbidity in Mexico using daily case-level data on emergency department (ED) triage visits from all public hospitals between 2008 and 2021. To assess the causal effect of temperature on the demand for ED services, we exploit exogenous daily variations on average temperatures within the same municipality, month, and year (municipality $\times$ month $\times$ year) and within the same municipality and day-of-the-week (municipality $\times$ weekday), while controlling for correlated weather variables, such as precipitation and relative humidity. Using distributed lag models (Deschenes and Moretti, 2009), we provide evidence of the effects of temperature changes on same-day and cumulative demand over the subsequent 30 days.

Our results show that an additional day with an average temperature above 30°C increases contemporaneous ED visits by 3.7 percent. In contrast, an additional day below 10°C reduces visits by 9.1 percent. For the cumulative effect over the next 30 days, the increase from heat slightly decreases to 2.7 percent (harvesting), while the reductions from cold almost double to 16 percent. Reinforcing the external validity of our results, these findings align with research in California, which also documents a linear relationship between the temperature gradient and ED visits (White, 2017; Gould et al., 2024).

Finding that ED visits grow linearly with temperature is relevant because it contrasts with the observed U-shaped relationship for mortality (Cohen and Dechezleprêtre, 2022; Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011). Using data from death certificates during the same period, we confirm the U-shaped relationship in Mexico. This difference in functional forms implies significant heterogeneities in the potential effects of climate change. While temperature-related mortality increases at both cold and warm temperatures, making the net mortality impact of climate change context dependent, the approximately linear temperature–ED relationship we document implies that global warming will place upward pressure on emergency care demand across the entire temperature distribution. In particular, a shift toward more hot days and fewer cold days is expected to translate into a net increase in emergency department utilization.

Our analysis by disease category shows that cumulative cold temperatures decrease visits for most conditions, particularly those related to infectious diseases. The only change in trend comes from raising cases of respiratory diseases. In contrast, hot temperatures increase visits for endocrine, genitourinary, and infectious-parasitic diseases as well as external causes. The coefficients across disease categories align in sign and significance with estimates from California (White, 2017). However, variations in the prevalence of certain conditions lead to differences in the average effect. Specifically, the cumulative increase in cold-related visits in California primarily originates from respiratory diseases and other communicable conditions. Although respiratory diseases respond similarly in our case, their contribution cannot offset declines in other categories, such as vector-borne diseases and encounters with venomous animals and plants, leading to a net reduction in cold-related visits. These differences emphasize the importance of local disease prevalence and health profiles in shaping temperature-morbidity outcomes.

Case-level data also allow us to aggregate ED visits for different demographics. First, we examine age differences. Younger populations respond more strongly to hot and cold temperatures, with significant immediate effects in children and adolescents. Variations in the demand for ED services and their interaction with temperatures explain these differences. For instance, people under 40 primarily visit the ED for respiratory, infectious, parasitic, and obstetric issues. In contrast, older cohorts typically seek care for circulatory and endocrine conditions, such as diabetes and hypertension, which exhibit less sensitivity to temperature variations. We also provide evidence that heat affects children differently due to the dynamics of respiratory diseases, which account for the majority of pediatric visits. Second, we identify slight variations in responses between men and women, which we attribute to differences in their demand for health services; for instance, the most common reasons for emergency department visits are obstetric issues for women and respiratory issues for men.

We then provide suggestive evidence of potential mechanisms behind the identified linear relationship between temperature and ED visits: (1) illness incidence, (2) ecosystem dynamics, and (3) behavioral changes. For illness incidence, we show that cold temperatures decrease the incidence of heat-related shocks, false labor, and dissociative disorders, whereas hot temperatures increase these instances. For ecosystem dynamics, our estimates suggest that cold temperatures reduce, while warm temperatures increase cases of dengue, foodborne intoxications, and visits due to contact with poisonous animals and plants. The behavioral channel includes two mechanisms. First, patients may postpone their visits during extremely cold or warm weather. Although we cannot directly test this with our data, we utilize heterogeneous responses from related but less acute conditions as suggestive evidence. For instance, we observe a greater reduction in ED visits for headaches compared to migraines-epilepsy and for urinary infections compared to chronic kidney disease. This pattern aligns with White (2017), which shows a greater reduction in visits during cold weather for more deferrable conditions. Finally, temperature changes can influence other behaviors and lead to riskier activities. For example, visits to the ED for alcohol-related disorders decrease in cold weather and increase in heat.

Finally, we extrapolate the observed short-run marginal effects over long horizons to estimate the potential midcentury levels of temperature-induced ED visits under future climate projections. Projections describe illustrative, no-adaptation scenarios, holding behavioral, institutional, and technological factors fixed: ceteris paribus, our estimates indicate a potential steady increase, starting with 197 thousand additional visits in the decade 2031–2040 and rising to more than 317 thousand in 2051–2060. This is equivalent to a 0.24–0.39 percent increase compared to a scenario without climate change, depending on the decade considered. A rough calculation suggests that temperature changes could increase public health spending by approximately 58.4–93.7 million USD per decade, implying annual costs of roughly 8.5 million USD by midcentury. Initially, the costs associated with having fewer cold days dominate. However, the costs related to an increase in heat-related urgent care visits become more significant over time.

Related literature. This paper makes several contributions. First, our findings contribute to the literature on temperature and health, as a key channel through which climate change impacts socioeconomic factors (Carleton and Hsiang, 2016). We focus on the relationship between morbidity and temperature, a topic that has received considerably less attention than the temperature-mortality gradient. Studies show that extreme temperatures can lead to sublethal yet significant health consequences (Lavigne et al., 2014; White, 2017; Karlsson and Ziebarth, 2018; Agarwal et al., 2021; Gould et al., 2024). We provide new evidence on this relationship using granular temporal and spatial data from all public hospitals in Mexico. This rich dataset allows us to explore all-cause and cause-specific responses to temperature across all age groups. Moreover, although most studies have a limited geographic scope (White, 2017; Gould et al., 2024; Zhao et al., 2017; Rahman et al., 2022; Wang et al., 2020) or are not representative of an entire national population (Agarwal et al., 2021), our study offers a comprehensive national coverage. A notable exception in the literature is Karlsson and Ziebarth (2018), which examines the effects of temperature on mortality and hospital admissions in Germany. Our study extends this analysis beyond high-income contexts, providing causal evidence of the effect of temperature on ED visits. The demand for ED services reflects acute health shocks better than hospital visits, many of which are scheduled or inevitable (White, 2017).

We are aware of only one other paper that examines how temperatures affect ED visits in a developing country context leveraging national data: Aguilar-Gomez et al. (2025) analyze the impact of extreme heat on hospital congestion in Mexico. Similar to our findings, they document a linear relationship between temperature and both ED visits and hospitalizations. Their study further demonstrates that increased heat-related ED visits lead to higher hospital congestion, ultimately raising the mortality risk for admitted patients. We view our work as complementary to Aguilar-Gomez et al. (2025). Although their analysis primarily focuses on extreme heat and its implications for hospital congestion and patient outcomes, we examine the full temperature distribution, revealing broader patterns and mechanisms that drive the temperature-morbidity relationship.

Second, we contribute to the literature on individuals' behavioral responses to temperature shocks (White, 2017; Graff Zivin and Neidell, 2014). Our data allow us to identify when individuals seek treatment, which differs from the timing of the health shock. Several other factors influence the decision to delay or forgo treatment, including external factors, disease type, age, and healthcare system (de Bartolome and Vosti, 1995; Jowett et al., 2004; Sahn et al., 2003; Das and Do, 2023). We advance this literature by identifying suggestive mechanisms behind treatment-seeking behavior within a *public* healthcare system, such as Mexico, and comparing it with a predominantly *private* system, such as the United States (White, 2017).

Third, we highlight the differences in the impact of temperature on mortality and ED visits. The rich administrative data available in Mexico provide a unique opportunity to study the effects of temperature within the same population and period. Using consistent exposure and econometric models, we present evidence that temperature affects mortality and the demand for ED services in significantly different ways, in line with studies for the United States and Germany (Gould et al., 2024; Karlsson and Ziebarth, 2018).

Finally, we contribute to the literature on the relationship between natural ecosystems and human health. For example, Frank and Sudarshan (2023) document that vulture extinction in India has increased human mortality due to declining sanitation. Dasgupta (2018) shows that warmer temperatures will facilitate the spread of malaria in regions that are currently disease-free. We show that a significant share of heat-driven ED visits in Mexico results from contact with venomous insects and animals, as well as vector-borne diseases such as dengue and other parasitic and infectious diseases, which are more prevalent at higher temperatures. This insight is crucial for tropical and subtropical climates, where sustained high ambient temperatures promote vectors and health issues related to envenomation (Harvell et al., 2002). Higher temperatures accelerate mosquito breeding cycles, increasing the transmission of diseases such as dengue (Mordecai et al., 2013) and elevating the activity of venomous arthropods (Dell et al., 2011). As ectothermic organisms thrive in warmer conditions, their interactions with humans increase (Harvell et al., 2002). Furthermore, elevated temperatures enhance pathogen replication in both vectors and hosts, raising the risk and severity of parasitic-infectious diseases (Patz et al., 2005).

2. Data

Weather. We use hourly weather data from the ERA5 reanalysis dataset, an atmospheric reanalysis product from the European Center for Medium-Range Weather Forecasts. We extract the average air temperature and precipitation for each day between January 2008 and December 2021. Next, we calculate daily population-weighted averages of all weather variables in each municipality using the gridded population of the world dataset curated by NASA's Socioeconomic Data and Applications Center (SEDAC). These population-weighted measures allow us to precisely characterize the temperature exposure of Mexican residents. Mexico's population-weighted average temperature is close to the global mean, while its within-country variation encompasses a wide range of temperatures (see Figure A.2), making it a compelling context for our analysis.

In a robustness check, we also use CONAGUA weather station data (*Sistema de Información Hidrológica*).[1] In this case, we construct municipality-level weather variables via inverse-distance weighting (IDW).[2]

[1] For our main analysis, we prefer ERA5 over the raw station data from CONAGUA for three reasons. First, ERA5 provides complete and balanced national coverage across our 14-year sample, whereas only 1,662 of Mexico's 2,457 municipalities ever contain a CONAGUA station, and the number of operating stations declines steadily from 1,201 in 2008 to 536 in 2022. Recovering a national panel from CONAGUA therefore requires interpolating to the municipalities and days without coverage, which introduces ad-hoc choices over the interpolation method, neighborhood radius, and treatment of station gaps. Second, ERA5 itself is a principled interpolation that assimilates surface stations (including the Mexican network) jointly with satellite radiances and pressure fields into a physically consistent atmospheric model, rather than relying on a single inverse-distance kernel. Third, point-located stations are not always representative of the population-weighted average exposure within a municipality, particularly in mountainous regions where elevation gradients are large within a single $\sim$31 km grid cell.

[2] We employ the $k = 5$ nearest stations with a power parameter $p = 2$, re-normalizing weights each day to accommodate station-day missing values. Target points are population-weighted municipality centroids computed. We also apply standard quality-control filters, dropping observations where $T_{\text{max}} > 55$ °C, $T_{\text{min}} < -30$ °C, $T_{\text{max}} < T_{\text{min}}$, or precipitation is negative.

ED visits. We obtain data on daily visits from the health information system of the Mexican Ministry of Health. The dataset includes all ED visits in Mexican public hospitals from 2008 to 2021. Each observation in the dataset records a single triage visit and includes patient characteristics (age, sex, residence, insurance), event characteristics (outcome, ICD-10 code, reason), and geographical identifiers (hospital ID, municipality, state).

Each triage record contains information about the initial assessment conducted by healthcare staff to evaluate a patient's health condition and determine its urgency. This process commonly uses a five-color code (red, orange, yellow, green, blue) that corresponds to the severity of the condition and the acceptable waiting time. This system ensures that life-threatening cases receive immediate attention, while minor "urgencias sentidas" (perceived urgencies) may either wait or be referred to primary care. Importantly, public EDs operate under policies designed to ensure universal access to emergency care; no patient seeking emergency assistance is turned away, regardless of bed availability or insurance status ("*cero rechazos*"). All patients must undergo at least triage and stabilization. These institutional features imply that the number of ED visits, as recorded at triage, serves as a direct indicator of demand for emergency services, rather than being limited by hospital capacity. In other words, if more people seek care due to extreme temperatures, they will be reflected in the ED visit data even if the hospital is crowded (they may experience longer waits, but they are not systematically excluded).

Using these data, we construct a panel of daily ED visits per 100,000 persons for each municipality that has at least one hospital with an emergency department. We compute visit rates using population data from the Mexican census and classify visits by gender (men and women), age (six age groups), and ICD-10 codes (e.g., respiratory, cardiovascular, obstetric).

A key feature of the dataset is that the set of reporting hospitals expands over time, producing an unbalanced panel of municipalities (Figure A.4). To ensure consistent identification, we construct panels that are balanced at the yearly level and base our estimates on within-year variation. In practice, this means that for each calendar year, we observe the same set of municipalities for all 365 (or 366) days, thereby avoiding compositional changes driven by reporting patterns.

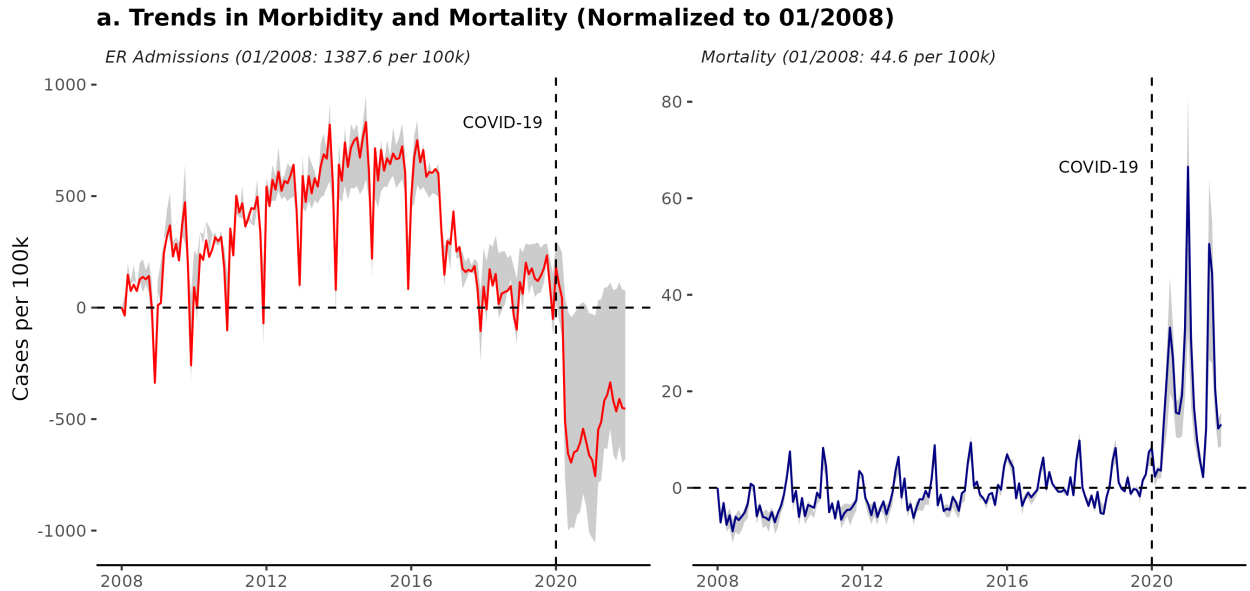
In terms of the relationship between the public and private health sectors, public hospitals account for roughly 35 percent of all hospitals in Mexico—higher than in the United States but lower than in the European Union (Figure S1). When adjusted for population size, Mexico has more than twice as many public hospitals per million people as the United States and more than most EU countries, with the exception of France. Although Mexico has approximately 2.5 private hospitals for every public one, most private facilities provide fewer than 20 beds and primarily operate as outpatient clinics, offering limited emergency care (Organization et al., 2017). Unfortunately, we cannot observe emergency visits in these private hospitals. However, the share of individuals affiliated with a public healthcare institution who seek care from private providers is relatively small—about 14 percent when combining hospitalizations and ED care (Juan López et al., 2015)—and is likely even lower for emergency visits, given the limited capacity and outpatient focus of most private hospitals (OECD, 2016). Thus, although our results cannot be generalized to the private sector, they should reflect the vast majority of emergency care delivered in Mexico. Additional institutional details regarding the Mexican healthcare system and emergency services are provided in Appendix A.1.

Mortality. We collect mortality data from the Mexican National Institute of Geography and Statistics (INEGI). The dataset includes municipality and date of death information for all people who died in the country between 1998 and 2021. Similar to ED visits, we construct a panel of daily municipal mortality rates per 100,000 people.

Descriptive statistics. Figure 1 presents the time series of ED visits and mortality rates per 100,000 persons, normalized to January 2008. The time series on ED visits exhibits clear seasonality, with a reduction in cases in November and December. We identify two breaks in the time series. The first occurred in 2018 when the flagship health care program, Seguro Popular, was replaced by a new scheme. The second break was in 2020 due to the COVID pandemic.[3]

[3] In 2018, the Mexican government implemented significant changes to the country's health system, replacing the Seguro Popular with the Instituto de Salud para el Bienestar (INSABI). Although the government

Figure 1: Time series of emergency room visits and mortality rates



Notes: These figures present the time series of the rate of ED visits and mortality per 100,000 people. We standardize the value of both time series to equal zero at the start of our sample in January 2008. The red and blue lines show monthly means; shaded gray areas denote the interquartile range (25th–75th percentile).

Understanding why people seek treatment is crucial, as it influences the relationship between temperature and ED visits. Due to the limited granular information on ED usage by country, Table 1 contextualizes our Mexican data by comparing them with data reported by White (2017) on outpatient ED visits in California. However, the datasets have two differences. First, although White (2017) identifies only outpatient ED visits, we can also identify inpatient visits. This distinction is significant because inpatient visits respond more closely to temperature shocks. Second, White (2017) reports aggregate descriptives using Clinical Classifications Software (CCS) codes instead of ICD-10 chapter codes. Although the two classifications are similar, they serve different purposes. The ICD-10 is a comprehensive diagnostic tool containing more than 70,000 codes for specific conditions. The CCS aggregates these codes into approximately 285 broader categories, facilitating the analysis of large health datasets. ICD-10 provides detailed precision, whereas CCS offers simplified, high-level summaries. One limitation of our case-level data is that they

introduced INSABI to expand health care access and eliminate financial barriers, its implementation faced significant challenges, particularly during the COVID-19 pandemic. The transition period saw interruptions in health care services, which may have temporarily worsened health coverage.

report ICD-10 classifications only up to four digits. This hampers our ability to aggregate into CCS group categories, as some require classifications of up to six digits. However, both classifications share the most important chapters. Therefore, we choose to compare the ICD-10 and CCS chapters directly.[4]

Table 1: Emergency department visits in Mexico and California

Chapter	Share of visits (percent)		ED visits per 100k		Total visits (Million)	
	California	Mexico	California	Mexico	California	Mexico
Total Visits	100	100	77.09	53.2	94.23	118.24
Injuries	20.54	15.10	15.84	8.1	19.36	17.86
Respiratory	12.82	14.78	9.88	9.5	12.08	17.47
Other	-	24.49	-	10.9	-	28.96
Digestive	7.83	7.47	6.04	4.1	7.38	8.84
Pregnancy	2.7	11.23	2.08	4.7	2.54	13.28
Nervous System	8.84	1.06	6.82	0.6	8.33	1.25
Circulatory	8.52	2.95	6.57	1.8	8.03	3.48
Genitourinary	6.04	5.77	4.66	3.2	5.69	6.82
Skin-Musculoskeletal	8.76	4.01	6.7	2.5	8.9	4.74
Mental Illness	4.23	1.56	3.26	0.7	3.99	1.85
Infections and Parasitic	2.78	6.26	2.1	4.1	2.62	7.40
Endocrine	2.16	2.86	1.6	1.6	2.03	3.38
Neoplasm	0.58	0.68	0.4	0.3	0.55	0.80
Blood	0.5	0.41	0.4	0.2	0.47	0.49
Congenital	0.05	-	0.04	-	0.04	-
Perinatal	0.24	-	0.18	-	0.23	-
Eye-Ear	-	1.37	-	0.9	0.00	1.62
Residual visits	13.4	-	-	-	12.63	-

Notes: Direct comparison of CCS and ICD-10 Codes, sorted by share of visits. Data from California come from Table 1 in White (2017) and cover 2005–2015. Data for Mexico come from the health information system of the Mexican health ministry and span all ED visits between 2008 and 2021.

The visit rate in California (77.09) exceeds that of Mexico (53.2), mainly because the state has an older population, with an average age nearly 10 years higher. Primary use patterns also differ significantly. In Mexico, a larger proportion of visits pertains to pregnancy and the perinatal period (11.23 percent) and to infectious and parasitic diseases (6.26 percent), which are common in warmer climates. In contrast, California has a higher prevalence of injuries, circulatory diseases, nervous conditions, and mental health issues, often linked to an older population. Despite these differences, interesting similarities exist, includ-

[4] Note that some ICD-10 chapters lack corresponding CCS chapters and vice versa (e.g., congenital for CCS and eye/ear for ICD-10)

ing a comparable share of visits for respiratory, digestive, genitourinary, and endocrine conditions. This observation is striking given the diverse populations, healthcare infrastructures, and risk factors.

3. Empirical strategy

Our research design leverages the plausibly exogenous temporal and spatial variation in daily temperature to identify its causal effect on ED visits (Deschenes and Moretti, 2009). Due to numerous zero values in the dependent variable, we implement a Poisson pseudo-maximum likelihood (PPML) estimation with high-dimensional fixed effects to identify the effects (Wooldridge, 1999).[5] Equation 1 presents our main specification.

$$Y_{idmy} = \exp\left[\sum_{j=0}^{30}\sum_{b=0}^{6}\lambda_{b,j} \times D_{b,idmy}^{t-j} + \sum_{j=0}^{30} X_{idmy}^{t-j}\gamma_j + \delta_{imy} + \delta_{iw}\right] + \varepsilon_{idmy} \tag{1}$$

Y_{idmy} represents the number of ED visits per 100,000 for municipality i on day d of month m in year y. We model temperature nonlinearly across six intervals, ranging from ≤ 10 to > 30 °C, using 20–25 °C as the reference. $D_{b,idmy}$ is an indicator variable denoting whether a day's average temperature falls within interval b.

The reference category (20-25 °C) aligns with the literature on the effects of temperature exposure on mortality. For example, Cohen and Dechezleprêtre (2022) use 24–28 °C for Mexico, and Helo Sarmiento (2023) use 23–25 °C for Colombia. These choices coincide with estimates from the World Health Organization, which places the thermal comfort range for healthy adults between 18 °C and 24 °C (64–75 °F) (Ormandy and Ezratty, 2012). We also define the lowest and highest bins ($\leq$ 10 °C and $>$ 30 °C) to ensure that at least one percent of observations falls into each category (Figure A.3).[6]

[5] In our setting, it is unlikely that the ordinary least squares (OLS) assumptions of homoskedasticity and normally distributed errors hold (Chen and Roth, 2023).

[6] In related studies of emergency department visits, Aguilar-Gomez et al. (2025) use 2 °C bins, with 22–24 °C as the reference, and specify $\leq$18 °C and $\geq$34 °C as the extremes; White (2017) use 5 °F bins (about 2.5 °C) with 60–65 °F (15–18 °C) as the reference for California; and Gould et al. (2024) adopt 4 °C bins with 18–22 °C as the reference and $<$ 6 °C and $>$ 34 °C as the extremes.

X_{idmy} is a matrix of additional controls, including a quadratic function of precipitation and relative humidity. δ_{imy} represents fixed effects for the municipality-month-year of observation. This approach controls for potential confounders, such as systematic differences across municipalities, seasonality, and other unobserved factors that vary within municipalities during the same month and year. δ_{iw} includes municipality-by-weekday fixed effects. ε_{idmy} is an idiosyncratic error term, assumed to be uncorrelated with $D_{b,idmy}$. We weigh our regression by population and cluster standard errors at the municipality level to address correlation among unobservables and autocorrelation over time.

As displacement effects can last several days (Deschenes and Moretti, 2009), we specify Equation 1 as a distributed lag model that considers the cumulative impact of temperature changes for up to 30 days after the shock. We include 30 lagged temperature intervals and weather controls to obtain a single coefficient for the effect of temperatures j days after the change.[7] Following previous research (Deschenes and Moretti, 2009), we combine $\lambda_{b,j}$ linearly to derive a long-term aggregate effect J periods after the shock $\lambda_{b,J}$. For instance, $J \in (3, 7, 30)$ estimates the cumulative effect over the next three, seven, and thirty days, effectively accounting for the displacement and anticipation of urgent care visits.

Accounting for displacement effects is crucial in our setting. White (2017) finds that in the United States, cold temperatures initially reduce individuals' willingness to seek treatment, but this trend reverses after 30 days due to the cumulative impact of respiratory conditions. Additionally, hot temperatures may shift the timing of ED visits. Vulnerable individuals who might have sought treatment in the near future may anticipate their visit due to acute heat stress (harvesting effect). Therefore, our empirical model allows us to compare changes in health outcomes that occur immediately after exposure (contemporaneous effect) with those that persist over a more extended period (cumulative effect).

[7] Note that a 30-day lag structure is more restrictive than what previous papers usually impose for temperature-related ED visits: e.g., seven (Aguilar-Gomez et al., 2025), five (Sun et al., 2021), and three-to-ten lags (Milando et al., 2025). We opt for thirty lags to capture longer-run dynamics, which is also consistent with other recent works such as White (2017) and Agarwal et al. (2021).

4. Results

Table 2 reports the estimated effects. Our estimates reveal a linear relationship between average daily temperature and ED visits. Cold temperatures reduce visits in both contemporaneous and cumulative models. An additional day with temperatures at or below 10°C decreases ED visits by 9.1 percent on the day of the event and by 16 percent when accounting for the following 30 days. Negative effects also occur for days with temperatures of 10–15 °C and 15–20 °C. Conversely, temperatures at or above 25 °C increase visits. An additional day at 25–30 °C results in a 2.5 percent increase on the event day and a 4.5 percent cumulative increase over the 30-day period. For the warmest interval (> 30 °C), the number of visits increases by 3.7 percent on the event day. However, this effect diminishes to 2.7 percent when examining the cumulative impact over 30 days (harvesting).[8]

Table 2: The effect of daily temperatures on emergency department (ED) visits

	ED visits per 100,000 people	
	Contemporaneous	Cumulative (30 days)
≤ 10 °C	-0.091***	-0.160***
	(0.005)	(0.019)
10–15 °C	-0.053***	-0.118***
	(0.002)	(0.011)
15–20 °C	-0.027***	-0.053***
	(0.002)	(0.007)
25–30 °C	0.025***	0.045***
	(0.002)	(0.008)
> 30 °C	0.037***	0.027**
	(0.003)	(0.012)

Notes: This table presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. The table presents results for two aggregation levels: *contemporaneous model* indicates the effect of temperatures on the same day, and *distributed lag model (30)* represents the linear combination of 30 temperature lags. The econometric design incorporates municipality-by-year-by-month and municipality-by-weekday fixed effects, and controls for a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. No. Obs used for inference: 2,642,643. The average ED admission rate is 53.173 per 100,000 people. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

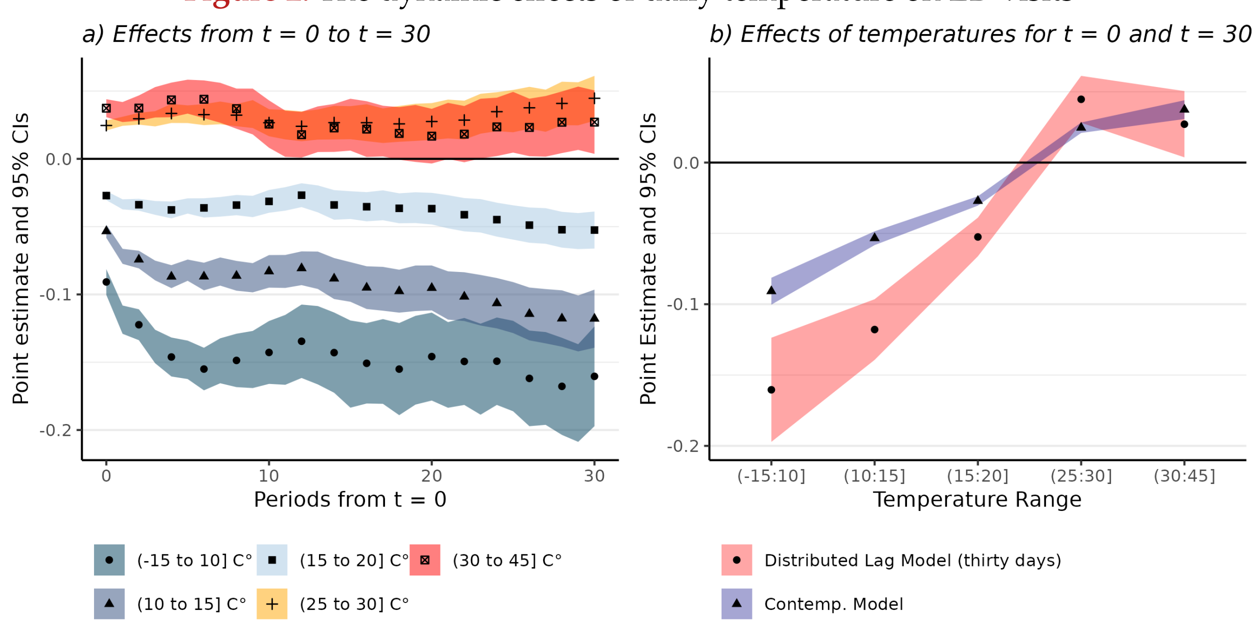
Our coefficients partially align with estimates from California (White, 2017; Gould et al.,

[8] Estimates resulting from using CONAGUA weather station data closely mirror our baseline results based on ERA5 reanalysis data, both in magnitude and statistical significance across specifications. The same pattern holds when we restrict the sample to the 506 municipalities containing a physical station, indicating that the result is not driven by the interpolation step. This similarity indicates that our findings are not sensitive to the choice of temperature data source. Detailed results are reported in the Supplementary Information.

2024). For cumulative impacts, we find a stable and significant effect for the hottest temperature bin, consistent with both White (2017) and Gould et al. (2024). In contrast, our results indicate that cold temperatures consistently reduce visits. This finding aligns with Gould et al. (2024) but differs from White (2017). The latter study suggests that the effect of cold temperatures shifts from negative in the short term to positive when aggregating all lag contributions. These dynamics of respiratory conditions align with the epidemiological literature, as cold weather facilitates transmission and leads to a higher incidence several days or weeks after the cold spell.

Figure 2 illustrates the cumulative effects over time. The left panel displays the coefficient for each value of $J \in (0, ..., 30)$. The right panel presents estimates for $J = 0$ and $J = 30$ across the temperature distribution. Cold temperatures significantly reduce visits immediately after exposure, followed by slight increases in the following weeks. Conversely, hot temperatures significantly increase the number of cases during the first 10 days post-exposure, with the effect gradually diminishing over the next 20 days.

Figure 2: The dynamic effects of daily temperature on ED visits



Notes: This figure presents the point estimates and 95 percent confidence intervals of a Poisson MLE distributed lag model aggregated across 30 different time windows. In panel a), we present the cumulative estimates over $t + k$ with $t + k \in (1, ...30)$. Each point refers to the linear combination of $t + k$ temperature lags on ED visits at time t. In panel b), we focus only on $t + k = 0$ and $t + k = 30$ to highlight contemporaneous and midterm differences in the coefficients. The coefficients refer to indicators for daily temperature intervals with reference category 20–25 °C. Standard errors are clustered at the municipality level.

The baseline results suggest a linear effect of temperature on ED visits. This effect contrasts with the dynamics between temperature variations and mortality (Cohen and Dechezleprêtre, 2022). Comparing our estimates with mortality underscores these differences for the same period and population. Although ED visits exhibit a linear pattern, mortality has a U-shaped relationship with temperature once cumulative effects over a 30-day horizon are taken into account (Figure A.5). These differences likely result from various mechanisms, including the types of illnesses affected, behavioral responses, and age groups most at risk (Gould et al., 2024).

Robustness checks. First, we assess the robustness of our estimates by explicitly accounting for the structural breaks identified in Figure 1: the 2018 policy reform that substituted Seguro Popular with INSABI and the Covid-19 pandemic. In Figure A.6 we estimate the relationship between ED visits and temperature across four sub-samples (pre-2018, post-2018, pre-Covid, and excluding Covid periods), and we compare it to our full sample estimates.[9] Our results show that the magnitudes of coefficients remain consistent across both the contemporaneous and DLM models. The only difference is a lack of precision in the post-2018 sample, which results from a smaller sample size. These exercises confirm that our preferred specification effectively isolates the temperature effects from concurrent structural shocks. Our coefficients remain consistent whether we use only pre-2018 observations or the entire sample period.

Next, we test the sensitivity of our estimates to alternative fixed-effects structures (Table A.5). Across all temperature bins, the contemporaneous effects remain consistent with our preferred specification. All alternative models reveal a clear linear relationship between temperature and ED visits: cold days ($\leq$ 10 °C) reduce same-day ED visits by 4.9–10 percent, while hot days (> 30 °C) increase visits by 3–4.1 percent. When considering cumulative effects over thirty days, mild intervals remain consistent with the main specification. Contrary, the estimates for the warmest interval depend on the source of identifying variation—whether interannual or intra–month-year. For instance, when we employ municipality $\times$ calendar day, municipality $\times$ year, and date fixed effects—similar

[9] Given that our preferred specification leverages daily temperature variation within municipality-year-month cells, it inherently controls for these shocks by design.

to Cohen and Dechezleprêtre (2022)—the coefficient suggests that very hot temperatures decrease cumulative ED visits by 6 percent. This estimate contradicts evidence from the literature (e.g., White, 2017; Aguilar-Gomez et al., 2025) and our preferred specification, which suggests that visits increase during very hot temperatures. This means that different sources of variation lead to heterogeneous estimates for the warmest interval in the 30 day lag. However, it is worth mentioning that specifications leveraging interannual variation, such as municipality $\times$ calendar day or municipality $\times$ week, might not adequately account for the unbalanced nature of our panel of municipalities (see Colmer and Doleac, 2023). Moreover, our 30-day lag structure is more restrictive than that used in most previous studies of temperature-related ED admissions (e.g., Aguilar-Gomez et al., 2025).

We further investigate the consistency of the previous results across different lag windows (7, 14, 21) and various fixed effects specifications (Table A.6). Interestingly, the cumulative effects of most extreme temperature intervals remain consistent across specifications until the fourteenth lag. This aligns with recent evidence that uses a shorter lag time window to study the effect of temperature on ED visits (Aguilar-Gomez et al., 2025; Sun et al., 2014, 2021; Milando et al., 2025). To further address concerns about our empirical design, we aggregate our data at the monthly level. If we accurately estimate the aggregate effect after thirty days, we should obtain a similar coefficient using monthly variation, especially since most of the effects materialize in the first two weeks (see Figure 2). In Table A.7, we estimate the impact by counting the number of days per month within each temperature interval. The coefficient represents the effect of an additional day per month in the specified interval b on the emergency department visit rate per 100,000 people. We present results for four fixed effects specifications. Our preferred specification includes fixed effects for municipality-by-year and municipality-by-month (Columns 4-5). In all specifications, we control for precipitation and average relative humidity. Given the monthly aggregation, in one of the specification we enrich the set of weather controls by including atmospheric pressure and wind speed. The coefficients from our preferred specification confirm the linear relationship between temperature and ED visits. For cold temperatures, the coefficients are negative and statistically significant across specifications. One day with temperatures below 10 °C decreases the monthly ED visit rate by 0.8-0.9 percent. For warm temperatures, estimates from the preferred specification are positive and significant. One day per month with temperatures above 30 °C increases visits by 0.06-0.2 percent.

These exercises show that our estimates remain consistent across different combinations of fixed effects, except on days when temperatures exceed 30 degrees. Here, we observe a change in the direction of the coefficient. However, we provide evidence that when we use shorter time windows for the distributed lag model, as well as a monthly model, the positive coefficient in the hottest interval remains consistent. This finding also aligns with the existing econometric literature on the effects of hot temperatures on ED visits (e.g., White, 2017; Aguilar-Gomez et al., 2025; Gould et al., 2024). As such, we believe our chosen specification provides a good balance by flexibly capturing both broad seasonal patterns (through municipality $\times$ month $\times$ year) and weekly cycles (through municipality $\times$ day-of-the-week), while maintaining sufficient variation to produce precise and externally comparable results, and taking into account the unbalanced nature of our panel setting.

4.1. Heterogeneity by ICD-10 chapter

Next, we use patient diagnosis information to assess how temperature effects vary across ICD-10 chapters.[10] For each chapter, we estimate Equation 1 separately and summarize the results in Table 3.[11]

[10] See Table A.4 for specific statistics about the main diseases in each ICD-10 chapter and the share of conditions per chapter and disease.

[11] The difference in the number of observations between Table 2 and the different chapters in Table 3 arises from the PPML estimator. PPML excludes municipality–year–month and municipality–weekday cells with no within-cell variation. To illustrate this, we re-estimate Table 3 by OLS using the same fixed effects and controls (see Supplementary Information); the number of observations then aligns closely with Table 2, with any residual differences also due to PPML dropping cells without variation, which is less likely when pooling all chapters together.

Table 3: The effect of daily temperatures on emergency department (ED) visits by disease category

	ED visits per 100,000 people									
	Blood and Immune		**Circulatory**		**Digestive**		**Endoc./Metabolic**		**External Causes**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤ 10 °C	−0.0869***	−0.3637***	−0.0590***	0.0247	−0.0708***	−0.2961***	−0.1457***	−0.1119***	−0.1404***	−0.3484***
	(0.0278)	(0.1202)	(0.0086)	(0.0363)	(0.0071)	(0.0307)	(0.0100)	(0.0402)	(0.0071)	(0.0233)
10–15 °C	−0.0567***	−0.2450***	−0.0151***	−0.0004	−0.0354***	−0.2066***	−0.0904***	−0.1010***	−0.0842***	−0.2396***
	(0.0119)	(0.0497)	(0.0051)	(0.0216)	(0.0038)	(0.0161)	(0.0064)	(0.0217)	(0.0045)	(0.0154)
15–20 °C	−0.0329***	−0.1751***	−0.0060*	−0.0015	−0.0172***	−0.0741***	−0.0466***	−0.0427***	−0.0419***	−0.1218***
	(0.0095)	(0.0319)	(0.0036)	(0.0151)	(0.0025)	(0.0114)	(0.0042)	(0.0146)	(0.0029)	(0.0086)
25–30 °C	0.0090	0.1051***	−0.0067	−0.0394**	0.0014	0.0312***	0.0434***	0.0534***	0.0430***	0.0968***
	(0.0111)	(0.0366)	(0.0043)	(0.0178)	(0.0030)	(0.0117)	(0.0046)	(0.0181)	(0.0032)	(0.0110)
> 30 °C	0.0163	0.2232***	−0.0324***	−0.0638***	−0.0006	0.0430**	0.1031***	0.1957***	0.0567***	0.1263***
	(0.0249)	(0.0672)	(0.0091)	(0.0233)	(0.0054)	(0.0184)	(0.0106)	(0.0318)	(0.0063)	(0.0196)
Observations	1,976,283		2,511,929		2,554,873		2,501,785		2,595,686	
Mean Outcome	0.215		1.744		3.969		1.581		8.052	
	Eye and Ear		**Genitourinary**		**Inf. and Parasitic**		**Mental**		**Neoplasms**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤ 10 °C	−0.0601***	0.0216	−0.0866***	−0.2956***	−0.1699***	−0.8253***	−0.1404***	−0.2489***	−0.0606***	−0.3222***
	(0.0117)	(0.0601)	(0.0086)	(0.0349)	(0.0089)	(0.0502)	(0.0175)	(0.0627)	(0.0172)	(0.0721)
10–15 °C	−0.0201***	0.0326	−0.0493***	−0.2486***	−0.0995***	−0.4946***	−0.0858***	−0.1619***	−0.0323***	−0.1660***
	(0.0072)	(0.0259)	(0.0039)	(0.0168)	(0.0055)	(0.0261)	(0.0081)	(0.0275)	(0.0106)	(0.0392)
15–20 °C	−0.0058	0.0131	−0.0279***	−0.1138***	−0.0505***	−0.1904***	−0.0444***	−0.0674***	−0.0149**	−0.0459*
	(0.0053)	(0.0196)	(0.0029)	(0.0115)	(0.0035)	(0.0190)	(0.0053)	(0.0204)	(0.0076)	(0.0260)
25–30 °C	0.0173***	0.0582**	0.0262***	0.1227***	0.0500***	0.0640***	0.0479***	0.0405	−0.0036	0.0314
	(0.0056)	(0.0243)	(0.0035)	(0.0139)	(0.0040)	(0.0210)	(0.0062)	(0.0254)	(0.0092)	(0.0331)
> 30 °C	0.0190	0.0959**	0.0475***	0.2098***	0.0859***	−0.0743**	0.0893***	0.0611	−0.0260	−0.0006
	(0.0128)	(0.0392)	(0.0065)	(0.0258)	(0.0081)	(0.0302)	(0.0126)	(0.0406)	(0.0177)	(0.0445)
Observations	2,356,368		2,543,332		2,533,607		2,397,262		2,012,485	
Mean Outcome	0.897		3.107		3.954		0.705		0.275	
	Nervous System		**Obstetric**		**Other**		**Respiratory**		**Skin/Musc.**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤ 10 °C	−0.1255***	−0.2001***	−0.0469***	−0.1301***	−0.0740***	−0.2119***	−0.0732***	0.3363***	−0.1097***	−0.2801***
	(0.0132)	(0.0623)	(0.0098)	(0.0449)	(0.0078)	(0.0286)	(0.0055)	(0.0292)	(0.0078)	(0.0314)
10–15 °C	−0.0641***	−0.0875***	−0.0318***	−0.0738***	−0.0508***	−0.1745***	−0.0372***	0.2578***	−0.0561***	−0.2138***
	(0.0077)	(0.0263)	(0.0036)	(0.0228)	(0.0031)	(0.0144)	(0.0033)	(0.0182)	(0.0052)	(0.0179)
15–20 °C	−0.0275***	−0.0411**	−0.0184***	−0.0271*	−0.0259***	−0.0815***	−0.0165***	0.1321***	−0.0256***	−0.0882***

Continued on next page

	(0.0051)	(0.0199)	(0.0028)	(0.0150)	(0.0021)	(0.0098)	(0.0026)	(0.0131)	(0.0034)	(0.0114)
25–30 °C	0.0175***	0.0438*	0.0194***	0.0745***	0.0286***	0.0831***	0.0073**	−0.1125***	0.0185***	0.0819***
	(0.0068)	(0.0229)	(0.0027)	(0.0137)	(0.0026)	(0.0128)	(0.0033)	(0.0139)	(0.0039)	(0.0137)
> 30 °C	0.0024	0.0654*	0.0405***	0.0767**	0.0413***	0.0716***	0.0109*	−0.3118***	0.0148**	0.1573***
	(0.0129)	(0.0384)	(0.0058)	(0.0299)	(0.0067)	(0.0206)	(0.0060)	(0.0260)	(0.0072)	(0.0271)
Observations	2,364,478		2,528,395		2,594,995		2,550,299		2,498,247	
Mean Outcome	0.608		4.641		10.707		9.150		2.449	

Notes: This table presents point estimates of the effects of daily temperature deviations on the rate of ED visits across all ICD-10 chapter codes. We use the standard Poisson maximum likelihood estimation (MLE) distributed lag model to estimate the effect. Our temperature intervals use the 20–25 °C category as the reference. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors cluster at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Contemporaneous effect. Cold temperatures consistently reduce urgent care visits for various illnesses, showing a decrease of 4.7 percent in obstetric cases and 17 percent in infectious and parasitic diseases during the coldest temperature range. Conversely, warmer temperatures increase the incidence of specific conditions. For instance, endocrine and metabolic illnesses show a 4.3 percent increase at temperatures of 25-30 °C, which rises to approximately 10.3 percent above 30 °C. Similarly, external causes, including injuries and poisonings, respond positively to warm temperatures. Other conditions that significantly increase with warm temperatures include genitourinary disorders, infectious and parasitic disorders, mental health issues, obstetric conditions, and skin-musculoskeletal disorders. In contrast, blood-immune and digestive categories show no significant contemporaneous effects under warm conditions, while effects for nervous, respiratory, and eye-ear categories are not consistently significant across warm bins. Circulatory diseases are the only category that has a negative contemporaneous coefficient under warm conditions. We provide further intuition for this result in a later section of the paper.

Cumulative effect of cold. Several health conditions exhibit amplified coefficients in the distributed lag model. Cumulative reductions for extreme cold reach 82.5 percent for infectious and parasitic diseases and 34.8 percent for external causes. The results for infectious-parasitic diseases are in line with White (2017), which reports a significant decrease of approximately 35 percent. However, this effect has a limited overall impact in California due to the low prevalence of these diseases, which account for about 3 percent of visits in the state. In contrast, the decrease in infectious and parasitic diseases significantly influences the overall trend in Mexico, where this category constitutes roughly 6 percent of visits (Table A.4). Particularly, we find significant reductions in dengue, food-borne bacterial intoxications, and gastroenteritis-colitis driving the 30-day reduction (Table A.11).[12] Other categories, such as genitourinary (30 percent), neoplasms (32 percent), and skin and musculoskeletal (28 percent), also exhibit statistically significant amplifications.

One exception to the amplification of short-term impacts after thirty days occurs with respiratory conditions, which exhibit a shift in sign between contemporaneous and cumulative models. Although extreme cold initially causes a 7.3 percent decrease in admissions, the 30-day cumulative effect shows a significant 33.6 percent increase, highlighting the delayed adverse impacts of cold. This pattern reflects the nature of respiratory viral infections, where cold weather encourages social gatherings, facilitating transmission and leading to higher incidence days or weeks after the cold spell (Matsuki et al., 2023). Interestingly, although the dynamics of respiratory conditions align with estimates from California (White, 2017), this increase does not result in an overall rise in visits during cold spells, as respiratory diseases contribute less to the demand for urgent care in Mexico.

Cumulative effect of heat. The cumulative effects of warm temperatures often differ from short-term impacts. For endocrine and metabolic disorders, cumulative admissions increase by 19.6 percent at high temperatures (> 30 °C), nearly doubling the immediate effect. Similar trends occur for genitourinary, obstetric and skin-musculoskeletal disorders, with cumulative increases of 20.9 percent, 7.7 percent and 15.7 percent, respectively, compared to immediate rises of 4.75 percent, 4.1 percent and 1.48 percent. Some conditions, despite having no significant contemporaneous effects, show positive cumulative impacts after 30 days, including Blood/Immune (22 percent), Eye/Ear (10 percent), and Digestive (4 percent). In contrast, respiratory diseases show a significant cumulative decrease in visits at hot temperatures (-31.18 percent) despite a weakly significant and small

[12] This difference highlights another source of heterogeneity between Mexico and California: in our sample, dengue accounts for 0.2 visits per 100,000 population, whereas California reports fewer than 200 cases annually in a population of approximately 39 million (California Department of Public Health, 2025).

immediate positive effect. This large decrease at the highest temperature interval explains the pooled reduction in the cumulative point estimate compared to the short-term effect (Figure 2). Additionally, infectious and parasitic diseases exhibit a cumulative decrease of 7.43 percent, contrasting with an 8.59 percent immediate increase. This pattern indicates that the impact slightly declines over the 30-day period.[13]

For circulatory diseases, the negative impact intensifies over time, reaching -6.38 percent in the 30-day cumulative window. While the decline in circulatory-related ED visits on hot days may appear at odds with some medical evidence—where heat is understood to place additional stress on the cardiovascular system (Anderson et al., 2013; Phung et al., 2016)—similar patterns have been documented in prior economic studies. For example, White (2017) and Gould et al. (2024) find reductions in cardiovascular admissions in California, while Agarwal et al. (2021) reports no cumulative effects in China. These results are also consistent with epidemiological work showing limited or inconclusive associations between heat and cardiovascular morbidity (Turner et al., 2012; Bunker et al., 2016; Sun et al., 2021). In the Mechanism section (Section 4.3), we provide suggestive evidence regarding the mechanisms that may explain these patterns.

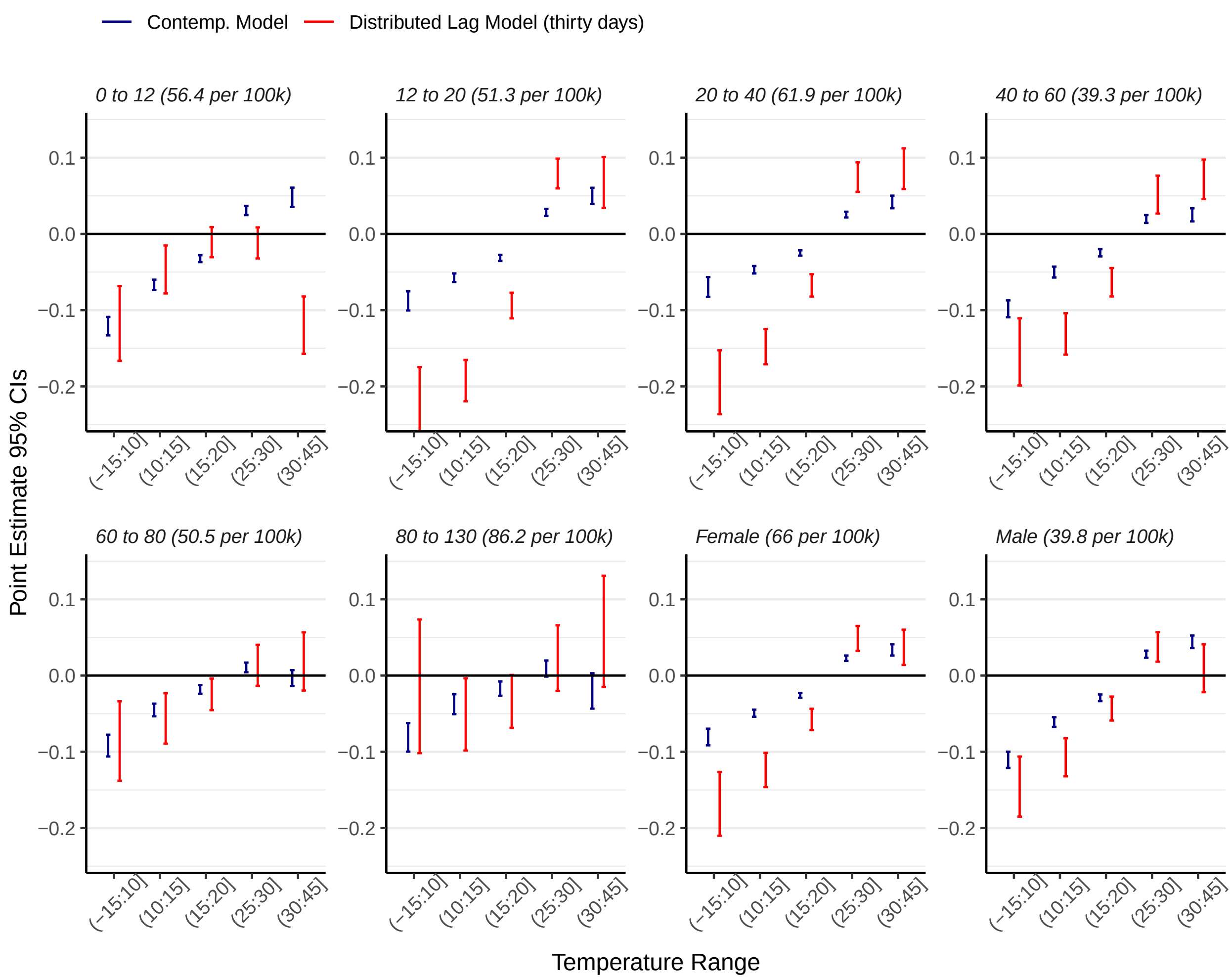
Comorbidities. Some diseases might be interlinked with other conditions (comorbidities), complicating the interpretation of single-cause outcomes. To test whether comorbidities alter our estimated effects, we estimate auxiliary specifications that control for ED visits from other ICD-10 categories within the same regression. While we need to interpret these coefficients with caution, as the number of cases for other conditions is also affected by temperature shocks (”bad controls”), this exercise helps clarify whether the single disease estimates capture genuine effects rather than artifacts arising from shifts in the composition of reported conditions at triage. Figure A.7 shows that our results are stable when we control for ED visits from other ICD codes. Taken together, these results indicate that, although comorbidities likely play a role, controlling for other disease categories leaves our estimates largely unchanged. This suggests that our main findings are not driven by differential reporting across diagnoses.

[13] Note, however, that infectious and parasitic diseases display a cumulative increase at temperatures between 25°C and 30°C, indicating heterogeneous heat effects across temperature ranges.

4.2. Heterogeneity by age and gender

Once we understand the most affected disease categories, we examine the heterogeneous effects across different demographics. Figure 3 presents the coefficients for the contemporaneous and cumulative effects, categorized by age group and gender.

Figure 3: Contemporaneous and cumulative effects by age and gender



Notes: This figure presents point estimates and 95 percent confidence intervals of the effects of daily temperature deviations on the rate of ED visits across six different age groups and for male and female people. We use the standard Poisson maximum likelihood estimation (MLE) distributed lag model to estimate the effect. Our temperature intervals use the 20–25°C category as the reference. The figure presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors cluster at the municipality level.

Contemporaneous effect. In response to cold temperatures, visits decrease across all age groups. This is in line with the reduction across all disease categories identified in Table 3. Among children aged 0–12, cases decrease by 12.10 percent on days with average temperatures below 10°C. Similar reductions occur in other age cohorts: 8.79 percent for ages 12–20, 6.96 percent for ages 20–40, 9.82 percent for ages 40–60, 9.19 percent for ages 60–80, and 8.11 percent for ages 80–130. Gender differences also emerge in response to cold. At very low temperatures, male individuals experience a larger reduction in visits (11.05 percent) compared to female individuals (8.06 percent), due to variations in their demand for ED services (Table A.3). For instance, over 15 percent of visits for women result from obstetric consultations, which report a contemporaneous decrease of 4.7 percent at cold temperatures. In contrast, most of the demand for men relates to respiratory conditions, which react more strongly to cold (7.3 percent).

In contrast to cold temperatures, hot temperatures consistently increase urgent care visits across all age groups, especially among younger populations. For children aged 0–12, each additional day with average temperatures of 25–30°C increases visits by 3.07 percent, while days at or above 30°C result in a 4.80 percent increase. Similarly, adolescents aged 12–20 experience increases of 2.82 percent and 4.99 percent, respectively. For adults aged 20–40, ED visits increase by 2.54 percent at warm temperatures and 4.19 percent at hot temperatures. In contrast, individuals aged 60–80 show no significant contemporaneous effect to days above 30°C and individuals over 80 show a reduction of 2 percent. This difference in effects between younger and older populations arises from the varied conditions triggering ED visits. For children and young adults, obstetric conditions, infections, and respiratory diseases are the most common. All three of these ICD-10 chapters show large increases during hot temperatures. For individuals over the age of 59, circulatory conditions, diabetes, and urinary tract infections are prevalent; however, these conditions show mixed coefficients. Regarding gender differences, at warm temperatures (25–30°C), male individuals show a 2.80 percent increase in cases, rising to 4.43 percent at hot temperatures (> 30°C), and female individuals exhibit increases of 2.27 and 3.36 percent, respectively.

Cumulative effect (30 days). The 30-day cumulative effects suggest that decreased visits at cold temperatures either intensify or remain stable over time across age groups. For children aged 0–12, the cumulative decrease in the coldest interval remains relatively stable to 11.74 percent, up from an initial decrease of 12.1 percent. For adolescents aged 12–20, the percentage increases to 22.9 percent. These amplified effects imply that cold temperatures cause sustained reductions in ED visits, primarily due to significant drops in the categories of digestive, external causes, infectious-parasitic, and obstetric conditions. Regarding gender, both males and females show significant cumulative decreases in visits at cold temperatures, with reductions of 14.56 percent and 16.83 percent in the coldest interval, respectively.

The cumulative effects of high temperatures differ across age groups. For children aged 0–12, cumulative visits decrease by 11.96 percent on very hot days ($>$ 30°C), despite an initial increase of 4.80 percent. Similarly, the cumulative effect of days with average temperatures of 25–30°C becomes statistically insignificant after 30 days. This reversal primarily comes from the dynamics of respiratory conditions, which account for about 30 percent of the demand for ED services in this age group. The large cumulative reductions for the youngest cohort explain why the pooled estimate for the cumulative effect of hot temperatures does not significantly differ from the contemporaneous impact (Figure 2). In contrast to children, other age groups exhibit cumulative increases in the effect of hot temperatures over the 30-day window due to the lower relevance of respiratory diseases. For instance, although over 30 percent of visits for children under 12 are due to respiratory conditions, this figure drops to less than 2 percent for adolescents aged 12–20. Regarding gender, cumulative effects at hot temperatures diverge: male individuals show no significant cumulative impact, while female individuals experience an increase of 3.71 percent.

4.3. Potential mechanisms: suggestive evidence

To further advance our understanding of the dynamics linking temperature variations and ED visits, we provide suggestive evidence about three potential channels that underpin these relationships: (i) physiological incidence, (ii) ecosystem dynamics, and (iii) behavioral responses. For each one, we present illustrative examples based on specific diseases. However, we note that these mechanisms often overlap and interact.[14] Therefore, we do not interpret these exercises as causal tests, as the available data do not allow us to separately identify each channel.

Physiological incidence. Physiological incidence refers to the direct effects that extreme temperatures can have on the human body. For instance, evidence shows that prolonged heat exposure disrupts thermoregulation and causes dehydration, electrolyte imbalances, and overheating (Weinberger et al., 2021; Sun et al., 2021; Hess et al., 2014). In line with these mechanisms, columns 1–2 of Table A.10 show how hot temperatures significantly increase visits for heatstroke. Epidemiological studies also indicate that heat exposure during pregnancy induces physical and psychological stress, which elevates systemic cortisol levels. This elevation in cortisol can impact fetal and placental membranes, which increases the likelihood of premature labor and preterm birth (Hunter et al., 2023). Consistent with these findings, we document a significant 5 percent increase in false labor following a day above 30 °C, which increases to 15 percent over the 30-day period (Columns 3–4).

Unlike heat shocks and false labor, we observe a statistically significant reduction in visits for heart failure during hot weather (Columns 5–6), in line with the results for circulatory conditions in Table A.4. To shed light on this result, we examine whether heat instead increases cardiovascular mortality. We find that deaths from circulatory diseases sharply rise on hot days, both contemporaneously and cumulatively over thirty days (Table A.8), with effects that grow steeply with age (Table A.9). This pattern suggests that heat may shift the burden of circulatory disease from morbidity to mortality: some patients who would otherwise appear in the ED may instead experience fatal events (Gould et al., 2024). However, this represents only one potential mechanism. For instance, older individuals might adapt to hot temperatures by staying at home during hot days, which decreases their overall likelihood of visiting the emergency department. Because we do not observe

[14] For instance, on particularly hot days, physiological stress may coincide with outdoor activities and increased exposure to insect-borne pathogens, compounding health risks and increasing ED demand. Conversely, cold temperatures may reduce mobility, temporarily suppressing the spread of certain illnesses while amplifying others, such as respiratory infections, over time.

the underlying behavioral changes that lead to fewer circulatory ED visits, we cannot disentangle these two mechanisms.[15]

We also find that higher temperatures exacerbate mental disorders, such as dissociative and conversion disorders (Columns 7–8). This effect likely arises from hot temperatures impairing cognitive function and disrupting sleep, which worsen mental health conditions (Nori-Sarma et al., 2022; Sun et al., 2021). For the common cold, the pattern parallels that of the ICD chapter on respiratory conditions: a short-term decrease at cold temperatures is followed by an increase after thirty days, and the negative impact of hot days intensifies when we account for displacement.

Ecosystem dynamics. Temperature fluctuations can indirectly affect health through changes in the ecosystem (Table A.11). These variations influence the activities of vectors and pathogens, impacting the prevalence of vector-borne and foodborne diseases (Carlton et al., 2016; Viana and Ignotti, 2013). Our estimates show that colder temperatures decrease the spread of vectors, such as dengue, as cooler conditions inhibit transmission dynamics (Columns 1–2). In contrast, hot days consistently increase infection rates from parasites, as shown by our estimates for foodborne intoxications (Columns 3–4) and infections during pregnancy (Columns 7–8). Moreover, higher temperatures increase the incidence of foodborne illnesses, such as gastroenteritis (Columns 5–6).

Shifts in temperature also impact the behavior of local fauna, altering the ecosystem's balance and influencing human health risks. Columns 9–10 provide evidence of increased incidents of intoxication caused by venomous animals and plants during hot days. Warmer temperatures elevate the activity levels of toxic species, such as spiders and snakes, especially during peak hours (Needleman et al., 2018). Behavioral factors further exacerbate these risks, as individuals are more likely to spend extended periods outdoors in warm weather, increasing the likelihood of encounters and bites.

[15] Another potential explanation is the correlation between circulatory ED visits and other conditions, which may lead to a reduction in visits due to an increase in other correlated diseases. We test for this additional mechanism for circulatory conditions, Figure A.8, by comparing contemporaneous and cumulative effects across three specifications (baseline, controlling for correlated diseases, and controlling for all diseases), again yielding consistent results.

Behavioral responses. Beyond incidence and ecosystem dynamics, temperature influences human activity patterns and health care-seeking behavior (Table A.12).

Individuals may change their health-seeking behavior in response to ambient temperatures. Our findings indicate a significant reduction in visits for less compared to more severe conditions within the same ICD categories during cold periods. For instance, cold temperatures result in a greater decrease in ED visits for headaches (Columns 1–2) compared to epilepsy (Columns 3–4) and urinary system diseases (Columns 5–6) compared to chronic kidney disease (CKD, Columns 7–8).[16] This pattern suggests that individuals with nonurgent needs may postpone or avoid ED visits during cold weather, reflecting the discretionary nature of health care use under adverse climatic conditions (White, 2017).

Moreover, warmer temperatures promote outdoor recreation, social gatherings, and alcohol consumption. These factors, along with heat-related physiological stress, increase the number of visits. For instance, hot days significantly amplify the cases of mental disorders linked to alcohol consumption (Columns 9–10). This estimate is consistent with previous research that finds a positive association between alcohol consumption and outdoor temperatures (Cohen and Gonzalez, 2024). Elevated temperatures also enhance the physiological and psychological effects of alcohol, increasing the likelihood of acute episodes that require emergency care. Additionally, we find that hot days exacerbate other mental health disorders, indicating that heat stress may worsen mood disorders and cognitive impairments, compounding the effects of alcohol on mental health.

Finally, we test whether postponing non-urgent hospital visits in response to ambient temperatures is potentially influenced by responses to hospital congestion news (Table A.13). To do so, we perform three exercises. First, we add seven lags of the dependent variable—*AR(7)*—in a pure autoregressive distributed lag model fashion. This specification directly tests whether serial persistence in admissions explains the dynamic temperature pattern. The results are virtually unchanged: same-day and cumulative effects retain identical signs and magnitudes, suggesting that persistence alone cannot account for our findings.

[16] The increase in CKD cases during cold temperatures aligns with epidemiological findings (Park et al., 2024).

Next, we include a *leave-one-out congestion index*, defined as the state-day ED admission rate excluding the focal municipality and its lags, up to a week. This control captures the "system load" that media reports could reflect.[17] Same-day coefficients remain highly significant with the expected pattern (cold reductions and heat increases), while cumulative cold effects attenuate modestly, and hot effects remain stable or even increase in precision.[18] Finally, we add date fixed effects, which absorb all national-day shocks—such as broad media attention or nationwide policy announcements—that could influence hospital use simultaneously across regions. The same-day effects persist, albeit with smaller magnitudes, and the 30-day cumulative estimates lose precision, as nearly all daily variation is absorbed. Comparing all specifications, the pattern of decreases in ED visits on cold-days and increases on hot-days proves robust. Therefore, even though we cannot fully rule out the mechanism, this evidence indicates that our temperature effects are not artifacts of media coverage or congestion-induced postponement; at most, such factors slightly dampen the persistence of cold-day responses without overturning the immediate physiological relationship between temperature and emergency care demand.

5. Midcentury projections

To estimate the potential impacts of climate change on ED visits under a no-adaptation scenario, we use climate projections from the CMIP6 framework, incorporating data from five global climate models (GCMs) to address uncertainty (see Appendix A.4). We analyze shifts in daily temperature distributions between a historical baseline (1991–2010) and future decades (2031–2060) to quantify changes in the frequency of specific daily ranges across these periods.[19] This method evaluates the short-run impact of temperature changes on health outcomes using age-specific semielasticities of ED visits and considers cumulative lagged effects over thirty days. These projections extrapolate the observed

[17] Even though we cannot fully rule out spillovers from temperature-related emergency department visits (which would make our index a "bad control"), we believe this represents an interesting test for our specification.

[18] According to the Bayesian Information Criterion (BIC), the model fit improves when including the congestion lags, indicating that these controls add information but do not drive the temperature effects.

[19] Temperature changes are aggregated at the municipality level using population-weighted averages.

short-run marginal effects over long horizons, holding behavioral, institutional, and technological factors constant. As such, they should be interpreted as illustrative upper-bound scenarios that assume no adaptation, rather than as precise forecasts of future healthcare demand.

We convert relative changes in ED visits due to climate-induced temperature shifts into absolute changes by incorporating age-group-specific population growth assumptions based on SSP2 demographic scenarios (Falchetta et al., 2024). Projections of Mexico's aging population allow for a detailed analysis of how changing climatic conditions could affect different age groups in the absence of adaptation.[20] We integrate age-specific mortality rates from Cohen and Dechezleprêtre (2022) to adjust future population projections to the effects of temperature variations on mortality. These mortality estimates reflect the differential sensitivity of age groups to temperature extremes and update the population size over time. The resulting demographic trajectories ensure that projected healthcare demand reflects population changes driven by temperature-induced mortality. Furthermore, we differentiate future changes in ED visits based on the main outcome—whether the patient is hospitalized or discharged. This distinction allows us to shed light on the mechanisms underlying our projections, as hospitalization outcomes can be viewed as proxies for urgent cases, while discharges capture non-urgent visits.[21] Finally, we estimate the economic impact of these changes using official 2024 medical care cost data for Mexico, which include ED and hospitalization costs per patient.[22] We calculate projected public health expenditures by averaging across GCMs and assuming constant baseline hospitalization rates relative to admissions over time.

The simulation exercise reveals a clear upward trend in public healthcare expenditures

[20] The relative population shares indicate that the combined share of individuals aged 20–60 remains substantial (see Table S2), decreasing from 54.6 percent in 2022 to 50.7 percent in 2050. Meanwhile, elderly population (ages 60–80 and over 80) increases from 12.2 to 24.5 percent. Despite this aging trend, the absolute number of younger adults is still projected to exceed that of the elderly. Consequently, even with similar temperature–health coefficients, the smaller total population and lower heat sensitivity among the elderly result in a more modest overall increase in heat-related admissions for these age groups.

[21] For this computation, we rely on the all-age, outcome-specific cumulative responses to cold and heat reported in Figure A.9.

[22] We exploit data from official government estimates of medical care unit costs in Mexico for the year 2024 by the FIMSS (2023). These data provide an average cost per visit (c^a) of 207 USD and an average cost of admissions leading to hospitalizations (c^h) of 691 USD.

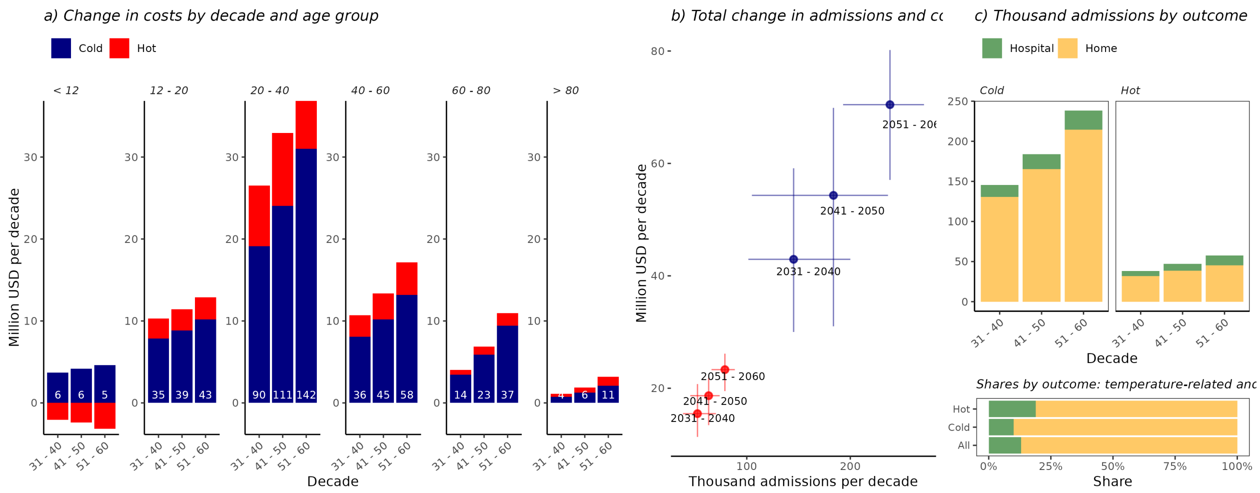
and visits over the decades under the no-adaptation assumption. By 2031–2040, we project that cumulative expenditures could reach approximately 58.4 million USD, resulting in an increase of roughly 197 thousand ED visits. In the following decade, 2041–2050, expenditures could rise to approximately 79.9 million USD, associated with an additional 246 thousand visits. By 2051–2060, projected expenditures could increase further to 93.7 million USD, with approximately 317 thousand additional visits. By midcentury,[23] this corresponds to approximately a 0.35 percent increase in annual ED visits relative to historical levels, implying roughly 8.5 million USD in additional annual medical expenditures. To contextualize our estimates, Gould et al. (2024) projects that ED visits in California will increase by 0.46 percent by midcentury. Both cold- and heat-related effects significantly increase ED visits in our no-adaptation scenario. From 2031 to 2040, cold-related cases will dominate. However, heat-related effects become more pronounced between 2041 and 2050, as well as between 2051 and 2060. Therefore, absent adaptation, healthcare planning must account for both rising temperatures and the reduced number of cold days, as the latter significantly contributes to increased health care demand.

We find that around 2050 roughly 18 percent of the excess visits attributable to heat and 10 percent of those attributable to cold correspond to severe cases requiring hospitalization. These shares are, respectively, higher and lower than the historical hospitalization rate of 13 percent across all visits. Hence, heat generates a disproportionate increase in severe cases, whereas cold-related changes are concentrated among lower-severity cases.

Extreme cold and heat significantly increase visits across all age groups, except for heat-related cases among children. The reduction in ED visits in this group results from a decrease in cases of nasopharyngitis (common cold) associated with higher temperatures. The 20–40 age group experiences the largest increase in cold-related visits, projecting 64.7 thousand additional visits for the period 2031–2040, which will rise to 104.8 by 2051–2060. The 40–60 age group also shows a notable increase, rising from 27.3 thousand additional visits in 2031–2040 to 44.6 thousand by 2051–2060. Younger (0–12) and older (80–130) age groups experience lower increases, with 12 and 2.5 thousand additional cases, re-

[23] Midcentury is defined as the 2041 to 2060 average.

Figure 4: Illustrative projections of temperature-related emergency department (ED) visits under a no-adaptation scenario



Notes: The left panel presents the total change in public ED visits' costs by age group, by decade (sum of 2031-2040, 2041-2050 and 2051-2060, respectively). Labels at the bottom of the bars show the change in cases (in thousands). The central panel presents the decadal change in public ED visits' costs and cases, due to changes in hot and cold temperatures, by time period and for all ages. Scatter points represent the GCM mean values; segments report the minimum and maximum value across GCMs. The right panel reports the total visits' change by all ages, split between outcomes, alternatively being sent home or hospitalized (the latter including deaths).

spectively, in 2031–2040, rising to 15.6 and 7 thousand by 2051–2060. Cold-related effects lead to higher expenditures, increasing from \$4 million in 2031–2040 to \$7 million by 2051–2060.

The 20–40 age group experiences also the highest increase in heat-related visits, totaling additional 25 thousand in 2031–2040, and rising to 36 thousand by 2051–2060. This finding aligns with literature indicating that temperature increases impose a greater burden on individuals in the middle of the age distribution (Wilson et al., 2024). The 40–60 age group also shows an increase, rising from 8.8 thousand cases in 2031–2040 to 13.4 thousand by 2051–2060. The older (80–130) group exhibits smaller increases, growing from one thousand in 2031–2040 to 3.6 thousand by 2051–2060 due to the relatively low share of this age group in the population. Decadal expenditures for heat-related visits rise from \$1.13 million in 2031–2040 to \$1.71 million by 2051–2060.

6. Conclusion

Our study highlights the importance of examining morbidity outcomes, such as ED visits, to assess the impact of temperature on health. In contrast to mortality, which exhibits a U-shaped response to extreme cold and hot days, ED visits show an approximately linear relationship. This finding corroborates research conducted in higher income settings (e.g., Gould et al., 2024; White, 2017). Moreover, our data, which cover nearly all public hospitals in Mexico, provide stronger national representativeness than many others. By examining morbidity and mortality concurrently in the same period and location, we demonstrate how temperature extremes affect health through distinct mechanisms, ultimately providing a more comprehensive view of climate-related risks.

Cold temperatures reduce ED visits both immediately and cumulatively. The observed heterogeneity across diseases reflects behavioral changes, such as postponing mild treatments, as well as the incubation periods of certain pathogens. In contrast, hot temperatures trigger immediate surges in heat-related conditions and injuries, followed by a partial attenuation over time. These trends may arise from ”harvesting” effects or a displacement of visits. Gender and age patterns reveal that children and adolescents are more sensitive to heat, while older populations are more vulnerable to cold. Disease-specific results show that our findings could stem from direct physiological responses, such as heatstroke; behavioral factors, including alcohol-related disorders; and ecosystem dynamics, including the increase in vector-borne diseases.

Climate projections provide illustrative evidence that ED usage could increase in the coming decades due to extreme temperatures, especially among younger adults during heat waves and older adults during cold spells. Policymakers must anticipate these trends by expanding ED capacity and establishing rapid-response protocols. The linear relationship between temperatures and visits could pose a serious risk of overburdening public hospitals, especially in resource-constrained settings (Aguilar-Gomez et al., 2025). The health and economic consequences of ED overcrowding could be significant. Research indicates that high occupancy levels (more than 90 percent) correlate with negative patient outcomes, including treatment delays, elevated mortality rates (20–30 percent), extended inpatient stays, and increased hospital readmission rates (Hoot and Aronsky, 2008).[24] A comprehensive assessment of climate-related health costs must extend beyond mortality estimates and account for morbidity, strain on healthcare systems, and indirect economic impacts. Our study highlights the need for future research to quantify these broader costs, ensuring that climate policy fully addresses the public health burden of rising temperatures.

Several caveats warrant caution in interpreting our findings. First, we use ambient temperature at the municipality-level as our exposure metric rather than focusing on micro-environments at homes and workplaces. Unobserved microclimates and behaviors (e.g., shade, cooling, hydration, work schedules) may either reduce or increase true exposure. Second, we should cautiously interpret the extent to which our results generalize beyond this setting. Although Mexico's temperature distribution makes it a compelling setting for studying heat and health, its health-sector organization, which includes a public–private mix, insurance coverage, co-payments, referrals, triage protocols, and time-varying capacity or congestion, differs from those in many other countries. As a result, the mapping from temperature to emergency department utilization may vary, even if the underlying physiological responses are similar. Nevertheless, the qualitative pattern we document—an approximately linear increase in ED demand at higher temperatures and a decline at colder temperatures—appears robust and is likely relevant for many low- and middle-income settings, with local health-system features changing the magnitudes. Third, our focus on public EDs likely captures the majority of serious emergency visits nationwide. However, the subset of patients who seek private care may respond differently to temperature. These patients tend to be wealthier or have private insurance, which might provide them with better preventive resources (such as air conditioning and easier access to general practitioners) or simply offer alternative avenues for care (e.g., private urgent care clinics). If higher-income individuals are less affected by temperature or can avoid public

[24] Numerous factors beyond temperature changes and climate variation have been identified as contributing to ED overcrowding, including the growing complexity of cases—potentially linked to an aging population—shortages of staff, delays in laboratory results, and limitations in physical capacity within hospitals (Trzeciak and Rivers, 2003).

EDs on extreme weather days, our estimates based on public hospital data would represent an upper bound relative to the true population-wide effect. Furthermore, ED visits represent only one point of entry into the health system, making it difficult to disentangle health-seeking behavior from true morbidity. We remain agnostic about the precise mechanisms underlying the temperature–ED relationship in Mexico. While we provide suggestive evidence on several plausible channels, these mechanisms cannot be causally isolated in our setting and are unlikely to generalize mechanically across contexts, given differences in disease environments, cultural norms, and health-system organization. Finally, our projection exercise should be interpreted with caution. It combines estimated short-run responses to transitory temperature variation with projected future temperature distributions from climate models. This approach implicitly extrapolates short-run marginal effects over long horizons and does not account for potential behavioral, institutional, or technological adaptation to changing climatic conditions. In addition, climate projections remain uncertain, particularly at fine spatial and temporal scales. For these reasons, the projections should be viewed as illustrative, no-adaptation scenarios that provide an upper-bound estimate of potential impacts under fixed behavior, rather than as precise forecasts of future emergency department demand. Addressing these limitations remains an important avenue for future research.

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Appendix A

A.1 The Mexican health care system

Mexico's health care system has a mixed structure, incorporating both public and private components. This configuration resembles that of other developing countries, such as Brazil, Argentina, Colombia, and South Africa. Public health care primarily operates through the Mexican Social Security Institute (IMSS) and Institute of Security and Social Services for State Workers (ISSSTE), serving formal employees and their families. In addition, the Seguro Popular program, now succeeded by the Institute of Health for Wellbeing (INSABI), aims to provide healthcare access to the uninsured population. Numerous private healthcare facilities also exist, offering high-quality services; however, these are typically accessible only at a higher price.

Table A.1 presents the share of people covered by each insurance provider. We estimate these values using data from the 2020 Mexican Census. "*Enrollment*" (self-reported) indicates whether the person has access to each provider. "*Use*" refers to whether a person has utilized the services of any of these institutions in the previous year. For example, an uninsured person can undergo surgery in an IMSS hospital.

Table A.1: Mexican health care sector enrollment and use

	Enrollment in Millions (percent)	Use in Millions (percent)
IMSS	47.0 (37.4 percent)	39.6 (31.6 percent)
INSABI or Seguro Popular	36.5 (29.1 percent)	37.4 (29.8 percent)
No enrollment—use	28.6 (22.8 percent)	2.4 (1.9 percent)
ISSSTE and Other	10.3 (8.2 percent)	9.5 (7.5 percent)
Private	3.0 (2.4 percent)	36.1 (28.8 percent)
Unknown enrollment—use	0.2 (0.1 percent)	0.4 (0.3 percent)

Notes: Data are obtained from the Mexican National Census 2020.

In 2020, approximately 23 percent of the Mexican population reported lacking access to healthcare, despite the theoretical guarantee of universal coverage. These figures contrast with the US healthcare system, where only 6 percent of people reported having no access to healthcare. The remaining 66 percent and 25 percent of US residents were enrolled in either private or public insurance programs (Berchick et al., 2019). The uninsured segment of the Mexican population can rely on either the public or private sector for out-of-pocket expenses, which, although expensive, remains significantly more affordable than in other North American countries.

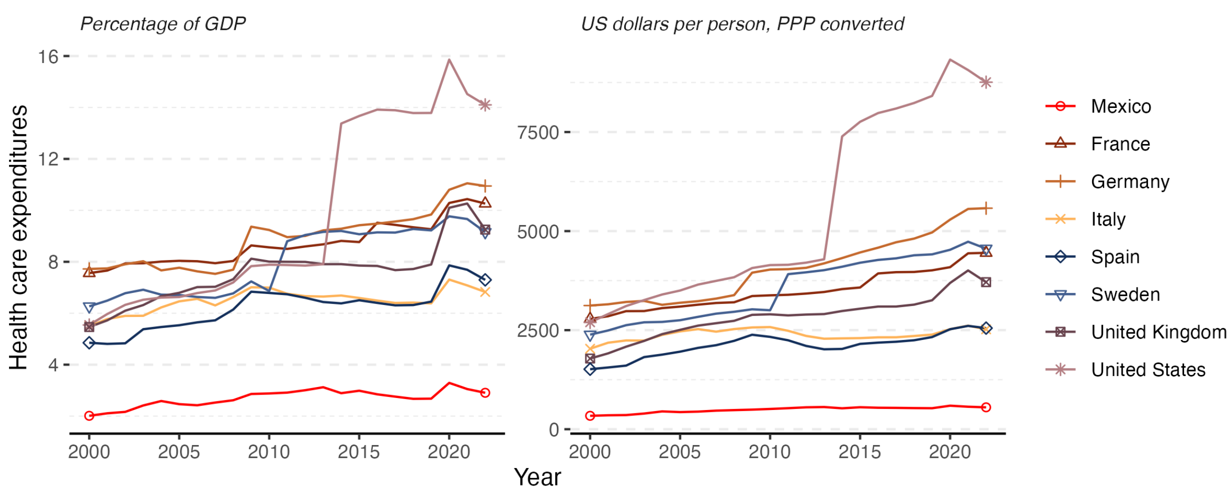
Private hospitals, although more numerous, tend to be smaller; most have fewer than twenty beds and function mainly as outpatient clinics rather than full-service emergency centers (OECD, 2016). Consequently, the majority of critical emergency cases are handled by the public sector. Official statistics indicate that roughly 19.7 million emergency visits occur in Mexico each year (Toche, 2023), reflecting the high demand for urgent care. The emergency system faces significant challenges as it struggles with chronic overcrowding and fragmentation. Emergency physicians note that encountering overcrowded EDs is "very routine," and the multiple public subsystems (IMSS, ISSSTE, state health services) often operate in parallel without effective coordination (Toche, 2023). This lack of integration can lead to duplication of efforts, resource waste, and extended wait times, potentially pushing some patients to seek private care despite the higher cost (Alcalde-Rabanal et al., 2017).

Inside the ED, both public and private hospitals work under a standardized triage system to manage patient flow. Upon arrival, staff quickly evaluate each patient and assign a priority level, commonly using a five-color code (red, orange, yellow, green, blue) that corresponds to severity and acceptable waiting time. This system ensures that life-threatening cases receive immediate attention, while minor "urgencias sentidas" (perceived urgencies) may wait or be referred to primary care. Importantly, public EDs operate under policies aimed at ensuring universal access to emergency care. For instance, IMSS emergency units follow a "zero rejection" principle; no patient seeking emergency attention gets turned away, regardless of bed availability or insurance status. All patients at least undergo triage and stabilization. These institutional features imply that the number of ED visits (as recorded at triage) serves as a direct indicator of demand for emergency services, rather than being capped by hospital capacity.

In addition to differences in the share of insured persons between public and private health systems, Mexico's healthcare structure has notable distinctions from and similarities with other OECD countries. Unlike the United States, which primarily relies on a privatized system with employer-based insurance and significant out-of-pocket expenses, Mexico aims for broader public provision to achieve universal coverage across various segments of the population. However, healthcare faces challenges related to funding and equitable access. In contrast, European systems, particularly those with single-payer models such as those in the United Kingdom and Sweden, generally ensure universal coverage funded through general taxation. This approach results in lower out-of-pocket costs and more equitable access to services.

Figure A.1 uses OECD data to illustrate the burden of health expenditures on government finances in selected OECD countries. Unlike many European systems that benefit from high health care spending as a percentage of GDP, Mexico's health care infrastructure and funding levels are significantly lower, presenting ongoing challenges for the comprehensive and equitable care observed in numerous European nations.

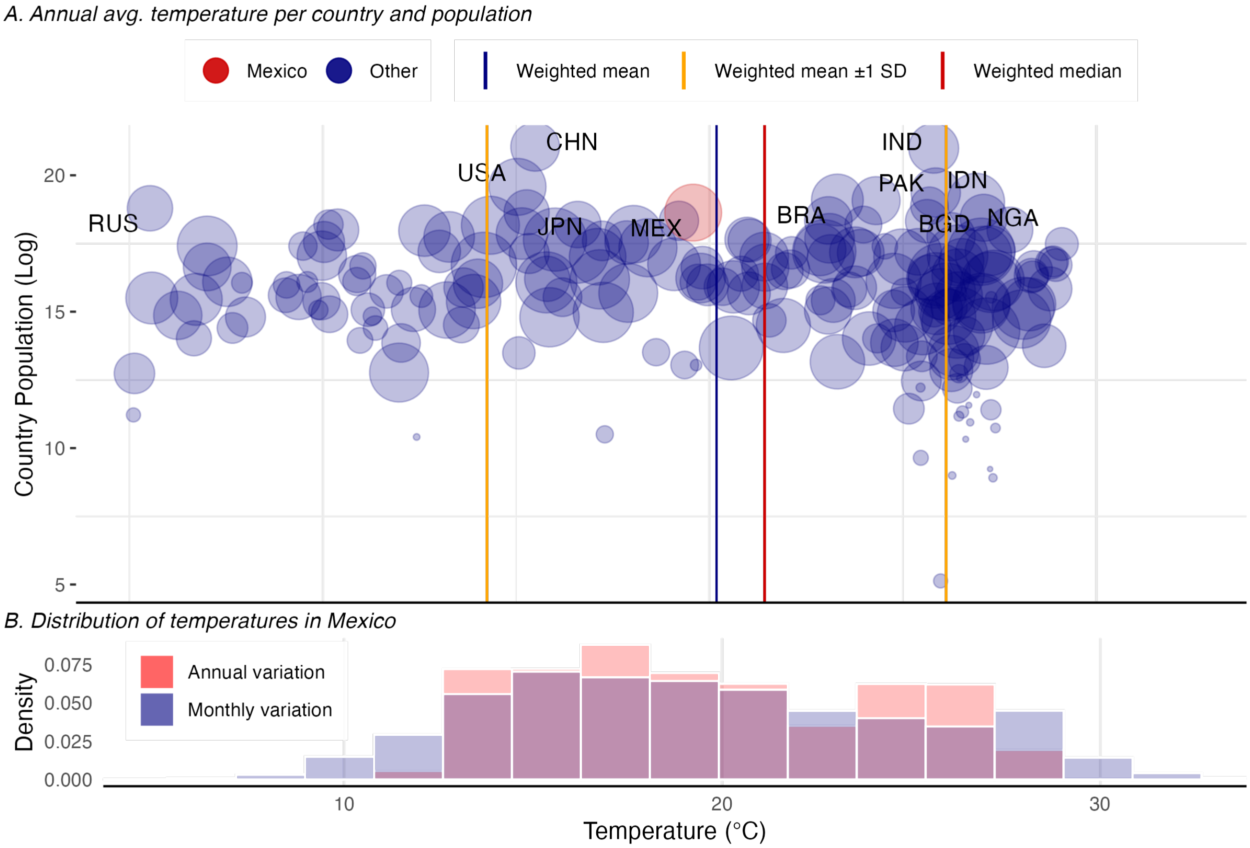
Figure A.1: Health expenditure in government and compulsory schemes



Notes: The figure displays health expenditure in government and compulsory schemes as a percentage of GDP, comparing Mexico with the United States and some European countries. We obtain the data from the OECD database on health and financing (https://data.oecd.org/healthres/health-spending.htm).

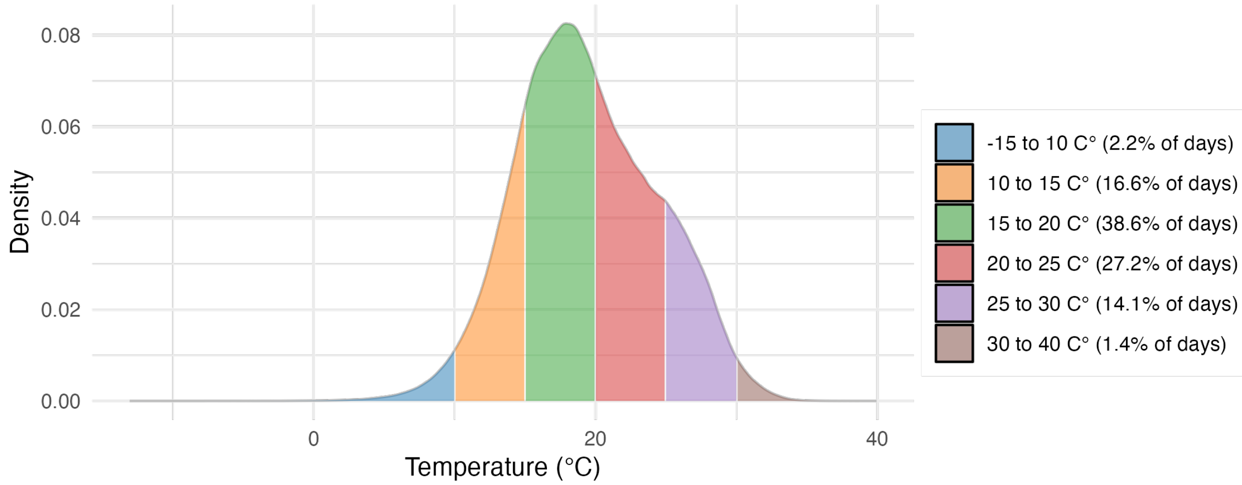
A.2 Additional descriptives

Figure A.2: Temperatures in Mexico compared to other countries worldwide



Notes: We use ERA5 2 m air temperature on a 0.25° grid. Let T_{gd} denote the mean temperature in grid cell g (belonging to country c) on month d, and let p_g be the SEDAC GPW population for grid g (held fixed over the study window). Define the grid's long-run annual mean as$\mu_g = \frac{1}{D}\sum_{d=1}^{D} T_{gd}$. **Panel (a): country scatter.** A country's *population-weighted mean annual temperature* is $\mu_c = \sum_{g\in c} w_g\,\mu_g, \qquad w_g = \frac{p_g}{\sum_{h\in c} p_h}$. The y-axis population is $P_c = \sum_{g\in c} p_g$. Marker size reflects *within-country temperature variability* via a variance decomposition, $\sigma_c = \sqrt{\sum_{g\in c} w_g \left(\mathrm{Var}_d(T_{gd}) + (\mu_g - \mu_c)^2\right)}$. Vertical reference lines show the *global, person-weighted* median and mean of μ_c, and the mean ± 1 standard deviation. Let $\tilde{w}_c = \frac{P_c}{\sum_{c'} P_{c'}}$; then $\bar{\mu} = \sum_c \tilde{w}_c\,\mu_c, \qquad \sigma_{\text{global}} = \sqrt{\sum_c \tilde{w}_c\,(\mu_c - \bar{\mu})^2}$. **Panel (b): Mexico densities.** The "annual" curve is the population-weighted density of $\{\mu_g\}_{g\in \text{MEX}}$ across Mexican grid cells. The "monthly" curve is the population-weighted density of grid–*month* means, $\bar{T}_{gm} = \frac{1}{D_m}\sum_{d\in m} T_{gd}$, across all grid–months. In both curves, each observation is weighted by p_g and densities are normalized to integrate to 1. All quantities are computed over 2013-2023.

Figure A.3: Density of temperatures across the defined non-parametric intervals



Notes: This figure presents the density distribution of daily average temperatures across the country. We include color indicators for the temperature intervals used in our empirical model. We also include the share the days in each temperature interval during our sample period.

Table A.2: Main diseases by sex

ER Type	ICD-10 Name	# Visits (Thousands)	Share of Category	Cumulative Share	Share of Total
Female (65.27%)	Encounter for supervision of normal pregnancy (Z34)	12,016.86	15.58%	15.58%	10.17%
	Infectious gastroenteritis and colitis, unspecified (A09)	2,785.87	3.61%	19.19%	2.36%
	Acute pharyngitis (J02)	2,562.75	3.32%	22.51%	2.17%
	False labor (O47)	2,420.36	3.14%	25.65%	2.05%
	Other disorders of urinary system (N39)	2,217.23	2.87%	28.52%	1.88%
Male (34.73%)	Acute pharyngitis (J02)	2344.96	5.71%	5.71%	1.98%
	Infectious gastroenteritis and colitis, unspecified (A09)	2,197.07	5.35%	11.07%	1.86%
	AURI of multiple and unspecified sites (J06)	1,473.68	3.59%	14.66%	1.25%
	Acute nasopharyngitis [common cold] (J00)	1,428.13	3.48%	18.14%	1.21%
	Abdominal and pelvic pain (R10)	1,023.34	2.49%	20.63%	0.87%

Notes: This table classifies emergency department visits by sex and disease by presenting values for the five most common diagnoses per sex. The columns show the number of visits between 2008 and 2021 (in thousands), share of visits within the category (female and male), cumulative share of visits in the category, and share of total visits across all conditions. The table starts with the most common sex and diagnoses. The last row is the least common condition within that category. Estimated values with data from the Health Information System of the Mexican Health Ministry. AURI: Acute upper respiratory infection.

Table A.3: Main diseases by age group

Age group	ICD-10 Name	# Visits (Thousands)	Share of Category	Cumulative Share	Share of Total
< 12 (23.00%)	Acute pharyngitis (J02)	3,319.97	12.21%	12.21%	2.81%
	Infectious gastroenteritis and colitis, unspecified (A09)	2,411.58	8.87%	21.08%	2.04%
	Acute nasopharyngitis [common cold] (J00)	2,196.66	8.08%	29.15%	1.86%
	AURI of multiple and unspecified sites (J06)	1,987.25	7.31%	36.46%	1.68%
	Acute tonsillitis (J03)	629.49	2.31%	38.78%	0.53%
12–19 (15.65%)	Encounter for supervision of normal pregnancy (Z34)	3,351.80	18.11%	18.11%	2.83%
	False labor (O47)	724.93	3.92%	22.03%	0.61%
	other (Z35)	647.13	3.50%	25.53%	0.55%
	Infections of genitourinary tract in pregnancy (O23)	496.90	2.69%	28.21%	0.42%
	Infectious gastroenteritis and colitis, unspecified (A09)	487.58	2.63%	30.85%	0.41%
20–39 (36.80%)	Encounter for supervision of normal pregnancy (Z34)	8,513.60	19.57%	19.57%	7.20%
	False labor (O47)	1,666.40	3.83%	23.40%	1.41%
	Other disorders of urinary system (N39)	1,108.57	2.55%	25.95%	0.94%
	Infectious gastroenteritis and colitis, unspecified (A09)	1,015.12	2.33%	28.28%	0.86%
	Infections of genitourinary tract in pregnancy (O23)	1,002.43	2.30%	30.58%	0.85%
40–59 (14.68%)	Essential (primary) hypertension (I10)	830.92	4.79%	4.79%	0.70%
	Infectious gastroenteritis and colitis, unspecified (A09)	640.21	3.69%	8.47%	0.54%
	Type 2 diabetes mellitus (E11)	602.54	3.47%	11.94%	0.51%
	Other disorders of urinary system (N39)	593.16	3.42%	15.36%	0.50%
	Abdominal and pelvic pain (R10)	508.11	2.93%	18.29%	0.43%
60–79 (7.70%)	Essential (primary) hypertension (I10)	654.74	7.19%	7.19%	0.55%
	Type 2 diabetes mellitus (E11)	473.72	5.20%	12.39%	0.40%
	Infectious gastroenteritis and colitis, unspecified (A09)	334.60	3.67%	16.06%	0.28%
	endocrine_metabolic (E14)	282.83	3.11%	19.17%	0.24%
	Other disorders of urinary system (N39)	277.16	3.04%	22.21%	0.23%
> 79 (2.16%)	Essential (primary) hypertension (I10)	166.04	6.49%	6.49%	0.14%
	Other chronic obstructive pulmonary disease (J44)	102.00	3.99%	10.47%	0.09%
	Infectious gastroenteritis and colitis, unspecified (A09)	96.73	3.78%	14.26%	0.08%
	Other disorders of urinary system (N39)	79.94	3.12%	17.38%	0.07%
	Type 2 diabetes mellitus (E11)	76.95	3.01%	20.39%	0.07%

Notes: This table classifies emergency department visits by age group and disease by presenting values for the five most common diagnoses per category. The columns show the number of visits 2008–2021 (in thousands), share of visits within the category (15–39, less than 12, 40–70, and more than 79), cumulative share of visits in the category, and share of total visits across all conditions. The table starts with the most common sex and diagnoses. The last row is the least common condition within that category. Estimated values with data from the Health Information System of the Mexican Health Ministry. AURI: Acute upper respiratory infection.

Table A.4: Main diseases by ICD-10 Chapter

Chapter	ICD-10 Name	ICD-10	# Visits (Ths.)	Share Chapter	Cumulative % Chapter	Share Total
Other (24.61%)	Encounter for supervision of normal pregnancy	Z34	12,677.35	41.11%	41.11%	10.12%
	Abdominal and pelvic pain	R10	2,971.17	9.64%	50.75%	2.37%
	Other	Z35	1,479.88	4.80%	55.55%	1.18%
External Causes (15.25%)	Contact with venomous animals and plants	T63	1,652.99	8.65%	8.65%	1.32%
	Injury of unspecified body region	T14	1,324.79	6.93%	15.59%	1.06%
	Open wound of head	S01	1,144.59	5.99%	21.58%	0.91%
Respiratory (14.54%)	Acute pharyngitis	J02	5,122.56	28.11%	28.11%	4.09%
	Acute nasopharyngitis [common cold]	J00	3,170.28	17.40%	45.50%	2.53%
	AURI of multiple and unspecified sites	J06	3,139.57	17.23%	62.73%	2.51%
Obstetric (11.24%)	False labor	O47	2,556.92	18.15%	18.15%	2.04%
	Infections of genitourinary tract in pregnancy	O23	1,619.75	11.50%	29.64%	1.29%
	Encounter for full-term uncomplicated delivery	O80	1,353.37	9.61%	39.25%	1.08%
Digestive (7.48%)	Gastritis and duodenitis	K29	1,594.70	17.02%	17.02%	1.27%
	Cholelithiasis	K80	960.22	10.25%	27.27%	0.77%
	Cholecystitis	K81	822.15	8.78%	36.05%	0.66%
Infectious Parasitic (6.17%)	Infectious gastroenteritis and colitis, unspecified	A09	5,206.90	67.38%	67.38%	4.16%
	Dengue fever [classical dengue]	A90	312.20	4.04%	71.42%	0.25%
	Other bacterial foodborne intoxications	A05	257.84	3.34%	74.76%	0.21%
Genitourinary (5.75%)	Other disorders of urinary system	N39	3,162.51	43.89%	43.89%	2.52%
	Other abnormal uterine and vaginal bleeding	N93	510.09	7.08%	50.97%	0.41%
	Chronic kidney disease (CKD)	N18	468.47	6.50%	57.47%	0.37%
Skin-Musculoskeletal (4.00%)	Dorsalgia	M54	1,129.44	22.55%	22.55%	0.90%
	Cutaneous abscess, furuncle and carbuncle	L02	362.16	7.23%	29.78%	0.29%
	Other and unspecified soft tissue disorders	M79	339.78	6.78%	36.57%	0.27%
Circulatory (2.96%)	Essential (primary) hypertension	I10	2,134.23	57.56%	57.56%	1.70%
	Other cerebrovascular diseases	I67	198.14	5.34%	62.90%	0.16%
	Heart failure	I50	187.99	5.07%	67.97%	0.15%

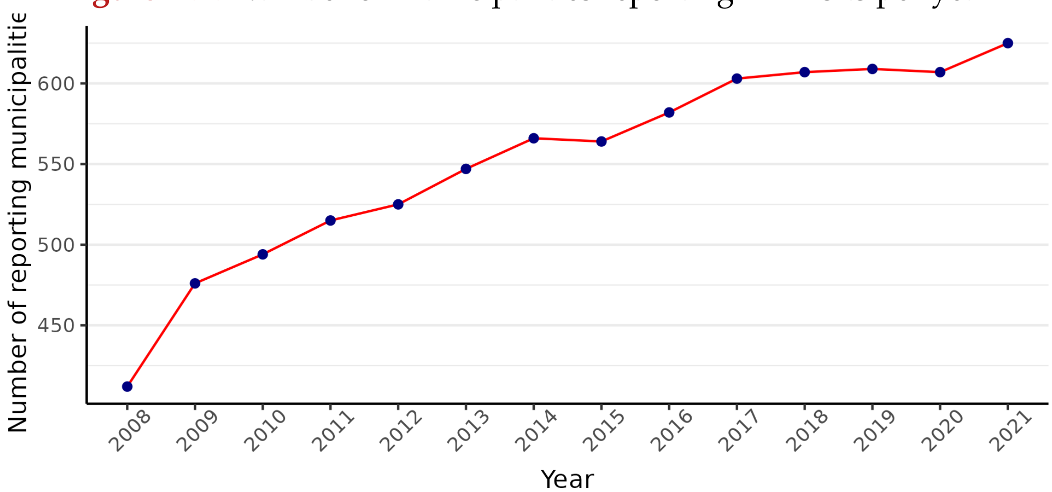
Continued on next page

Table A.4 – continued from previous page

Chapter	ICD-10 Name	ICD-10	# Visits (Ths.)	Share Chapter	Cumulative % Chapter	Share Total
Endocrine Metabolic (2.87%)	Type 2 diabetes mellitus	E11	1,419.05	39.49%	39.49%	1.13%
	Endocrine Metabolic	E14	884.88	24.63%	64.12%	0.71%
	Other disorders of pancreatic internal secretion	E16	285.33	7.94%	72.06%	0.23%
Mental (1.62%)	Other anxiety disorders	F41	545.13	26.93%	26.93%	0.44%
	Alcohol-related disorders	F10	412.50	20.38%	47.31%	0.33%
	Dissociative and conversion disorders	F44	188.15	9.30%	56.61%	0.15%
Eye Ear (1.36%)	Suppurative and unspecified otitis media	H66	593.82	34.89%	34.89%	0.47%
	Conjunctivitis	H10	356.14	20.92%	55.81%	0.28%
	Nonsuppurative otitis media	H65	165.62	9.73%	65.54%	0.13%
Nervous System (1.06%)	Epilepsy and recurrent seizures	G40	352.47	26.48%	26.48%	0.28%
	Other headache syndromes	G44	293.91	22.08%	48.57%	0.23%
	Migraine	G43	279.68	21.02%	69.58%	0.22%
Neoplasms (0.69%)	Leiomyoma of uterus	D25	193.02	22.41%	22.41%	0.15%
	Other neoplasm	D48	66.49	7.72%	30.13%	0.05%
	Benign lipomatous neoplasm	D17	45.61	5.30%	35.43%	0.04%
Blood And Immune (0.42%)	Other anemias	D64	337.12	64.14%	64.14%	0.27%
	Purpura and other hemorrhagic conditions	D69	73.27	13.94%	78.08%	0.06%
	Iron deficiency anemia	D50	37.24	7.09%	85.17%	0.03%

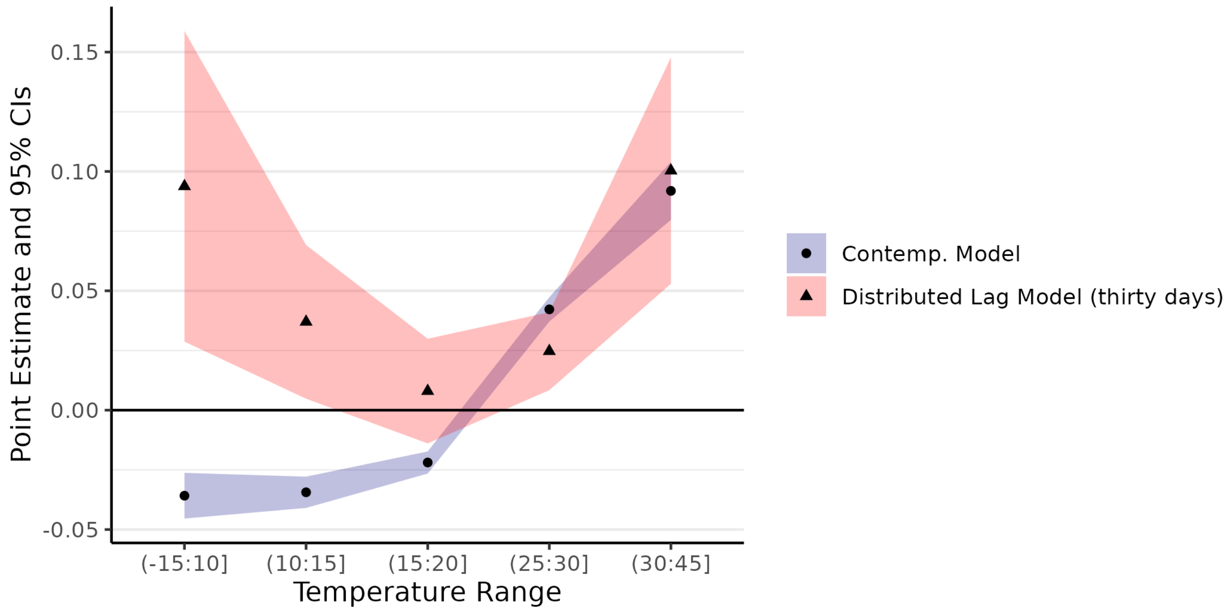
Notes: This table classifies emergency department visits by ICD-10 chapter and disease, presenting values for the three most common diagnoses per chapter. The columns show the number of visits 2008–2022 (in thousands), share of visits within the chapter, cumulative share of visits in the chapter, and share of total visits across all conditions. The table starts with the most common chapters and diagnoses. The last row is the least common condition within that chapter. Estimated values with data from the Health Information System of the Mexican Health Ministry. AURI: Acute upper respiratory infection.

Figure A.4: Number of municipalities reporting ED visits per year



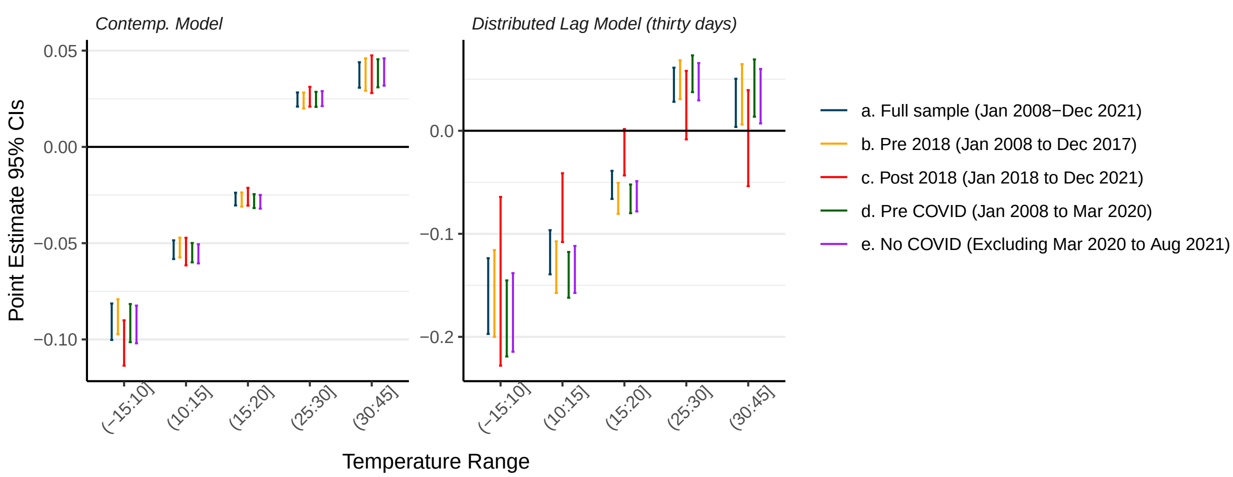
A.3 Additional results

Figure A.5: Mortality-temperature relationship in Mexico



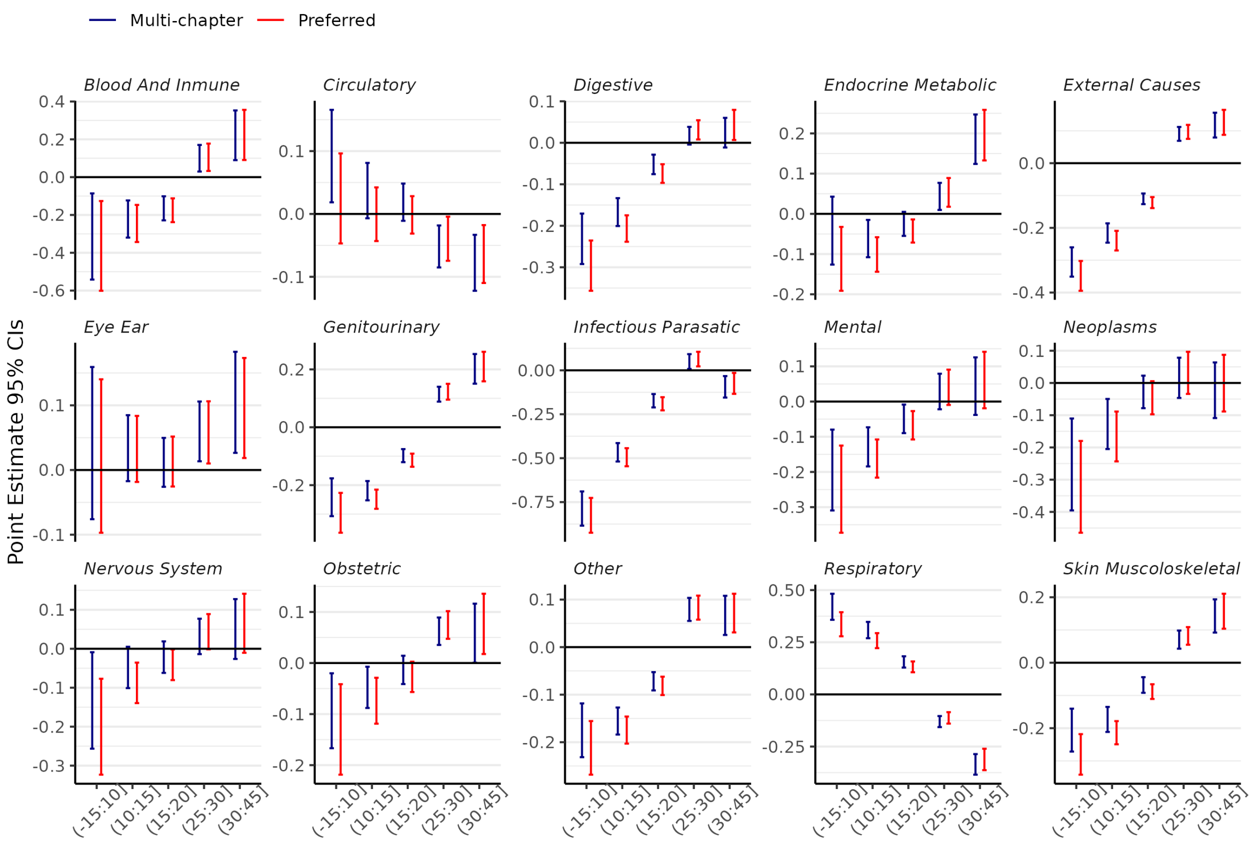
Notes: This figure presents the point estimates of a PPMLE model of mortality rates per 100,000 people as function of temperatures. The fixed-effects specification follows the preferred model of Cohen and Dechezleprêtre (2022). The effects refer to indicators for daily temperature intervals with reference category 20–25°C. The figures also presents the results for two levels of aggregation: the *contemporaneous model* refers to the effect of temperatures in the the same day; the *distributed lag model (30 days)* refers to the linear combination of 30 temperature lags. Standard errors are clustered at the municipality level.

Figure A.6: The effect of daily temperatures on emergency department (ED) visits (Different time periods)



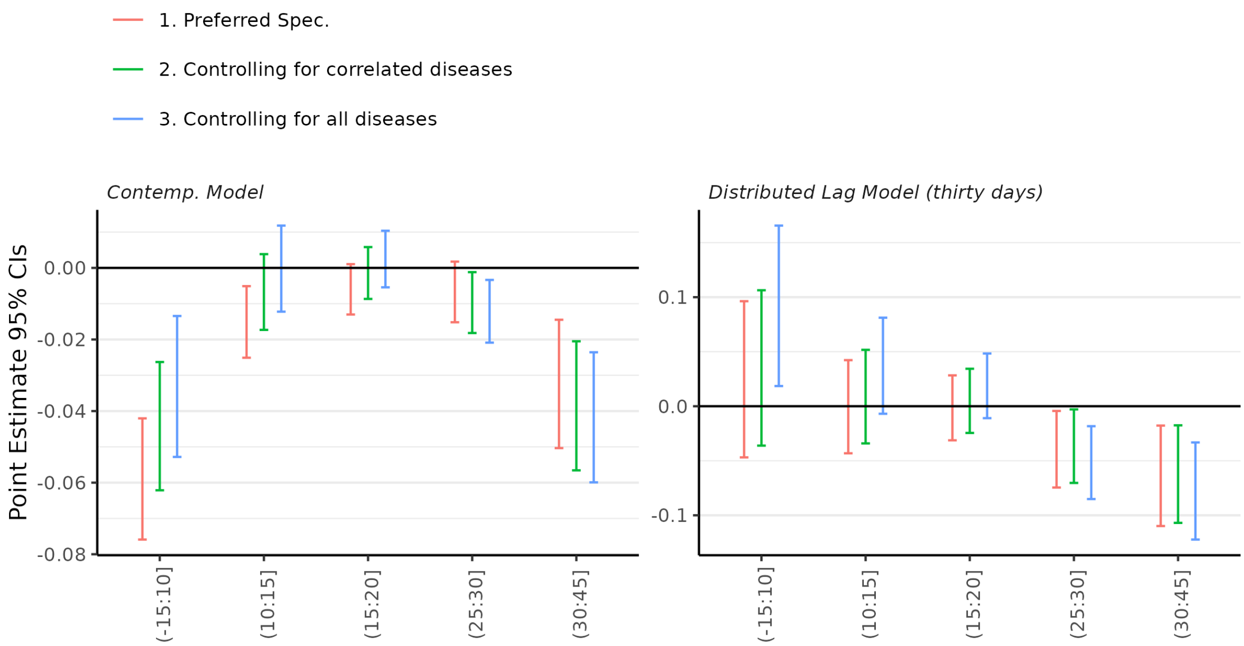
Notes: This figure presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. The figure presents results for two aggregation levels: *contemporaneous model* indicates the effect of temperatures on the a same day, and *distributed lag model (30)* represents the linear combination of 30 temperature lags. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. We also include results for different time periods. Standard errors are clustered at the municipality level.

Figure A.7: The effect of daily temperatures on emergency department (ED) visits for different ICD chapters (Comparison of multi-chapter model and preferred specification)



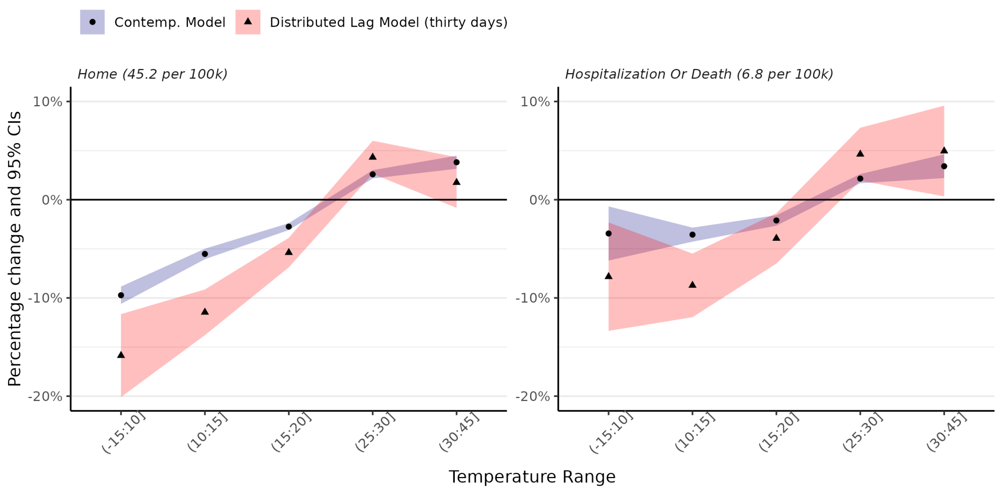
Notes: This figure presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. We present results for all ICD10 Chapters and two different models. 1) The multi-chapter model estimates the effect of temperatures on ED visits for each chapter while including the visit rate for all other chapters as controls. 2) is the preferred specification, which estimates the effect of temperatures separately for each chapter. The coefficients represent the effects of the presented daily temperature intervals, using a reference category of 20–25°C. The dependent variable is the ED visits rate 100,000 people. The figure presents results for the effect on 30 days after the temperature shock. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level.

Figure A.8: The effect of daily temperatures on emergency department (ED) visits related to circulatory conditions (Controlling for all ICD chapters)



Notes: This figure presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients represent the effects of the presented daily temperature intervals, using a reference category of 20–25°C. The dependent variable is the ED visits rate 100,000 people for circulatory conditions. Specifically, we estimate the effect on Chapter IX — Diseases of the circulatory system (I00–I99), which include conditions like ischemic heart disease, cerebrovascular disease, heart failure, and arrhythmias. The figure presents results for the contemporaneous and cumulative effect after 30 days. We present results for three different models. 1) is the preferred specification, which estimates the effect of temperatures on the number of circulatory-related triage visits without controlling for other conditions. 2) accounts for the variation in correlated diseases (respiratory, endocrine-metabolic, genitourinary, and infectious-parasitic) within the same specification. 3) is a multi-chapter model that estimates the effect on circulatory conditions while including the visit rate for all other ICD-10 chapters as controls. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level.

Figure A.9: The effect of daily temperatures on emergency department (ED) visits by outcome



Notes: This figure presents the point estimates and 95 percent confidence intervals of a Poisson MLE distributed lag model aggregated across 30 different time windows. The focus is only on $t + k = 0$ and $t + k = 30$ to highlight contemporaneous and midterm differences in the coefficients. The coefficients refer to indicators for daily temperature intervals with reference category 20–25 °C. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level.

Table A.5: The effect of daily temperatures on emergency department (ED) visits (Alternative fixed effects)

	ED visits per 100,000 people						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Contemporaneous							
≤10°C	−0.055***	−0.056***	−0.100***	−0.094***	−0.091***	−0.091***	−0.049***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
10–15°C	−0.038***	−0.037***	−0.059***	−0.056***	−0.054***	−0.053***	−0.033***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
15–20°C	−0.021***	−0.020***	−0.031***	−0.030***	−0.027***	−0.027***	−0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
25–30°C	0.020***	0.022***	0.027***	0.026***	0.024***	0.025***	0.019***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
>30°C	0.030***	0.032***	0.041***	0.038***	0.037***	0.037***	0.030***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)
Cumulative							
≤10°C	−0.026	−0.026	−0.223***	−0.061**	−0.160***	−0.160***	0.025
	(0.036)	(0.043)	(0.044)	(0.026)	(0.019)	(0.019)	(0.026)
10–15°C	−0.032**	−0.053**	−0.080***	−0.030**	−0.120***	−0.118***	0.001
	(0.015)	(0.023)	(0.025)	(0.014)	(0.011)	(0.011)	(0.015)
15–20°C	−0.033***	−0.039**	−0.043***	−0.038***	−0.052***	−0.053***	−0.003
	(0.010)	(0.016)	(0.015)	(0.008)	(0.007)	(0.007)	(0.009)
25–30°C	0.016	0.013	0.008	0.042***	0.044***	0.045***	0.005
	(0.011)	(0.015)	(0.022)	(0.010)	(0.008)	(0.008)	(0.009)
>30°C	−0.000	−0.060***	−0.048	0.001	0.026**	0.027**	−0.032**
	(0.016)	(0.023)	(0.033)	(0.015)	(0.012)	(0.012)	(0.013)
Municipality	✓			✓			
Municipality-Calendar Day		✓					
Municipality-Week			✓				
Municipality-Weekday						✓	
Municipality-Month-Year					✓	✓	✓
Municipality-Year		✓					
State-Year			✓	✓			
Weekday			✓	✓	✓		
Calendar Day				✓			
Date	✓	✓					✓
Observations	2,761,626	2,738,859	2,748,411	2,761,626	2,643,528	2,642,643	2,643,528
Mean Outcome	53.173	53.173	53.173	53.173	53.173	53.173	53.173

Notes: The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. The table presents results for two aggregation levels: *contemporaneous model* indicates the effect of temperatures on the same day, and *distributed lag model* represents the linear combination of 30 temperature lags. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01$, $^{**} < 0.05$, $^{*} < 0.1$.

Table A.6: The effect of daily temperatures on emergency department (ED) visits (Alternative fixed effects and lag structure)

	ED visits per 100,000 people						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cumulative: 7 lags							
≤10°C	−0.084***	−0.080***	−0.189***	−0.152***	−0.149***	−0.149***	−0.062***
	(0.016)	(0.015)	(0.013)	(0.011)	(0.008)	(0.008)	(0.011)
10–15°C	−0.053***	−0.051***	−0.093***	−0.082***	−0.084***	−0.083***	−0.035***
	(0.008)	(0.008)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)
15–20°C	−0.025***	−0.025***	−0.046***	−0.042***	−0.035***	−0.035***	−0.016***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
25–30°C	0.022***	0.026***	0.035***	0.036***	0.033***	0.034***	0.021***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)
>30°C	0.023*	0.021**	0.044***	0.038***	0.041***	0.041***	0.022***
	(0.012)	(0.009)	(0.011)	(0.012)	(0.007)	(0.007)	(0.008)
Cumulative: 14 lags							
≤10°C	−0.057***	−0.053**	−0.196***	−0.122***	−0.143***	−0.143***	−0.023
	(0.021)	(0.024)	(0.022)	(0.015)	(0.015)	(0.015)	(0.017)
10–15°C	−0.045***	−0.045***	−0.086***	−0.067***	−0.090***	−0.088***	−0.016*
	(0.011)	(0.013)	(0.013)	(0.008)	(0.008)	(0.008)	(0.009)
15–20°C	−0.023***	−0.023***	−0.043***	−0.038***	−0.034***	−0.034***	−0.006
	(0.007)	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
25–30°C	0.013*	0.017*	0.023**	0.027***	0.026***	0.027***	0.009
	(0.008)	(0.009)	(0.012)	(0.008)	(0.006)	(0.006)	(0.006)
>30°C	0.006	−0.005	0.015	0.013	0.022**	0.023**	0.000
	(0.014)	(0.013)	(0.017)	(0.014)	(0.009)	(0.009)	(0.009)
Cumulative: 21 lags							
≤10°C	−0.036	−0.027	−0.203***	−0.087***	−0.151***	−0.152***	0.009
	(0.025)	(0.031)	(0.030)	(0.018)	(0.016)	(0.016)	(0.021)
10–15°C	−0.041***	−0.044***	−0.082***	−0.051***	−0.102***	−0.101***	−0.005
	(0.012)	(0.017)	(0.018)	(0.010)	(0.009)	(0.009)	(0.012)
15–20°C	−0.025***	−0.025**	−0.041***	−0.035***	−0.039***	−0.039***	−0.001
	(0.008)	(0.012)	(0.010)	(0.006)	(0.006)	(0.006)	(0.007)
25–30°C	0.010	0.013	0.015	0.027***	0.028***	0.029***	0.004
	(0.009)	(0.011)	(0.016)	(0.009)	(0.007)	(0.007)	(0.007)
>30°C	−0.003	−0.027	−0.012	−0.001	0.019*	0.021**	−0.015
	(0.016)	(0.017)	(0.023)	(0.015)	(0.010)	(0.010)	(0.011)
Municipality	✓			✓			
Municipality-Calendar Day		✓					
Municipality-Week			✓				
Municipality-Weekday						✓	
Municipality-Month-Year					✓	✓	✓
Municipality-Year		✓					
State-Year			✓	✓			
Weekday			✓	✓	✓		
Calendar Day				✓			
Date	✓	✓					✓
Observations	2,761,626	2,738,859	2,748,411	2,761,626	2,643,528	2,642,643	2,643,528
Mean Outcome	53.173	53.173	53.173	53.173	53.173	53.173	53.173

Notes: The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. The table presents results for two aggregation levels: *contemporaneous model* indicates the effect of temperatures on the same day, and *distributed lag model* represents the linear combination of 30 temperature lags. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table A.7: The effect of daily temperatures on emergency department (ED) visits (Monthly aggregation)

	ED visits per 100,000 people				
	(1)	(2)	(3)	(4)	(5)
≤ 10	-0.014	-0.003**	-0.001	-0.008***	-0.009***
	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
10-15	-0.005	-0.003***	-0.0010*	-0.004***	-0.004***
	(0.004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)
15-20	-0.002	-0.001***	-0.0007**	-0.002***	-0.002***
	(0.003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
25-30	-0.005*	0.001***	6.2×10^{-5}	0.002***	0.002***
	(0.003)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
$>$ 30°C	-0.006	-0.0007	-0.0004	0.0006	0.002**
	(0.005)	(0.0007)	(0.0006)	(0.0007)	(0.0008)
Municipality		✓	✓		
Month-Year			✓		
Municipality $\times$ Year				✓	✓
Municipality $\times$ Month				✓	✓
Additional weather controls					✓
Observations	92,052	92,052	92,052	91,665	91,665
Mean Outcome	1573.10	1573.10	1573.10	1573.10	1573.10

Notes: The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. All specifications include linear and squared precipitation, relative humidity, and in column 5 wind speed and atmospheric pressure as well. Significance codes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.8: The effect of daily temperatures on mortality rates (circulatory vs other conditions)

	Deaths per 100,000 people					
	Circulatory		**Non-circulatory**		**Other + Unknown**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
$\leq$ 10°C	0.003	0.665 ***	-0.033 ***	0.458 ***	-0.005	0.601 ***
	(0.005)	(0.024)	(0.005)	(0.022)	(0.012)	(0.075)
10-15 °C	-0.013 ***	0.379 ***	-0.036 ***	0.234 ***	-0.011	0.466 ***
	(0.004)	(0.015)	(0.003)	(0.012)	(0.008)	(0.056)
15-20 °C	-0.012 ***	0.160 ***	-0.024 ***	0.088 ***	-0.011 *	0.130 ***
	(0.003)	(0.012)	(0.003)	(0.008)	(0.006)	(0.040)
25-30 °C	0.044 ***	-0.029 **	0.043 ***	-0.018 **	0.055 ***	0.146 ***
	(0.004)	(0.012)	(0.003)	(0.007)	(0.008)	(0.055)
$>$ 30°C	0.118 ***	0.095 ***	0.092 ***	0.058 ***	0.121 ***	0.208 **
	(0.009)	(0.027)	(0.006)	(0.017)	(0.015)	(0.101)
Observations	12 187 862		15 588 381		6 576 306	
Mean Outcome	0.379		0.907		0.119	

Notes: This table presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is the mortality rate for circulatory conditions per 100,000 people. In columns 1-2, we estimate the effect for Chapter IX — Diseases of the circulatory system (I00–I99), which include conditions like ischemic heart disease, cerebrovascular disease, heart failure, and arrhythmias. In columns 3-4 we estimate the effect for all other ICD chapters. In columns 5-6 we estimate the effect for "Other" and unknown diseases. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level. Significance codes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.9: The effect of daily temperatures on mortality rates across different age groups (circulatory diseases)

	Deaths per 100,000 people											
	0–12		**12–20**		**20–40**		**40–60**		**60–80**		**80–120**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤10°C	0.208 **	0.342	−0.023	0.170	0.036	0.530 ***	0.037 **	0.522 ***	0.023 ***	0.641 ***	−0.031 ***	0.751 ***
	(0.088)	(0.332)	(0.116)	(0.415)	(0.033)	(0.128)	(0.016)	(0.064)	(0.008)	(0.032)	(0.008)	(0.033)
10–15°C	0.124 **	0.207	−0.064	−0.208	0.012	0.353 ***	0.013	0.258 ***	−0.001	0.374 ***	−0.036 ***	0.432 ***
	(0.050)	(0.213)	(0.066)	(0.238)	(0.020)	(0.069)	(0.011)	(0.037)	(0.005)	(0.020)	(0.006)	(0.021)
15–20°C	0.081 *	−0.073	−0.046	0.069	0.000	0.148 ***	0.006	0.101 ***	−0.009 **	0.167 ***	−0.022 ***	0.176 ***
	(0.043)	(0.200)	(0.049)	(0.155)	(0.015)	(0.050)	(0.008)	(0.030)	(0.004)	(0.016)	(0.005)	(0.017)
25–30°C	0.003	−0.181	0.006	0.152	0.014	0.147 ***	0.023 ***	0.030	0.033 ***	−0.060 ***	0.066 ***	−0.031 *
	(0.070)	(0.181)	(0.069)	(0.193)	(0.023)	(0.051)	(0.009)	(0.032)	(0.006)	(0.019)	(0.007)	(0.019)
>30°C	0.016	−0.121	0.022	−0.120	0.045	0.168	0.069 ***	0.133 **	0.091 ***	0.060 *	0.171 ***	0.116 ***
	(0.135)	(0.343)	(0.152)	(0.414)	(0.045)	(0.114)	(0.020)	(0.066)	(0.012)	(0.036)	(0.015)	(0.038)
Observations	281 337		226 577		1 529 238		3 909 241		7 856 296		9 456 802	
Mean Outcome	0.004		0.006		0.027		0.176		1.308		9.553	

Notes: This table presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is the mortality rate per 100,000 people related to cardiovascular conditions. We estimate the effect on Chapter IX — Diseases of the circulatory system (I00–I99), which include conditions like ischemic heart disease, cerebrovascular disease, heart failure, and arrhythmias. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include municipality-by-year-month and municipality-by-weekday fixed effects, and a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors are clustered at the municipality level. Significance codes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.10: Potential mechanisms of the temperature-morbidity relationship (Physiological incidence)

	ED visits per 100,000 people									
	Heat Shock		**False Labor**		**Heart Failure**		**Dissoc. Disorder**		**Common Cold**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
$\leq$ 10°C	-0.193^{***}	-0.563^{***}	-0.061^{**}	-0.062	-0.144^{***}	0.441^{***}	-0.230^{***}	-0.369^{***}	-0.021^{**}	0.503^{***}
	(0.030)	(0.109)	(0.029)	(0.117)	(0.029)	(0.161)	(0.034)	(0.120)	(0.009)	(0.054)
10–15°C	-0.135^{***}	-0.328^{***}	-0.044^{***}	-0.014	-0.086^{***}	0.014	-0.151^{***}	-0.192^{***}	-0.003	0.431^{***}
	(0.017)	(0.058)	(0.008)	(0.056)	(0.017)	(0.067)	(0.019)	(0.066)	(0.006)	(0.028)
15–20°C	-0.079^{***}	-0.227^{***}	-0.026^{***}	0.009	-0.047^{***}	0.009	-0.086^{***}	-0.047	-0.001	0.238^{***}
	(0.011)	(0.037)	(0.006)	(0.039)	(0.013)	(0.053)	(0.014)	(0.049)	(0.005)	(0.024)
25–30°C	0.134^{***}	0.195^{***}	0.026^{***}	0.088^{***}	-0.014	-0.018	0.072^{***}	0.032	-0.010	-0.209^{***}
	(0.013)	(0.040)	(0.006)	(0.032)	(0.019)	(0.050)	(0.015)	(0.055)	(0.006)	(0.028)
$>$ 30°C	0.407^{***}	0.705^{***}	0.050^{***}	0.150^{***}	-0.113^{***}	-0.170^{*}	0.146^{***}	0.064	-0.038^{***}	-0.537^{***}
	(0.025)	(0.086)	(0.009)	(0.057)	(0.033)	(0.100)	(0.030)	(0.104)	(0.012)	(0.051)
Observations	1,730,726		1,493,488		1,221,414		1,289,869		2,273,776	
Mean Outcome	0.163		0.675		0.068		0.099		1.663	
Municipality-Month-Year	✓		✓		✓		✓		✓	
Municipality-Weekday	✓		✓		✓		✓		✓	

Notes: This table presents point estimates of the effects of daily temperature deviations on the rate of emergency department admissions across all ICD-10 chapter codes. We use the standard Poisson maximum likelihood estimation (MLE) distributed lag model to estimate the effect. Our temperature intervals use the 20–25°C category as the reference. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors cluster at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table A.11: Potential mechanisms of the temperature-morbidity relationship (Ecosystem dynamics)

	ED visits per 100,000 people									
	Dengue		**Foodborne Intox.**		**Gastroenteritis**		**Infect. Pregnancy**		**Animals and Plants**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
$\leq$ 10°C	−0.481***	−3.476***	−0.118***	−0.424**	−0.176***	−0.887***	−0.089***	−0.258***	−0.633***	−1.582***
	(0.104)	(0.894)	(0.029)	(0.168)	(0.010)	(0.055)	(0.015)	(0.058)	(0.029)	(0.118)
10–15°C	−0.267***	−3.934***	−0.054***	−0.176**	−0.102***	−0.498***	−0.052***	−0.175***	−0.337***	−1.016***
	(0.050)	(0.281)	(0.017)	(0.069)	(0.006)	(0.028)	(0.007)	(0.030)	(0.014)	(0.056)
15–20°C	−0.045***	−0.924***	−0.041***	−0.096**	−0.049***	−0.159***	−0.026***	−0.069***	−0.143***	−0.433***
	(0.017)	(0.135)	(0.013)	(0.048)	(0.004)	(0.019)	(0.005)	(0.023)	(0.009)	(0.020)
25–30°C	0.068***	0.506***	0.045***	−0.006	0.056***	0.006	0.031***	0.179***	0.106***	0.367***
	(0.018)	(0.078)	(0.013)	(0.051)	(0.004)	(0.022)	(0.006)	(0.025)	(0.008)	(0.029)
$>$ 30°C	−0.008	−0.497	0.080**	0.029	0.105***	−0.151***	0.035***	0.242***	0.156***	0.339***
	(0.066)	(0.597)	(0.036)	(0.101)	(0.009)	(0.035)	(0.011)	(0.046)	(0.019)	(0.057)
Observations	444,698		1,500,532		2,405,195		1,837,747		1,976,594	
Mean Outcome	0.172		0.133		2.781		0.625		1.194	
Municipality-Month-Year	✓		✓		✓		✓		✓	
Municipality-Weekday	✓		✓		✓		✓		✓	

Notes: This table presents point estimates of the effects of daily temperature deviations on the rate of emergency department visits across all ICD-10 chapter codes. We use the standard Poisson maximum likelihood estimation (MLE) distributed lag model to estimate the effect. Our temperature intervals use the 20–25°C category as the reference. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors cluster at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table A.12: Potential mechanisms of the temperature-morbidity relationship (Behavioral changes)

	ED visits per 100,000 people									
	Headache		**Epilepsy**		**Other Urinary Inf.**		**CKD**		**Alcohol Disorders**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
$\leq$ 10°C	−0.211***	−0.233***	−0.052**	−0.151	−0.124***	−0.386***	−0.013	0.141	−0.140***	−0.365***
	(0.025)	(0.089)	(0.023)	(0.123)	(0.010)	(0.043)	(0.027)	(0.097)	(0.024)	(0.091)
10–15°C	−0.096***	−0.188***	−0.035**	−0.073	−0.071***	−0.302***	−0.022	−0.047	−0.078***	−0.074
	(0.016)	(0.056)	(0.015)	(0.047)	(0.005)	(0.021)	(0.014)	(0.056)	(0.011)	(0.051)
15–20°C	−0.040***	−0.058	−0.015	−0.051	−0.036***	−0.137***	−0.022**	0.004	−0.048***	−0.041
	(0.011)	(0.038)	(0.010)	(0.036)	(0.004)	(0.015)	(0.011)	(0.039)	(0.009)	(0.035)
25–30°C	0.030**	0.054	0.011	0.061	0.029***	0.146***	0.020	−0.053	0.063***	0.055
	(0.014)	(0.044)	(0.012)	(0.043)	(0.005)	(0.016)	(0.015)	(0.049)	(0.013)	(0.047)
> 30°C	−0.000	0.194**	0.010	0.035	0.056***	0.219***	0.021	0.045	0.110***	0.021
	(0.032)	(0.080)	(0.024)	(0.078)	(0.010)	(0.029)	(0.027)	(0.099)	(0.031)	(0.093)
Observations	1,394,576		1,804,754		2,451,373		1,280,549		1,855,700	
Mean Outcome	0.161		0.160		0.154		0.013		0.187	
Municipality-Month-Year	✓		✓		✓		✓		✓	
Municipality-Weekday	✓		✓		✓		✓		✓	

Notes: This table presents point estimates of the effects of daily temperature deviations on the rate of emergency department admissions across all ICD-10 chapter codes. We use the standard Poisson maximum likelihood estimation (MLE) distributed lag model to estimate the effect. Our temperature intervals use the 20–25°C category as the reference. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Standard errors cluster at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table A.13: The effect of daily temperatures on emergency department (ED) visits (congestion and autoregressive dynamics)

	ED visits per 100,000 people			
	Baseline	AR(7)	Congestion lags	Date FE
Contemporaneous				
$\leq$ 10°C	−0.091***	−0.088***	−0.075***	−0.049***
	(0.005)	(0.005)	(0.005)	(0.006)
10–15°C	−0.053***	−0.051***	−0.044***	−0.033***
	(0.003)	(0.003)	(0.003)	(0.003)
15–20°C	−0.027***	−0.026***	−0.022***	−0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
25–30°C	0.025***	0.024***	0.021***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
$>$ 30°C	0.037***	0.036***	0.033***	0.030***
	(0.003)	(0.003)	(0.003)	(0.003)
Cumulative (30 days)				
$\leq$ 10°C	−0.160***	−0.150***	−0.133***	0.026
	(0.019)	(0.018)	(0.016)	(0.026)
10–15°C	−0.118***	−0.111***	−0.110***	0.003
	(0.011)	(0.011)	(0.010)	(0.015)
15–20°C	−0.053***	−0.049***	−0.046***	−0.003
	(0.007)	(0.007)	(0.006)	(0.009)
25–30°C	0.045***	0.043***	0.043***	0.006
	(0.008)	(0.008)	(0.007)	(0.009)
$>$ 30°C	0.027**	0.027**	0.034***	−0.032**
	(0.012)	(0.011)	(0.010)	(0.013)
Observations	2,642,643	2,642,643	2,642,643	2,642,643

Notes: This table presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. The table presents results for two aggregation levels: *contemporaneous model* indicates the effect of temperatures on the same day, and *distributed lag model (30)* represents the linear combination of 30 temperature lags. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. The econometric design incorporates municipality-by-year-by-month and municipality-by-weekday fixed effects. Besides the baseline model, we include results for three robustness exercises: AR(7) includes seven lags of the ED visit rate. Congestion lags uses the contemporaneous and seven lags of a self-constructed congestion index defined as the average ED visit rate in the state of municipality i excluding municipality i from the average. Date FE simply includes national date fixed effects. Standard errors are clustered at the municipality level. Significance codes: $^{***} < 0.01$,$^{**} < 0.05$,$^{*} < 0.1$.

A.4 Climate projections

In this section, we outline the method used to estimate the impact of midcentury temperature increases on emergency department (ED) visit costs resulting from temperature changes.

First, we compute the climate-change-induced shifts in average daily temperature from the historical period to the future period for each grid cell c, calendar day t, future decade d, and GCM g ($\Delta\mathcal{T}_{c,t,d,g}$).

To compute $\Delta\mathcal{T}_{c,t,d,g}$ we use a representative 20-year period of daily temperatures from the GCM-simulated historical epoch ($\mathcal{T}^H$, average of years 1991–2010) and the decade-by-decade daily temperatures in future epochs ($\mathcal{T}^F$, average of years 2031–2040, 2041–2050, 2051–2060). We use projections developed within the CMIP6 framework (O'Neill et al., 2016) and incorporate five alternative global climate models (GCMs) to address uncertainty.

We aggregate grid cell-level shocks at the municipality level (i) using population weights. Next, we add $\Delta\mathcal{T}_{i,t,d,g}$ to the observed average historical daily temperatures used in our regressions ($\overline{\mathcal{T}}^{Hist}$) to obtain the projected daily temperature under climate change ($\mathcal{T}^{Fut}$):

$$\Delta\mathcal{T}_{i,t,d,g} = \sum_i (\mathcal{T}^F_{c,t,d,g} - \mathcal{T}^H_{c,t,d,g}) \tag{1}$$

$$\mathcal{T}^{Fut}_{i,t,d,g} = \overline{\mathcal{T}}^{Hist}_{i,t,d,g} + \Delta\mathcal{T}_{i,t,d,g} \tag{2}$$

We calculate the annual occurrence of daily temperature bins b for both historical and future epochs. For clarity, we omit subscripts for municipality i, calendar day t, decade d, and climate model g. Each temperature bin b is defined by its lower ($\underline{\mathrm{T_b}}$) and upper ($\widetilde{\mathrm{T_b}}$) bounds, as follows:

$$\mathcal{D}_b^{Hist.} = \mathbb{1}[\mathcal{T}_b^{Hist} \in (\underline{\mathrm{T_b^{Hist}}}, \widetilde{\mathrm{T_b^{Hist}}})] \tag{3}$$

$$\mathcal{D}_b^{Fut} = \mathbb{1}[\mathcal{T}_b^{Fut} \in (\underline{\mathrm{T_b^{Fut}}}, \widetilde{\mathrm{T_b^{Fut}}})] \tag{4}$$

where

$$k \in \{\leq 10, 10-15, 15-20, 25-30, > 30\} \tag{5}$$

In a second step, we combine the estimated age group-specific (z) semielasticity (see Eq. 1) with climate change projections to calculate the temperature-induced relative change in visits, $\widetilde{\Psi}$. This process accounts for cumulative effects over 30-day lags to compute the relative change in visits resulting from the temperature shift from $\mathcal{D}^{Hist}$ to $\mathcal{D}^{Fut}$.

$$\widetilde{\Psi}_{i,d,g}^{z} = \frac{\sum_{b=0}^{6} \mathcal{D}_{i,d,g,b}^{Fut} exp(\sum_{j=0}^{30} \widetilde{\lambda}_b^z)}{\sum_{b=0}^{6} \mathcal{D}_{i,d,g,b}^{Hist} exp(\sum_{j=0}^{30} \widetilde{\lambda}_b^z)} - 1 \tag{6}$$

We calculate the absolute change in visits $\widetilde{\Gamma}$ by assuming that the average age-specific admission rate ($\overline{y}_z$) remains constant from the historical period to future decades. The population increases at the decade-specific rate θ_d, specific by age groups, according to the SSP2 demographic shifts. SSP2 age-specific population projections in Mexico from Falchetta et al. (2024) are adjusted to account for temperature-related mortality effects. Age-specific mortality rates from Cohen and Dechezleprêtre (2022) were integrated into the demographic projections to capture both heat- and cold-related deaths.

$$\widetilde{\Gamma}_{i,d,g}^{z} = \widetilde{\Psi}_{i,d,g}^{z} \cdot (\overline{y}_z \cdot p_i \cdot \theta_d), \tag{7}$$

where p_i is the historical population (in 100,000s) in municipality i.

Finally, we compute annual expenditures by decade and age group $\mathcal{C}$, averaging across the GCMs and the entire set of municipalities in our sample. We exploit data from official government estimates of 2024 medical care unit costs by the FIMSS (2023). These data provides an average cost per admission (c^a) of 207 USD and an average cost of visits leading in hospitalizations (c^h) of 691 USD. Moreover, we assume the hospitalization rate relative to total visits s observed in our sample remains constant over time:

$$\mathcal{C}_d = \frac{\sum_g \left[\sum_i (\widetilde{\Gamma}^z_{i,d,g} \cdot c^a + \widetilde{\Gamma}^z_{i,d,g} \cdot c^h \cdot s) \right]}{g} \tag{8}$$

A.5 Review of the epidemiological literature

Overall, the epidemiological literature finds that heat exerts clear impacts on respiratory, renal, mental health, and infectious outcomes, particularly among the elderly and those with comorbidities. Cardiovascular evidence is less consistent, potentially reflecting differential exposure, pre-hospital mortality, or adaptive behaviors. Young and middle-aged adults remain at substantial risk, particularly from occupational or recreational exposure. Epidemiological studies are constrained by population focus, regional specificity, and methodological heterogeneity, emphasizing the need for broader, multi-age, multi-region analyses. Results from specific studies are reported below groped by main clinical outcomes.

A.5.1 Cardiovascular effects

Epidemiological evidence on cardiovascular heat effects is mixed. Heat-related cardiovascular outcomes are generally attributed to stress imposed on the cardiovascular system via thermoregulatory responses (Anderson et al., 2013). However, large-scale studies found no positive association between heat and emergency department (ED) visits for cardiovascular disease (Sun et al., 2021). Systematic reviews similarly report no significant associations between heat exposure and cardiovascular morbidity in either the general population (Turner et al., 2012; Phung et al., 2016) or elderly populations (Bunker et al., 2016).

A.5.2 Respiratory effects

In contrast, heat exposure consistently affects respiratory morbidity among older adults. Anderson et al. (2013) report that high daily temperatures increase hospitalizations for chronic obstructive pulmonary disease (COPD) more than for other respiratory tract infections. Effects occur predominantly on the same day as exposure (lag 0), suggesting exacerbation of existing conditions rather than increased transmission of new infections. Minimal differences by age, sex, or local climate imply that thermoregulatory stress is not the sole mechanism; direct inhalation of hot air likely contributes.

While Sun et al. (2021) found no association between extreme heat and ED visits for respiratory disease, they observed strong same-day effects on heat-related illness, renal disease, and mental disorders, with stronger associations among younger and middle-aged adults. These findings may reflect higher occupational and recreational exposure among working-age populations, as well as effective public health interventions for the elderly.

A.5.3 Renal and endocrine outcomes

Heat exposure has been linked to renal morbidity, including acute renal failure, urinary tract infections, and renal calculi. Fletcher et al. (2012) report increased risk among Black and Hispanic individuals, adults aged 25–44, low-income populations, and urban residents. Mechanisms likely involve fluid balance disruption, dehydration, and rhabdomyolysis. Li et al. (2012) further identified heat-related admissions for endocrine, genitourinary, renal, accidental, and self-harm causes, affecting both young and older adults.

A.5.4 Mental health outcomes

Heat also affects mental health. Nori-Sarma et al. (2022) found elevated ED visits for a range of mental health conditions, including substance use, anxiety, mood disorders, schizophrenia spectrum disorders, self-harm, and childhood behavioral disorders. Potential mechanisms include general stress from heat, sleep disruption, daytime discomfort, and climate-change-related anxiety.

A.5.5 Infectious diseases

High temperatures have been linked to infectious outcomes, particularly bacterial and all-cause diarrhea (Carlton et al., 2016), but not viral diarrhea. Dengue fever is sensitive to temperature and rainfall fluctuations (Viana and Ignotti, 2013). In Brazil, seasonal peaks in temperature and rainfall create mosquito breeding conditions, while endemic transmission persists year-round due to vector biology and regional climatic heterogeneity.

A.5.6 Age-specific susceptibility and exposure patterns

Evidence on age-specific vulnerability is complex. Younger adults experience higher heat illness prevalence due to occupational and recreational exposure but generally exhibit greater physiological resilience, leading to lower hospitalization rates (Hess et al., 2014). Older adults face higher hospitalization rates and mortality in the ED due to frailty, comorbidities, and reduced thermoregulatory capacity.

A.5.7 Systematic reviews and meta-analyses

Systematic reviews confirm heterogeneity in heat-related morbidity. Early meta-analyses (Turner et al., 2012; Ye et al., 2012) report increased respiratory morbidity with each 1°C rise in temperature, but no consistent cardiovascular effects. Later reviews focusing on the elderly (Bunker et al., 2016) show diverse outcomes for cardiovascular and cerebrovascular diseases: during warm periods, risks of intracerebral hemorrhage and myocardial infarction decreased, while respiratory morbidity, heat-induced diabetes, genitourinary, and infectious conditions increased.

A.5.8 Limitations of the epidemiological literature

Most U.S. studies focus on Medicare beneficiaries aged 65 years and older, often comprising insured adults who may be healthier, wealthier, or less vulnerable to heat than the general population. As a result, associations observed may underestimate risks among populations without commercial health insurance. While heat-related risks are well-documented in older adults, less is known about younger and middle-aged adults, although emerging evidence indicates that heat also poses significant health risks for these groups (Sun et al., 2021).

Supplementary information (not for publication)

We include results using OLS as a robustness exercise for disease-specific regressions in Table S1. Overall, the direction of effects remains consistent between PPML and OLS. The main differences lie in magnitude and some marginal significance: PPML effects typically show larger absolute values and have higher statistical significance. These differences are expected because the models address slightly different questions and use different weighting/samples: (i) functional form: PPML estimates a multiplicative mean (log link), so a given bin shifts the outcome proportionally, which tends to produce larger level changes when the baseline rate is high; OLS imposes an additive effect on the rate, which reduces impacts when true effects scale with the mean. (ii) variance weighting/heteroskedasticity: PPML remains consistent under general heteroskedasticity and effectively up-weights high-mean cells (where variance is larger), while OLS on rates weights cells more evenly, shrinking extremes. (iii) sample composition: PPML with high-dimensional fixed effects drops all-zero cells (perfect prediction), focusing inference on cells with within-cell variation; OLS retains those cells, which pulls coefficients toward zeros.

Table S1: The effect of daily temperatures on emergency department (ED) visits by disease category (OLS)

	ED visits per 100,000 people									
	Blood and Immune		**Circulatory**		**Digestive**		**Endoc./Metabolic**		**External Causes**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤ 10°C	−0.0008***	−0.0033***	−0.0042***	0.0012	−0.0126***	−0.0505***	−0.0096***	−0.0073***	−0.0490***	−0.1175***
	(0.0003)	(0.0011)	(0.0007)	(0.0025)	(0.0017)	(0.0076)	(0.0010)	(0.0026)	(0.0046)	(0.0149)
10–15°C	−0.0005***	−0.0024***	−0.0012***	−0.0001	−0.0068***	−0.0375***	−0.0061***	−0.0063***	−0.0326***	−0.0878***
	(0.0001)	(0.0005)	(0.0004)	(0.0016)	(0.0008)	(0.0034)	(0.0006)	(0.0015)	(0.0029)	(0.0087)
15–20°C	−0.0003***	−0.0017***	−0.0005	0.0000	−0.0034***	−0.0127***	−0.0031***	−0.0023**	−0.0177***	−0.0457***
	(0.0001)	(0.0004)	(0.0003)	(0.0012)	(0.0006)	(0.0024)	(0.0004)	(0.0011)	(0.0020)	(0.0059)
25–30°C	0.0001	0.0011***	−0.0005	−0.0033**	0.0002	0.0051**	0.0035***	0.0038***	0.0154***	0.0341***
	(0.0001)	(0.0004)	(0.0004)	(0.0015)	(0.0006)	(0.0023)	(0.0005)	(0.0014)	(0.0020)	(0.0052)
> 30°C	0.0002	0.0022***	−0.0026***	−0.0055***	−0.0003	0.0065*	0.0082***	0.0139***	0.0194***	0.0446***
	(0.0003)	(0.0008)	(0.0008)	(0.0020)	(0.0010)	(0.0034)	(0.0012)	(0.0027)	(0.0029)	(0.0083)
Observations	2,762,296		2,762,296		2,762,296		2,762,296		2,762,296	

Continued on next page

Mean Outcome	0.215		1.744		3.969		1.581		8.052	

	Eye and Ear		**Genitourinary**		**Inf. and Parasitic**		**Mental**		**Neoplasms**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
$\leq$ 10°C	−0.0021***	0.0007	−0.0116***	−0.0380***	−0.0208***	−0.0982***	−0.0056***	−0.0097***	−0.0010***	−0.0046***
	(0.0004)	(0.0021)	(0.0015)	(0.0057)	(0.0020)	(0.0127)	(0.0006)	(0.0019)	(0.0003)	(0.0011)
10–15°C	−0.0007***	0.0012	−0.0070***	−0.0331***	−0.0144***	−0.0686***	−0.0035***	−0.0061***	−0.0005***	−0.0025***
	(0.0003)	(0.0010)	(0.0007)	(0.0032)	(0.0012)	(0.0063)	(0.0003)	(0.0012)	(0.0002)	(0.0006)
15–20°C	−0.0002	0.0006	−0.0039***	−0.0141***	−0.0087***	−0.0304***	−0.0019***	−0.0024***	−0.0002	−0.0005
	(0.0002)	(0.0008)	(0.0005)	(0.0023)	(0.0009)	(0.0044)	(0.0002)	(0.0009)	(0.0001)	(0.0004)
25–30°C	0.0008***	0.0023**	0.0039***	0.0172***	0.0105***	0.0096**	0.0017***	0.0016*	−0.0001	0.0005
	(0.0003)	(0.0010)	(0.0007)	(0.0025)	(0.0013)	(0.0045)	(0.0003)	(0.0008)	(0.0002)	(0.0005)
> 30°C	0.0008	0.0034**	0.0072***	0.0285***	0.0168***	−0.0130***	0.0033***	0.0022	−0.0004	0.0000
	(0.0005)	(0.0015)	(0.0013)	(0.0051)	(0.0024)	(0.0048)	(0.0006)	(0.0014)	(0.0003)	(0.0006)
Observations	2,762,296		2,762,296		2,762,296		2,762,296		2,762,296	
Mean Outcome	0.897		3.107		3.954		0.705		0.275	

	Nervous System		**Obstetric**		**Other**		**Respiratory**		**Skin/Musc.**	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
$\leq$ 10°C	−0.0034***	−0.0054***	−0.0133***	−0.0345***	−0.0451***	−0.1232***	−0.0343***	0.1386***	−0.0108***	−0.0278***
	(0.0004)	(0.0017)	(0.0028)	(0.0121)	(0.0055)	(0.0168)	(0.0039)	(0.0175)	(0.0013)	(0.0045)
10–15°C	−0.0018***	−0.0023***	−0.0089***	−0.0176***	−0.0324***	−0.1056***	−0.0160***	0.1053***	−0.0057***	−0.0211***
	(0.0003)	(0.0007)	(0.0011)	(0.0063)	(0.0032)	(0.0124)	(0.0017)	(0.0118)	(0.0007)	(0.0023)
15–20°C	−0.0008***	−0.0009	−0.0049***	−0.0046	−0.0177***	−0.0515***	−0.0067***	0.0532***	−0.0027***	−0.0085***
	(0.0002)	(0.0006)	(0.0008)	(0.0043)	(0.0021)	(0.0096)	(0.0014)	(0.0075)	(0.0005)	(0.0015)
25–30°C	0.0004**	0.0011*	0.0047***	0.0191***	0.0180***	0.0505***	0.0024	−0.0406***	0.0020***	0.0084***
	(0.0002)	(0.0006)	(0.0008)	(0.0035)	(0.0023)	(0.0092)	(0.0015)	(0.0071)	(0.0005)	(0.0017)
> 30°C	0.0001	0.0016	0.0101***	0.0178**	0.0256***	0.0431***	0.0019	−0.0970***	0.0015*	0.0158***
	(0.0003)	(0.0010)	(0.0022)	(0.0074)	(0.0046)	(0.0119)	(0.0026)	(0.0133)	(0.0009)	(0.0030)
Observations	2,762,296		2,762,296		2,762,296		2,762,296		2,762,296	
Mean Outcome	0.608		4.641		10.707		9.150		2.449	

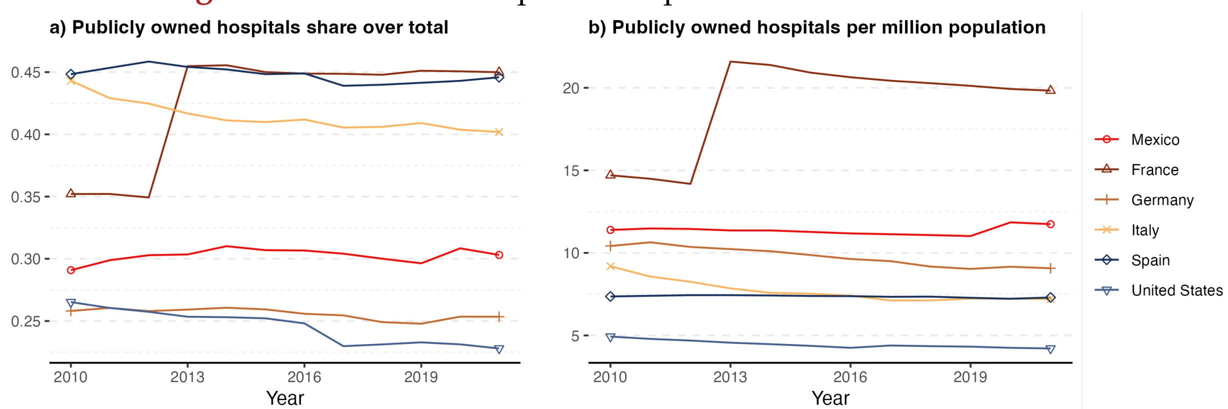
Notes: This table presents point estimates of the effects of daily temperature deviations on the rate of ED admissions across all ICD-10 chapter codes. We use the an ordinary least squares distributed lag model to estimate the effect. All models include year-by-month-by-municipality and weekday-by-municipality fixed effects. All models include a second-degree polynomial in precipitation (current and 30 lags), as well as linear terms for relative humidity and its lags. Our temperature intervals use the 20–25 °C category as the reference. The table presents results for two aggregation levels: *contemporaneous model* indicates effects of temperatures on the same day, and *distributed lag model (30 days)* represents the linear combination of 30 temperature lags. Standard errors cluster at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

Table S2: Population by age group, 2022 and 2050

Age group	Population 2022 (millions)	Population 2050 (millions)	Share 2022 (percentage)	Share 2050 (percentage)
0–12	18.4	15.1	19.5	14.6
12–20	12.8	10.6	13.6	10.2
20–40	29.2	29.7	31.0	28.7
40–60	22.3	22.8	23.6	22.0
60–80	9.92	21.7	10.5	21.0
80–130	1.65	3.58	1.8	3.5
Total	**94.27**	**103.48**	**100.0**	**100.0**

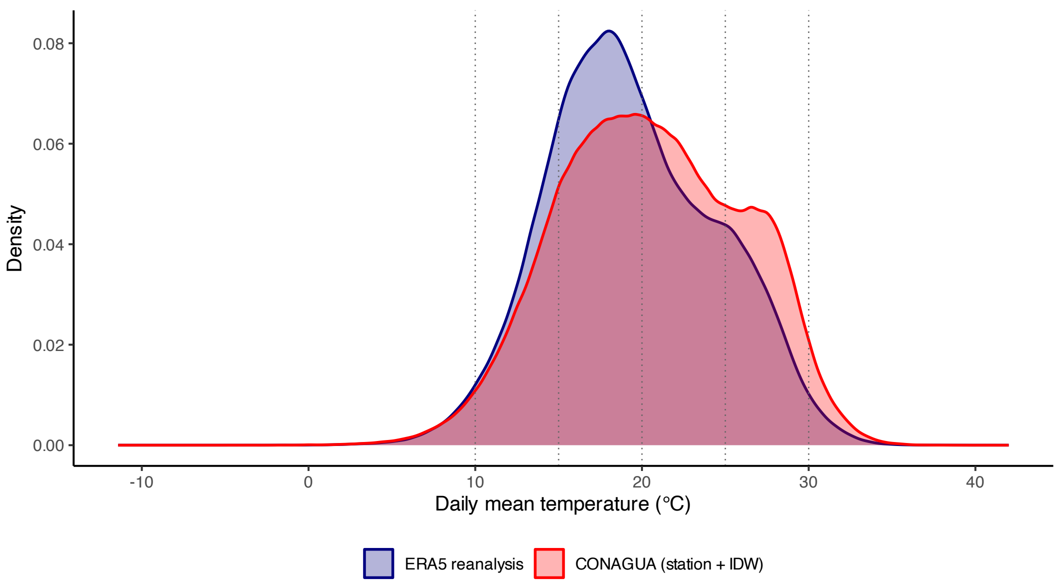
Notes: Population data by age group refer to the municipalities for which ED visits from public hospitals are observed.

Figure S1: Prevalence of public hospitals in selected countries.



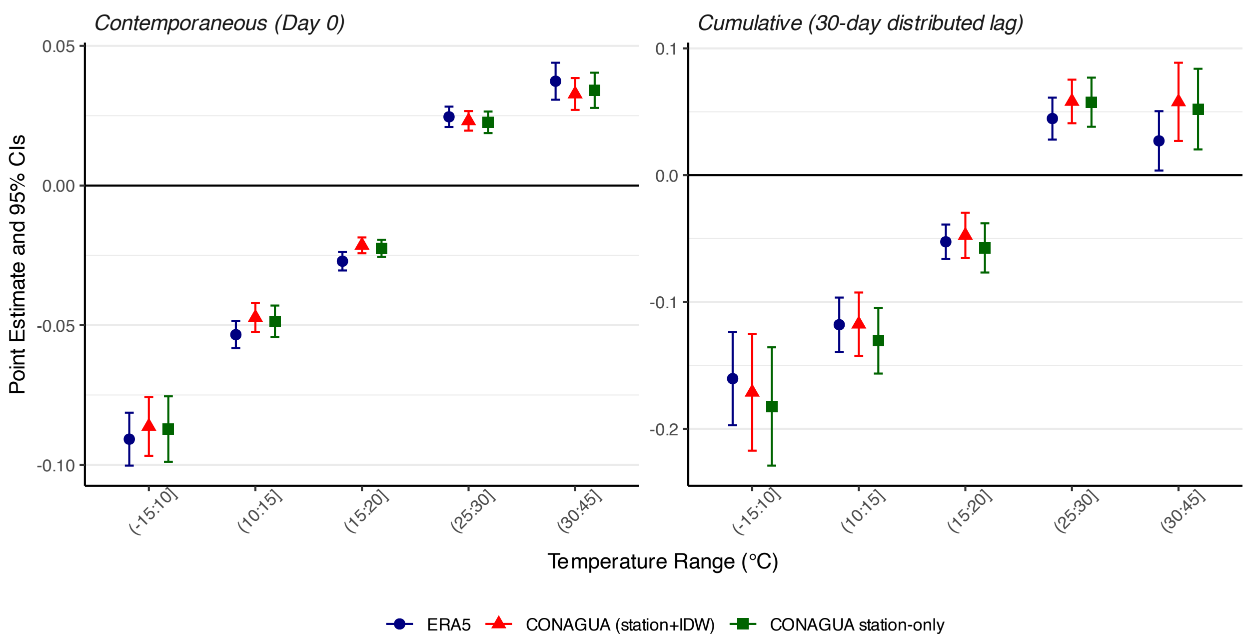
Notes: The figure displays the share of public hospitals as a share of the total in a) along with the number of public hospitals per million people in b). We obtain the data from the OECD database on health and financing (https://data.oecd.org/healthres/health-spending.htm).

Figure S2: Density of daily mean temperature: ERA5 vs CONAGUA



Notes: Kernel density estimates of daily mean temperature at the municipality-day level. ERA5 reanalysis (navy) is the source used in the main text. CONAGUA (red) is constructed from the universe of CONAGUA SIH climatological stations interpolated to each municipality's population-weighted centroid using inverse-distance weighting ($p = 2$) from the five nearest stations, with weights recomputed each day to use only stations with valid observations. Vertical dotted lines mark the bin cut-points used in the regression specification. Based on a random sample of 1,000,000 municipality-days drawn from 17,717,793 matched observations spanning 1998–2021.

Figure S3: Effects of daily temperature on ED visits — ERA5 vs CONAGUA station data



Notes: Point estimates and 95% confidence intervals from the preferred Poisson distributed-lag model in equation (1), estimated separately with three temperature sources: ERA5 reanalysis (the baseline used in the main text), CONAGUA station data interpolated to municipality population centroids using inverse-distance weighting from the five nearest stations, and CONAGUA station data restricted to the 506 municipalities containing a physical station. The reference category is 20–25°C. The left panel shows the contemporaneous (Day 0) effect; the right panel shows the cumulative 30-day distributed lag effect. Standard errors cluster at the municipality level. All specifications include the same set of weather controls (precipitation, precipitation squared, and relative humidity, each with 30 lags) and fixed effects (municipality × year × month and municipality × weekday).