

Emergency Department Visits and Temperature: Evidence from Mexico

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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 2022. We find that cold temperatures decrease visits by up to 8.9 percent on the same day, and warm temperatures increase visits by as much as 3.6 percent. Using distributed lag models, we then show that cold temperatures can reduce visits for the next 30 days by up to 16.3 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 relevant mechanisms, such as ecosystem dynamics and behavioral changes. Finally, we project that temperature-driven annual emergency department visits will increase by 0.24 percent by midcentury, resulting in an estimated increase of 92 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 temperature's effect on mortality, its influence on subfatal health conditions remains largely overlooked. A primary reason for this gap in the literature is the lack of comprehensive morbidity data, hindering large-scale assessments and leading 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) visits from all public hospitals between 2008 and 2022. To assess the causal effect of temperature on ED services, we exploit exogenous daily variations on average temperatures within the same municipality, month, and year, while controlling for correlated weather variables, such as precipitation and relative humidity, and day-of-the-week seasonal factors. Using distributed lag models (Deschenes and Moretti, 2009), we provide evidence of the effects of temperature changes on same-day and cumulative demand for ED services over the following 30 days.

Our results show that an additional day with an average temperature above 30°C increases contemporaneous ED visits by 3.6 percent. In contrast, an additional day below 10°C reduces visits by 8.9 percent. For the cumulative effect over the next 30 days, the increase from heat slightly decreases to 2.5 percent (harvesting), and the reductions from cold almost double, to 16.3 percent. These findings align with research in California, which indicates a linear relationship between the temperature gradient and ED visits (White, 2017; Gould et al., 2024). Observing the same effect in Mexico and California enhances the external validity of our results, suggesting that this relationship holds in different contexts.

Finding a linear relationship between ED visits and temperature changes is crucial be-

cause it contrasts with the U-shaped relationship observed 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 this U-shaped relationship in Mexico. This difference in functional forms implies significant heterogeneities in the potential effects of climate change. Nonlinear and concave relationships make the consequences context dependent, influenced by climatic and social conditions. In contrast, when the relationship is linear, climate change's shift toward warmer temperatures will consistently increase demand for ED services across the entire temperature distribution.

Our analysis by disease category shows that cumulative cold temperatures decrease overall visits, particularly those related to infectious diseases, despite raising admissions for respiratory diseases over time. In contrast, hot temperatures raise admissions for endocrine, genitourinary, and infectious-parasitic diseases and 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 to the overall rise in visits during cold spells 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 admissions. 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 are less sensitive to temperature variations. We also demonstrate 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, attributed to differences in their demand for health services; for instance, the most common reasons for ED visits are obstetric and respiratory issues for women and men, respectively.

We then propose a classification of mechanisms linking temperature to ED visits: (1) illness incidence, (2) ecosystem dynamics, and (3) behavioral changes. For each one, we provide examples of related illnesses. For illness incidence, we highlight that cold temperatures decrease admissions for heat-related shocks, false labor, and dissociative disorders, and hot temperatures increase them. Ecosystem dynamics show that cold temperatures reduce cases of dengue, foodborne intoxications, and visits due to contact with poisonous animals and plants, whereas hot temperatures increase these cases. The behavioral channel includes two mechanisms. First, patients may postpone visits during cold weather. Although we cannot directly test this with our data, we use 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 and epilepsy and for urinary infections compared to chronic kidney disease. This pattern aligns with [White \(2017\)](#) which shows a greater reduction in ED visits during cold weather for more deferrable conditions. Finally, temperature changes can influence other behaviors, leading to riskier activities. For example, admissions for alcohol-related disorders decrease in cold weather and increase in heat.

Finally, we estimate midcentury levels of temperature-induced ED visits using our results and climate projections. *Ceteris paribus*, our estimates indicate a steady annual increase, starting with 193,000 additional visits in 2031–2040 and rising to more than 300,000 in 2051–2060. This is equivalent to an 0.24 percent increase compared to a no-climate-change scenario. A rough calculation then suggests that temperature changes could raise public health spending by approximately 92 million USD per year by midcentury due to increased cold- and heat-related admissions. Initially, the decline in cold-related hospitalizations dominates, but heat-related admissions become more prominent 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 subfatal yet significant health consequences (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) 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). This focus on the ED provides a clearer picture of acute health responses to temperature variations.

We are aware of only one other paper that examines how temperatures affect ED visits in a developing country context: 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 focuses primarily 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 tempera-

ture 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 health care system (de Bartolome and Vosti, 1995; Jowett et al., 2004; Sahn et al., 2003; Das and Do, 2023). We advance this literature by identifying the mechanisms behind treatment-seeking behavior within a *public* health care system, such as Mexico,¹ 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) found that vulture extinction in India increased human mortality due to declining sanitation. Dasgupta (2018) shows that warmer temperatures will facilitate the spread of malaria in currently disease-free regions. We show that a significant share of heat-driven ED visits in Mexico stems from contact with venomous insects and animals and 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 semitropical climates, where sustained high ambient temperatures promote vector-borne and envenomation-related health issues (Harvell et al., 2002). Higher temperatures accelerate mosquito breeding cycles, increasing the transmission of diseases, such as dengue (Mordecai et al., 2013), and elevate the activity of venomous arthropods and animals (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,

¹ For more information on the Mexican health care system, see Appendix A.1.

raising the risk and severity of parasitic and 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 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).

ED visits. We obtain data on daily visits from the health information system of the Mexican health ministry. The dataset includes all ED visits in Mexican public hospitals from 2008 to 2022.² Each observation records a single admission and includes patient characteristics (age, sex, residence, insurance), event characteristics (outcome, ICD-10 code, reason), and geographical identifiers (hospital ID, municipality, state). Using these data, we construct a panel of daily ED admissions per 100,000 persons for each municipality with at least one hospital. We use population data from the Mexican census to estimate admission rates. We classify visits by gender (men and women), age (six age groups), and ICD-10 codes (e.g., respiratory, cardiovascular, obstetric).

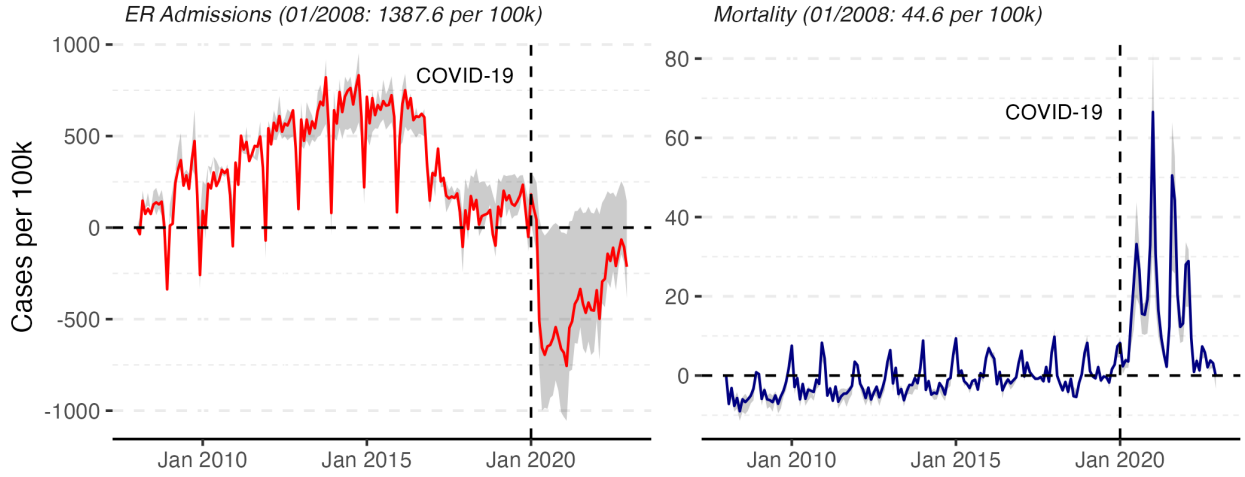
Mortality. We collect mortality data from the Mexican National Institute of Geography and Statistics (INEGI). The dataset includes municipality and date of death information for all people who died in the country between 1998 and 2021. Similar to ED admissions, we construct a panel of daily municipal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

Descriptive statistics. Figure 1 presents the time series of ED admissions and mortality rates per 100,000 persons, normalized to January 2008. It exhibits clear seasonality, with

² Figure A.2 shows that public hospitals in Mexico are approximately 35 percent of the total, higher than in the United States but lower than in the European Union. Despite approximately 2.5 private hospitals for every public hospital, most private hospitals have fewer than 20 beds and function mainly as outpatient clinics, offering primary care and some specialized diagnostic and treatment services (Organization et al., 2017). Only approximately 14 percent of people affiliated with a public health care institution choose to receive care in private hospitals (Juan López et al., 2015). Per million people, Mexico has more than twice as many public hospitals as the United States and more than most EU states, except France.

reduced admissions 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

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



Notes: These figures present the time series of the rate of emergency room admissions and mortality per 100,000 persons. We standardize the value of both time series to equal zero at the start of our sample in January 2008.

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, we contextualize 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 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.

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 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.

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 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.

[Table 1](#) presents descriptive statistics comparing admissions in Mexico and California,⁴ showing distinct patterns. First, the visit rate in California (77.09) exceeds that of Mexico (53.2), mainly because of the state's older population, which has an average age nearly 10 years higher. Second, primary use patterns differ significantly. In Mexico, a larger proportion of visits pertains to pregnancy and the perinatal period (10.81 percent) and infectious and parasitic diseases (5.93 percent), 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, including a comparable share of admissions due to respiratory, digestive, genitourinary, and endocrine conditions. This is striking given the diverse populations, health care infrastructures, and risk factors.

⁴ Some ICD-10 chapters lack corresponding CCS chapters and vice versa (e.g., congenital for CCS and eye/ear for ICD-10).

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	130.30
Injuries	20.54	14.66	15.84	8.1	19.36	19.11
Respiratory	12.82	13.99	9.88	9.5	12.08	18.22
Other	-	23.66	-	10.9	-	30.84
Digestive	7.83	7.19	6.04	4.1	7.38	9.37
Pregnancy	2.7	10.81	2.08	4.7	2.54	14.09
Nervous System	8.84	1.02	6.82	0.6	8.33	1.33
Circulatory	8.52	2.85	6.57	1.8	8.03	3.71
Genitourinary	6.04	5.53	4.66	3.2	5.69	7.21
Skin-Musculoskeletal	8.76	3.84	6.7	2.5	8.9	5.00
Mental Illness	4.23	1.55	3.26	0.7	3.99	2.02
Infections and Parasitic	2.78	5.93	2.1	4.1	2.62	7.73
Endocrine	2.16	2.76	1.6	1.6	2.03	3.59
Neoplasm	0.58	0.66	0.4	0.3	0.55	0.86
Blood	0.5	0.4	0.4	0.2	0.47	0.53
Congenital	0.05	-	0.04	-	0.04	-
Perinatal	0.24	-	0.18	-	0.23	-
Eye-Ear	-	1.31	-	0.5	0.00	1.70
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 2022.

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.

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

Y_{idmy} represents the number of ED admissions per 100,000 for municipality i on day d of

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

month m and year y . We model temperature nonlinearly across six intervals, ranging from ≤ 10 to $> 30^\circ\text{C}$, using $20\text{--}25^\circ\text{C}$ as the reference interval. $D_{b,idmy}$ is an indicator variable denoting whether a day's average temperature falls within interval b . 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. δ_{iw} includes fixed effects for the municipality and weekday of observation. X_{idmy} is a matrix of additional controls, including a quadratic function of precipitation and relative humidity. 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. 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, $J \in (3, 7, 30)$ provides estimates for the cumulative effect over the next three, seven, and 30 days, effectively accounting for the displacement and anticipation of admissions.

Accounting for displacement effects is crucial in our setting. White (2017) finds that in the United States, cold temperatures initially reduce 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. Specifically, vulnerable individuals who would 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 health outcome changes that occur immediately after exposure (contemporaneous effect) to those that persist over a more extended period (cumulative effect).

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. Specifically, an additional day with temperatures at or below 10°C decreases ED visits by 8.9 percent on the event day and 16.3 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 2.4 percent increase on the event day and a 4.5 percent cumulative increase over the 30-day period. For the warmest interval ($> 30^\circ\text{C}$), visits increase by 3.6 percent on the event day. However, this effect diminishes to 2.5 percent when examining the cumulative impact over 30 days (harvesting).

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

	Visits per 100,000 people	
	Contemporaneous	Cumulative (30 days)
$\leq 10^\circ\text{C}$	-0.089*** (0.006)	-0.163*** (0.023)
10–15°C	-0.052*** (0.003)	-0.111*** (0.017)
15–20°C	-0.026*** (0.002)	-0.051*** (0.008)
25–30°C	0.024*** (0.002)	0.045*** (0.009)
$> 30^\circ\text{C}$	0.037*** (0.003)	0.025** (0.012)

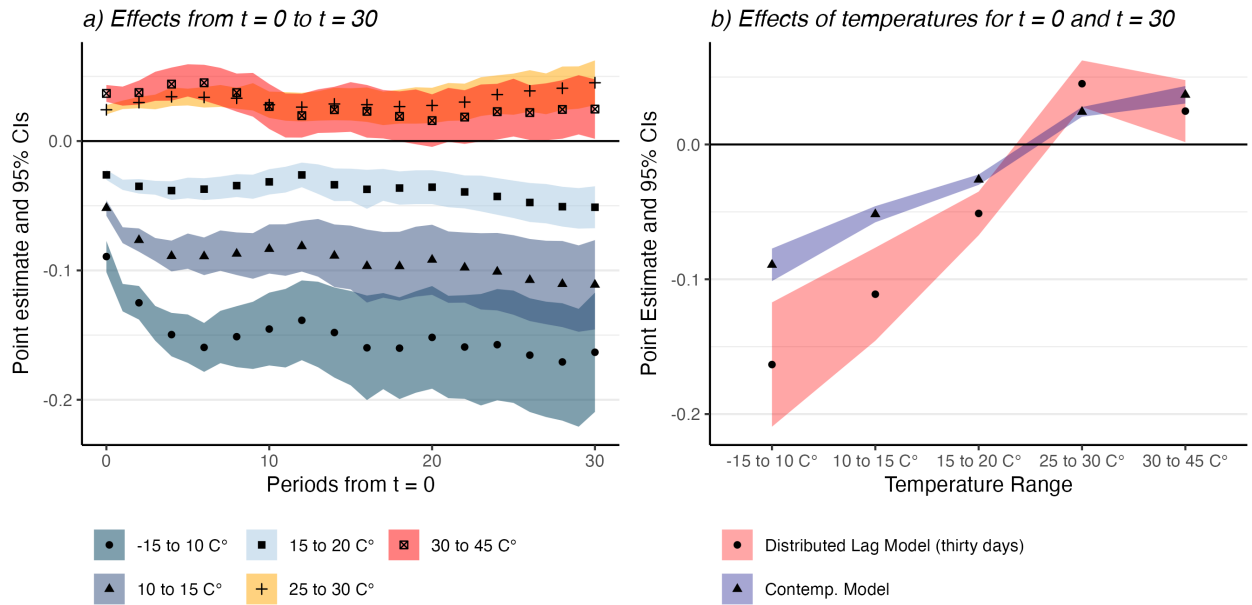
Notes: This table presents the coefficients of a Poisson maximum likelihood estimator distributed lag model with 30 lags. The coefficients estimate the effects of daily temperature intervals, using a reference category of 20–25°C. The dependent variable is ED visits per 100,000 people. The table presents results for two aggregation levels: *contemporaneous model* indicates the effect of temperatures on the a same day, and *distributed lag model (30)* represents the linear combination of 30 temperature lags. Weather controls include linear and squared precipitation, relative humidity, atmospheric pressure, and the leaf area index. The econometric design incorporates municipality-by-year-by-month and municipality-by-weekday fixed effects. No. Obs: 2,659,917. The average ER 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., 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 admissions. 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 epidemiological literature, as cold weather facilitates transmission and leads to higher incidence 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 $J \in (0, \dots, 30)$. The right panel presents estimates for $J = 0$ and $J = 30$ across the temperature distribution. Cold temperatures significantly reduce admissions immediately after exposure, followed by slight increases in the subsequent weeks. Conversely, hot temperatures substantially increase admissions during the first 10 days postexposure, with the effect gradually diminishing over the next 20 days.

Figure 2: The dynamic effects of daily temperature on emergency room 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 $t + k \in (1, \dots, 30)$. Each point refers to the linear combination of $t + k$ temperature lags on mortality 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 temperatures on ED visits. This effect contrasts with the dynamics between temperature variations and mortality [Cohen and Dechezeprêtre \(2022\)](#). 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 (Figure A.3). 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).

4.1. Heterogeneity by ICD-10 chapter

Next, we use patient diagnosis information to assess how temperature effects vary across ICD-10 chapters. For each chapter, we estimate Equation 1 separately and summarize the results in Table 3.⁶

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

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	-0.0852*** (0.0268)	-0.2302** (0.1126)	-0.0574*** (0.0091)	-0.0196 (0.0378)	-0.0689*** (0.0085)	-0.2456*** (0.0311)	-0.1443*** (0.0116)	-0.1686*** (0.0509)	-0.1378*** (0.0089)	-0.3338*** (0.0328)
10–15°C	-0.0567*** (0.0121)	-0.1625*** (0.0481)	-0.0127** (0.0052)	-0.0102 (0.0205)	-0.0332*** (0.0042)	-0.1699*** (0.0215)	-0.0871*** (0.0071)	-0.1328*** (0.0332)	-0.0813*** (0.0051)	-0.2180*** (0.0246)
15–20°C	-0.0334*** (0.0095)	-0.1470*** (0.0330)	-0.0046 (0.0036)	-0.0102 (0.0139)	-0.0161*** (0.0028)	-0.0613*** (0.0120)	-0.0446*** (0.0045)	-0.0651*** (0.0179)	-0.0406*** (0.0033)	-0.1157*** (0.0120)
20–25°C	0.0094 (0.0110)	0.0952** (0.0419)	-0.0076* (0.0043)	-0.0102 (0.0184)	0.0015 (0.0030)	0.0347*** (0.0120)	0.0426*** (0.0046)	0.0566*** (0.0187)	0.0425*** (0.0031)	0.0963*** (0.0111)
>30°C	0.0160 (0.0251)	0.2079*** (0.0664)	-0.0335*** (0.0090)	-0.0652*** (0.0239)	-0.0006 (0.0054)	0.0403** (0.0182)	0.1020*** (0.0106)	0.1992*** (0.0321)	0.0563*** (0.0061)	0.1216*** (0.0191)
Observations	1,983,791		2,523,536		2,566,908		2,513,261		2,608,349	
Mean Outcome	0.02		0.18		0.41		0.16		0.81	
	Eye and Ear		Genitourinary		Inf. and Parasitic		Mental		Neoplasms	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤10°C	-0.0597*** (0.0118)	0.0014 (0.0572)	-0.0849*** (0.0103)	-0.2703*** (0.0385)	-0.1692*** (0.0090)	-0.7271*** (0.0468)	-0.1397*** (0.0169)	-0.2451*** (0.0623)	-0.0577*** (0.0176)	-0.2484*** (0.0600)
10–15°C	-0.0190*** (0.0072)	0.0166 (0.0242)	-0.0468*** (0.0046)	-0.2043*** (0.0237)	-0.1001*** (0.0055)	-0.4250*** (0.0211)	-0.0842*** (0.0080)	-0.1417*** (0.0306)	-0.0321*** (0.0106)	-0.1169*** (0.0410)
15–20°C	-0.0046	0.0033	-0.0264***	-0.0977***	-0.0512***	-0.1652***	-0.0439***	-0.0572***	-0.0142*	-0.0199

Continued on next page

⁶ 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.

	(0.0053)	(0.0177)	(0.0032)	(0.0131)	(0.0035)	(0.0166)	(0.0053)	(0.0190)	(0.0075)	(0.0279)
20–25°C	0.0167***	0.0641***	0.0260***	-0.2043***	0.0500***	0.0698***	0.0478***	0.0619**	-0.0028	0.0272
	(0.0056)	(0.0245)	(0.0035)	(0.0237)	(0.0040)	(0.0211)	(0.0062)	(0.0293)	(0.0093)	(0.0363)
>30°C	0.0177	0.0971**	0.0475***	0.2048***	0.0858***	-0.0734**	0.0887***	0.0720*	-0.0256	-0.0153
	(0.0129)	(0.0391)	(0.0064)	(0.0385)	(0.0080)	(0.0300)	(0.0126)	(0.0397)	(0.0178)	(0.0446)
Observations	2,367,496		2,555,135		2,545,679		2,407,824		2,019,983	
Mean Outcome	0.09		0.32		0.41		0.07		0.03	
	Nervous System		Obstetric		Other		Respiratory		Skin/Musc.	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
≤10°C	-0.1233***	-0.1752***	-0.0483***	-0.1074***	-0.0704***	-0.1737***	-0.0737***	0.1816***	-0.1098***	-0.2567***
	(0.0131)	(0.0513)	(0.0097)	(0.0361)	(0.0099)	(0.0294)	(0.0060)	(0.0316)	(0.0084)	(0.0279)
10–15°C	-0.0638***	-0.0620***	-0.0323***	-0.0393**	-0.0489***	-0.1578***	-0.0357***	0.1621***	-0.0552***	-0.1805***
	(0.0077)	(0.0224)	(0.0036)	(0.0188)	(0.0043)	(0.0248)	(0.0036)	(0.0243)	(0.0054)	(0.0169)
15–20°C	-0.0269***	-0.0298*	-0.0182***	-0.0393**	-0.0247***	-0.0730***	-0.0153***	0.0841***	-0.0250***	-0.0767***
	(0.0050)	(0.0178)	(0.0028)	(0.0144)	(0.0026)	(0.0248)	(0.0028)	(0.0145)	(0.0035)	(0.0110)
20–25°C	0.0172*	0.0404*	0.0197***	0.0735***	0.0282***	0.0797***	0.0059*	-0.1130***	0.0184***	0.0810***
	(0.0068)	(0.0227)	(0.0026)	(0.0126)	(0.0027)	(0.0130)	(0.0033)	(0.0147)	(0.0039)	(0.0141)
>30°C	0.0015	0.0584	0.0408***	0.0698**	0.0412***	0.0656***	0.0089	-0.3041***	0.0147**	0.1517***
	(0.0129)	(0.0387)	(0.0057)	(0.0289)	(0.0066)	(0.0210)	(0.0060)	(0.0262)	(0.0073)	(0.0270)
Observations	2,375,375		2,540,413		2,607,472		2,562,380		2,509,903	
Mean Outcome	0.06		0.47		0.41		0.95		0.25	

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 standard Poisson maximum likelihood estimation (MLE) distributed lag model to estimate the effect. All models include year-by-month-by-municipality and weekday-by-municipality fixed effects along with second-degree polynomial of precipitation and relative humidity. 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.

Contemporaneous effect. Cold temperatures consistently reduce admissions across various illnesses, with a 4.83 and 16.92 percent decrease in obstetric cases and infectious and parasitic diseases, respectively, for the coldest temperature range. Conversely, warmer temperatures increase admissions for specific conditions. For instance, endocrine and metabolic illnesses show a 4.26 percent rise in admissions at temperatures of 25–30°C, which grows to approximately 10.20 percent at 30–45°C. Similarly, external causes, including injuries and poisonings, respond positively to warm temperatures. Other conditions that significantly increase with warm temperatures include genitourinary, infectious and parasitic, mental, obstetric, and skin-musculoskeletal disorders. In contrast, blood-immune, digestive, nervous system, respiratory, and eye-ear categories show no signifi-

cant effects. Circulatory diseases are the only category with a negative contemporaneous coefficient under warm conditions.

Cumulative effect of cold. Several health conditions show amplified coefficients in the distributed lag model. These amplifications across disease categories explain the higher pooled coefficients in cumulative models compared to contemporaneous models in the main results. Notably, cumulative reductions for extreme cold reach 72.7 percent for infectious and parasitic diseases and 33.4 percent for external causes. The results for infectious-parasitic diseases are in line with [White \(2017\)](#), who 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 contrast, it significantly influences the overall admission trend in Mexico, where this category constitutes roughly 6 percent of visits ([Table A.4](#)). Significant reductions in dengue, foodborne bacterial intoxications, and gastroenteritis-colitis drive this 30-day decline ([Table 4](#)).⁷ Other categories, such as genitourinary (27 percent), neoplasms (25 percent), and skin and musculoskeletal (26 percent), also exhibit statistically significant amplifications.

One exception to the amplification of short-term impacts after 30 days occurs with respiratory conditions, which exhibit a shift in signs between contemporaneous and cumulative models. Although extreme cold initially causes a 7.37 percent decrease in admissions, the 30-day cumulative effect shows a significant 18.2 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 is insufficient to produce an overall rise in visits during cold spells, as observed in California.

⁷ 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](#)).

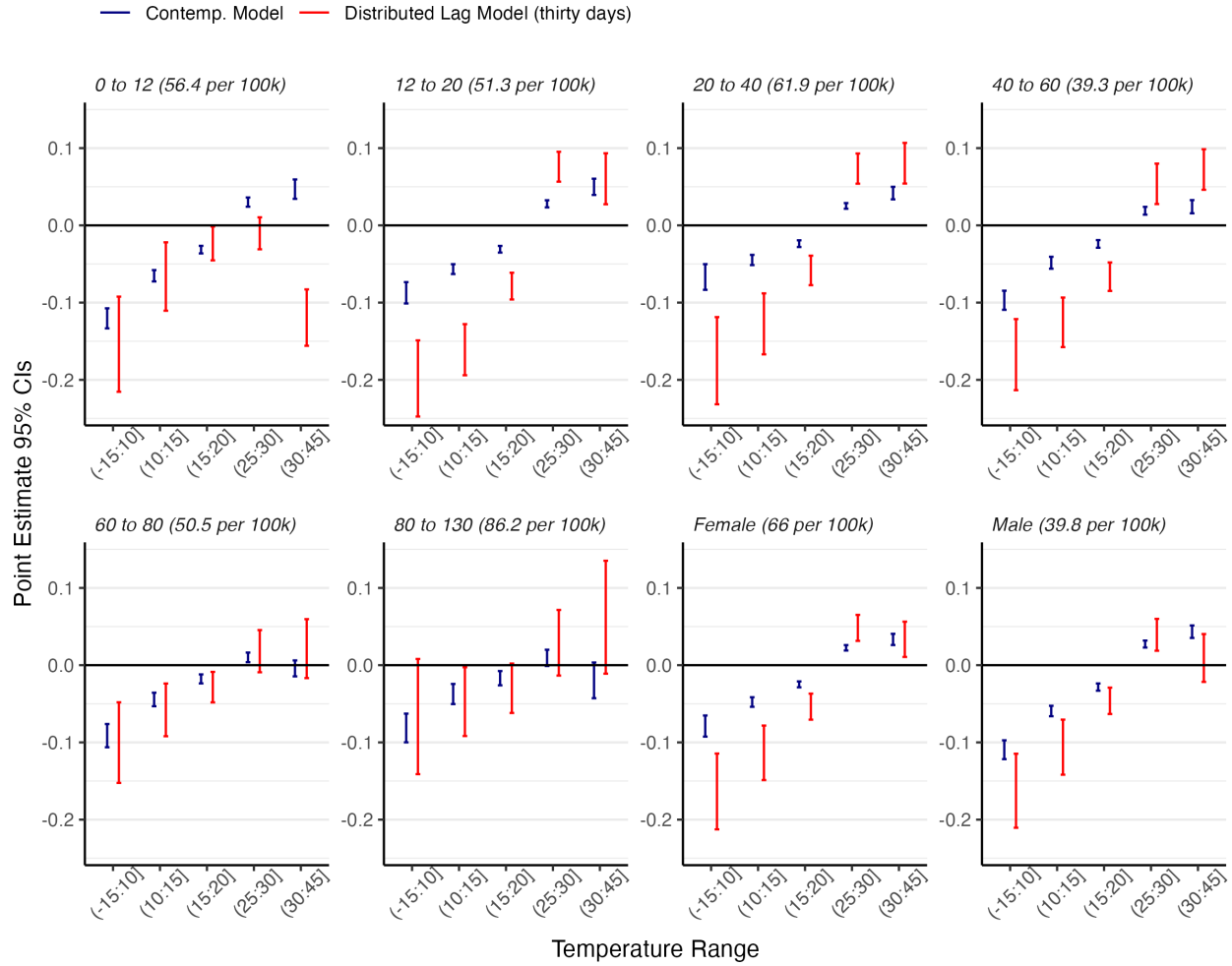
Cumulative effect of heat. The cumulative effects of warm temperatures often differ in magnitude and direction from short-term impacts. For endocrine and metabolic disorders, cumulative admissions increase by 19.9 percent at hot temperatures (30–45°C), nearly doubling the immediate effect. Similar trends occur for genitourinary and skin-musculoskeletal disorders, with cumulative increases of 20.48 percent and 15.17 percent, respectively, compared to immediate rises of 4.75 percent and 1.47 percent. Some conditions, despite no significant contemporaneous effects, show positive cumulative impacts after 30 days, including Blood/Immune (21 percent), Eye/Ear (10 percent), Digestive (4 percent), and Obstetric (3 percent). For circulatory diseases, the negative impact intensifies over time, reaching -6.52 percent in the 30-day cumulative window. Respiratory diseases show a significant cumulative decrease in admissions at hot temperatures (-30.41 percent) despite an insignificant immediate 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 7.34 percent, contrasting with an 8.56 percent immediate increase. This pattern indicates a slight decline in impact over the 30-day period.

4.2. Heterogeneity by age and gender

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

Contemporaneous effect. In response to cold temperatures, admissions decrease across all age groups. This is in line with the reduction in admissions across all categories identified in Table 3. Among children aged 0–12, admissions decrease by 11.33 percent on days with average temperatures below 10°C. Similar reductions occur in other age cohorts: 8.35 percent for ages 12–20, 6.46 percent for ages 20–40, 9.24 percent for ages 40–60, 8.71 percent for ages 60–80, and 7.80 percent for ages 80–130. Gender differences also emerge in response to cold. At very low temperatures, male individuals experience a larger reduction in admissions (10.36 percent) compared to female individuals (7.58 percent), due to

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 ER admissions 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. Standard errors cluster at the municipality level.

variations in their demand for ED services (Table A.3). For instance, over 15 percent of admissions for women are due to obstetric consultations, which report a contemporaneous decrease of 4.3 percent at cold temperatures. In contrast, most of the demand for men relates to respiratory conditions, which react more strongly to cold (7.4 percent).

In contrast to cold temperatures, hot temperatures consistently increase admissions across all age groups, especially among younger populations. For children aged 0–12, each additional day with average temperatures of 25–30°C raises admissions by 3.06 percent, and

days at or above 30°C result in a 4.80 percent increase. Similarly, adolescents aged 12–20 experience increases of 2.83 percent and 5.11 percent, respectively. For adults aged 20–40, admissions rise by 2.55 percent at warm temperatures and 4.27 percent at hot temperatures. In contrast, people older than 60 show no significant contemporaneous effect. 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 most common. All three of these ICD-10 chapters show large increases during hot temperatures. For people older than 59, circulatory conditions, diabetes, and urinary tract infections are prevalent, but these show mixed coefficients. Regarding gender differences, at warm temperatures (25–30°C), male individuals show a 2.77 percent increase in admissions, rising to 4.43 percent at hot temperatures ($\geq 30^\circ\text{C}$), and female individuals exhibit increases of 2.28 and 3.39 percent, respectively.

Cumulative effect (30 days). The 30-day cumulative effects suggest that decreased admissions at cold temperatures intensify over time across most age groups. For children aged 0–12, the cumulative decrease in the coldest interval reaches 14.23 percent, up from an immediate decrease of 11.33 percent. For adolescents aged 12–20, it increases to 18.00 percent. These amplified effects imply that cold temperatures cause sustained reductions in admissions, primarily due in significant drops in the digestive, external causes, infectious-parasitic, and obstetric categories. Regarding gender, both male and female people show significant cumulative decreases in admissions at cold temperatures, with reductions of 15.01 percent and 15.07 percent in the coldest interval, respectively.

The cumulative effects of hot temperatures differ across age groups. For children aged 0–12, cumulative admissions decrease by 11.26 percent on very hot days ($\geq 30^\circ\text{C}$), 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 stems 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 (Fig-

ure 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, but female individuals have an increase of 3.40 percent.

4.3. Mechanisms

To further advance our understanding of the dynamics linking temperature variations and ED visits, we propose a classification of the mechanisms that underpin these relationships. Table 4 summarizes three primary channels: (1) physiological incidence, (2) ecosystem dynamics, and (3) behavioral responses. For each one, we present illustrative examples based on specific diseases.

Physiological incidence. This highlights the direct effects of extreme temperatures (Table 4, Panel A). Columns 1–2 show that hot temperatures significantly increase visits for heat-related conditions, such as heatstroke, consistent with extensive epidemiological literature (Weinberger et al., 2021; Sun et al., 2021; Hess et al., 2014).⁸ Studies also indicate that heat exposure during pregnancy induces physical and psychological stress, elevating systemic cortisol levels, which impacts fetal and placental membranes, increasing the likelihood of premature labor and preterm birth (Hunter et al., 2023). Consistent with these findings, we document a significant 5 percent increase in admissions for false labor following a day above 30°C, increasing 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 circulatory problems, particularly heart failure, during hot weather (Columns 5–6). This pattern may reflect increased disease severity under extreme heat, leading to heightened mortality before hospital admission (Gould et al., 2024). Research suggests that heat-

⁸ Prolonged heat exposure disrupts thermoregulation, causing dehydration, electrolyte imbalances, and overheating.

induced cardiovascular outcomes arise from thermoregulatory demands, which impose acute stress on the circulatory system (Anderson et al., 2013). This stress can trigger severe complications, preventing some individuals from accessing emergency care in time.

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 worsens 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 30 days, and the negative impact of hot days intensifies when we account for displacement.

Ecosystem dynamics. Temperature fluctuations affect health indirectly through changes in the ecosystem (Table 4, Panel B). These variations influence the activity 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 vector-borne diseases, 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 elevate 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 incidences of intoxications 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.

Behavioral responses. Beyond incidence and ecosystem dynamics, temperature influences human activity patterns and health care-seeking behavior (Table 4, Panel C).

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 admissions 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).⁹ 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 admissions. For instance, hot days significantly amplify admissions for mental disorders linked to alcohol consumption (Columns 9–10). This effect likely arises from the interaction between high temperatures and behavioral responses, such as increased alcohol intake as a coping mechanism (e.g., Cohen and Gonzalez (2024) find that alcohol consumption is positively associated with outdoor temperatures). Elevated temperatures also enhance the physiological and psychological effects of alcohol, raising 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, these mechanisms often overlap and interact. 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.

⁹ The increase in CKD admissions during cold temperatures is consistent with epidemiological findings (Park et al., 2024).

Table 4: Mechanisms of the temperature-morbidity relationship

	Emergency room visits per 100,000 people									
	Heat Shock		False Labor		Heart Failure		Dissociative Disorder		Common Cold	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
<i>Panel A: Incidence</i>										
≤10°C	-0.193*** (0.029)	-0.424*** (0.089)	-0.064** (0.028)	-0.083 (0.099)	-0.144*** (0.030)	0.257* (0.147)	-0.228*** (0.033)	-0.393*** (0.096)	-0.020** (0.009)	0.357*** (0.052)
10–15°C	-0.135*** (0.016)	-0.310*** (0.049)	-0.043*** (0.008)	-0.004 (0.047)	-0.089*** (0.018)	-0.041 (0.058)	-0.150*** (0.019)	-0.213*** (0.061)	-0.000 (0.006)	0.308*** (0.033)
15–20°C	-0.078*** (0.011)	-0.228*** (0.034)	-0.025*** (0.006)	0.009 (0.038)	-0.048*** (0.013)	0.011 (0.048)	-0.086*** (0.014)	-0.089* (0.046)	0.001 (0.005)	0.170*** (0.023)
25–30°C	0.133*** (0.013)	0.206*** (0.039)	0.027*** (0.006)	0.090*** (0.028)	-0.015 (0.019)	-0.010 (0.051)	0.071*** (0.015)	0.054 (0.054)	-0.011 (0.006)	-0.221*** (0.027)
>30°C	0.406*** (0.025)	0.713*** (0.085)	0.050*** (0.009)	0.151*** (0.054)	-0.115*** (0.033)	-0.157 (0.098)	0.146*** (0.030)	0.081 (0.104)	-0.039*** (0.012)	-0.533*** (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	
	Dengue		Foodborne Intox.		Gastroenteritis		Infect. Pregnancy		Animals and Plants	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
<i>Panel B: Ecosystem dynamics</i>										
≤10°C	-0.519*** (0.113)	-2.399** (0.986)	-0.119*** (0.029)	-0.365*** (0.136)	-0.175*** (0.010)	-0.787*** (0.052)	-0.088*** (0.016)	-0.171*** (0.056)	-0.643*** (0.028)	-1.319*** (0.097)
10–15°C	-0.257*** (0.058)	-1.495*** (0.354)	-0.055*** (0.017)	-0.131** (0.059)	-0.103*** (0.006)	-0.439*** (0.023)	-0.051*** (0.008)	-0.132*** (0.034)	-0.338*** (0.013)	-0.847*** (0.050)
15–20°C	-0.047** (0.017)	-0.704*** (0.153)	-0.042*** (0.013)	-0.058 (0.046)	-0.050*** (0.004)	-0.143*** (0.017)	-0.025*** (0.006)	-0.051** (0.022)	-0.144*** (0.009)	-0.400*** (0.019)
25–30°C	0.070*** (0.018)	0.530*** (0.081)	0.043*** (0.013)	0.001 (0.049)	0.056*** (0.004)	0.017 (0.022)	0.031*** (0.006)	0.170*** (0.024)	0.106*** (0.008)	0.358*** (0.029)
>30°C	-0.002 (0.066)	-0.476 (0.575)	0.078** (0.036)	0.034 (0.101)	0.105*** (0.009)	-0.144*** (0.035)	0.036*** (0.011)	0.228*** (0.045)	0.158*** (0.019)	0.327*** (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	
	Headache		Epilepsy		Other Urinary Inf.		CKD		Alcohol Disorders	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
<i>Panel C: Behavioral changes</i>										
≤10°C	-0.214*** (0.025)	-0.258** (0.081)	-0.044** (0.022)	-0.121 (0.106)	-0.108*** (0.013)	-0.407*** (0.049)	0.0159 (0.030)	0.192** (0.081)	-0.133*** (0.025)	-0.323*** (0.095)
10–15°C	-0.100*** (0.016)	-0.167*** (0.047)	-0.032** (0.014)	-0.021 (0.039)	-0.059*** (0.005)	-0.311*** (0.028)	-0.007 (0.015)	-0.0150 (0.054)	-0.073*** (0.012)	-0.081 (0.058)
15–20°C	-0.042*** (0.011)	-0.050 (0.034)	-0.013 (0.010)	-0.027 (0.032)	-0.028*** (0.004)	-0.146*** (0.019)	-0.0135 (0.011)	0.0001 (0.039)	-0.046*** (0.009)	-0.053 (0.039)
25–30°C	0.029** (0.014)	0.052 (0.044)	0.011 (0.012)	0.052 (0.042)	0.0208*** (0.005)	0.159*** (0.017)	0.0085 (0.014)	-0.088* (0.053)	0.061*** (0.013)	0.085* (0.047)
>30°C	-0.002 (0.032)	0.183** (0.079)	0.011 (0.024)	0.026 (0.079)	0.041 *** (0.010)	0.218*** (0.030)	-0.0010 (0.027)	-0.0002 (0.10)	0.107*** (0.031)	0.043 (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. Standard errors cluster at the municipality level. Significance codes: *** < 0.01, ** < 0.05, * < 0.1.

5. Midcentury projections

To estimate the impacts of climate change on ED visits, 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.¹⁰ This method evaluates the impact of temperature changes on health outcomes using age-specific semielasticities of hospital admissions and considers cumulative lagged effects over 30 days.

We convert relative changes in admissions 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 affect different age groups. Finally, we estimate the economic impact of these changes using official 2024 medical care cost data for Mexico, which include admission and hospitalization costs.¹¹ 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 annual public health care expenditures and admissions over the decades. By 2031–2040, expenditure is projected to reach approximately 57.1 million USD, resulting in an increase of 193,000 admissions. In the following decade, 2041–2050, it will rise significantly to 71.4 million USD, driven by an additional 241,000 admissions. By 2051–2060, it is expected to escalate further to 91.9 million USD, with an anticipated increase of 311,000 admissions, corresponding to a 0.24 percent increase in ED admissions.¹²

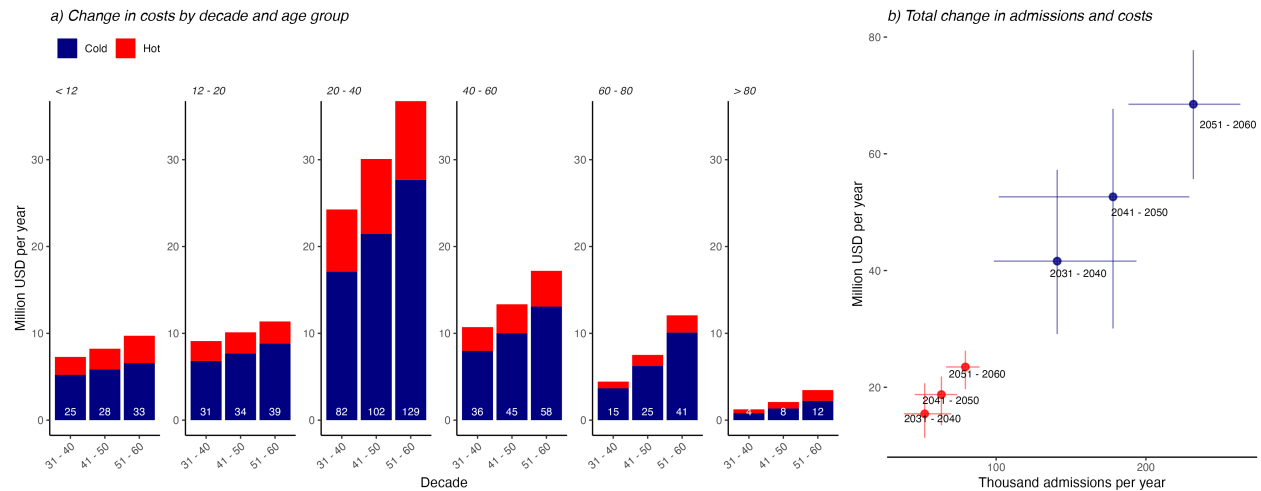
Extreme cold and heat significantly increase hospital admissions across all age groups.

¹⁰ Temperature changes are aggregated at the municipality level using population-weighted averages.

¹¹ We exploit data from official government estimates from medical care unit costs in Mexico for the year 2024 by the FIMSS (2023). These data provides an average cost per admission (c^a) of 207 USD and an average cost of admissions leading to hospitalizations (c^h) of 691 USD.

¹² To contextualize our estimates, Gould et al. (2024) projects a 0.46 percent increase in ED admissions in California by midcentury.

Figure 4: Projections of temperature-related emergency department (ED) visits



Notes: The left panel presents the annual change in public ED admission costs by age group, by decade. Labels at the bottom of the bars show the change in admission cases (in thousands). The right panel presents the annual change in public ED admission costs and admission cases, due to changes in hot and cold temperatures, by decade and for all ages. Scatter points represent the GCM mean values; segments report the minimum and maximum value across GCMs.

The 20–40 age group experiences the largest rise in cold-related admissions, with an additional 58,000 projected for 2031–2040, increasing to 94,000 by 2051–2060. The 40–60 age group also shows a notable increase, from 27,000 additional admissions in 2031–2040 to 44,000 by 2051–2060. Younger (0–12) and older (80–130) age groups experience lower increases, with 18,000 and 3,000 additional admissions, respectively, in 2031–2040, rising to 22,000 and 8,000 by 2051–2060. Cold-related effects lead to higher expenditures, increasing from \$5.2 million in 2031–2040 to \$27 million by 2051–2060.

The 20–40 age group experiences the highest increase in heat-related admissions, totaling an additional 24,000 in 2031–2040, rising to 35,000 by 2051–2060. This finding aligns with literature indicating that temperature increases impose a greater burden on the middle age distribution (Wilson et al., 2024). The 40–60 age group also shows an increase, from 9,000 admissions in 2031–2040 to 14,000 by 2051–2060. Younger (0–12) and older (80–130) groups exhibit smaller increases, from 7,000 and 1,000 in 2031–2040 to 11,000 and 4,000 by 2051–2060, respectively. Expenditures for heat-related admissions rise from \$2.1 million in 2031–2040 to \$10.4 million by 2051–2060.

Summing the effects of cold and hot extremes, total additional admissions rise from 193,000 in 2031–2040 to 311,000 by 2051–2060. Cold and heat-related effects significantly increase

admissions. From 2031 to 2040, cold-related admissions dominate. However, heat-related effects become more pronounced in 2041–2060 and 2051–2060. Therefore, health care planning must account for both rising temperatures and the reduced number of cold days, as the latter significantly contributes to increasing health care demand.

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 admissions show an approximately linear relationship. This finding corroborates research in developed countries and is the first to document a similar effect in a middle-income context. Moreover, our data, covering nearly all public hospitals in Mexico, provide a 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 but lead to delayed cumulative increases, as for respiratory illnesses. This pattern reflects behavioral changes, such as postponing mild treatments, and the incubation periods of certain pathogens. In contrast, hot temperatures trigger immediate surges for heat-related conditions and injuries, followed by 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, and older populations are more vulnerable to cold. Disease-specific results show that our findings stem from direct physiological responses, such as heatstroke; behavioral factors, including alcohol-related disorders; and ecosystem dynamics, such as the incidence of vector-borne diseases.

Climate projections indicate that ED usage will 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 rise in admissions on hot days and delayed spikes during cold spells 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](#)).¹³ A comprehensive assessment of climate-related health costs must extend beyond mortality estimates and account for morbidity, health care system strain, 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.

¹³ Numerous factors beyond temperature changes and climate change 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](#)).

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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 mainly 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 health care access to the uninsured population. Numerous private health care facilities also exist, offering high-quality services, though these are typically accessible only for 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 and display the total numbers for two categories. Enrollment (self-reported) indicates whether the option provides coverage. Use refers to whether a person has used the services of any of these institutions in the previous year. For example, an uninsured person can have 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.

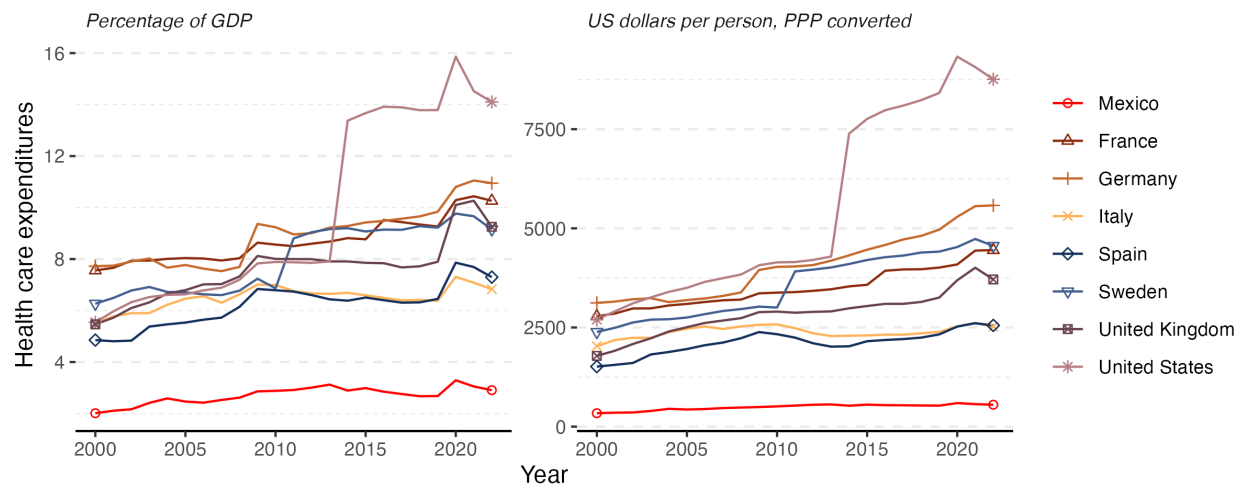
In 2020, about 20 percent of the Mexican population reported lacking access to health care, despite the theoretical guarantee of universal coverage. These figures contrast with the US health care system, where private health insurance covered 66 percent of people in

2019, public insurance programs, such as Medicare or Medicaid, covered about 25 percent, and nearly 30 million people, or 9 percent, lacked insurance (Berchick et al., 2019). The uninsured segment of the Mexican population can also rely on the public sector paying out-of-pocket expenses or the private sector, which, although expensive, remains significantly more affordable than in other North American countries. Our data set only includes public hospitals, thus excluding emergency department (ED) visits in private institutions.

In addition to differences in the share of insured persons between public and private systems, Mexico's health care structure has notable distinctions from and similarities with other OECD nations. 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 population segments. However, health care faces challenges related to funding and equitable access. In contrast, European systems, particularly those with single-payer models, such as 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.

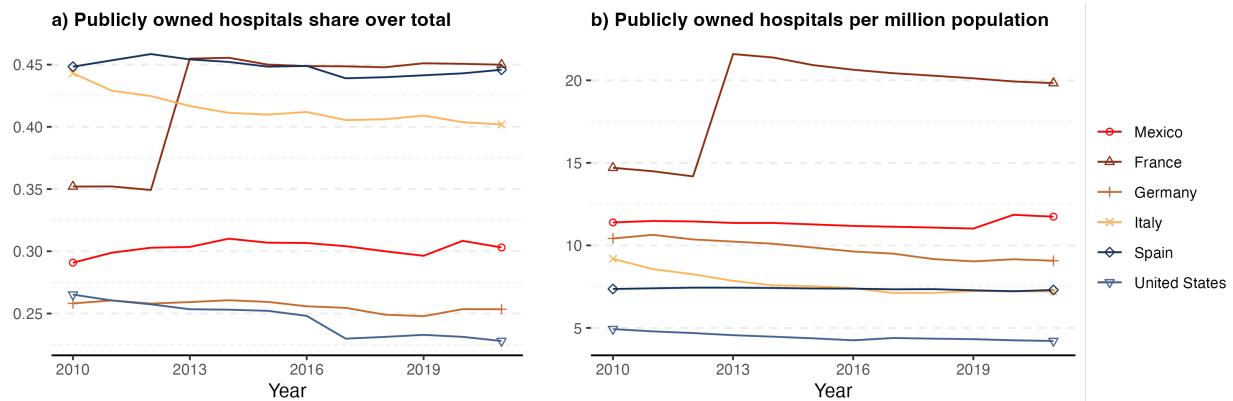
Figure A.1: Health expenditure in government and compulsory schemes



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: 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>).

Table A.2: Main diseases by sex

ER Type	ICD-10 Name	# Visits (Thousands)	Share of Category	Cumulative Share	Share of Total
Female (65.19%)	Encounter for supervision of normal pregnancy (Z34)	1,2676.21	15.52%	15.52%	10.12%
	Infectious gastroenteritis and colitis, unspecified (A09)	2,909.33	3.56%	19.09%	2.32%
	Acute pharyngitis (J02)	2,673.40	3.27%	22.36%	2.13%
	False labor (O47)	2,556.31	3.13%	25.49%	2.04%
	Other disorders of urinary system (N39)	2,324.45	2.85%	28.34%	1.86%
Male (34.81%)	Acute pharyngitis (J02)	2,447.24	5.61%	5.61%	1.95%
	Infectious gastroenteritis and colitis, unspecified (A09)	2,294.56	5.26%	10.88%	1.83%
	Acute nasopharyngitis [common cold] (J00)	1,521.57	3.49%	14.37%	1.21%
	AURI of multiple and unspecified sites (J06)	1,519.94	3.49%	17.85%	1.21%
	Abdominal and pelvic pain (R10)	1,106.31	2.54%	20.39%	0.88%

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 2022 (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.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%

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Table A.4 – continued from previous page

Chapter	ICD-10 Name	ICD-10	# Visits (Ths.)	Share Chapter	Cumulative % Chapter	Share Total
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%
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%

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Table A.4 – continued from previous page

Chapter	ICD-10 Name	ICD-10	# Visits (Ths.)	Share Chapter	Cumulative % Chapter	Share Total
Eye Ear (1.36%)	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%
	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%)	Leucomaine 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 anemia	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.

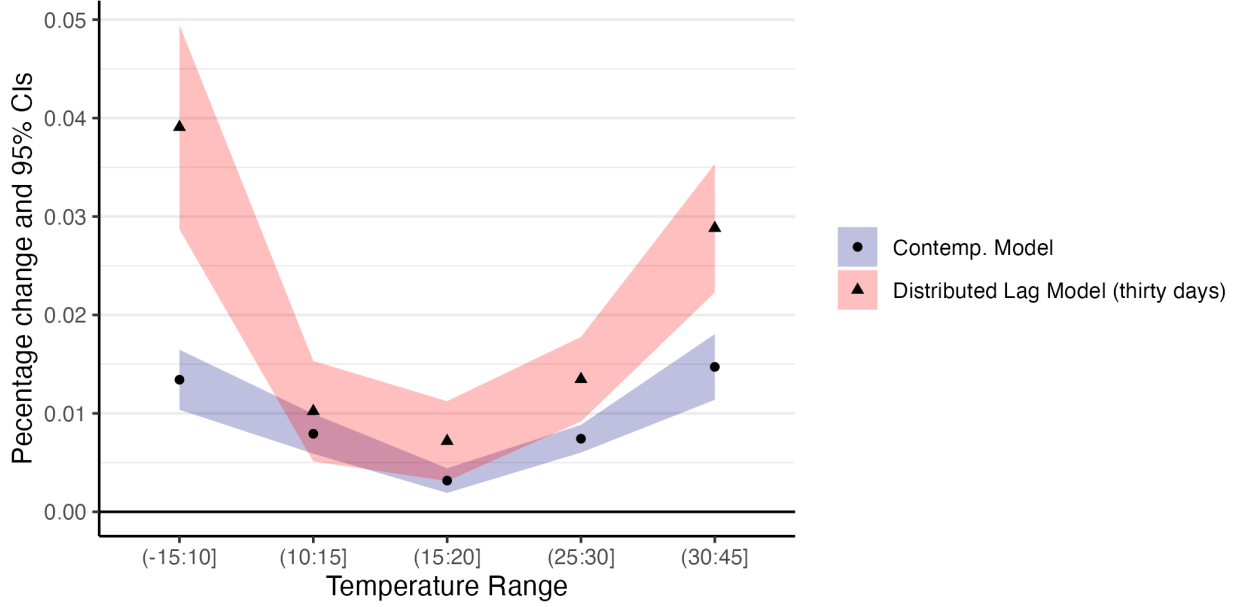
Table A.3: Main diseases by age group

Age group	ICD-10 Name	# Visits (Thousands)	Share of Category	Cumulative Share	Share of Total
20–39 (36.89%)	Encounter for supervision of normal pregnancy (Z34)	8,997.20	19.46%	19.46%	7.18%
	False labor (O47)	1,763.34	3.81%	23.28%	1.41%
	Other disorders of urinary system (N39)	1,159.81	2.51%	25.79%	0.93%
	Infections of genitourinary tract in pregnancy (O23)	1,071.53	2.32%	28.11%	0.86%
	Infectious gastroenteritis and colitis, unspecified (A09)	1,065.61	2.31%	30.41%	0.85%
< 12 (22.79%)	Acute pharyngitis (J02)	3,455.47	12.10%	12.10%	2.76%
	Infectious gastroenteritis and colitis, unspecified (A09)	2,508.56	8.79%	20.89%	2.00%
	Acute nasopharyngitis [common cold] (J00)	2,328.77	8.16%	29.04%	1.86%
	AURI of multiple and unspecified sites (J06)	2,044.30	7.16%	36.20%	1.63%
	Acute tonsillitis (J03)	647.17	2.27%	38.47%	0.52%
12–19 (15.59%)	Encounter for supervision of normal pregnancy (Z34)	3,518.03	18.00%	18.00%	2.81%
	False labor (O47)	761.96	3.90%	21.90%	0.61%
	other (Z35)	686.78	3.51%	25.42%	0.55%
	Infections of genitourinary tract in pregnancy (O23)	526.51	2.69%	28.11%	0.42%
	Infectious gastroenteritis and colitis, unspecified (A09)	509.50	2.61%	30.72%	0.41%
40–59 (14.80%)	Essential (primary) hypertension (I10)	883.52	4.76%	4.76%	0.71%
	Infectious gastroenteritis and colitis, unspecified (A09)	672.08	3.62%	8.39%	0.54%
	Type 2 diabetes mellitus (E11)	642.65	3.46%	11.85%	0.51%
	Other disorders of urinary system (N39)	624.69	3.37%	15.22%	0.50%
	Abdominal and pelvic pain (R10)	555.43	2.99%	18.21%	0.44%
60–79 (7.77%)	Essential (primary) hypertension (I10)	695.82	7.15%	7.15%	0.56%
	Type 2 diabetes mellitus (E11)	505.95	5.20%	12.35%	0.40%
	Infectious gastroenteritis and colitis, unspecified (A09)	350.54	3.60%	15.95%	0.28%
	endocrine_metabolic (E14)	298.12	3.06%	19.01%	0.24%
	Other disorders of urinary system (N39)	293.15	3.01%	22.03%	0.23%
> 79 (2.16%)	Essential (primary) hypertension (I10)	175.56	6.48%	6.48%	0.14%
	Other chronic obstructive pulmonary disease (J44)	105.48	3.89%	10.37%	0.08%
	Infectious gastroenteritis and colitis, unspecified (A09)	100.61	3.71%	14.09%	0.08%
	Other disorders of urinary system (N39)	83.98	3.10%	17.19%	0.07%
	Type 2 diabetes mellitus (E11)	81.40	3.00%	20.19%	0.06%

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 2008–2022 (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.

A.3 Additional results

Figure A.3: 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.

A.4 Climate projections

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

To compute the climate change shock, we use a representative 20-year period from the historical epoch (1991–2010) and decade-by-decade periods for future epochs (2031–2040, 2041–2050, 2051–2060), indexed by the superscripts $e = \{H, F\}$. We use projections developed within the CMIP6 framework ([O’Neill et al., 2016](#)) and incorporate five alternative global climate models (GCMs) to address uncertainty.

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 ($\Delta\mathcal{T}_{c,t,d,g}$). 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 temperatures used in our regressions ($\overline{\mathcal{T}}^{Hist}$) to obtain the projected temperature under climate change ($\mathcal{T}^{Fut}$):

$$\Delta\mathcal{T}_{i,t,d,g} = \sum_i (\mathcal{T}_{c,t,d,g}^F - \mathcal{T}_{c,t,d,g}^H) \quad (1)$$

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

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 .

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

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

Where

$$k \in \{< 10, 10 - 20, 25 - 30, > 30\} \quad (5)$$

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

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

We calculate the absolute change in admissions $\tilde{\Gamma}$ by assuming that the average age-specific admission rate ($\bar{y}_z$) remains constant from the historical period to future decades. The population increases uniformly at the decade-specific rate θ_d across all age groups,

according to the SSP2 demographic shifts (estimated in [Riahi et al. \(2017\)](#)):

$$\tilde{\Gamma}_{i,d,g}^z = \tilde{\Psi}_{i,d,g}^z \cdot (\bar{y}_z \cdot p_i \cdot \theta_d), \quad (7)$$

where p_i is the historical population in municipality i expressed as people per 100k.

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 admissions leading in hospitalizations (c^h) of 691 USD. Moreover, we assume the hospitalization rate relative to total admissions s observed in our sample remains constant over time:

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

