Emergency department visits and temperature

Evidence from Mexico*

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This paper estimates 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% on the same day, while warm temperatures increase visits by as much as 3.6%. Using distributed lag models, we then show that cold temperatures can reduce visits for the next 30 days by up to 16.3%. 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 like ecosystem dynamics and behavioral changes. Finally, we project that temperature-driven annual emergency department visits will increase by 0.24% by mid-century, resulting in an estimated increase of 92 million USD in annual medical expenditures in Mexico.

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1. Introduction

In the context of global warming, the impact of adverse temperature conditions on health emerges as a significant public health concern worldwide. While 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).

This paper estimates 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, as well as 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 thirty days.

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

Finding a linear relationship between ED visits and temperature changes is crucial because 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. Non-linear and concave relationships make the consequences of climate change context-dependent, influenced by current 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 increase admissions for respiratory and infectious diseases over time. In contrast, hot temperatures raise admissions for endocrine, genitourinary, and infectious-parasitic diseases, as well as for 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. While respiratory diseases respond similarly in our case, their contribution to the overall rise in visits during cold spells cannot offset declines in other categories, like 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.

Having case-level data also allows us to aggregate ED visits across different demographics. First, we examine age differences. Younger populations respond more strongly to hot and cold temperatures, showing significant immediate effects in children and adolescents. Variations in the demand for ED services and their interaction with temperatures explain the differences in effects between age groups. For instance, people under 40 primarily visit the emergency department 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 consultations for women and men, respectively, respectively.

We then propose a classification of mechanisms linking temperature to emergency room visits: (1) illness incidence, (2) ecosystem dynamics, and (3) behavioral changes. For each mechanism, we provide examples of related illnesses. For the illness incidence channel, we highlight that cold temperatures decrease admissions for heat-related shocks, false labor, and dissociative disorders, while 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 mechanism 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, as well as 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 behavior beyond deferral, leading to riskier activities. For example, admissions for alcohol-related disorders decrease in cold weather and increase in heat.

Finally, we estimate future levels of temperature-induced ED visits by mid-century using our results along with climate projections. Ceteris paribus, our estimates indicate a steady annual increase in admissions, starting with 193,000 additional visits between 2031 and 2040 and rising to over 300,000 visits between 2051 and 2060. This is equivalent to 0.24%-increase in ED visits with respect 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 mid-century. These rising costs result from 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 socio-economic 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. Recent 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 data set allows us to explore all-cause and cause-specific responses to temperature across all age groups. Moreover, while most existing studies have a limited geographic scope (White, 2017; Gould et al., 2024) or are not representative of the entire population within a country (Agarwal et al., 2021), our study offers a comprehensive national coverage. A notable exception in the literature is the work of 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 in this setting. Importantly, 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. In concurrent work, Aguilar-Gomez et al. (2025) analyzes 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). While 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 temperature shocks (White, 2017; Graff Zivin and Neidell, 2014). Our data allows us to identify when individuals seek treatment, which differs from the timing of the health shock. Several factors influence the decision to delay or forgo treatment beyond temperature, 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 the mechanisms behind treatment-seeking behavior within a *public* healthcare system like Mexico,[1] and comparing it with a predominantly *private* system like 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 on significantly different ways in line with previous studies for US 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) recently 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. In this study, we show that a significant share of heat-driven ED visits in Mexico stems from contact with venomous insects and animals, as well as vector-borne diseases like dengue and other parasitic and infectious diseases, which are more prevalent at higher temperatures.

This insight is crucial for tropical and semi-tropical climates, where sustained high ambi-

[1] For more information on the Mexican health case system, see Appendix A.1.

ent temperatures promote vector-borne and envenomation-related health issues (Harvell et al., 2002). Higher temperatures accelerate mosquito breeding cycles, increasing the transmission of diseases like dengue (Mordecai et al., 2013). Increased temperatures also 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, 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).

Emergency department 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

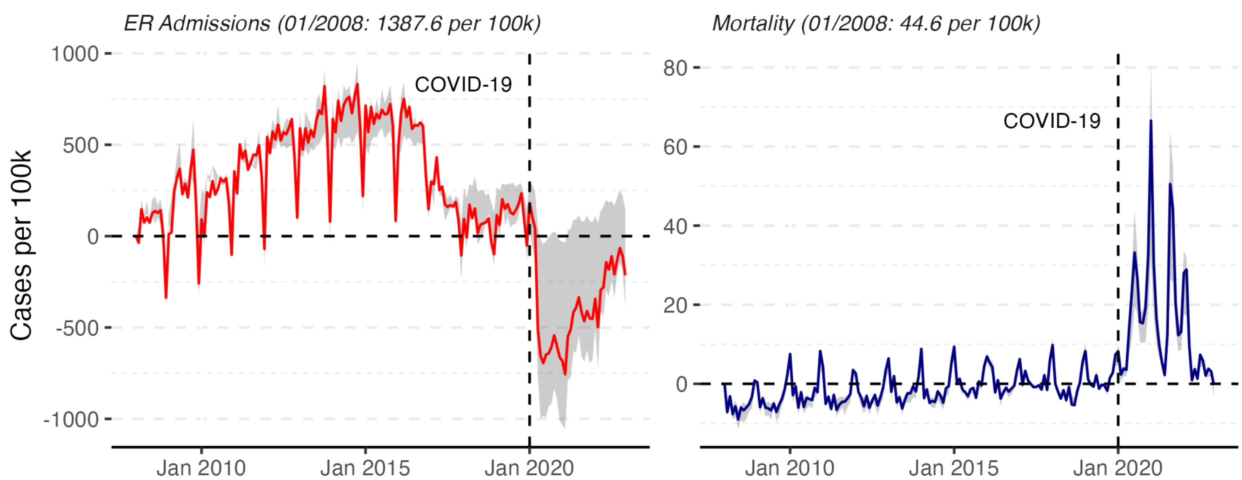
[2] Figure A.2 shows that public hospitals in Mexico are approximately 35% of the total, a higher figure than in the United States but lower than in the European Union. Although there are approximately 2.5 private hospitals for every public hospital, most private hospitals have less than 20 beds and function mainly as outpatient clinics, offering primary care and some specialized diagnostic and treatment services (Organization et al., 2017). In fact, only approximately 14% of people affiliated with a public healthcare institution choose to receive care in private hospitals (Juan López et al., 2015). Looking at the number of public hospitals per million people, Mexico has more than two times the number of hospitals than the United States and a higher number than most EU states, except France.

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 emergency room 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. The time series exhibits clear seasonality, with reduced admissions in November and December. We identify two breaks in the time series. The first break occurred in 2018 when the flagship healthcare program, Seguro Popular, was replaced by a new scheme. The second break took place 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 so that it is equal to 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

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

by country, we contextualize our Mexican data by comparing them with data reported by White (2017) on outpatient ED visits in California. However, we need to clarify a couple of differences between the two data sets. First, while 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 a two classifications are similar, they serve different purposes. The ICD-10 is a comprehensive diagnostic tool containing over 70,000 codes for specific conditions. In contrast, the CCS aggregates these codes into approximately 285 broader categories, facilitating the analysis of large health data sets. ICD-10 provides detailed precision, whereas CCS offers simplified, high-level summaries. One limitation of our case-level data is that it reports ICD-10 classifications only up to four digits. This restriction hampers our ability to aggregate into CCS group categories, as some require more detailed 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] Distinct patterns emerge when comparing the two datasets. First, the visit rate in California (77.09) exceeds that of Mexico (53.2). This difference arises mainly from California's older population, which has an average age nearly 10 years higher than that of Mexico. Second, primary utilization patterns differ significantly. In Mexico, a larger proportion of visits pertains to pregnancy and the perinatal period (10.81%) as well as infectious and parasitic diseases (5.93%), 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, healthcare infrastructures, and risk factors.

[4] Some ICD-10 chapters lack corresponding CCS chapters and vice versa (e.g., congenital for CCS and

Table 1: Emergency department visits in Mexico and California

Chapter	Share of visits (%)		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 comes from Table 1 in White (2017) and spans between 2005 and 2015. Data for Mexico comes 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.

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

eye/ear for ICD-10).

[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).

In this empirical model, Y_{idmy} represents the number of ED admissions per 100,000 for municipality i on day d of month m and year y. We model temperature non-linearly across six intervals, ranging from $\leq$10 to $>$30 °C, using 20 to 25°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.

Since 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 thirty 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 thirty days, effectively accounting for the displacement and anticipation of admissions.

Accounting for displacement effects is crucial in our setting. Prior research by White (2017) finds that in the US, 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. 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 emergency department 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% on the event day. This effect intensifies to a 16.3% reduction when accounting for the following 30 days. Negative effects also occur for days with temperatures between 10 and 15 °C, as well as between 15 and 20 °C. Conversely, temperatures at or above 25 °C increase visits. An additional day between 25 and 30 °C results in a 2.4% increase on the event day, growing to a 4.5% cumulative increase over the 30-day period. For the warmest interval (> 30 °C), visits increase by 3.6% on the event day. However, this effect diminishes to 2.5% when examining the cumulative impact over 30 days (harvesting).

Table 2: The effect of daily temperatures on emergency room visits

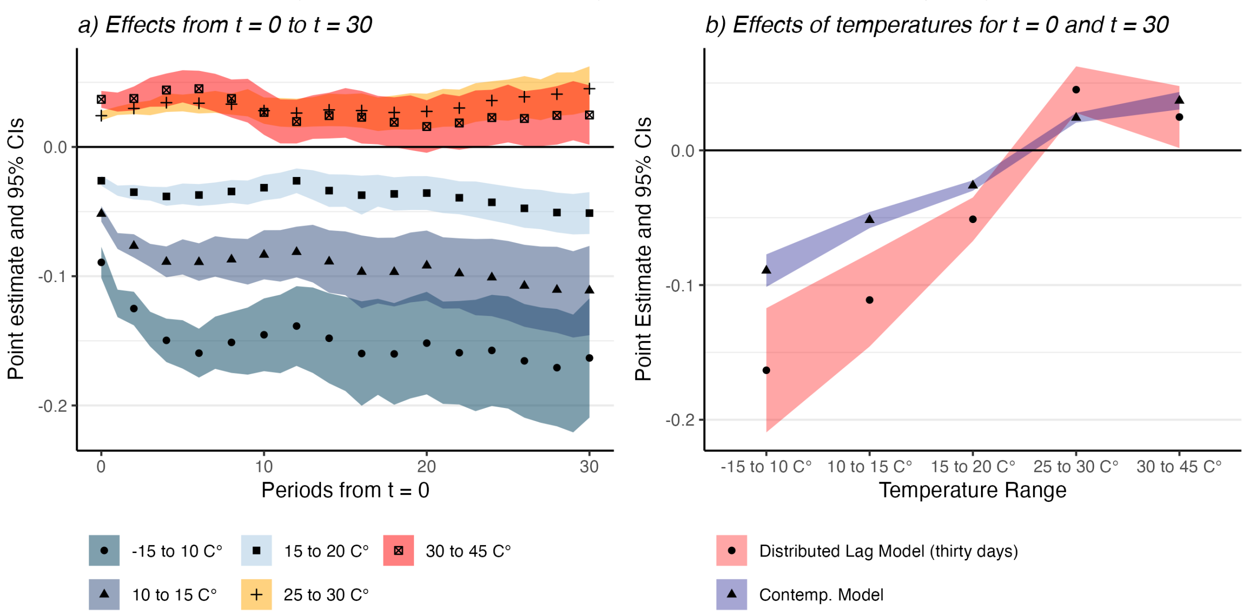
	Emergency room visits per 100,000 people	
	Contemporaneous	Cumulative (30 days)
$\leq$ 10 °C	-0.089***	-0.163***
	(0.006)	(0.023)
10 to 15 °C	-0.052***	-0.111***
	(0.003)	(0.017)
15 to 20 °C	-0.026***	-0.051***
	(0.002)	(0.008)
25 to 30 °C	0.024***	0.045***
	(0.002)	(0.009)
$>$ 30 °C	0.037***	0.025**
	(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 emergency room 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, while *distributed lag model (thirty days)* represents the linear combination of thirty 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. N.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 previous 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 ten days post-exposure, 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% 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 mid-term 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 Dechezleprêtre (2022). Comparing our estimates with mortality underscores these differences for the same period and population. While 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 the 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 room visits by disease category

	Emergency room 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***	-0.2302**	-0.0574***	-0.0196	-0.0689***	-0.2456***	-0.1443***	-0.1686***	-0.1378***	-0.3338***
	(0.0268)	(0.1126)	(0.0091)	(0.0378)	(0.0085)	(0.0311)	(0.0116)	(0.0509)	(0.0089)	(0.0328)
10–15°C	-0.0567***	-0.1625***	-0.0127**	-0.0102	-0.0332***	-0.1699***	-0.0871***	-0.1328***	-0.0813***	-0.2180***
	(0.0121)	(0.0481)	(0.0052)	(0.0205)	(0.0042)	(0.0215)	(0.0071)	(0.0332)	(0.0051)	(0.0246)
15–20°C	-0.0334***	-0.1470***	-0.0046	-0.0102	-0.0161***	-0.0613***	-0.0446***	-0.0651***	-0.0406***	-0.1157***
	(0.0095)	(0.0330)	(0.0036)	(0.0139)	(0.0028)	(0.0120)	(0.0045)	(0.0179)	(0.0033)	(0.0120)
20–25°C	0.0094	0.0952**	-0.0076*	-0.0102	0.0015	0.0347***	0.0426***	0.0566***	0.0425***	0.0963***
	(0.0110)	(0.0419)	(0.0043)	(0.0184)	(0.0030)	(0.0120)	(0.0046)	(0.0187)	(0.0031)	(0.0111)
>30°C	0.0160	0.2079***	-0.0335***	-0.0652***	-0.0006	0.0403**	0.1020***	0.1992***	0.0563***	0.1216***
	(0.0251)	(0.0664)	(0.0090)	(0.0239)	(0.0054)	(0.0182)	(0.0106)	(0.0321)	(0.0061)	(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***	0.0014	-0.0849***	-0.2703***	-0.1692***	-0.7271***	-0.1397***	-0.2451***	-0.0577***	-0.2484***

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.

	(0.0118)	(0.0572)	(0.0103)	(0.0385)	(0.0090)	(0.0468)	(0.0169)	(0.0623)	(0.0176)	(0.0600)
10–15°C	-0.0190***	0.0166	-0.0468***	-0.2043***	-0.1001***	-0.4250***	-0.0842***	-0.1417***	-0.0321***	-0.1169***
	(0.0072)	(0.0242)	(0.0046)	(0.0237)	(0.0055)	(0.0211)	(0.0080)	(0.0306)	(0.0106)	(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
	(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, while *distributed lag model (thirty days)* represents the linear combination of thirty 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% decrease in obstetric cases and a 16.92% decrease in infectious and parasitic diseases for the coldest temperature range. Conversely, warmer temperatures increase admissions for specific conditions. For instance, endocrine and metabolic illnesses show a 4.26% rise in admissions at temperatures between 25°C and 30°C, which grows to approximately 10.20% at temperatures between 30°C and 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 significant 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 coefficients for extreme cold reach 72.7% for infectious and parasitic diseases and 33.4% for external causes. The results for infectious-parasitic diseases differ from White (2017), who reports a significant decrease of approximately 35%. However, this effect has a limited overall impact in California due to the low prevalence of these diseases, which account for about 3% of visits. In contrast, our cumulative negative effect significantly influences the overall admission trend in Mexico, where this category constitutes roughly 6% 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%), neoplasms (25%), and skin and musculoskeletal (26%), 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 signs between contemporaneous and cumulative models. While extreme cold initially causes a 7.37% decrease in admissions, the 30-day cumulative effect shows a significant 18.2% increase, highlighting the delayed adverse impacts of cold on respiratory health. 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 (CDPH, 2024).

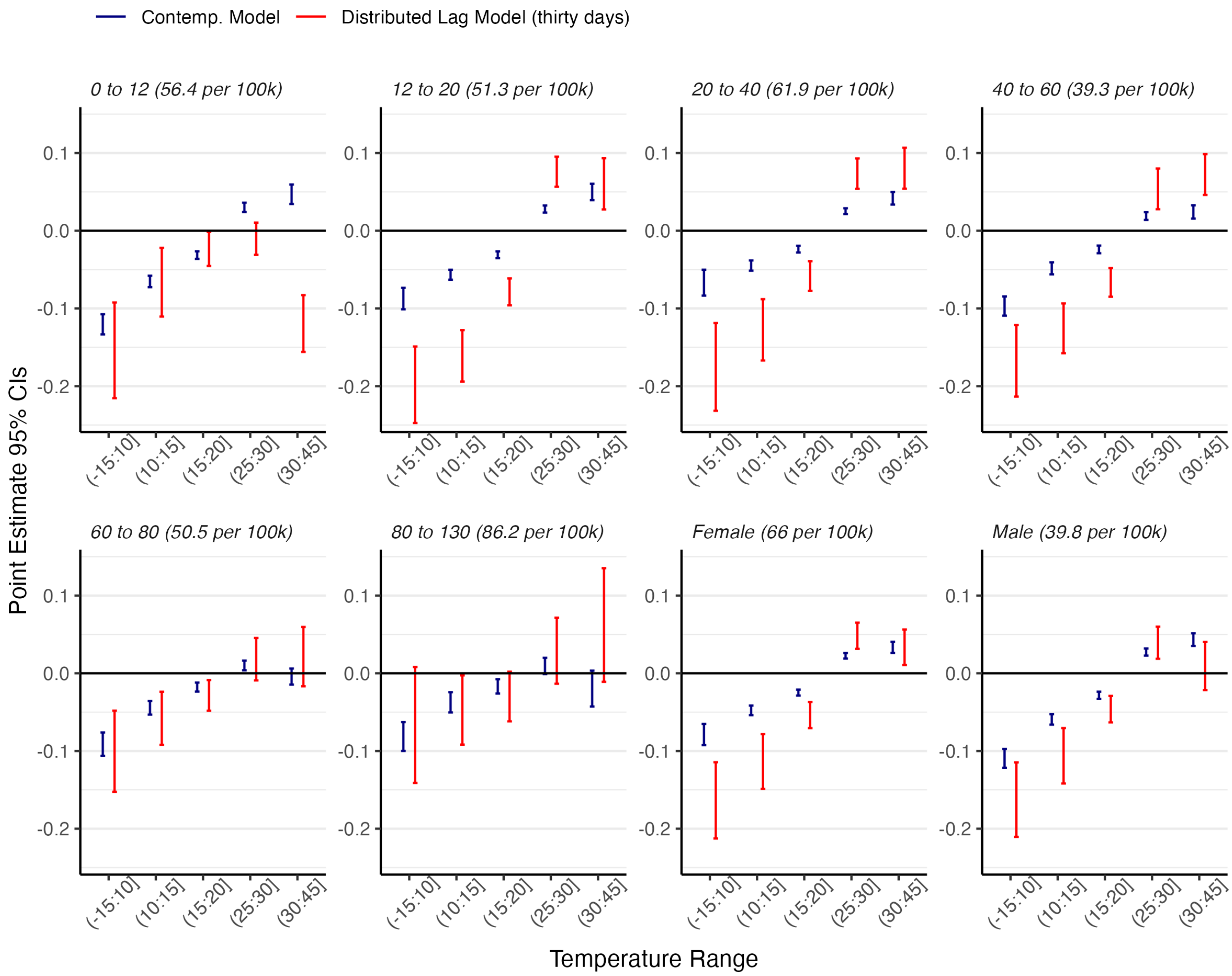
Cumulative effect of heat. The cumulative effects of warm temperatures often differ in magnitude and direction from short-term impacts. For endocrine and metabolic disorders, cumulative admissions increase by 19.9% at hot temperatures (30 °C to 45 °C), nearly doubling the immediate effect. Similar trends occur for genitourinary and skin-musculoskeletal disorders, with cumulative increases of 20.48% and 15.17%, respectively, compared to immediate rises of 4.75% and 1.47%. Some conditions, despite no significant contemporaneous effects, show positive cumulative impacts after 30 days, including Blood/Immune (21%), Eye/Ear (10%), Digestive (4%), and Obstetric (3%). For circulatory diseases, the negative impact intensifies over time, reaching -6.52% in the 30-day cumulative window. Respiratory diseases show a significant cumulative decrease in admissions at hot temperatures (-30.41%), despite an insignificant immediate effect. This large decrease in respiratory disease visits 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%, contrasting with an 8.56% immediate increase. This pattern indicates a slight decline in the initial 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 to 12 years, admissions decrease by 11.33% on days with average temperatures below 10 °C. Similar reductions occur in other age cohorts: admissions decrease by 8.35% for ages 12 to 20, 6.46% for ages 20 to 40, 9.24% for ages 40 to 60, 8.71% for ages 60 to 80, and 7.80% for ages 80 to 130. Gender differences also emerge in response to cold. At very low temperatures, males experience a larger reduction in admissions (10.36%) compared to females (7.58%). Differences in the effects of cold be-

Figure 3: Contemporaneous and cumulative effects by age and gender



Notes: This table presents point estimates and 95% confidence intervals of the effects of daily temperature deviations on the rate of ER admissions across six different age groups and for male and females. 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, while *distributed lag model (thirty days)* represents the linear combination of thirty temperature lags. Standard errors cluster at the municipality level.

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

In contrast to cold temperatures, hot temperatures consistently increase admissions across all age groups, especially among younger populations. For children aged 0 to 12 years, each additional day with average temperatures between 25 and 30 °C raises admissions by 3.06%, while days at or above 30 °C result in a 4.80% increase. Similarly, adolescents aged 12 to 20 years experience increases of 2.83% and 5.11%, respectively. For adults aged 20 to 40 years, admissions rise by 2.55% at warm temperatures and 4.27% 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), males show a 2.77% increase in admissions, rising to 4.43% at hot temperatures ($\geq$ 30 °C), while females exhibit increases of 2.28% and 3.39%, 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 to 12 years, the cumulative decrease in the coldest interval reaches 14.23%, up from an immediate decrease of 11.33%. For adolescents aged 12 to 20 years, the cumulative reduction increases to 18.00%. These amplified effects imply that cold temperatures cause sustained reductions in admissions, primarily due in significant drops in digestive, external causes, infectious-parasitic, and obstetric categories. Regarding gender, both males and females show significant cumulative decreases in admissions at cold temperatures, with reductions of 15.01% and 15.07% in the coldest interval, respectively.

Interestingly, the cumulative effects of hot temperatures differ across age groups. For children aged 0 to 12 years, cumulative admissions decrease by 11.26% on very hot days ($\geq$ 30 °C), despite an initial increase of 4.80%. Similarly, the cumulative effect of days with average temperatures between 25 and 30 °C becomes statistically insignificant after 30 days. This reversal primarily stems from the dynamics of respiratory conditions, which account for about 30% 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 in these groups. For instance, while over 30% of visits for children under 12 are due to respiratory conditions, this figure drops to less than 2% for adolescents aged 12 and 20. Regarding gender, cumulative effects at hot temperatures diverge: males show no significant cumulative impact, while females exhibit a cumulative increase of 3.40%.

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 mechanism, we present illustrative examples based on specific diseases.

Physiological incidence. Physiological incidence highlights the direct effects of extreme temperatures on the human body (Table 4, Panel A). Columns 1-2 show that hot temperatures significantly increase visits for heat-related conditions like heatstroke, consistent with extensive epidemiological literature (Weinberger et al., 2021; Sun et al., 2021; Hess et al., 2014).[8] Recent 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% increase in admissions for false labor following a day above 30 °C, with this effect amplifying to 15% 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 height-

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

ened mortality before hospital admission (Gould et al., 2024). Previous research suggests that heat-induced cardiovascular outcomes arise from thermo-regulatory 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 is likely arises from hot temperatures impairing cognitive function and disrupting sleep, which worsens preexisting 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, like 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, like 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 healthcare-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 severe conditions 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 in admissions for other urinary system diseases (Columns 5-6) relative to Chronic Kidney Disease (CKD, Columns 7-8).[9] This pattern suggests that individuals with non-urgent needs may postpone or avoid ED visits during cold weather, reflecting the discretionary nature of healthcare utilization 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, note that 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 emergency room 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 prior 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.
Panel A: Incidence										
≤10 °C	-0.193***	-0.424***	-0.064**	-0.083	-0.144***	0.257*	-0.228***	-0.393***	-0.020**	0.357***
	(0.029)	(0.089)	(0.028)	(0.099)	(0.030)	(0.147)	(0.033)	(0.096)	(0.009)	(0.052)
10-15 °C	-0.135***	-0.310***	-0.043***	-0.004	-0.089***	-0.041	-0.150***	-0.213***	-0.000	0.308***
	(0.016)	(0.049)	(0.008)	(0.047)	(0.018)	(0.058)	(0.019)	(0.061)	(0.006)	(0.033)
15-20 °C	-0.078***	-0.228***	-0.025***	0.009	-0.048***	0.011	-0.086***	-0.089*	0.001	0.170***
	(0.011)	(0.034)	(0.006)	(0.038)	(0.013)	(0.048)	(0.014)	(0.046)	(0.005)	(0.023)
25-30 °C	0.133***	0.206***	0.027***	0.090***	-0.015	-0.010	0.071***	0.054	-0.011	-0.221***
	(0.013)	(0.039)	(0.006)	(0.028)	(0.019)	(0.051)	(0.015)	(0.054)	(0.006)	(0.027)
>30 °C	0.406***	0.713***	0.050***	0.151***	-0.115***	-0.157	0.146***	0.081	-0.039***	-0.533***
	(0.025)	(0.085)	(0.009)	(0.054)	(0.033)	(0.098)	(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	

	Dengue		Foodborne Intox.		Gastroenteritis		Infect. Pregnancy		Animals and Plants	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
Panel B: Ecosystem dynamics										
≤10 °C	-0.519***	-2.399**	-0.119***	-0.365***	-0.175***	-0.787***	-0.088***	-0.171***	-0.643***	-1.319***
	(0.113)	(0.986)	(0.029)	(0.136)	(0.010)	(0.052)	(0.016)	(0.056)	(0.028)	(0.097)
10-15 °C	-0.257***	-1.495***	-0.055***	-0.131**	-0.103***	-0.439***	-0.051***	-0.132***	-0.338***	-0.847***
	(0.058)	(0.354)	(0.017)	(0.059)	(0.006)	(0.023)	(0.008)	(0.034)	(0.013)	(0.050)
15-20 °C	-0.047**	-0.704***	-0.042***	-0.058	-0.050***	-0.143***	-0.025***	-0.051**	-0.144***	-0.400***
	(0.017)	(0.153)	(0.013)	(0.046)	(0.004)	(0.017)	(0.006)	(0.022)	(0.009)	(0.019)
25-30 °C	0.070***	0.530***	0.043***	0.001	0.056***	0.017	0.031***	0.170***	0.106***	0.358***
	(0.018)	(0.081)	(0.013)	(0.049)	(0.004)	(0.022)	(0.006)	(0.024)	(0.008)	(0.029)
>30 °C	-0.002	-0.476	0.078**	0.034	0.105***	-0.144***	0.036***	0.228***	0.158***	0.327***
	(0.066)	(0.575)	(0.036)	(0.101)	(0.009)	(0.035)	(0.011)	(0.045)	(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	

	Headache		Epilepsy		Other Urinary Inf.		CKD		Alcohol Disorders	
	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.	Cont.	Cumul.
Panel C: Behavioural changes										
≤10 °C	-0.214***	-0.258**	-0.044**	-0.121	-0.108***	-0.407***	0.0159	0.192**	-0.133***	-0.323***
	(0.025)	(0.081)	(0.022)	(0.106)	(0.013)	(0.049)	(0.030)	0.081	(0.025)	(0.095)
10-15 °C	-0.100***	-0.167***	-0.032**	-0.021	-0.059***	-0.311***	-0.007	-0.0150	-0.073***	-0.081
	(0.016)	(0.047)	(0.014)	(0.039)	(0.005)	(0.028)	(0.015)	(0.054)	(0.012)	(0.058)
15-20 °C	-0.042***	-0.050	-0.013	-0.027	-0.028***	-0.146***	-0.0135	0.0001	-0.046***	-0.053
	(0.011)	(0.034)	(0.010)	(0.032)	(0.004)	(0.019)	(0.011)	(0.039)	(0.009)	(0.039)
25-30 °C	0.029**	0.052	0.011	0.052	0.0208***	0.159***	0.0085	-0.088*	0.061***	0.085*
	(0.014)	(0.044)	(0.012)	(0.042)	(0.005)	(0.017)	(0.014)	(0.053)	(0.013)	(0.047)
>30 °C	-0.002	0.183**	0.011	0.026	0.041 ***	0.218***	-0.0010	-0.0002	0.107***	0.043
	(0.032)	(0.079)	(0.024)	(0.079)	(0.010)	(0.030)	(0.027)	(0.10)	(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 ER 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, while *distributed lag model (thirty days)* represents the linear combination of thirty temperature lags. Standard errors cluster at the municipality level. Significance codes: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.1$.

5. Mid-century projections

To estimate the impacts of climate change on ER visits, we utilize 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 temperature ranges across these periods.[10] This method evaluates the impact of temperature changes on health outcomes using age-specific semi-elasticities 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 the 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 includes 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.

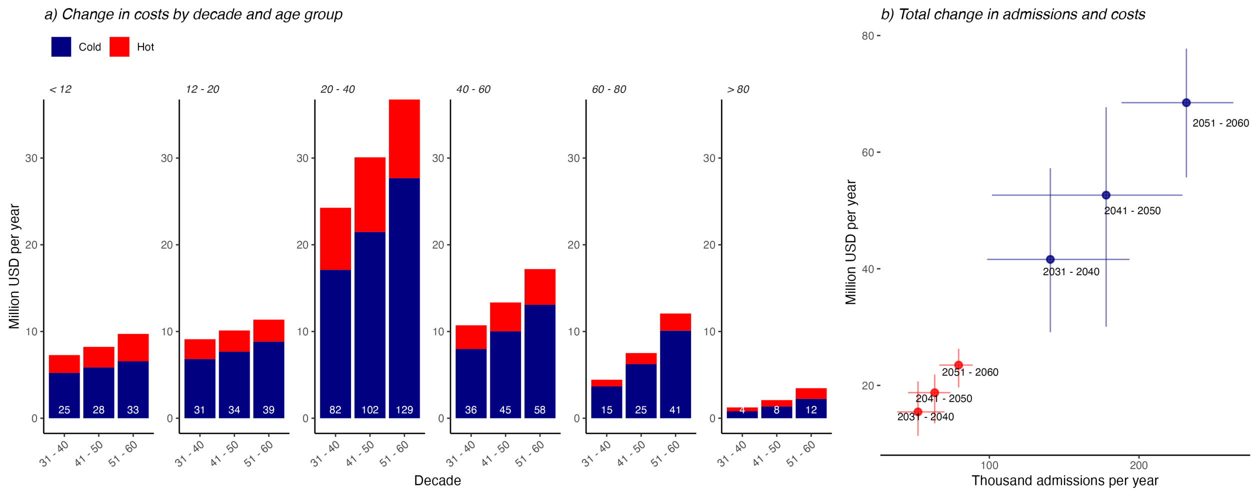
The simulation exercise reveals a clear upward trend in public healthcare expenditures and admissions over the decades. By 2031–2040, annual public healthcare expenditures is projected to reach approximately 57.1 million USD, resulting in an increase of 193,000 admissions. In the following decade, 2041–2050, expenditures will rise significantly to 71.4 million USD annually, driven by an additional 241,000 admissions. By 2051–2060, expenditures are expected to escalate further to 91.9 million USD per year, with an anticipated increase of 311,000 admissions, corresponding to a 0.24% increase in ED admissions.[12]

[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). This 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%-increase in ED admissions in California by mid-century.

Figure 4: Projections of temperature-related ED visits



Notes: The left panel presents the annual change in public ER 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 ER 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 while segments report the minimum and maximum value across GCMs.

Extreme cold and heat significantly increase hospital admissions across all age groups. 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 previous 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 hot-related effects significantly increase admissions. From 2031 to 2040, cold-related admissions dominate. However, hot-related effects become more pronounced in 2041–2060 and 2051–2060. Therefore, healthcare planning must account for both rising temperatures and the reduced number of cold days, as the latter significantly contributes to increase healthcare demands.

6. Conclusion

Our study highlights the importance of examining morbidity outcomes, like 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 previous 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 stronger national representativeness than many past studies. 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 health 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, like 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, while 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, like 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 (over 90%) correlate with negative patient outcomes, including treatment delays, elevated mortality rates (20%–30%), 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, healthcare 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 the overcrowding in emergency departments, one of the primary reasons being 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).

References

Agarwal S., Qin Y., Shi L., Wei G., and Zhu H. (2021) Impact of temperature on morbidity: New evidence from China. *Journal of Environmental Economics and Management*, 109: 102495. 5

Aguilar-Gomez S., Zivin J. S. G., and Neidell M. (2025) Killer Congestion: Temperature, healthcare utilization and patient outcomes.Technical report, National Bureau of Economic Research (forthcoming). 5, 27

Anderson G. B., Dominici F., Wang Y., McCormack M. C., Bell M. L., and Peng R. D. (2013) Heat-related emergency hospitalizations for respiratory diseases in the Medicare population. *American journal of respiratory and critical care medicine*, 187(10): 1098–1103. 21

de Bartolome C. A. and Vosti S. A. (1995) Choosing between public and private healthcare: a case study of malaria treatment in Brazil. *Journal of Health Economics*, 14(2): 191–205. 6

Berchick E. R., Barnett J. C., and Upton R. D. (2019) *Health insurance coverage in the United States, 2018*: US Department of Commerce, US Census Bureau Washington, DC. 34

Carleton T. A. and Hsiang S. M. (2016) Social and economic impacts of climate. *Science*, 353(6304): aad9837. 5

Carlton E. J., Woster A. P., DeWitt P., Goldstein R. S., and Levy K. (2016) A systematic review and meta-analysis of ambient temperature and diarrhoeal diseases. *International journal of epidemiology*, 45(1): 117–130. 21

CDPH (2024) Monthly Update on Number of Dengue Infections in California. 16

Chen J. and Roth J. (2023) Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economics*: qjad054. 10

Cohen F. and Dechezleprêtre A. (2022) Mortality, temperature, and public health provision: evidence from Mexico. *American Economic Journal: Economic Policy*, 14(2): 161–192. 3, 14, 40

Cohen F. and Gonzalez F. (2024) Understanding the Link between Temperature and Crime. *American Economic Journal: Economic Policy*, 16(2): 480–514. 22

Das J. and Do Q.-T. (2023) The prices in the crises: What we are learning from 20 years of health insurance in low-and middle-income countries. *Journal of Economic Perspectives*, 37(2): 123–152. 6

Dasgupta S. (2018) Burden of climate change on malaria mortality. *International journal of hygiene and environmental health*, 221(5): 782–791. 6

Davis L., Gertler P., Jarvis S., and Wolfram C. (2021) Air conditioning and global inequality. *Global Environmental Change*, 69: 102299. 2

Dell A. I., Pawar S., and Savage V. M. (2011) Systematic variation in the temperature dependence of physiological and ecological traits. *Proceedings of the National Academy of Sciences*, 108(26): 10591–10596. 7

Deschênes O. and Greenstone M. (2011) Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4): 152–185. 3

Deschenes O. and Moretti E. (2009) Extreme weather events, mortality, and migration. *The Review of Economics and Statistics*, 91(4): 659–681. 2, 3, 10, 11

Falchetta G., De Cian E., Sue Wing I., and Carr D. (2024) Global projections of heat exposure of older adults. *Nature Communications*, 15(1): 3678. 24

FIMSS F. d. I. M. d. S. S. (2023) Diario Oficial de la Federación (DOF), publicado el 14 de diciembre de 2023. December. 24, 42

Frank E. and Sudarshan A. (2023) The social costs of keystone species collapse: Evidence from the decline of vultures in india. *University of Chicago, Becker Friedman Institute for Economics Working Paper*(2022-165). 6

Gould C. F., Heft-Neal S., Heaney A. K., Bendavid E., Callahan C. W., Kiang M., Zivin J. S. G., and Burke M. (2024) Temperature Extremes Impact Mortality and Morbidity Differently.Technical report, National Bureau of Economic Research. 2, 5, 6, 12, 13, 14, 21, 24

Graff Zivin J. and Neidell M. (2014) Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1): 1–26. 6

Harvell C. D., Mitchell C. E., Ward J. R., Altizer S., Dobson A. P., Ostfeld R. S., and Samuel M. D. (2002) Climate warming and disease risks for terrestrial and marine biota. *Science*, 296(5576): 2158–2162. 7

Hess J. J., Saha S., and Luber G. (2014) Summertime acute heat illness in US emergency departments from 2006 through 2010: analysis of a nationally representative sample. *Environmental health perspectives*, 122(11): 1209–1215. 20

Hoot N. R. and Aronsky D. (2008) Systematic review of emergency department crowding: causes, effects, and solutions. *Annals of emergency medicine*, 52(2): 126–136. 27

Hunter P. J., Awoyemi T., Ayede A. I., Chico R. M., David A. L., Dewey K. G., Duggan C. P., Gravett M., Prendergast A. J., Ramakrishnan U. et al. (2023) Biological and pathological mechanisms leading to the birth of a small vulnerable newborn. *The Lancet*, 401(10389): 1720–1732. 20

Jowett M., Deolalikar A., and Martinsson P. (2004) Health insurance and treatment seeking behaviour: evidence from a low-income country. *Health economics*, 13(9): 845–857. 6

Juan López M., Martínez Valle A., and Aguilera N. (2015) Reforming the Mexican Health System to achieve effective health care coverage. *Health Systems & Reform*, 1(3): 181–188. 7

Karlsson M. and Ziebarth N. R. (2018) Population health effects and health-related costs of extreme temperatures: Comprehensive evidence from Germany. *Journal of Environmental Economics and Management*, 91: 93–117. 5, 6

Matsuki E., Kawamoto S., Morikawa Y., and Yahagi N. (2023) The impact of cold ambient temperature in the pattern of influenza virus infection. in *Open Forum Infectious Diseases*, 10: ofad039, Oxford University Press US. 16

Mordecai E. A., Paaijmans K. P., Johnson L. R., Balzer C., Ben-Horin T., de Moor E., McNally A., Pawar S., Ryan S. J., Smith T. C. et al. (2013) Optimal temperature for malaria transmission is dramatically lower than previously predicted. *Ecology letters*, 16(1): 22–30. 7

Needleman R. K., Neylan I. P., and Erickson T. (2018) Potential environmental and ecological effects of global climate change on venomous terrestrial species in the wilderness. *Wilderness & environmental medicine*, 29(2): 226–238. 21

Nori-Sarma A., Sun S., Sun Y., Spangler K. R., Oblath R., Galea S., Gradus J. L., and Wellenius G. A. (2022) Association between ambient heat and risk of emergency department visits for mental health among US adults, 2010 to 2019. *JAMA psychiatry*, 79(4): 341–349. 21

O'Neill B. C., Tebaldi C., Van Vuuren D. P., Eyring V., Friedlingstein P., Hurtt G., Knutti R., Kriegler E., Lamarque J.-F., Lowe J. et al. (2016) The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, 9(9): 3461–3482. 40

Organization W. H. et al. (2017) Primary health care systems (primasys): case study from Mexico.Technical report, World Health Organization. 7

Park M. Y., Ahn J., Bae S., Chung B. H., Myong J.-P., Lee J., and Kang M.-Y. (2024) Effects of cold and hot temperatures on the renal function of people with chronic disease. *Journal of Occupational Health*, 66(1): uiae037. 22

Patz J. A., Campbell-Lendrum D., Holloway T., and Foley J. A. (2005) Impact of regional climate change on human health. *Nature*, 438(7066): 310–317. 7

Riahi K., Van Vuuren D. P., Kriegler E., Edmonds J., O'neill B. C., Fujimori S., Bauer N., Calvin K., Dellink R., Fricko O. et al. (2017) The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global environmental change*, 42: 153–168. 42

Sahn D. E., Younger S. D., and Genicot G. (2003) The demand for health care services in rural Tanzania. *Oxford Bulletin of Economics and statistics*, 65(2): 241–260. 6

Sun S., Weinberger K. R., Nori-Sarma A., Spangler K. R., Sun Y., Dominici F., and Wellenius G. A. (2021) Ambient heat and risks of emergency department visits among adults in the United States: time stratified case crossover study. *Bmj*, 375. 20, 21

Trzeciak S. and Rivers E. P. (2003) Emergency department overcrowding in the United States: an emerging threat to patient safety and public health. *Emergency medicine journal*, 20(5): 402–405. 27

Viana D. V. and Ignotti E. (2013) The ocurrence of dengue and weather changes in Brazil: a systematic review. *Revista brasileira de epidemiologia*, 16: 240–256. 21

Weinberger K. R., Wu X., Sun S., Spangler K. R., Nori-Sarma A., Schwartz J., Requia W., Sabath B. M., Braun D., Zanobetti A. et al. (2021) Heat warnings, mortality, and hospital admissions among older adults in the United States. *Environment international*, 157: 106834. 20

White C. (2017) The dynamic relationship between temperature and morbidity. *Journal of the Association of Environmental and Resource Economists*, 4(4): 1155–1198. 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 16, 22

Wilson A. J., Bressler R. D., Ivanovich C., Tuholske C., Raymond C., Horton R. M., Sobel A., Kinney P., Cavazos T., and Shrader J. G. (2024) Heat disproportionately kills young people: Evidence from wet-bulb temperature in Mexico. *Science Advances*, 10(49): eadq3367. 25

Wooldridge J. M. (1999) *Quasi-Likelihood Methods for Count Data*: 321–368: John Wiley & Sons, Ltd. 10

Appendix A

A.1 The Mexican health care system

Mexico's healthcare 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 healthcare mainly operates through the Mexican Social Security Institute (IMSS) and the 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, 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 any of the insurance options 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 healthcare sector enrollment and use

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

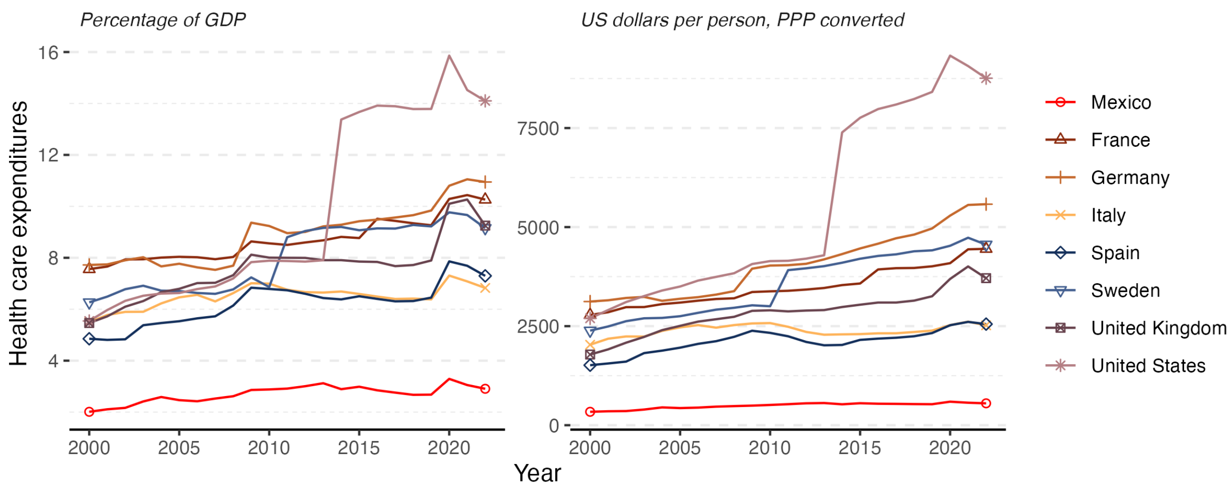
Notes: Data are obtained from the Mexican National Census 2020.

In 2020, about 20% of the Mexican population reported lacking access to healthcare, despite the government theoretical guarantee of universal coverage. These figures contrast with the U.S. healthcare system, where private health insurance covered 66% of people in 2019, public insurance programs like Medicare or Medicaid covered about 25%, and nearly 30 million people, or 9%, lacked health 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, while expensive, remains significantly more affordable than in other North American countries. Importantly, our data set only includes public hospitals, thus excluding emergency department visits in private institutions.

In addition to differences in the share of insured persons between public and private systems, Mexico's healthcare structure has notable distinctions 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, Mexican healthcare faces challenges related to funding and equitable access. In contrast, European healthcare 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 healthcare spending as a percentage of GDP, Mexico's healthcare infrastructure and funding levels are significantly lower, presenting ongoing challenges for the comprehensive and equitable care observed in numerous European nations.

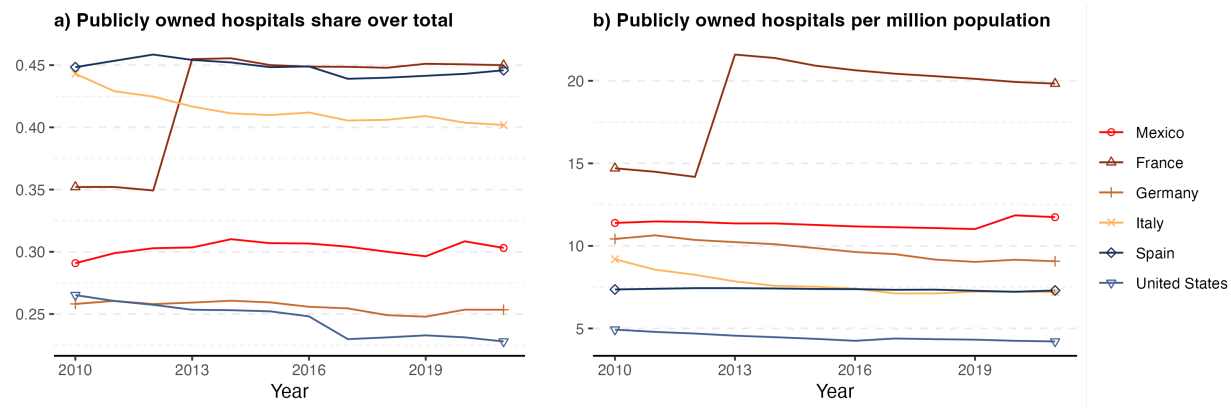
Figure A.1: Health expenditure in government and compulsory schemes



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 owned 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)	12676.21	15.52%	15.52%	10.12%
	Infectious gastroenteritis and colitis, unspecified (A09)	2909.33	3.56%	19.09%	2.32%
	Acute pharyngitis (J02)	2673.40	3.27%	22.36%	2.13%
	False labor (O47)	2556.31	3.13%	25.49%	2.04%
	Other disorders of urinary system (N39)	2324.45	2.85%	28.34%	1.86%
Male (34.81%)	Acute pharyngitis (J02)	2447.24	5.61%	5.61%	1.95%
	Infectious gastroenteritis and colitis, unspecified (A09)	2294.56	5.26%	10.88%	1.83%
	Acute nasopharyngitis [common cold] (J00)	1521.57	3.49%	14.37%	1.21%
	AURI of multiple and unspecified sites (J06)	1519.94	3.49%	17.85%	1.21%
	Abdominal and pelvic pain (R10)	1106.31	2.54%	20.39%	0.88%

Notes: This table classifies ED 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), the share of visits within the category (female and male), the cumulative share of visits in the category, and the 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	12677.35	41.11%	41.11%	10.12%
	Abdominal and pelvic pain	R10	2971.17	9.64%	50.75%	2.37%
	Other	Z35	1479.88	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	1652.99	8.65%	8.65%	1.32%
	Injury of unspecified body region	T14	1324.79	6.93%	15.59%	1.06%
	Open wound of head	S01	1144.59	5.99%	21.58%	0.91%
Respiratory (14.54%)	Acute pharyngitis	J02	5122.56	28.11%	28.11%	4.09%
	Acute nasopharyngitis [common cold]	J00	3170.28	17.40%	45.50%	2.53%
	AURI of multiple and unspecified sites	J06	3139.57	17.23%	62.73%	2.51%
Obstetric (11.24%)	False labor	O47	2556.92	18.15%	18.15%	2.04%
	Infections of genitourinary tract in pregnancy	O23	1619.75	11.50%	29.64%	1.29%
	Encounter for full-term uncomplicated delivery	O80	1353.37	9.61%	39.25%	1.08%
Digestive (7.48%)	Gastritis and duodenitis	K29	1594.70	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	5206.90	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	3162.51	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	1129.44	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	2134.23	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	1419.05	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
	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%)	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 ED visits by ICD-10 chapter and disease, presenting values for the three most common diagnoses per chapter. The columns show the number of visits between 2008 and 2022 (in thousands), the share of visits within the chapter, the cumulative share of visits in the chapter, and the 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.

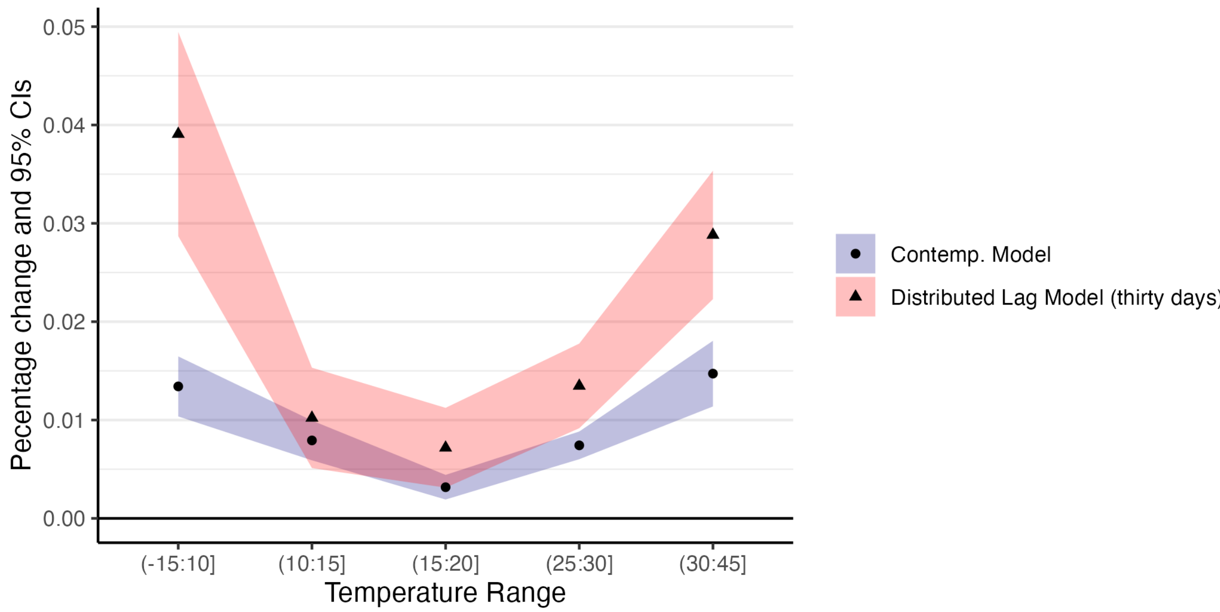
Table A.3: Main diseases by age group

Age group	ICD-10 Name	# Visits (Thousands)	Share of Category	Cumulative Share	Share of Total
20 to 39 (36.89%)	Encounter for supervision of normal pregnancy (Z34)	8997.20	19.46%	19.46%	7.18%
	False labor (O47)	1763.34	3.81%	23.28%	1.41%
	Other disorders of urinary system (N39)	1159.81	2.51%	25.79%	0.93%
	Infections of genitourinary tract in pregnancy (O23)	1071.53	2.32%	28.11%	0.86%
	Infectious gastroenteritis and colitis, unspecified (A09)	1065.61	2.31%	30.41%	0.85%
< 12 (22.79%)	Acute pharyngitis (J02)	3455.47	12.10%	12.10%	2.76%
	Infectious gastroenteritis and colitis, unspecified (A09)	2508.56	8.79%	20.89%	2.00%
	Acute nasopharyngitis [common cold] (J00)	2328.77	8.16%	29.04%	1.86%
	AURI of multiple and unspecified sites (J06)	2044.30	7.16%	36.20%	1.63%
	Acute tonsillitis (J03)	647.17	2.27%	38.47%	0.52%
12 to 19 (15.59%)	Encounter for supervision of normal pregnancy (Z34)	3518.03	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 to 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 to 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 ED visits by age group and disease by presenting values for the five most common diagnoses per category. The columns show the number of visits between 2008 and 2022 (in thousands), the share of visits within the category (15 to 39, less than 12, 40 to 70, and more than 79), the cumulative share of visits in the category, and the 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 (thirty days)* refers to the linear combination of thirty 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 mid-century temperature increases on emergency room (ER) 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 ($\mathcal{T}^{Fut}$):

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

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

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.

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

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

Where

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

In a second step, we combine the estimated age group-specific (z) semi-elasticity (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 $\mathcal{D}^{Fut}$.

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

We calculate the absolute change in admissions $\widetilde{\Gamma}$ by assuming that the average age-specific admission rate ($\overline{y}_{z}$) remains constant from the historical period to future decades. At the same time, 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)):

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

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 from medical care unit costs in Mexico for the year 2024 by the FIMSS (2023). This 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:

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