Killer Congestion: Temperature, healthcare utilization and patient outcomes

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Abstract

This study explores how temperature-induced hospital crowding influences care transitions and patient outcomes. Utilizing comprehensive data from Mexico's largest healthcare system, we explore the impact of daily temperature shocks on healthcare service dynamics. Our findings confirm a linear increase in healthcare demand as temperature rises, measured as ED visits and hospitalizations. While more patients are admitted from EDs into hospitals, the likelihood of an individual patient's admission decreases as temperatures climb, suggesting a capacity constraint in healthcare facilities. This trend leads to more severe patients being sent home on hotter days. Furthermore, we find heightened excess mortality rates inside hospitals, suggesting capacity constraints lead to deterioration in care quality. Data from death certificates confirm an overall increase in mortality on extreme heat days, particularly for deaths outside hospitals. Our results shed light on the potential spillover effects of hospital crowding and their potential contribution to health impacts from climate change.

JEL-codes: I15, I18, Q54
Keywords: temperature, healthcare utilization, overcrowding, Mexico

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1. Introduction

Extreme heat imperils health, increasing both morbidity and mortality (Deschenes, 2014; Basu, 2009), and results in more emergency room visits and hospitalizations (e.g. Gould et al., 2024; White, 2017). Since temperature simultaneously impacts many individuals within a region, these health impacts could lead to surges in healthcare demand that generate hospital congestion. Hospital capacity constraints may lead some patients that require care to be turned away from the hospital and may also generate spillover effects to other patients within the healthcare system given the need to spread scarce resources across a larger number of patients. In this paper, we provide the first exploration of the health impacts from extreme heat that unpacks the direct effects from the indirect ones that arise due to hospital congestion.

Understanding these impacts is important because, unlike idiosyncratic shocks to healthcare demand, we know that climate change will make those associated with extreme heat far more common. Indeed, health-related costs are already estimated to be the largest component of the economic consequences of climate change (Carleton and Greenstone, 2022) and spillover effects will only make those numbers larger. Moreover, the existence of spillover effects is likely to alter our understanding of the distributional impacts of extreme heat and climate change. Those groups directly susceptible to the harms of extreme heat may look very different than the groups harmed by diminished care in other parts of the healthcare system.

This also highlights a potentially important new avenue of adaptation to climate change. If hospital congestion contributes to the excess health damages from a changing climate, then expanding labor and capital investments as well as better surge management tools can help reduce those damages. The benefits and costs of these investments relative to the protective effect of residential air conditioning (Barreca et al., 2016) will clearly depend on the context. In developing countries where residential air conditioning prevalence is very low and electricity reliability is a concern, expanding healthcare infrastructure may be a particularly promising climate adaptation strategy. Furthermore, health system expansions may offer considerable co-benefits in settings where healthcare demand far outstrips supply.

The focus of our empirical work is Mexico, and in particular those with public insurance (Seguro Popular). Studying this setting is especially important since evidence on the relationship between extreme heat and health in developing countries is much more limited (Sapari et al., 2024). Moreover, like many other developing countries, health staffing and infrastructure in Mexico is quite constrained, particularly in the facilities where patients with Seguro Popular seek care.[1] Furthermore, the incidence of extreme heat

[1] Mexico has a multi-tiered healthcare system where people seek care in different facilities based on their insurance coverage. Seguro Popular, currently under restructuring, was the largest provider of healthcare in the country.

days under climate change in Mexico is likely to be disproportionately high relative to those in higher latitudes (Bednar-Friedl, 2022; Murray-Toratolo, 2021), underscoring the potential welfare and policy implications of our findings.

Our primary analysis covers nearly 57 percent of the Mexican population over an 8-year period. In particular, we employ data on the universe of 2012-2019 emergency department and hospital visits to Mexico's Ministry of Health (MoH) hospitals, that serve patients with public insurance under Seguro Popular, and uninsured patients. We use these data to examine the impact of temperature on hospital crowding, patient transitions within the healthcare system, and patient outcomes. Vital statistics data for the entire population supplement our core analyses to allow us to examine mortality outside of the hospital. Using the exact date and municipality of each facility, we link reanalysis weather data to estimate distributed lag models. Our core econometric analysis relies on a nonparametric binned model specification for temperature that includes facility fixed effects as well as fixed effects to capture intraweek patterns in admissions, seasonality, and municipality specific trends.

Our analyses reveal a series of changes in healthcare demand and supply in response to temperature. To begin, we find that higher temperatures increase emergency department (ED) and hospital admissions. When the daily maximum temperature reaches the highest bin of >34C, we estimate an additional 3 ED visits compared to 22-24C. From a mean of approximately 40 daily visits, this translates to a 7.5 percent increase. The corresponding figure for hospitalizations is 0.5 additional admissions, a roughly 4 percent increase. These results are consistent with prior literature in different contexts (e.g. White, 2017).

The gap between ED and hospital admissions motivates a deeper investigation of transitions within the healthcare system. Our examination of ED discharges is illuminating in this regard. While the absolute number of patients admitted to the hospital from the ED increases, that increase is small, such that the probability that any given patient in the ED is admitted to the hospital decreases. It appears that direct hospital admissions due to extreme heat create congestion within the hospital that limits its ability to admit ED transfers. This congestion, in turn, appears to push the ED toward its capacity constraints, leading to more patients being sent home on extreme heat days.

The astute reader will note that our choice of the word 'seems' when offering congestion and capacity constraints as the mechanism driving our findings. While our findings thus far are consistent with congestion, this pattern of results could also arise due to changes in the composition of patients on extreme heat days. If, for example, less sick patients show up to the ED on hot days, it is perfectly reasonable for EDs to send fewer patients to the hospital and to send more home. Fortunately, we can examine this directly based on measures of severity of illness (Hoe, 2022). In fact, we find that severity of illness in the

ED increases with temperature. Furthermore, those sent home on extreme heat days are significantly less healthy than those being discharged on cooler days. On the other hand, while those sent to the hospital from the ED are amongst the sickest patients in that department, those transferred to the hospital are no more infirmed than those already admitted there. Congestion is the most plausible explanation for these results.

The final piece of the puzzle is estimating the repercussions of this congestion. Inside the hospital, this is relatively straightforward. Since the composition of illness severity is not changing, we can simply look at excess mortality for hospitalized patients. We find that one day where maximum temperature exceeds 34C leads to a five percent increase in excess deaths. When we limit our attention to traumatic injuries, which should not be impacted by temperature conditional on hospital admission, we find a similar increase, underscoring the spillover effects generated by heat-driven overcrowding in the hospital. Assessing the health consequences for those sent home from the ED is more challenging as we cannot follow patients once they leave the healthcare system. We can, however, use vital statistics data to measure the number of deaths that occur on hot days in specific settings. Although we find that deaths increase both inside and outside of hospitals, we see a larger relative increase in deaths outside the hospital. While we cannot know whether these deaths occur amongst patients sent home from the ED, this result is consistent with crowding impacts: more severe patients are sent home from the ED, and deaths disproportionately increase outside the ED. Taken together, these results suggest that the additional crowding caused by higher temperatures leads to increased mortality.

Our paper builds upon the extensive literature focused on the health impacts of climate change (see reviews by Basu, 2009; Ye et al., 2012; and Bunker et al., 2016) to reveal a new channel through which those impacts may arise. In so doing, it also illuminates a new approach to add to the climate adaptation armamentarium (see reviews by Kahn, 2016; Fankhauser, 2017; and Owen, 2020 and canonical papers focused on air conditioning by Deschenes and Greenstone, 2011; and Barreca et al., 2016). Our paper is also closely related to three papers that examine the impact of non-heat-related surges in hospital demand on healthcare quality. Hoe (2022) is focused on external injuries and finds that shocks to the trauma and orthopedic departments of UK hospitals leads to reduced quality of care within those departments as measured by readmission rates. Gutierrez and Rubli (2021) utilize data similar to ours from Mexico and show that surges in hospital demand due to an outbreak in H1N1 influenza led to more in-hospital deaths with other conditions. Lastly, a recent working paper examines the impacts of spikes in pollution on pediatric hospital demand in Sao Paolo, Brazil (Guidetti et al., 2024). They find evidence consistent with congestion effects for hospitals with limited bed capacity. We extend this work by broadening our purview

to spillovers between emergency departments and the entire hospital system as well as to the health impacts for those outside of the hospital system.

3. Background and data

3.1. *The Mexican Healthcare System*

The Mexican healthcare system is fragmented and multi-tiered.[2] People obtain insurance through the private sector (~2-3% of the population), social insurance through the Mexican Social Security Institute (IMSS) and the Institute for Social Security and Services for State Employees (ISSSTE) (~40-45%), and the safety net Seguro Popular (SP) program (~40-45%). Roughly 14% of the population are uninsured. [3] IMSS and ISSSTE are for formally employed individuals in the private and public sectors, respectively, with funding provided by contributions from employees and employers and government subsidies. SP is safety net insurance for those who are informally employed or unemployed, with funding provided entirely by the government.

In line with the different tiers of insurance, health care services are highly fragmented. Privately insured individuals seek care in a private and largely unregulated market. IMSS and ISSSTE "organize, provide and regulate most of their own health services through vertically integrated, national organizations" (Block et al., 2020). Those with SP obtain care from facilities managed directly by the Ministry of Health (MoH). Those without insurance can also obtain care from MoH facilities.

Resources at public health care facilities are highly constrained, especially in more rural areas. Mexico spends 5.5% of its GDP on healthcare, compared to an OECD average of 9.2%. Mexico also faces a notable deficit in its medical workforce, with a ratio of 2.5 physicians per 1,000 inhabitants, considerably lower than the OECD's recommended threshold of 3.2. This shortfall extends to nursing personnel, where shortages are even more significant, with only 2.9 nurses per 1,000 people, significantly below the OECD's recommendation of 8.8 (OECD, 2023). Access to medical technology is also limited. For example, magnetic resonance imaging (MRI) machines per

[2] For more details, see Block et al. (2020).

[3] Uninsured people are eligible for SP but have not enrolled. SP was superseded by the Institute of Health for Welfare (INSABI) in 2020. Our analysis, however, ends in 2019 to avoid confounding due to COVID-19, so we refer to SP throughout.

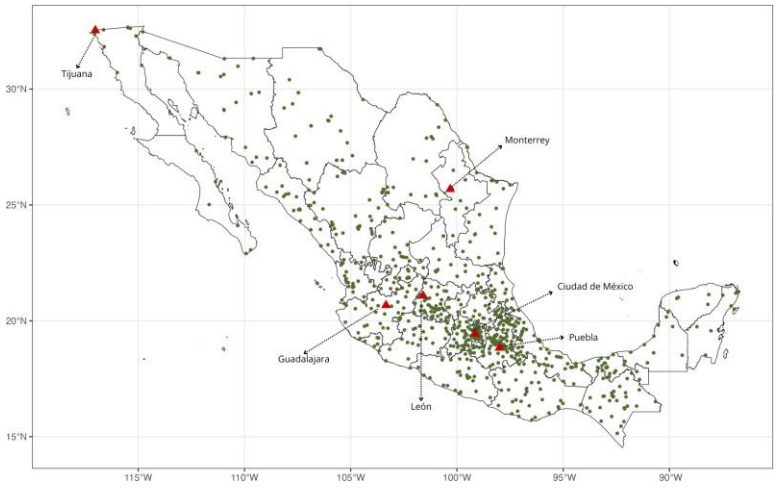
million inhabitants is 2.6 compared as compared to an OECD average of 15.6 (Block et al., 2020). As a result, long wait times and lack of medical supplies is a common concern, and any surge in patients is likely to further stress an already constrained health care system. It is worth noting that despite its failure to meet OECD guidelines, Mexico is quite representative of the type of healthcare access constraints that inhabitants of most countries face. Mexico's density of doctors per capita ranks 47 out of 96 countries with available data (Our World in Data, 2024).

3.2. Data

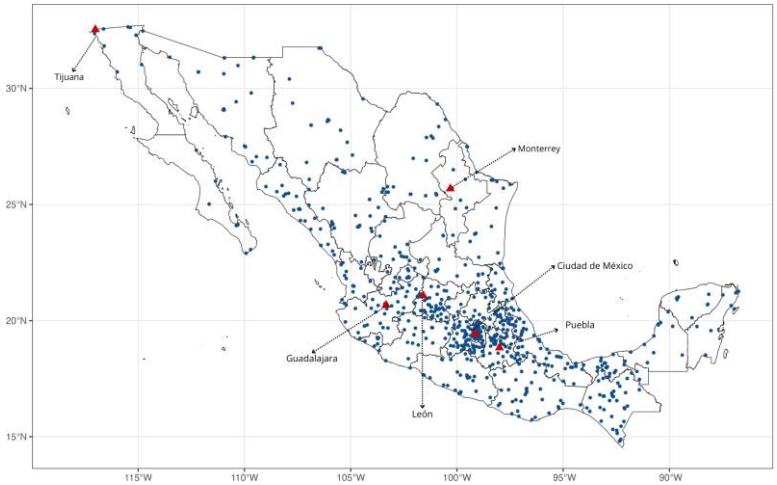
To evaluate the relationship between temperature, healthcare usage, and health outcomes, we combine public hospital administrative records from the Ministry of Health (MoH) and mortality records for the entire population with weather data for the years 2012-2019. Our use of MoH-managed hospitals, who provide healthcare to the uninsured and those enrolled in Seguro Popular (SP), concentrates our focus on health care usage to the lower and middle part of the income distribution. The mortality records come from a census and thus reflect the entire population.

Healthcare utilization and mortality data

Our study draws on patient-level records from the complete network of hospitals in Mexico's non-contributory public healthcare system, overseen by the Ministry of Health (MoH), for the years 2012-2019. Although many hospitals in our sample operate an Emergency Department (ED) that subsequently admits patients for inpatient care, data for these two care phases are recorded separately by distinct information subsystems: the Emergency Department Subsystem and the Hospital Discharge Subsystem. The data come from 828 emergency departments and 772 hospitals, plotted in Figure 1, which account for healthcare of 57% of the national population.



(a) Emergency departments



(b) Hospitals with inpatient services

Figure 1: Distribution of hospitals

Notes: Figure illustrates the distribution of hospitals in our sample. Top: Data from 828 emergency departments in Mexico for 2019. Bottom: Data from 772 hospitals with inpatient services in Mexico for 2019

In both subsystems, detailed diagnostic information is recorded for each patient, including a primary diagnosis and up to six secondary diagnoses. Specialized coders are tasked with converting handwritten diagnostic notes into standardized 4-digit codes based on the International Classification of Diseases, Tenth Revision (ICD-10). Although ICD-10 comprises over 70,000

possible diagnosis codes, the Mexican health system utilizes only the first four digits, which delineate 9,795 distinct categories.

Although we have detailed information on the diagnosis of the patient, we primarily focus our analysis on all ED and hospital visits regardless of cause (we rely on diagnosis to define illness severity as described below). The reason for this is twofold. First, it is difficult to identify specific illnesses related to heat. Very few patients are coded as having a heat-related illness, such as heat stroke or exhaustion.[4] Instead, heat often exacerbates conditions without a heat-related code. For example, heat stresses the cardiovascular system by making the heart work harder, which increases the risk of a heart attack. Epidemiological studies have shown that heat increases ED or hospital visits for conditions related to the heart (Ebi et al, 2004), kidney (cite), lungs (cite), mental health (cite) and so on. Furthermore, as we show in Appendix Figure A.1, excluding patients with explicitly heat-related codes results in nearly identical results.

Two, as discussed earlier, our goal is to estimate not only those directly impacted by heat but also the spillover effects that arise through resource constraints. This spillover effects suggest heat could impact any condition sensitive to these resource constraints. By considering all admissions regardless of diagnosis, we capture both the direct and indirect spillover effects.

Both datasets record the discharge status of each patient, which we use to explore how patients flow through the healthcare system. For the ED, the following five options exists: 1) sent home; 2) hospitalized; 3) referred to another hospital; 4) exit without discharge; and 5) death.[5] For the hospital, the following three options exists: 1) sent home; 2) transferred to another facility; and 3) deceased. The data, however, are not linked, such that we are unable to analyze the mortality outcomes from ED admissions.

The municipality of each facility and the date of admission are reported in both data, which enables us to merge the weather data. We aggregate individual visits, which consists of roughly 70 million ED and 22 million hospital visits during our study period[6], to the daily-facility level. This results in 1,577,423 ED-days and 1,828,566 hospital-days.

[4] Monitoring of heat-related illness highlighted through specific diagnosis codes has been highlightedas a problem around the world (Morano and Warkins, 2017; Fox et al, 2019).

[5] For administrative reasons, very few patients die in the ED. They are transferred to the hospital before being pronounced dead.

[6] The ED visits are split evenly between SP and uninsured patients, while roughly 75% of the hospital visits are patients with SP.

Severity of illness. We use the hospital data to calculate a measure of illness severity in order to understand the composition of patients admitted to the ED and hospital on any given date. Following Hoe (2022), we define severity as the estimated mortality rate within the hospital for each diagnosis code, conditional on age and sex.[7] Since there are nearly 10,000 four-digit ICD-10 codes, we calculate this rate based on groupings of the first three digits of the ICD-10 codes, following the disease categories listed in the ICD-10 manual. For example, codes A00-A09 indicate "intestinal infectious disease," A15-A19 indicate "tuberculosis," and A20-A28 indicate "certain zoonotic bacterial diseases." This results in a total of 290 disease categories for which we calculate mean mortality rates. We assign this severity measure to each patient based on their age, sex and diagnosis code determined at admission. We aggregate this to the hospital-date level by taking an average of patients admitted for each date in our data frame.

Excess deaths. To investigate the role of heat in contributing to additional deaths in the hospital, we define excess deaths, according to the risk-adjusted mortality procedure described by NHS (2022). We define excess mortality as $min\{0, 1(m) - s\}$, where $1(m) = 1$ if the patient died and 0 otherwise and s is severity assigned to each patient as defined above. In this definition, excess mortality equals zero for patients who do not die in the hospital, and $1 - s$ for patients who do. As with the ED and hospital data, we aggregate excess deaths to the hospital-date level.

Mortality data

We utilize a comprehensive dataset comprising all death certificates in the country from 2012 to 2019, regardless of insurance status. We continue to use all deaths regardless of cause in order to capture the direct and indirect effects of heat. These records provide the date and location of each death, enabling us to merge these observations to the relevant weather data. Furthermore, they provide the setting of each death, such as a private hospital, a public hospital, a public space, or a residence, which we will use to analyze events that happen outside of the healthcare system. This enables us to explore the impacts of heat on mortality outcomes regardless of the setting,

[7] More formally, we perform a Poisson regression of the mortality rate on the diagnosis category, age and sex fixed effects. The Poisson regression ensures no predictions fall below zero. (Although predictions can exceed one in theory, this does not occur in practice.)

capturing patients who may be sent home from the ED or hospital but still succumb to their illness.

Weather Data

For the weather data, we use the Daymet reanalysis data product from NASA's Oak Ridge National Laboratory (ORNL) (Thornton et al., 2021). These data are based on statistical models that interpolate and extrapolate from weather stations, thus enabling weather calculations in areas where stations do not exist. Daymet data includes daily measures of minimum and maximum temperature on a 1km x 1km gridded surface. We average all grids within a municipality on a daily basis to obtain the average daily maximum temperature and assign this to each ED and hospital at the daily-municipality level.

3.3. *Descriptive statistics*

Summary statistics for ED visits are shown in the first panel of Table 1. The average number of ED visits was 40.46 daily, but considerable variability exists, with a standard deviation (SD) of 40.14. This variability is partly due to changes in visits over time within an ED, as reflected by the standard deviation within EDs of 16.42, but largely due to the sample consisting of EDs of different sizes. This reflects the diverse contexts in which the Mexican healthcare system operates and the different capacities of these facilities. The nature of this variation is highlighted in Figure 2, which shows the distribution of daily ED visits separately for EDs at the 25th, 50th and 75th percentile of the mean daily admissions.

The average length of stay in the ED was 0.80 hours (SD = 1.34). In terms of discharge status, the majority of patients (73.44%) are sent home, followed by being hospitalization (12.58%) and being referred to another hospital (10.55%). Very few patients exit without an official discharge (3.08%) or die (0.23%). The mean severity of ED patients is 0.02, indicating the overall mean mortality rate for patients navigating the system their diagnosis code.

	Mean	**SD**	**Min**	**Max**	**Within SE**
Panel A: Emergency Department					
ED visits per day	40.46	40.14	0	5889	16.42

Length of stay (hours)	0.81	1.39	0	24	0.69
Patients sent home	29.74	32.04	0	5784	14.07
Patients hospitalized	5.47	10.45	0	3779	4.05
Patients referred to another hospital	3.89	9.59	0	659	4.15
Exit without discharge	0.20	1.21	0	99	0.48
Daily deaths in the ED	0.06	0.32	0	50	0.18
Patients sent home (%)	73.42	27.75	0	100	17.12
Patients hospitalized (%)	12.51	16.88	0	100	10.07
Patients referred to another hospital (%)	10.76	19.88	0	100	11.71
Exits without discharge (%)	0.47	3.04	0	100	1.61
Deaths in the ED (%)	0.23	3.19	0	100	1.13
Panel B: Inpatient					
Hospital admissions per day	12.37	22.18	1	286	4.84
Hospital admissions (Outpatient)	1.04	5.31	0	271	1.12
Hospital admissions (Inpatient)	11.32	13.44	0	261	4.29
Length of stay (days)	3.59	6.60	0	365	3.34
Patients transferred out	0.14	0.52	0	37	0.34
Reason for leaving: voluntary	0.02	0.12	0	1	0.10
Reason for leaving: improvement	11.58	14.30	0	284	4.68
Daily deaths - inpatient and outpatient	0.26	0.72	0	19	0.40
Patients transferred out (%)	2.44	10.33	0	100	7.05
Reason for leaving: voluntary (%)	0.55	6.08	0	100	3.81
Reason for leaving: improvement (%)	92.77	16.54	0	100	12.13
Deaths - inpatient and outpatient (%)	1.64	5.66	0	100	4.73
Panel C: Deaths					
Daily deaths	3.02	5.06	1	96	
Deaths in private hospitals (%)	23.17	35.17	0	1	
Deaths in public hospitals (%)	2.83	12.71	0	1	
Deaths outside of hospitals (%)	73.99	37.05	0	1	

Table 1: Hospital demand and average patient outcomes (daily) 2012-2019

Data from 828 emergency departments (A), 772 hospitals with inpatient services (B) and municipality-level mortality data. in Mexico between 2012 and 2019. Unit of observation: hospital-day, with cohorts based on the date of admission of the patient. Shares might not sum to 100 because patients who fled the hospital or whose outcome is otherwise unknown are excluded from the analysis.

Shown in the second panel of Table 1 are descriptive statistics on hospital admissions. Admissions average 12.37 per day, again with considerable variability driven by daily factors as well as hospital features, with the second panel of Figure 2 reflecting the latter. Patients stay, on average, 3.6 days in the hospital. When they leave, most patients were deemed healthy enough to

be sent home (92.8%), followed by transferring to another facility (2.4%) and death (1.6%).[8] The severity score for the inpatient services was also low, averaging 0.02 (SD = 0.02), with an excess mortality rate of 0.25 (SD = 0.70).

The mortality data in the last panel indicates a mean of 3.02 deaths per day (SD = 5.06). These deaths are distributed across various settings, with 23.17% occurring in public hospitals, 2.83% in private hospitals, and 73% occurring outside of hospitals.

4. Empirical methodology

The initial focus of our empirical strategy is to estimate the causal effect of a temperature realization on a given day on ED or hospital visits in the same location. Given that daily ED and hospital visits are count data, we estimate a Poisson Pseudo-Maximum likelihood model (PPML). The PPML point estimates are consistent as long as the conditional mean is correctly specified, irrespective of the distribution of the outcome or errors (Gourieroux et al., 1984). PPML models also readily accommodate fixed effects without an incidental parameters problem (Correia et al., 2019). Furthermore, the PPML estimator performs well with a large number of zeros and over- or under-dispersion in the data (Silva and Tenreyro, 2011).[9]

Our baseline model for ED and hospital visits is specified according to the conditional exponential mean function in equation (1), where h is the number of ED or hospital visits on date t in hospital h in municipality m:

$$E\left[Y_{h\mathrm{mt}} \mid \sum_{l=0}^{7} f\left(t_{\max_{h\mathrm{mt}l}}\right),\ \rho_h,\ \Omega_{\mathrm{t}} \right] = \exp\left(\sum_{l=0}^{7} \sum_{b=1}^{9} \beta_b 1\left(t_{\max_{h\mathrm{mt}l}} \in (t_b, \bar{t_b}) \right) + \rho_h + \Omega_d + \epsilon_{h\mathrm{m}d} \right)$$

We model patient outcomes and composition, denoted as $\mathrm{Y_{hmt}}$, and a semi-parametric function of lags l ∈ [0, 7] of temperature. The key variable of interest is $Tmax$, which measures the average daily maximum temperature in a municipality.[10] In line with previous work, we allow

[8] The remaining patients leave without a formal discharge.

[9] Our results are robust to using a linear fixed effects regression model.

[10] In Section A.2, we show that our results are robust to using wet-bulb temperature, a measure that attempts to account more fully for heat stress. The calculations of wet bulb temperature were made from the variables of temperature (degrees C) and Water vapor pressure (Pa), using PsychroLib library in Python. This library contains

for a nonlinear effect of temperature by using a series of indicator variables for each 2C, with 22-24C serving as the reference. Thus, we interpret the coefficient β in bin *b* as the impact of maximum temperature in that bin relative to 22-24C. This allows each 2C bin to have an independent impact on outcomes. Based on the distribution of temperature, we specify <18C as the lowest bin and >34C as the highest. Since temperatures in Mexico are, on average, higher than in the US, we do not necessarily expect a full "U-shaped" relationship between temperature and the health outcomes typically found in the US. Recent studies, however, have indicated that ED visits have different responses at lower temperatures than hospital visits (Gould et al., 2024), with temperature displaying a monotonically increasing impact, perhaps due to behavioral responses (White 2017).

Since temperature impacts may arrive with delay, we also include 7-day lags of these temperature bins.[11] As we demonstrate below, the contemporaneous effects are considerably stronger than any lag, so we only show the full set of temperature bin coefficients for same day temperature.

Our model includes several fixed effects (FEs) to improve identification of the temperature impacts. Consistent with the standard approach in the climate economics literature (Dell et al., 2014; Deschenes and Moretti, 2009; Barreca et al., 2016; Mullins and White, 2020), we include hospital-specific fixed effects (ϱ_h) to compare changes in temperature within an area with changes in ED or hospital visits. We include several additional FEs, denoted by Ω_t, to control for other important factors affecting ED and hospital visits. This includes day-of-the year (doy) FEs to adjust for seasonality, municipality-by-year FEs to control for annual trends specific to each municipality, and day-of-the-week (dow) by year FEs to capture evolving intra-week patterns. The identification assumption is that, after accounting for baseline factors such as annual trends and seasonality, the remaining fluctuations in daily temperature at a given facility are exogenous.

The error term, ε, includes both an i.i.d. and a municipality level component. The municipality level component accounts for the assignment of temperature to all hospitals at that

functions for calculating thermodynamic properties of gas-vapor mixtures and standard atmosphere suitable for most engineering, physical and meteorological applications. Most of the functions are an implementation of the formulae found in American Society of Heating and Engineers (2017).

[11] We also employed specifications with 30-day lags of temperature and found our results do not appreciably change (results available upon request).

level, and also allows for serial correlation within municipalities (and the hospitals nested within them). We cluster standard errors at the municipality level to allow for these features.

The second, and more novel, focus of our empirical strategy is to explore transitions within the health care system and their implications for patient health. To do so, we consider several additional outcomes, such as cases transferred from the ED to the hospital and excess deaths inside the hospital, using the same econometric model but with these different dependent variables. When using vital statistics data to explore mortality for the entire nation, the model is modified to include municipality FEs instead of hospital FEs.

5. Results

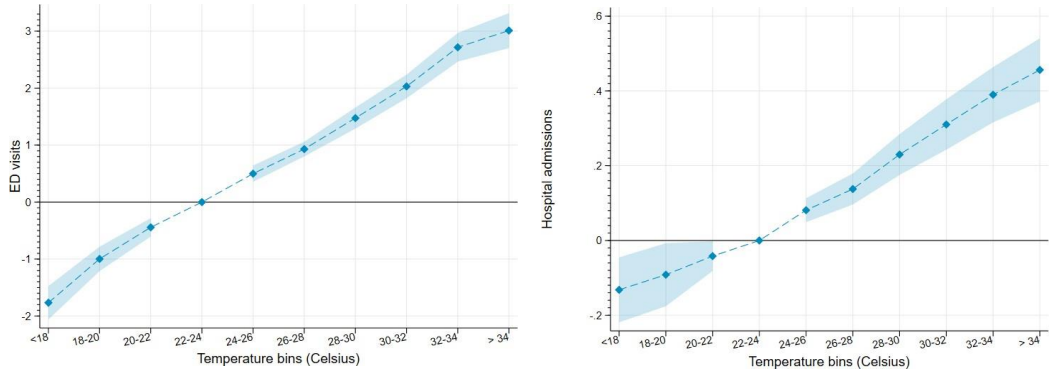
5.1. ED and hospital visits

The first set of results documents the relationship between temperature and either ED or hospital visits. These results set the stage for our subsequent analyses, and also serve as a validation exercise since previous studies document heat impacts on healthcare utilization. In these results, we report $exp(\beta\text{-}1)$, which represents the percent change in ED or hospital visits for maximum temperature falling in a certain bin relative to 22-24C. We also report the change in levels by multiplying the percent change by the outcome mean, which is helpful for studying the flow of patients through the healthcare system.

Results show that, consistent with previous studies, higher temperatures lead to increased health care utilization. Figure 2(a) shows the results for ED visits. We find a monotonically increasing relationship between temperature and ED visits that is statistically significant for all temperature bins. When temperature reaches the highest bin of >34C, we estimate an additional 3 ED visits compared to 22-24C. From a mean of ~40 daily visits, this translates to a 7.5 percent increase. The effects decrease as we move to colder temperatures, with an estimate of 2 additional visits at 30-32C and 1 at 26-28C. The impacts do not level out with cooler temperatures, with a decrease in visits occurring at each temperature bin below 22-24C. At first blush, this pattern seems surprising, but is consistent with recent evidence in California (Gould et al. 2024). The most likely explanation for this pattern is that heat produces a change in health care seeking behaviors.

Turning to hospital visits in Figure 2(b), we also find statistically significant increases resulting from higher temperatures. At the highest temperature bin of >34C, we estimate an X%

impact, which translates into roughly .5 additional hospital admissions. The estimates are progressively smaller as temperature decreases, with the convex shape consistent with a U-shaped relationship, noting that we only observe higher temperatures in the Mexican setting.

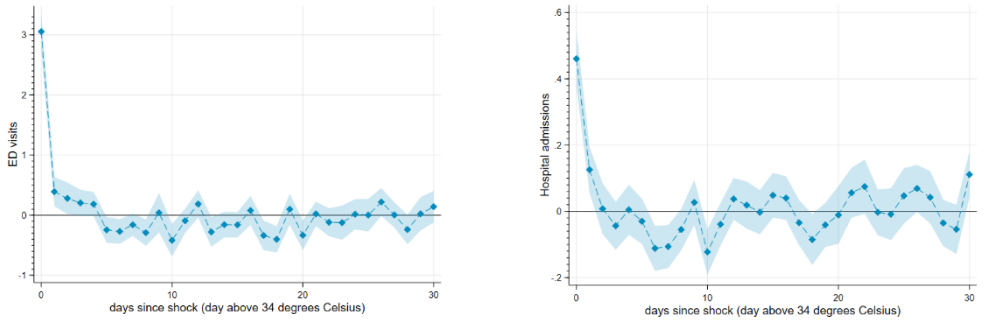


(a) ER visits (b) Inpatient + outpatient

Figure 2: Temperature and number of visits per day

Notes: ED visits between 2012-2019. Econometric specification includes 7 lags of 9 bins. Shaded area represents 95% confidence intervals. Omitted category: 22-24 ˚C.

As previously mentioned, we include 7 lags of the temperature bins in our econometric model. To display the impact from these lags, Figure 3 shows the coefficients for contemporaneous and each lag for the highest temperature bin only. Panel A shows that, for ED visits, the impact of contemporaneous temperature far outweighs that of any of the lags, although the impacts from lags one to three are statistically significant. The coefficient of X% for same day is followed by X% for 1-lag, a considerable drop in magnitude, and only gets smaller from there. A similar pattern arises for hospital visits, shown in Panel B, though only the coefficient from lag one is statistically significant. For the remaining analyses, we employ the lagged specification but only display the estimates for contemporaneous temperature given its dominance in impacting healthcare utilization.



(a) ER visits (b) Inpatient + outpatient

Figure 3: Temperature and number of visits per day

Notes: ED visits between 2012-2019. Econometric specification includes 30 lags of the >34C bin. Shaded area represents 95% confidence intervals.

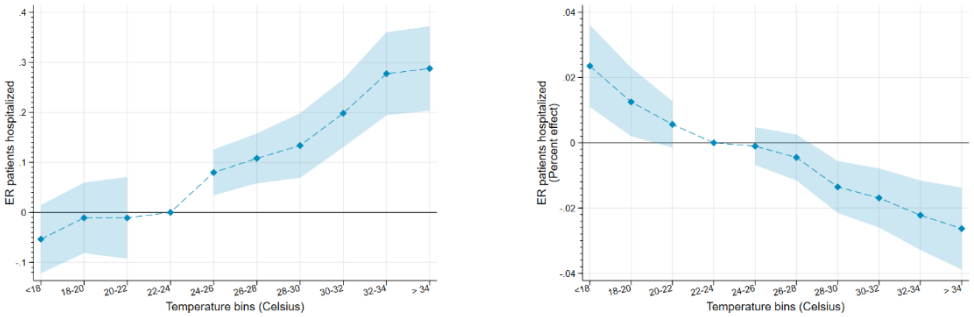
5.2. Transitions within the health care system

The above results demonstrate an increase in both ED and hospital visits when temperature increases but highlight an important gap in care. Focusing solely on the highest temperature bin, an additional 3 patients visit the ED when temperatures exceed 34C, whereas only 0.5 additional patients enter the hospital. What happens to these extra patients? We investigate this using the discharge status of ED patients.

One possibility is that hospitals admit less ED patients directly into inpatient care to free up space for the overall rise in demand for care. We explore this possibility by looking at the number of ED patients discharged directly to the hospital. The results, shown in Figure 4 (a), demonstrate an increase in discharges to the hospital as temperatures increase. When temperatures exceed 34C, we find a statistically significant increase of 0.3 patients admitted to the hospital. This implies that part of the increase in hospital visits comes from patients admitted through the ED, but that more of the increase arises due to direct admissions. Moreover, this still does not fully explain what happens to the three additional patients admitted to the ED.

Although the number of hospital admissions from the ED increases on hot days, the probability of being hospitalized decreases, as shown in Figure 4 (b). At the highest temperature bin, we estimate a 2.6% decrease in the probability of being admitted to the hospital. The next

figure shows that more patients are discharged home as heat increases.[12] When temperatures exceed 34C, we estimate a 0.7% probability increase in being sent home. Together, these results suggest that hospitals are unable to accommodate the additional patients admitted to the ED in their inpatient or outpatient units, likely due to resource constraints, and end up sending these patients home.



(a) Hospital level (b) Patient level

Figure 4: Temperature and hospitalization, ER patients

Notes: ED visits between 2012-2019. Econometric specification includes 30 lags of 9 bins. Shadedarea represents 95% confidence intervals. Omitted category: 22-24 ˚C.

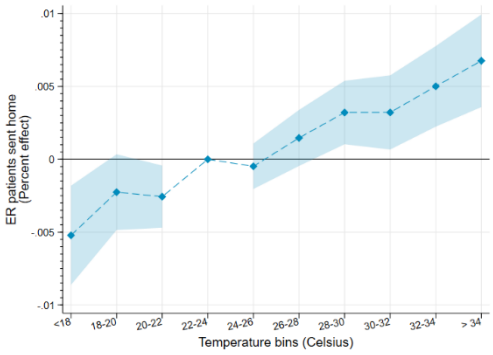


Figure 5: Probability of discharge, ER patients

Notes: ED visits between 2012-2019. Econometric specification includes 30 lags of 9 bins. Shaded area represents 95% confidence intervals. Omitted category: 22-24 ˚C.

[12] The third major discharge category is transferred, but we find no effect of temperature.

5.3. Patient composition

One explanation for the increase in patients being sent home could be patient composition. If less sick patients show up to the ED on hot days – perhaps driven by behavioral factors – it is perfectly reasonable for EDs to send more patients home. To explore this possibility, we estimate the impact of temperature on the severity of patient illness. (Recall that severity is the mortality rate based on diagnosis codes by age and sex, assigned to each patient at admission.) The results, shown in Figure 7, reveal that patient severity increases with temperature. When temperature exceeds 34C, there is a statistically significant 0.014 increase in severity, which translates to a 1.3% percent increase from the mean. This implies that EDs are treating more, rather than less, severe cases as temperatures rise, which strains the health care system.

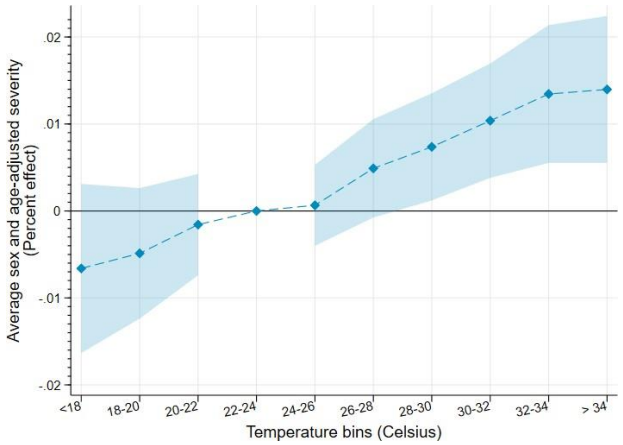


Figure 7: Severity of incoming patients, ED

Notes: Dependent variable is the average severity of patients admitted. Changes are expressed in percentage points. Shaded area represents 95% confidence intervals. Omitted category: 22-24C. Lagged specification includes bins for lags 1 to 7.

Heterogeneity in patient severity could arise whereby more severe patients are admitted to the hospital and less severe are sent home. When we specifically examine the severity of patients discharged home, shown in Figure 8, however, we produce nearly the same pattern of results. Compared to days with milder temperatures, on average, sicker patients show up at the ED as temperature rises. Perhaps even more concerning, the average patient sent home instead

of being asmitted is also sicker on hotter days. This pattern supports a "quicker and sicker" scenario in which patients are discharged more rapidly despite being sicker, a finding consistent with constrained hospital resources.

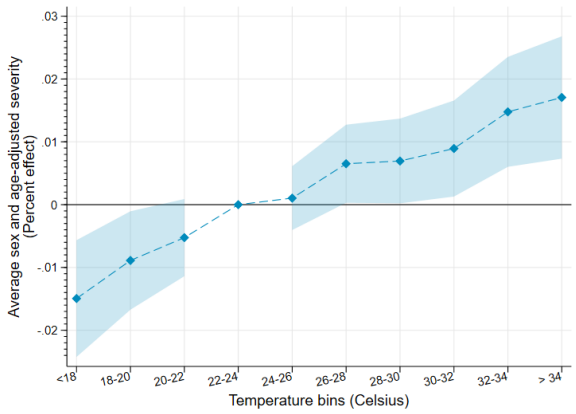


Figure 8: Severity of patients sent home, ED

Notes: Dependent variable is the average severity of patients discharged home. Changes are expressed in percentage points. Shaded area represents 95% confidence intervals. Omitted category: 22-24 C. Lagged specification includes bins for lags 1 to 7

We also explore the severity of patients admitted to the hospital, shown in Figure 9. We find that patient severity is unrelated to heat, with no clear pattern of results. Combined with the results from the previous figure, this suggests that the marginal patient transferred from the ED to the hospital is a more severe case on a hotter day than an average ED patient on a cooler day, but comparable to the average severity of patients in the hospital. The pattern of hospital patients being, on average, more severe than ED patients is consistent with the purpose of the two subsystems and the ED serving as a gatekeeper for more severe cases. It also indicates that the increasing admissions to hospitals on hot days consists of patients with similar health status, thus placing significant strain on the hospital system.

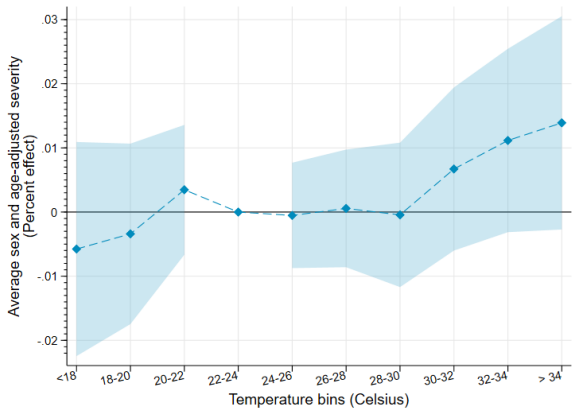


Figure 9: Severity of incoming inpatients

Notes: Dependent variable is the average severity of patients admitted. Changes are expressed in percentage points. Shaded area represents 95% confidence intervals. Omitted category: 22-24
C. Lagged specification includes bins for lags 1 to 7

5.4. Mortality impacts

We have thus far established that heat leads to an increased threat to the patient who receives health care, either through more crowding at the hospital that diminishes available resources or more patients being sent home despite being sicker. To investigate these possibilities, we probe the mortality impacts of heat both inside and outside of the hospital.

For examining mortality within the hospital, recall that heat leads to an increase in admitted patients, but the composition of patients remains similar. Therefore, if heat leads to an increase in mortality for hospital admits, the increased crowding from the additional admissions is the likely explanation. For this test, we examine the impact of temperature on excess deaths. Recall that we define excess deaths as $min\{0, 1(m) - s\}$, where $1(m) = 1$ if the patient died and 0 otherwise and s is severity assigned to each patient. The results, shown in Figure 10, indicate that excess deaths increase with temperature. A day that exceeds 34C leads to a five percent increase in excess deaths. Given that the severity of patients does not change with temperature, but the number of patients admitted does, this suggests additional crowding drives this increase in mortality.

One possible explanation for this pattern could be that heat impacts physician care. Just as patients succumb to the stress from heat, physicians may experience the same stress. Although we are unable to directly test this, two factors suggest this is an unlikely explanation. One, nearly all hospitals have air conditioning (AC)[13], which greatly minimizes heat exposure and the impacts of heat (Barreca et al). Two, the level of residential AC ownership is low in Mexico, with approximately 10-15 percent of the population owning them (Davis et al., 2021). Physicians, as a higher earning profession, are far more likely to own them than the patients we study, who are drawn from the lower rungs of the income distribution within Mexico. Regardless, given the predominant contemporaneous effect of temperature, residential AC is less likely to be a contributing factor for physicians. While we cannot rule out other possible explanations, our results are consistent with crowding as a mechanism behind these results.

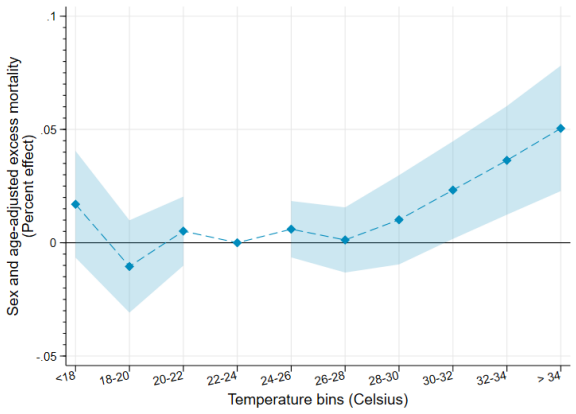


Figure 10: Excess deaths in hospitals

Notes: Dependent variable is the excess mortality in hospitals. Changes are expressed in percentage points. Shaded area represents 95% confidence intervals. Omitted category: 22-24 C. Lagged specification includes bins for lags 1 to 7

[13] Using Mexico's information requests platform (Plataforma Nacional de Transparencia), we sent information requests to each of the 32 states asking about their hospitals' climatization infrastructure. We obtained information regarding 200, 197 of them had air conditioning.

These results suggest patients who stay within the healthcare system experience increased mortality due to the heat. What about discharged patients? As shown above, patients with more severe conditions are more likely to be sent home on hotter days. Given that so few of our patients are likely to have AC, this lack of treatment is likely to increase their mortality. Although we do not observe the mortality specifically for these patients, we observe it for the entire population along with the setting of each death, enabling us to explore the potential role of the healthcare system.

We first estimate the overall municipality-level mortality effects of heat, which serves to validate our model since many previous studies estimate such a relationship (Figure 11). Consistent with these studies, we find that higher temperatures increase mortality, where a day that exceeds 34C leads to a statistically significant 0.18 increase in total deaths. From a mean of 3.02, this indicates a 6% percent increase in mortality. The convex shape is also consistent with the U-shaped pattern found elsewhere.

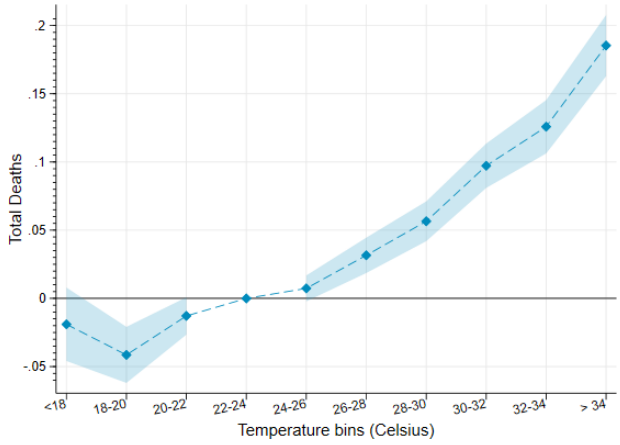
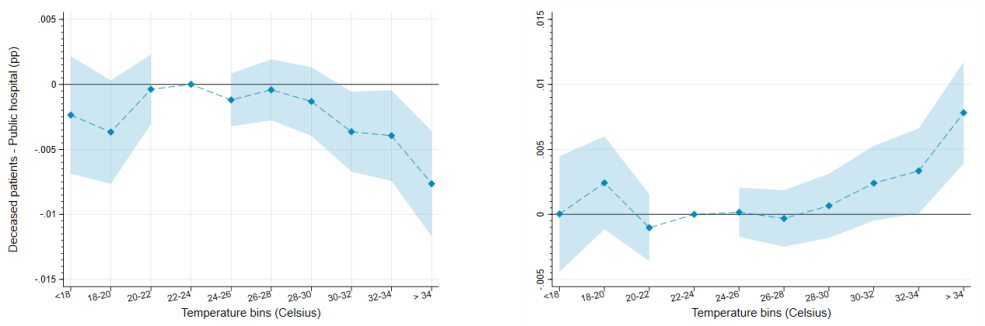


Figure 11: Temperature and daily deaths

Notes: Data from the universe of 2012-2019 death certificates. Lagged specification. The shadedarea represents 95% confidence intervals. Omitted category: 22-24 ˚C.

Given that we have established an expected relationship between temperature and mortality, we next explore the setting of each death. We have shown that more deaths occur in hospitals, but we have also shown that a disproportionately higher number of patients are

discharged home than admitted to the hospital. If this holds true for patients with IMSS and ISSSTE, the other source of social insurance in Mexico, and going home offers less protection from the heat than the hospital, then we would expect a disproportionate increase in deaths at home relative to the hospital. This pattern is supported by the results shown in Figure 12. Panel (a) indicates that the share of deaths in a public hospital decreases by almost one percentage point when temperatures exceed 34C, whereas the share of deaths outside of the hospital increases by roughly the same amount (Panel (b)). These results indicate that although more patients die in the hospital when temperatures increase, they rise even more outside of the hospital. Given that patients are more likely to be sent home on hotter days, this decision has mortal impacts on these patients. Thus, the additional demand on the healthcare system that arises from more patients seeking health care, and the resulting decision to send most of these patients home, leads to an increase in mortality.



(a) Share in public hospitals (b) Share outside of the hospital system

Figure 4: Temperature and the probability of hospitalization, ER patients

Notes: ED visits between 2012-2019. Econometric specification includes 30 lags of 9 bins. Shaded area represents 95% confidence intervals. Omitted category: 22-24 ˚C.

6. Conclusion

Globally, in 2018-2022, people experienced on average 86 days of health-threatening high temperatures annually. 60% of such temperatures were made more than twice as likely to occur by human-caused climate change (The Lancet Countdown, 2022) Climate change is expected to

modify prevailing temperature trends and intensify the occurrence of severe weather phenomena. Though a robust body of research details the immediate health consequences of extreme weather events, the implications for healthcare management and the strain they might represent for healthcare systems still need to be understood.

This study provides empirical evidence on the effects of temperature extremes, exacerbated by climate change, on the operational dynamics of healthcare systems in the context of a middle-income country. Utilizing a comprehensive dataset from Mexico's largest healthcare subsystem, we document a robust relationship between increased temperatures and hospital crowding, evidenced by increased emergency department visits and alterations in patient admission and discharge patterns.

The findings indicate that higher temperatures lead to an increase in emergency department visits and hospitalizations. However, the data also reveal a decrease in the likelihood of individual patient admission during these periods, suggesting a strain on hospital capacity. We employ a measure of healthcare quality through excess mortality and show that this measure deteriorates during extreme episodes. Moreover, the observed increase in mortality rates within and outside hospital settings during periods of extreme temperatures underscores the potential public health implications of climate-induced stress on healthcare infrastructure.

Policy implications from this study suggest a need for strategic planning in healthcare infrastructure to account for the anticipated increase in healthcare demand due to temperature extremes as climate change unravels. Our finding suggests that climate adaptation might include capacity expansion and emergency preparedness strategies to mitigate the potential adverse effects on patient outcomes.

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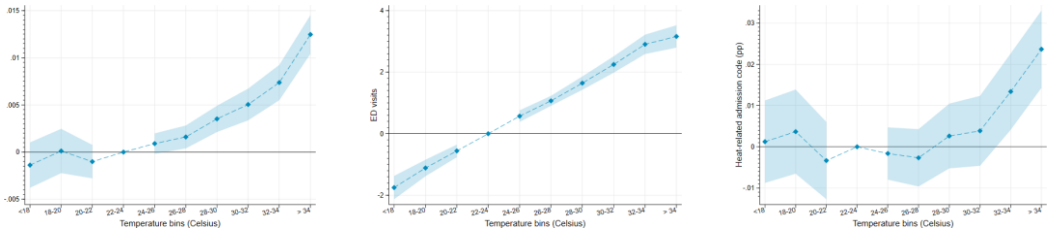
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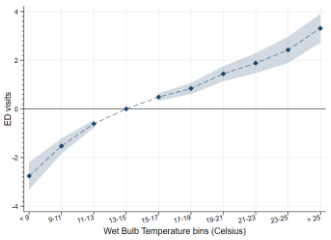
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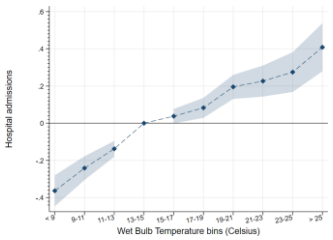
(a) Heat-related admissions (b) Total admissions excluding heat-related (c) Heat-related share

Figure A.1: ED admissions

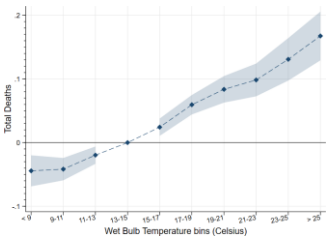
Notes: Share of heat related admissions is expressed in percentage points. Shaded area represents 95% confidence intervals. Omitted category: 22-24 ˚C. Lagged specification.



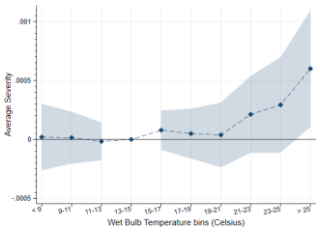
(d) ER visits



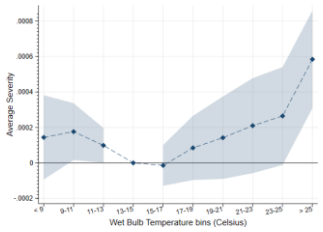
(b) Inpatient + outpatient



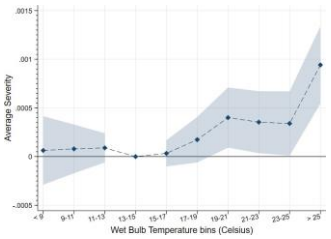
(c) Mortality rate



(d) Severity of incoming patients - Hospitalization



(e) Severity of incoming patients - ED visits



Severity of incoming patients - ED visits sent home

Figure A.2: Wet bulb temperature