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Can hospitals protect patients from extreme heat? Evidence from hospital-acquired dehydration

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Can Hospitals Protect Patients from Extreme Heat? Evidence from Hospital-Acquired Dehydration

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Can Hospitals Protect Patients from Extreme Heat? Evidence from Hospital-Acquired Dehydration*

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Abstract

Is the healthcare system equipped to protect patients from extreme heat? Linking daily temperatures to administrative records covering 41.3 million German hospital admissions, we examine hospital-acquired dehydration among patients without dehydration at admission. Relative to stays at 15–20°C, exposure above 30°C increases dehydration by 0.63 percentage points (17%) and acute kidney failure, an objective dehydration-related outcome, by 0.08 percentage points (4.7%). Effects are concentrated among older patients and those with dementia. Our findings show that extreme heat not only increases demand for care, but also compromises patient protection within hospitals, highlighting the need for adaptation to prevent avoidable in-hospital deterioration.

Keywords: Healthcare quality; Climate change; Heat; Dehydration
JEL Codes: I10, I11, Q51

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1 Introduction

Climate change is increasing the frequency and intensity of extreme heat events, with substantial consequences for population health (IPCC Working Group I, 2021, Miller et al., 2021). A large literature shows that heat raises mortality, worsens morbidity, and increases demand for medical care (Barreca et al., 2016, Deschênes, 2014, Deschênes & Greenstone, 2011, Karlsson & Ziebarth, 2018, Mullins & White, 2020). Healthcare systems are therefore central to climate adaptation: they must absorb the additional burden created by heat-related illness. Yet much less is known about whether hospitals are equipped to protect admitted patients from heat-related health risks. This distinction matters because hospitals are not only responders to climate shocks; they are also protective environments whose ability to shield vulnerable patients may itself be compromised by heat.

Heat is associated with increased in-hospital mortality (Stafoggia et al., 2006, Stafoggia et al., 2008), harming admitted patients through two reinforcing mechanisms. Inpatients are physiologically vulnerable and especially susceptible to heat-induced complications such as dehydration and electrolyte imbalance (Ebi et al., 2021). At the same time, the hospital's capacity to protect them erodes as temperatures rise — organizationally, because heat raises clinical workload and reduces staff productivity (Aguilar-Gomez et al., 2025, LoPalo, 2023, Somanathan et al., 2021, Ward et al., 2021), and physically, because many hospital buildings cannot maintain safe indoor temperatures during heat events. Design standards for hospital ventilation differ markedly across regions: US standards specify temperature ranges that effectively require mechanical cooling of general inpatient wards, whereas standards in most of Europe do not, and ward-level air conditioning is correspondingly uncommon across much of the global hospital stock.[1] Even where mechanical cooling is standard, however, organizational responses to heat – rising clinical workload and reduced staff productivity – may continue to compromise inpatient protection. Climate change therefore affects health not only by altering who is admitted, but by degrading the conditions of care once inside.

In this paper, we study whether hospitals protect patients from heat-related health deterioration using hospital-acquired dehydration as a clinically relevant and potentially preventable outcome. We link daily temperature data to administrative hospital records from Germany – a high-income setting where strong baseline care quality coexists with largely uncooled hospital wards – and estimate how heat exposure during a patient's stay affects dehydration diagnoses recorded at discharge. To isolate dehydration that develops

[1] ANSI/ASHRAE/ASHE Standard 170 specifies design temperatures and minimum air-change rates for patient care areas in the United States (ASHRAE & ASHE, 2021), whereas Germany's DIN 1946-4 prescribes filtration and ventilation requirements for general patient rooms but does not require mechanical cooling (Deutsches Institut für Normung, 2018). A survey of 263 German hospitals found that air conditioning is not a hospital-wide standard and is largely confined to specialised functional areas such as operating theatres and intensive care units (Filser & Levsen, 2022). In England, air conditioning is similarly not routinely installed across NHS estates (Iqbal et al., 2023). In India, a survey of 623 hospitals found that 27 percent reported no air-conditioning system of any kind, and only 11 percent used central AC (National Centre for Disease Control et al., 2024).

within the hospital, we restrict the sample to patients without a dehydration code at admission. We then examine whether the effects differ across patient groups and hospital characteristics, shedding light on both physiological vulnerability and the role of hospital adaptation.

Our empirical strategy exploits plausibly exogenous variation in daily temperature across hospitals and admission dates. We compare patients exposed to different temperature conditions during their hospital stay while controlling for hospital fixed effects, temporal shocks, and patient characteristics. The identifying variation therefore comes from short-run deviations in local temperature, rather than from persistent differences across hospitals or patient populations. Because we restrict the sample to patients without a dehydration diagnosis at admission, the estimates capture the effect of heat exposure during hospitalization on newly recorded dehydration diagnoses.

We find that heat exposure during hospitalization increases the probability of hospital-acquired dehydration. The temperature-response relationship is nonlinear: dehydration risk is largely flat across cold and moderate temperatures but increases sharply on days with maximum temperatures above 30°C. Replacing the full inpatient exposure window with days above 30°C rather than days between 15 and 20°C raises the probability of hospital-acquired dehydration by approximately 0.63 percentage points, corresponding to an increase of about 17 percent relative to the baseline incidence. For an average hospital stay of 7 days an additional day of extreme heat is then equal to a 2.4 percent increased risk of dehydration. We find similar effects for hospital-acquired acute kidney failure, a more severe dehydration-related outcome diagnosed through laboratory measurements. Full-stay exposure above 30°C raises the probability of acute kidney failure by 0.08 percentage points, or 4.7 percent relative to a baseline incidence of 1.7 percent, indicating that the effects of inpatient heat exposure extend beyond fluid imbalance to more serious physiological deterioration.

The effects are particularly pronounced among older patients and patients with dementia, consistent with greater vulnerability among groups that may depend more strongly on monitoring and support during hospitalization. We also find that the effects are substantially smaller in the largest hospitals, consistent with greater infrastructure or organizational capacity to protect patients during periods of extreme heat. We subject the main results to a broad set of robustness checks. The estimates remain stable when we exclude admissions occurring during or shortly after extreme pre-admission heat. For our sample, excluding dehydration-related admissions, balancing tests also show no systematic heat-related changes in patients' age, comorbidities, or pre-existing dementia, reducing concerns about selection into hospitalization. Because time at risk is a central concern, we additionally test whether our estimates are mechanically driven by length of stay: we show that extreme heat does not prolong hospitalizations. Moreover, the results remain similar when we include length-of-stay fixed effects, measure heat exposure over a fixed three-day inpatient window, and estimate the effects of additional hot days separately

across stays of different durations. Finally, statistical inference is robust to clustering standard errors at different spatial levels.

This paper contributes to three strands of literature. First, it adds to the climate-health literature by shifting the focus from the effect of heat on healthcare demand (Drescher & Janzen, 2025, Karlsson & Ziebarth, 2018, Masiero et al., 2022, White, 2017) to whether heat-related health risks persist during hospitalization. Closest to our work are Wu et al. (2025) and Aguilar-Gomez et al. (2025), who find that ambient temperatures disrupt internal hospital processes by causing demand shocks, which subsequently alters staffing and increases mortality. We advance this frontier by demonstrating that heat affects inpatient outcomes not only through increased demand, but directly, as patients remain vulnerable to thermal stress even while under medical supervision.

Second, we contribute to the literature on hospital quality. This literature has documented systematic differences in patient outcomes across hospitals (Chandra et al., 2016, Doyle et al., 2019, Doyle Jr et al., 2015) and has examined determinants such as market structure, case volume, and workforce organization (Avdic et al., 2019, Gaynor et al., 2005, Rachet-Jacquet, 2022, Roos et al., 2020). We expand this framework by using heat as a stress test exposing limitations in hospital infrastructure, such as inadequate cooling systems, and constraints in organizational processes, such as insufficient targeted heat-response plans and adapted care protocols for highly vulnerable patients.

Third, this paper speaks to the economics of climate adaptation. A growing literature documents that populations adapt to heat over time through behavioral and institutional responses, including air conditioning adoption and improvements in healthcare, which gradually attenuate the temperature–mortality relationship (Barreca et al., 2016, Carleton et al., 2022, Mullins & White, 2020). This literature has largely treated healthcare systems as part of the adaptive capacity that mitigates climate damages (Mullins & White, 2020). We show that one component of this capacity – the hospital – does not fully protect admitted patients from extreme heat, suggesting that hospitals themselves may require adaptation investments rather than being treated only as adaptation infrastructure.

The results have direct policy relevance. If extreme heat increases avoidable health deterioration during hospital stays, climate adaptation in the healthcare sector should not only focus on emergency preparedness and surge capacity, but also on protecting admitted patients during heat events. Investments in cooling infrastructure, monitoring routines, hydration protocols, and staffing adjustments may be necessary to protect vulnerable patients as heat exposure becomes more frequent.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting and explains why hospital-acquired dehydration is a clinically relevant marker of heat-related health deterioration during inpatient care. Section 3 presents the data. Section 4 outlines the empirical strategy. Section 5 reports the main results, discusses mechanisms and shows robustness checks. Section 6 concludes.

2 Institutional Background and Outcome Definition

Hospitals are a central part of climate adaptation in the healthcare sector. During heat events, they must not only treat patients admitted because of heat-related illness, but also protect already admitted patients from avoidable deterioration. This role is particularly important because hospitalized patients are often older, acutely ill, mobility-constrained, or dependent on staff for fluid intake and monitoring. The hospital setting is therefore conceptually distinct from exposure at home: once admitted, patients are under medical supervision and should, in principle, be less exposed to preventable consequences of heat. In practice, however, the physical infrastructure of many facilities limits this protective capacity. While cooling systems are associated with improved clinical outcomes (Hoffmann et al., 2021, Lenzer et al., 2020), only a minority of German hospitals currently report having air-conditioned patient rooms (Filser & Levsen, 2022).

We study this question using hospital-acquired dehydration. Dehydration is clinically relevant in the context of heat because it occurs when fluid losses exceed fluid intake and can be aggravated by sweating, fever, medication use, impaired thirst, limited mobility, or insufficient access to fluids (Ebi et al., 2021, Taylor & Tripathi, 2025). These risks are especially salient among older and medically vulnerable patients during heat episodes (Meade et al., 2020, Taylor & Tripathi, 2025).

In the administrative hospital records, we define hospital-acquired dehydration as a stay in which dehydration is recorded in the final inpatient diagnosis information, but not among the diagnoses coded at admission. Our outcome is based on three ICD-10-GM codes. E86 (volume depletion) covers dehydration and hypovolemia regardless of cause, whereas T67.3 (heat exhaustion due to water loss) and T67.4 (heat exhaustion due to salt depletion) specifically record fluid or salt loss attributed to heat. Combining these codes allows us to capture heat-related dehydration irrespective of whether the heat cause is documented. We exclude all admissions with E86, R57.1 (hypovolemic shock), N17 (acute kidney failure) or any diagnosis in the T67 category (effects of heat and light) recorded at admission, whether as a primary or secondary diagnosis. The remaining cases therefore capture dehydration that was not coded as present when the patient entered the hospital but appears in the completed hospital record.

This definition has two implications for interpretation. First, our outcome should not be interpreted as the exact timing of dehydration onset. German inpatient diagnoses are finalized after the hospital stay, and secondary diagnoses may be completed or revised during administrative coding.[2] We therefore do not observe the precise day on which dehydration developed or was first recognized. Second, the outcome should not be interpreted as a pure measure of care quality, but as a measure of how well hospitals can protect patients from heat. While a substantial literature uses administrative discharge

[2]While hospital diagnoses in Germany determine reimbursement under the G-DRG system, coding accuracy is monitored through regular audits conducted by the Medical Service (*Medizinischer Dienst*) (Medizinischer Dienst Bund, 2024).

information to characterize hospital quality through broad outcomes such as mortality and readmission (Chandra et al., 2016, Doyle et al., 2019, Doyle Jr et al., 2015), our outcome is clinically more specific and is shaped by multiple factors. Hospital-acquired dehydration may reflect hospital infrastructure, staffing, monitoring routines, or hydration practices.

This outcome is well suited to studying hospital adaptation to extreme heat. If hospitals fully shielded admitted patients from heat-related risks, short-run variation in outdoor temperature during a hospital stay should have little effect on newly recorded dehydration. Conversely, an increase in hospital-acquired dehydration on hot days would indicate that heat-related health risks can persist even inside hospitals, despite medical supervision. Such a finding would imply that climate adaptation in the hospital sector must go beyond managing higher admission volumes and also address the protection of patients already receiving inpatient care.

3 Data

Our primary data source is administrative health insurance records from one of Germany's largest statutory health insurers. The data cover approximately nine million insured individuals between 2005 and 2025, corresponding to roughly ten percent of the German population. For each inpatient episode, the records contain detailed information on admission and discharge dates, diagnoses coded according to the German modification of the International Classification of Diseases (ICD-10-GM), and patient characteristics, including age and sex.

We complement the claims data with hospital-level information from the German hospital quality reports. These reports provide information on hospital characteristics, including geographic location, bed capacity, and ownership type. We use this information both to characterize the hospital sector and to assign local weather conditions to each inpatient stay.

Weather exposure is measured using HOSTRADA, a high-resolution gridded weather dataset provided by the German Weather Service (DWD) (Krähenmann et al., 2018). HOSTRADA provides meteorological information on a 1 km^2 grid. We assign daily weather conditions to each hospital based on its geographic location. Our main weather variable is maximum temperature at the hospital-day level. This matching procedure allows us to measure short-run variation in local heat exposure during each hospital stay.

The unit of observation is a hospital admission. Starting from all inpatient episodes observed in the claims data, we restrict the sample based on the admission reason recorded for each episode. We exclude transfers from other hospitals, because patients' health status at admission and part of their heat exposure reflect care at the sending hospital. We further exclude readmissions due to complications, admissions for organ removal, psychiatric home-equivalent treatment, and transitional care. The remaining sample consists of

full inpatient admissions, including admissions following pre-inpatient treatment, deliveries, and births, regardless of whether they are planned, emergency, or accident-related.[3] We then exclude all admissions for which dehydration or heat-related illness was coded at admission, either as a primary or secondary diagnosis. Specifically, we exclude admissions with ICD-10-GM codes E86, R57.1, N17, or T67 recorded at admission. In the remaining sample, hospital-acquired dehydration is defined as an inpatient episode in which dehydration or heat-related dehydration is recorded in the final diagnosis information, but not at admission. Our main outcome of dehydration is based on ICD-10-GM codes E86, T67.3 and T67.4. Finally, we exclude outliers in the top one percent for length of stay (66 days or longer). The final estimation sample contains approximately 41.3 million admissions across 2,108 hospitals.

Table A.1 reports summary statistics for the final estimation sample. The sample contains 41.3 million hospital admissions. Patients are on average 58.1 years old, and 59.7 percent are female. The incidence of hospital-acquired dehydration is 3.7 percent, while the incidence of kidney failure is 1.7 percent. The average length of stay is 7 days. The table also reports patient health status before admission, measured by the Elixhauser comorbidity score (Quan et al., 2005), as well as hospital characteristics such as annual inpatient cases and bed capacity.

Figure A.1 shows the distribution of daily maximum temperature across hospital-days in the estimation sample. The data contain substantial variation in temperature exposure, including exposure to extreme heat: 3.2 percent of hospital-days have maximum temperatures of at least 30°C. Figure A.2 shows the spatial distribution of the 2,108 hospitals in the estimation sample together with the mean annual number of hot days, defined as days with daily maximum temperature of at least 30°C, averaged over the 2005–2025 period. The figure highlights the broad geographic coverage of the hospital sample and substantial spatial variation in exposure to extreme heat.

4 Empirical Strategy

We estimate the effect of heat exposure during hospitalization on hospital-acquired dehydration. The outcome variable, Y_{iht}, is an indicator equal to one if patient i, admitted to hospital h on day t, receives a dehydration diagnosis during the hospital stay despite not having dehydration coded at admission.

Our main explanatory variables measure temperature exposure during the hospital stay. For each admission, we calculate the share of inpatient days on which the daily maximum temperature at the hospital falls into temperature bin b. Because hospital stays

[3]The German claims data record a four-digit admission reason code, where the first two digits indicate the type of admission and the last two digits the admission circumstance. We retain episodes whose first two digits are 01 (full inpatient treatment), 02 (full inpatient treatment following pre-inpatient treatment), 05 (delivery), or 06 (birth).

vary substantially in length, this normalization captures the intensity of heat exposure during the stay rather than its cumulative duration. We verify in Section 5.3 that the temperature-response pattern is similar when using different measures of heat exposure. Temperature bins are defined in five-degree Celsius intervals, with days between 15 and 20°C serving as the reference category. The lowest and highest bins collect days below 0°C and above 30°C, respectively, following the common approach in the temperature-health literature (Aguilar-Gomez et al., 2025, Deschênes & Greenstone, 2011). We estimate the following specification:

$$Y_{iht} = \sum_{b \neq 15-20°C} \beta_b \text{TempShare}^b_{iht} + X'_{iht}\gamma + \alpha_h + \delta_{d(i)} + \lambda_{ym(t)} + \rho_{dow(t)} + \eta \text{Holiday}_t + \varepsilon_{iht}. \quad (1)$$

Here, $TempShare^b_{iht}$ denotes the share of days during patient i's hospital stay in which the daily maximum temperature at hospital h falls into bin b. The coefficients β_b therefore measure how the probability of hospital-acquired dehydration changes with exposure to temperatures in bin b, relative to exposure to mild days between 15 and 20°C.

The vector X_{iht} includes patient-level controls for age, sex, and pre-admission Elixhauser comorbidity categories constructed from diagnoses recorded in the year before hospitalization. Hospital fixed effects, α_h, absorb time-invariant differences across hospitals, including persistent differences in infrastructure, local climate, patient catchment areas, and coding practices. Primary diagnosis fixed effects, $\delta_{d(i)}$, are defined at the three-digit ICD-10-GM level and ensure that comparisons are made among patients admitted for similar clinical conditions. Year-by-month fixed effects, $\lambda_{ym(t)}$, flexibly control for common seasonal and annual shocks, while day-of-week fixed effects and holiday indicators account for systematic differences in admissions and hospital operations across the calendar. We estimate Equation (1) by ordinary least squares and cluster standard errors at the county level.

This setup addresses three central sources of confounding. First, hospital fixed effects ensure that identification does not rely on permanent differences between hospitals, such as their location in hotter or cooler areas. Second, diagnosis fixed effects ensure that comparisons are made among patients admitted for the same clinical condition, while pre-admission comorbidity controls account for differences in patient sickness. Third, we conduct balancing tests (Section 5.3) showing that unobserved patient characteristics do not shift systematically with heat exposure. Conditional on these controls and checks, identification rests on short-run deviations in local temperature, net of persistent hospital characteristics, common seasonal and annual shocks, and differences across clinical conditions.

5 Results

5.1 Main Results

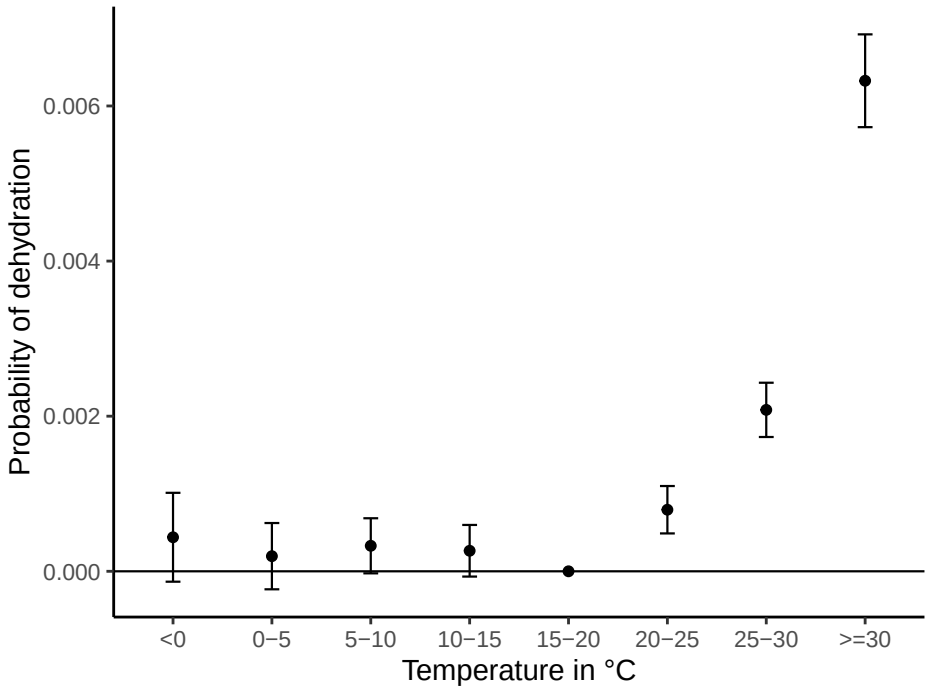
Figure 1 reports the estimated temperature-response relationship for hospital-acquired dehydration, revealing a strongly nonlinear pattern. The omitted category is the share of inpatient days with maximum temperatures between 15 and 20°C. The estimates show little evidence that cold or moderately warm days affect dehydration risk; coefficients below 20°C are close to zero and statistically indistinguishable from the reference category. In contrast, risk increases sharply at higher temperatures. Replacing the full inpatient exposure window with days above 30°C rather than days between 15 and 20°C raises the probability of hospital-acquired dehydration by approximately 0.63 percentage points. Relative to a baseline incidence of 3.7 percent, this corresponds to a 17 percent increase. To interpret this magnitude in terms of daily exposure, we evaluate the effect at the sample mean. For an average hospital stay of 7 days, experiencing one additional day above 30°C increases the absolute probability of dehydration by 0.09 percentage points, translating to a 2.4 percent relative increase in risk per day of extreme heat. This demonstrates that even short-duration heat shocks actively compromise patient hydration.

As a consistency check, we replace daily maximum temperature with daily minimum temperature, which we use as a proxy for nighttime heat exposure. Daily minimum temperature is closely related to daytime heat exposure, as hot days and warm nights typically occur during the same heat events. The exercise therefore does not isolate a separate nighttime-heat mechanism. It is nevertheless informative because it tests whether the estimated temperature-response relationship depends on the specific use of daily maximum temperature. Appendix Figure B.1 shows a pattern consistent with the baseline results. Dehydration risk is flat at low and moderate nighttime temperatures and increases substantially when nighttime temperatures exceed 20°C. This suggests that the relationship is not specific to daytime temperature peaks, but also appears when heat exposure is measured using daily minimum temperature as a proxy for sustained overnight heat.[4]

We next examine whether inpatient heat exposure also triggers acute organ distress. Specifically, we estimate the effect of heat on hospital-acquired acute kidney failure (ICD-10-GM code N17), which is a direct physiological consequence of severe, uncompensated dehydration. Because a dehydration diagnosis relies partly on clinical judgment, one might worry that the estimated increase reflects heightened physician attention or changes in coding practices during hot periods rather than a deterioration in patient health. Acute kidney failure, by contrast, is diagnosed from objective laboratory criteria, such as an acute rise in serum creatinine or a measured decline in urine output. It is therefore less susceptible to discretionary diagnosis or upcoding. Figure 2 demonstrates that heat

[4]The results are also robust to excluding the COVID-19 period. Appendix Figure B.2 shows a temperature-response function that is very similar to the baseline specification.

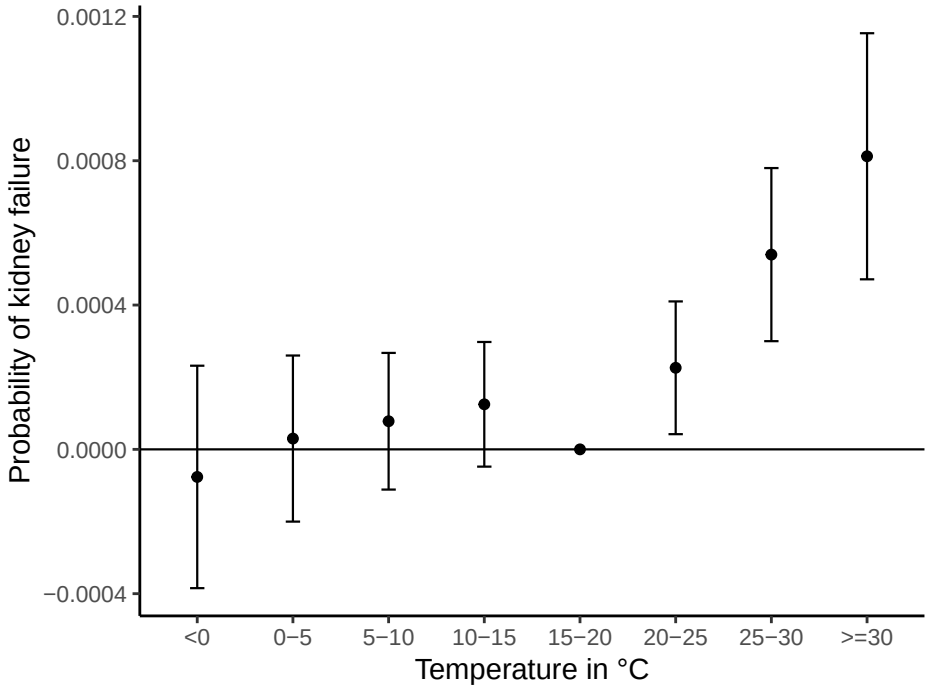
Figure 1: Temperature Exposure During Hospitalization and Hospital-Acquired Dehydration



Notes: The figure reports coefficient estimates from Equation (1). The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

exposure substantially increases the risk of hospital-acquired acute kidney failure. The temperature-response relationship closely mirrors our dehydration results, with risk remaining flat at moderate temperatures and rising on days with temperatures above 30°C. Replacing the full inpatient exposure window with days above 30°C rather than days between 15 and 20°C raises the probability of a kidney failure by approximately 0.08 percentage points. Relative to a baseline incidence of 1.7 percent, this corresponds to a 4.7 percent increase. For an average hospital stay of 7 days, experiencing one additional day above 30°C increases the absolute probability of acute kidney failure by approximately 0.011 percentage points, translating to a 0.7 percent relative increase in risk per day of extreme heat. This confirms that extreme heat in the hospital setting does not merely cause mild fluid imbalances, but leads to severe, objectively measured physiological harm.

Figure 2: Temperature Exposure During Hospitalization and Hospital-Acquired Acute Kidney Failure



Notes: The figure reports coefficient estimates from Equation (1), using hospital-acquired acute kidney failure (ICD-10-GM N17) as the dependent variable. The outcome is an indicator equal to one if acute kidney failure is recorded during the hospital stay among patients without the diagnosis coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

5.2 Heterogeneity

We next examine whether the effect of heat exposure differs across patients and hospitals. These analyses are motivated by two distinct channels. First, heat-related dehydration risk may be larger among patients who are physiologically vulnerable or more dependent on hospital staff for fluid intake and monitoring. Second, the effect may vary across hospitals if infrastructure, routines, or adaptation capacity differ across institutional settings. We therefore study heterogeneity by patient age and dementia status, and by hospitals' long-run heat exposure and bed capacity. Additional heterogeneity analyses by sex, emergency admission, and ownership type are reported in Appendix Figures B.4–B.6.

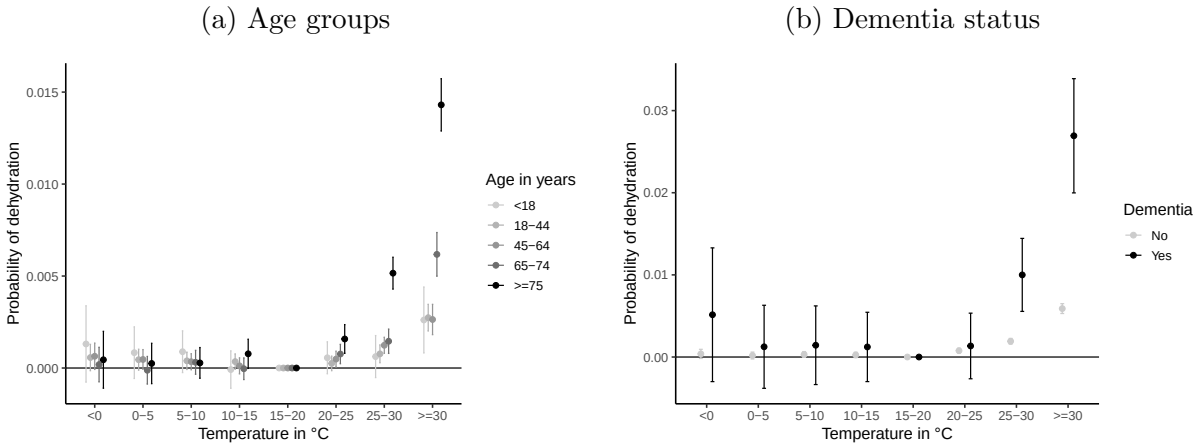
Figure 3 shows substantial heterogeneity across patient groups. The effect of heat exposure rises sharply with age. For patients below age 65, the estimated effects are small at moderate temperatures and increase only modestly at the highest temperature bin. In contrast, the effect is much larger among patients aged 75 and above, especially on days with maximum temperatures above 30°C. This pattern is consistent with older patients being more vulnerable to heat-related dehydration during hospitalization.

The effects are also larger among patients with dementia.[5] While estimates for dementia patients are less precise because the subgroup is smaller, the point estimates increase strongly at high temperatures. For an inpatient stay with each day having a maximum temperature above 30°C, the effect size for patients with dementia is 2.69 percentage points, compared with 0.59 percentage points for those without dementia. This difference does not appear to be driven solely by the older age of dementia patients. Restricting the sample to patients aged 65 and older, the corresponding estimates are approximately 2.8 percentage points for patients with dementia and 1.0 percentage point for those without dementia (Appendix Figure B.3). Thus, although the dementia–non-dementia gap narrows somewhat in the older sample, a substantial difference remains. This pattern is consistent with dementia increasing dependence on staff for hydration, monitoring, and response to heat-related symptoms. Together, these results suggest that heat-related dehydration during hospital stays is concentrated among patients who are most likely to require active protection from heat exposure.

Figure 4 examines whether the temperature-response relationship differs across hospital environments. We first split hospitals into quartiles of long-run heat exposure, measured by the mean annual number of days with maximum temperatures above 30°C over 2005–2025. Populations in hotter regions have been shown to adapt to extreme heat (e.g., Harris, 2026), and hospitals in these regions may likewise be better adapted due to repeated experience with heat events (Carleton et al., 2022). The estimates show that heat increases hospital-acquired dehydration in all four quartiles, with no evidence that hospitals in the warmest quartile are better protected against high-temperature days.

[5]Dementia cases were identified based on an inpatient diagnosis during the year prior to admission.

Figure 3: Heterogeneity by Patient Vulnerability



Notes: The figure reports coefficient estimates from variants of Equation (1) estimated separately by patient subgroup. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

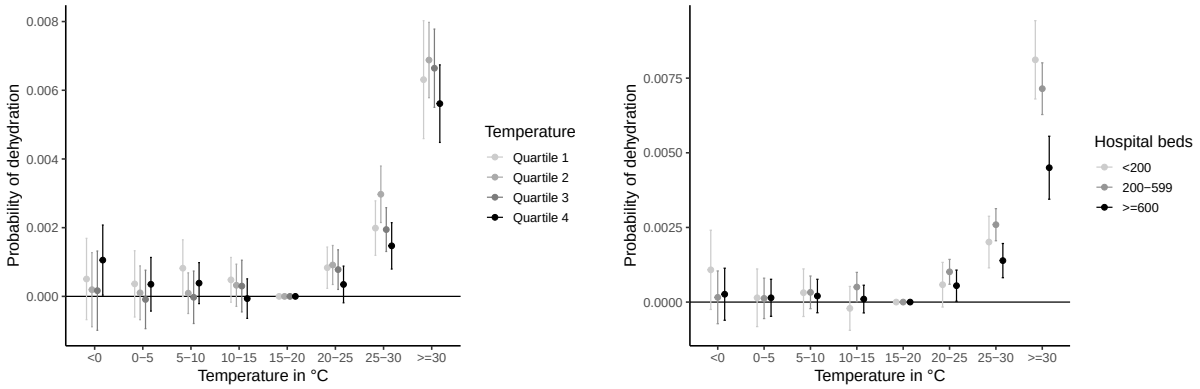
This suggests that any regional adaptation to more frequent heat is incomplete, at least for the prevention of hospital-acquired dehydration.

We also examine heterogeneity by hospital size, measured by the number of beds. The heat effect is present across hospital-size categories but is substantially smaller in the largest hospitals. This pattern is consistent with larger hospitals having greater infrastructure or organizational capacity to protect patients during heat events, although we interpret this evidence cautiously because bed capacity may also proxy for differences in patient composition, specialization, and coding practices.

Appendix Figures B.4, B.5, and B.6 report additional heterogeneity analyses. The heat effect is larger for non-emergency admissions than for emergency admissions, which may reflect differences in patient selection, planned procedures, or length of stay rather than a pure difference in heat vulnerability. Patients admitted through the emergency department may also receive more intensive monitoring for their acute conditions, which could help detect and prevent dehydration during hot periods. Effects are also larger for men than for women in absolute terms, although this difference is driven by the reference bin and disappears when interpreting coefficients relative to the 10 and 15°C range. Finally, we find no strong systematic differences by hospital ownership type. If anything, public hospitals seem to be less affected by heat than non-profit or for-profit hospitals.

Figure 4: Heterogeneity by Hospital Characteristics

(a) Long-run temperature exposure (b) Hospital bed capacity



Notes: The figure reports coefficient estimates from variants of Equation (1) estimated separately by hospital subgroup. Panel (a) splits hospitals into quartiles of long-run temperature exposure. Panel (b) splits hospitals by bed capacity. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

5.3 Robustness Checks

We conduct four main robustness checks to address concerns about the interpretation of hospital-acquired dehydration. A first concern is that some patients may already be close to dehydration at admission, even if dehydration is not recorded as an admission diagnosis. This could occur if patients arrive during or shortly after extreme heat exposure and dehydration is only added as a secondary diagnosis once laboratory results become available or the hospital record is completed. To address this concern, we restrict the sample to admissions without extreme heat on the admission day and, in stricter specifications, without extreme heat on multiple days preceding admission. Appendix Figure B.7 shows that the temperature-response relationship remains strongly positive at high temperatures. The estimates are close to zero below 20°C and increase sharply for days above 30°C across all restrictions. If anything, the high-temperature estimates are larger after excluding admissions with recent heat exposure, which is inconsistent with the main results being driven by patients who entered the hospital already at the margin of dehydration. We interpret these larger estimates cautiously, as the restrictions change the composition of admissions and the set of heat events used for identification.

Second, a related concern is that extreme heat may alter the composition of admitted patients. If older or more medically vulnerable patients are disproportionately admitted during heat waves, the estimated increase in dehydration could simply reflect an unobserved shift in patient frailty rather than the direct effect of heat exposure during the stay. To test for selection into admission, we conduct balancing checks by replacing our main

outcome with predetermined patient characteristics. Appendix Figures B.8, B.9, and B.10 show the estimated effects of temperature exposure on patient age, pre-admission Elixhauser comorbidity score, and dementia diagnoses. The estimates reveal no systematic differences between hospital stays during extreme heat and our reference category in terms of these baseline characteristics.[6] This suggests that our model absorbs heat-induced changes in patient composition, ensuring that our main results are not driven by a shift to more vulnerable patients.

A third concern is that heat may affect length of stay, which in turn may influence the probability of hospital-acquired dehydration. If heat increased length of stay, the estimated effect of heat could therefore partly reflect a longer exposure and observation window in which patients may develop dehydration. To assess this concern, we estimate the effect of temperature on length of stay directly, using admission-day temperature as the exposure. Appendix Figure B.11 shows no evidence that heat on the day of admission increases length of stay. If anything, stays are somewhat shorter at high temperatures, with the largest negative coefficient for admission days above 30°C. This pattern is consistent with patients being discharged earlier during periods of extreme heat, potentially because of discomfort in the hospital environment, although we cannot directly test this mechanism. More importantly, it suggests that our main results are unlikely to be driven by heat-induced increases in the time available for dehydration to occur or be diagnosed. To the extent that shorter stays reduce the time during which dehydration can be diagnosed, our estimates may understate the effect of heat on hospital-acquired dehydration. We also re-estimate the main specification including fixed effects for each length-of-stay duration, thereby absorbing unobserved characteristics of stays with different lengths. Appendix Figure B.12 shows that the temperature-response relationship remains very similar to the baseline specification, with estimates close to zero at cold and moderate temperatures and rising sharply at high temperatures.

Fourth, expressing temperature exposure as a share of inpatient days may mask heterogeneity across stays of different durations. The same exposure share can correspond to very different numbers of hot days: for example, a 50 percent exposure share represents one hot day during a two-day stay but five hot days during a ten-day stay. We therefore conduct two complementary checks. First, we construct temperature exposure over a fixed window consisting of the first three hospital days and restrict the sample to admissions lasting at least three days. Within this sample, all patients have the same exposure window, so the treatment measure no longer depends on the realized duration of the stay beyond the three-day threshold. Appendix Figure B.13 shows a temperature-response relationship similar to the baseline specification, indicating that the main pattern is not driven by measuring exposure over the entire realized hospital stay. Second, we examine

[6]Prior work documents that extreme temperatures shift the composition of hospital admissions (Aguilar-Gomez et al., 2025, Karlsson & Ziebarth, 2018). We find no such compositional changes in our sample, likely because we exclude admissions with heat-related primary diagnoses and control for admission reason and patient characteristics.

whether the effect of heat varies systematically with length of stay. We re-estimate the temperature specification separately by realized stay duration and, within each subsample, measure exposure as the number of inpatient days in each temperature bin rather than as a share. Because total inpatient days are fixed within each subsample, the coefficient on a temperature bin can be interpreted as the effect of replacing one day in the 15–20°C reference category with one day in that temperature range. Appendix Figure B.14 reports the estimated effect of an additional day above 30°C across stay durations. The estimates are positive across the length-of-stay distribution and show no systematic tendency to increase or decrease with stay duration. Their magnitudes are also broadly consistent with the effects implied by the baseline specification in Section 5.1. Taken together, these exercises provide little evidence that the baseline results are driven by a particular segment of the length-of-stay distribution or by expressing temperature exposure as a share rather than as a count of inpatient days.

Finally, Figure B.15 demonstrates that our inference is robust to alternative clustering choices. To account for the spatial dependence inherent in local weather shocks, we re-estimate our standard errors at the hospital and state levels, finding no meaningful change in the statistical significance of our main results.

6 Conclusion

This paper studies whether hospitals protect admitted patients from heat-related health risks. Using administrative hospital records from Germany linked to high-resolution daily weather data, we find that heat exposure during hospitalization increases the probability of hospital-acquired dehydration among patients without dehydration coded at admission. The relationship is nonlinear: dehydration risk is largely flat across cold and moderate temperatures but increases sharply at maximum temperatures above 30°C. The effects extend to dehydration-related acute kidney failure, a more severe outcome diagnosed using objective laboratory measures. The effects on dehydration are particularly pronounced among older patients and patients with dementia, consistent with greater vulnerability among groups that may depend more strongly on monitoring and support during hospitalization.

The estimates should not be interpreted as isolating a single mechanism or as a pure measure of care quality. Hospital-acquired dehydration may reflect patient vulnerability, physiological responses to heat, monitoring practices, hydration routines, staffing constraints, or infrastructure limitations. The central result is that heat-related risks persist even in supervised inpatient settings.

These findings suggest that climate adaptation in the healthcare sector should not only focus on higher demand for care during heat events. It should also consider how hospitals can protect patients already receiving inpatient care. As extreme heat becomes more frequent, hospital-level adaptation may be necessary to prevent avoidable in-hospital

deterioration.

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Supplemental Appendix

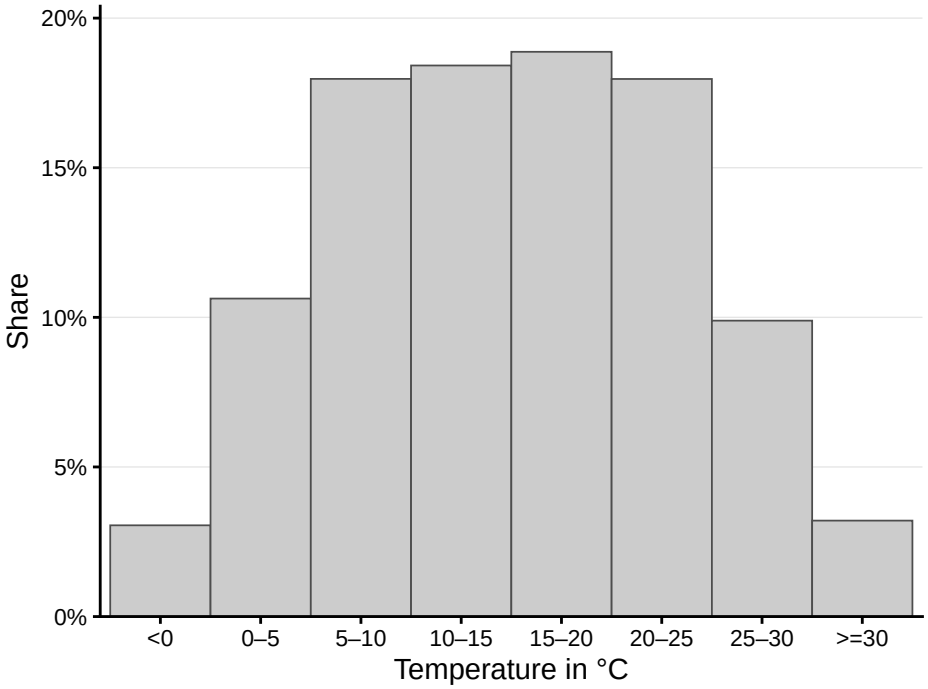
A Descriptives

Table A.1: Summary Statistics

Variable	Mean	SD
Outcomes		
Dehydration	0.037	0.188
Kidney failure	0.017	0.130
Patient characteristics		
Age	58.080	24.180
Female	0.597	0.491
Elixhauser comorbidity score	3.642	9.511
Hospital stay		
Length of stay in days	7.026	9.059
Case costs in Euro	3,910.000	6,148.350
Emergency admission	0.409	0.492
Hospital characteristics		
Annual inpatient cases	22,022.000	20,681.200
Hospital beds	549.004	467.720
Observations	41,332,775	

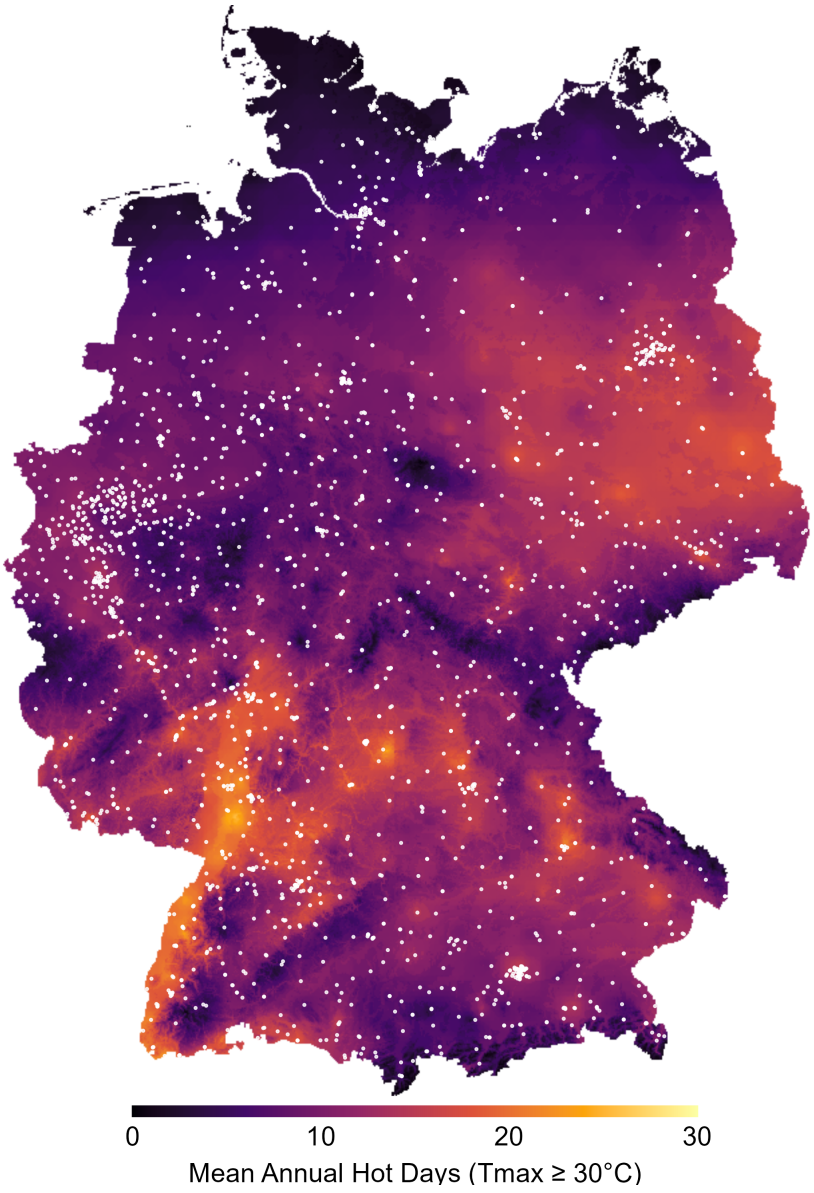
Notes: The table reports summary statistics for the final estimation sample. The unit of observation is a hospital admission. Dehydration and kidney failure are indicators equal to one if dehydration or kidney failure are recorded during the hospital stay among patients without them being coded at admission. Binary variables are reported as proportions. The Elixhauser comorbidity score is measured using information from the year before admission and based on Quan et al. (2005). Annual inpatient cases and hospital beds are measured at the hospital-year level.

Figure A.1: Distribution of Daily Maximum Temperature Across Hospital-Days



Notes: The figure shows the distribution of daily maximum temperature across hospital-days in the estimation sample. The vertical axis reports the share of hospital-days in each temperature bin. Temperature is assigned to hospitals based on their geographic location using HOSTRADA, a 1 km^2 gridded weather dataset provided by the German Weather Service (DWD).

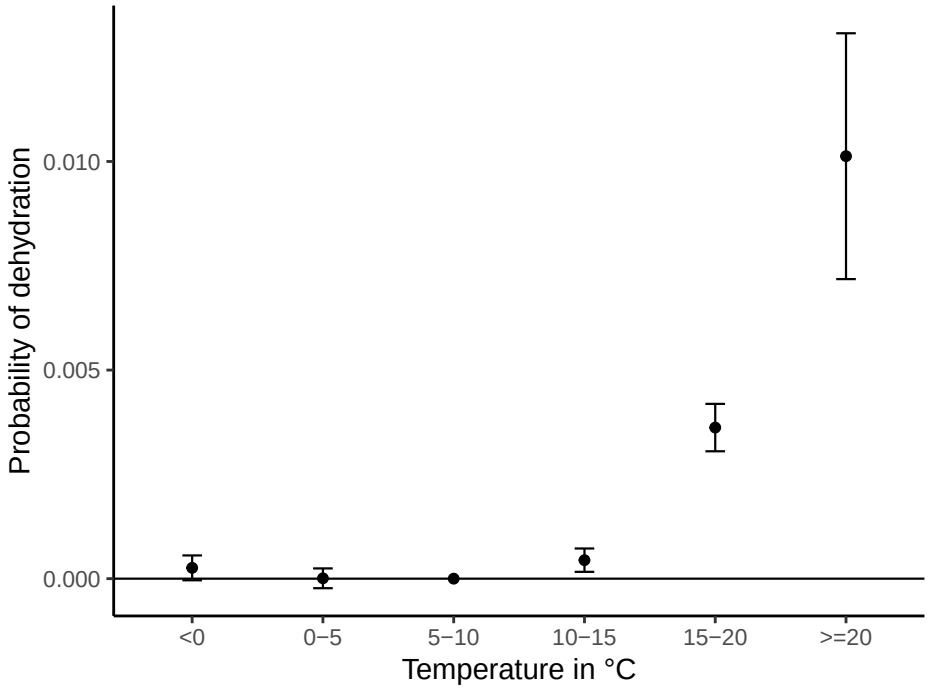
Figure A.2: Hospital Locations and Exposure to Extreme Heat



Notes: The figure shows the spatial distribution of hospitals in the estimation sample and local exposure to extreme heat. White dots indicate hospital locations. The background raster shows the mean annual number of hot days, defined as days with daily maximum temperature of at least 30°C, averaged over the period 2005–2025. Weather data come from HOSTRADA, a 1 km^2 gridded dataset provided by the German Weather Service (DWD).

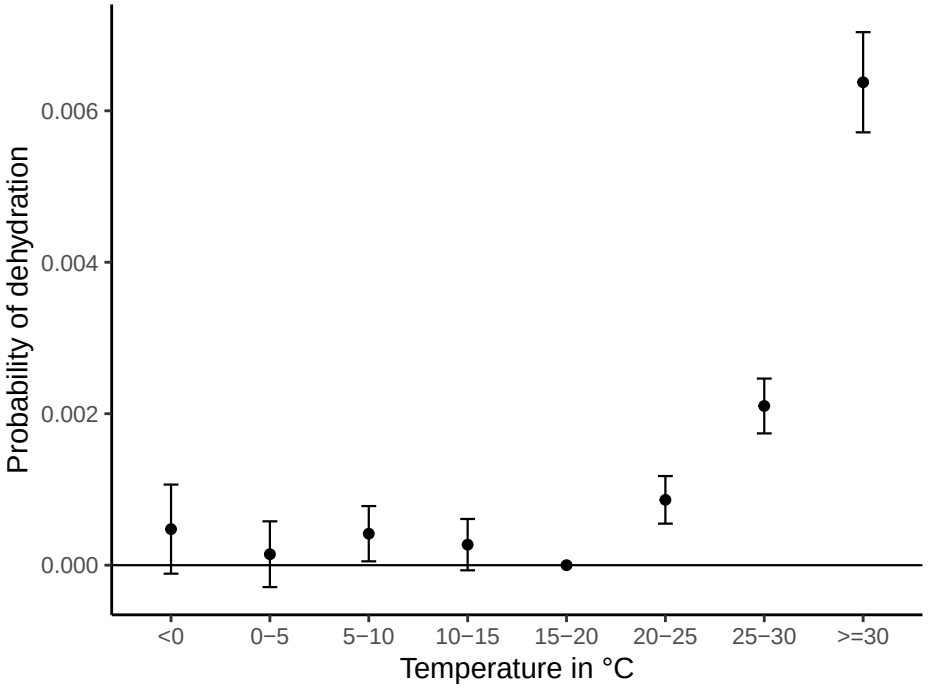
B Additional Analyses

Figure B.1: Nighttime Temperature Exposure During Hospitalization and Hospital-Acquired Dehydration



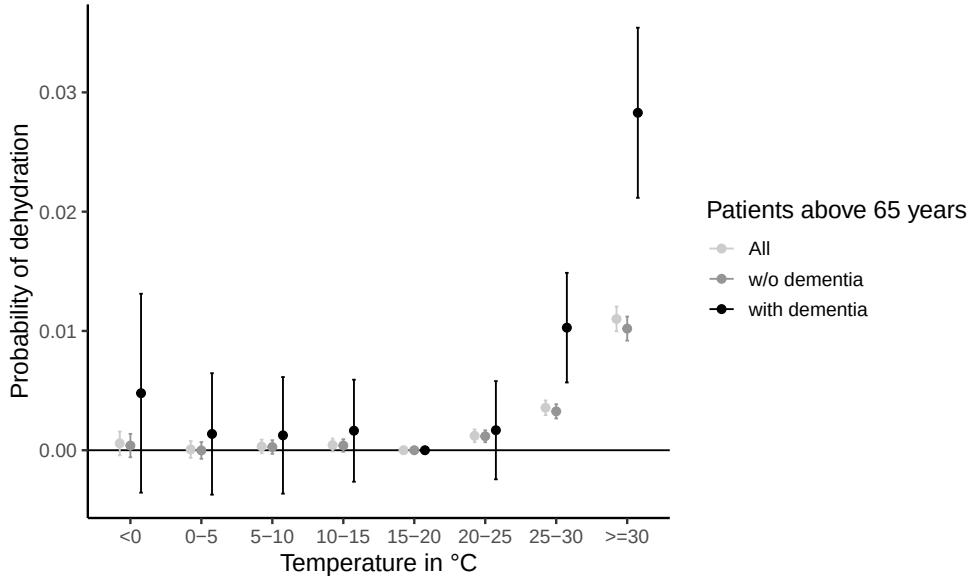
Notes: The figure reports coefficient estimates from a specification analogous to Equation (1), replacing daily maximum temperature with nighttime temperature measured as daily minimum temperature. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each nighttime temperature bin. The reference category is 5–10°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.2: Temperature Exposure and Hospital-Acquired Dehydration Excluding the COVID-19 Period



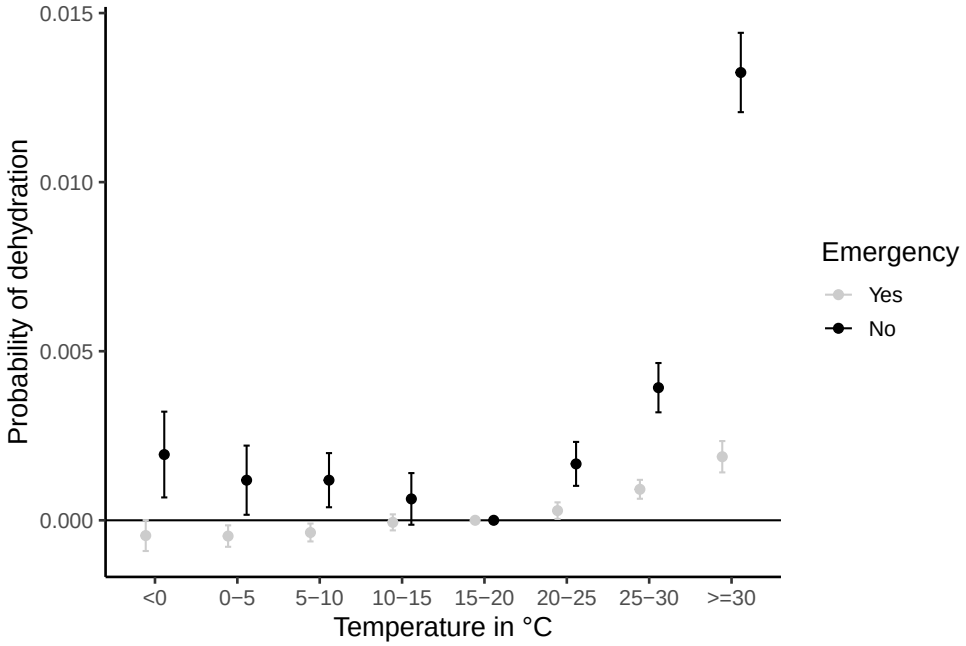
Notes: The figure reports coefficient estimates from the baseline specification after excluding admissions during the COVID-19 period, defined as the years 2020 to 2022. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.3: Heterogeneity by Dementia Status among Patients Aged 65 and Older



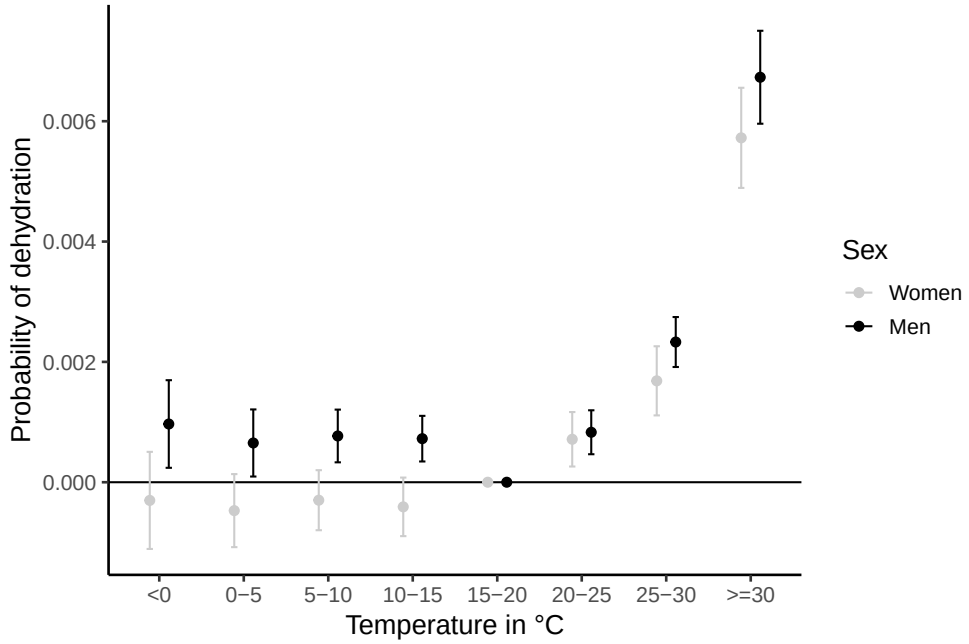
Notes: The figure reports coefficient estimates from variants of Equation (1) for patients aged 65 and older, for the full subsample and separately by dementia status. Dementia is defined based on an inpatient diagnosis during the year prior to admission. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.4: Heterogeneity by Emergency Admission



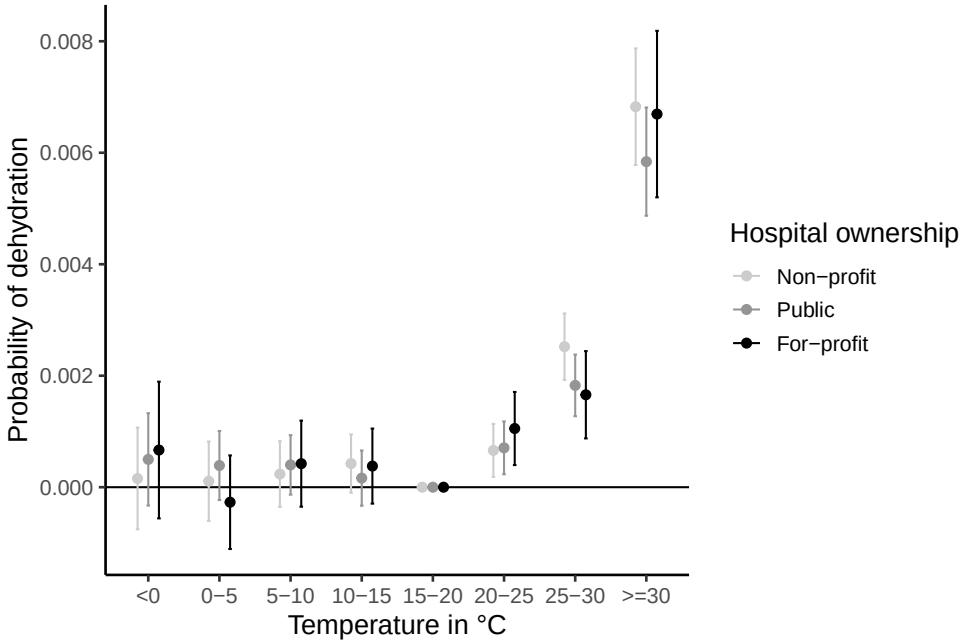
Notes: The figure reports coefficient estimates from variants of Equation (1) estimated separately by emergency admission status. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.5: Heterogeneity by Sex



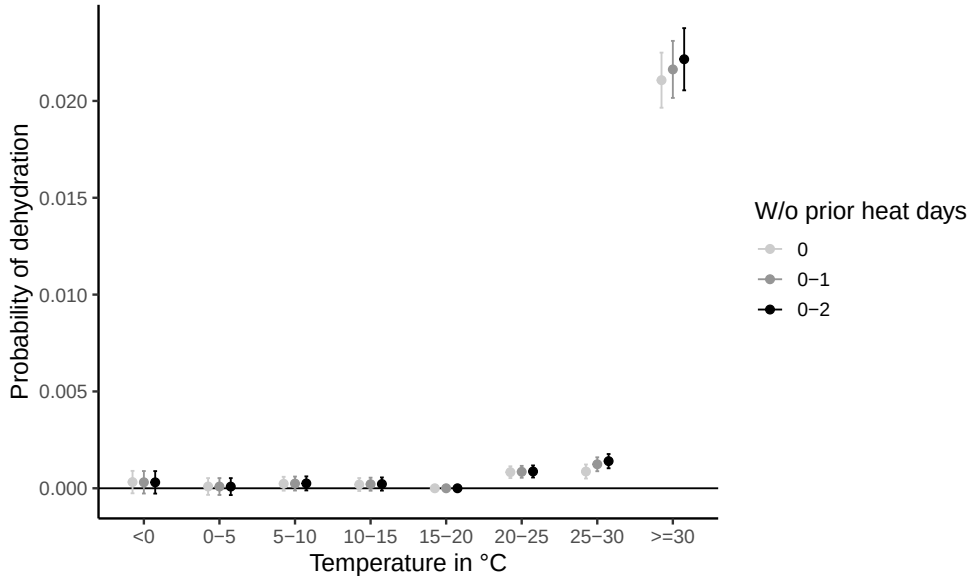
Notes: The figure reports coefficient estimates from variants of Equation (1) estimated separately by sex. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.6: Heterogeneity by Hospital Ownership



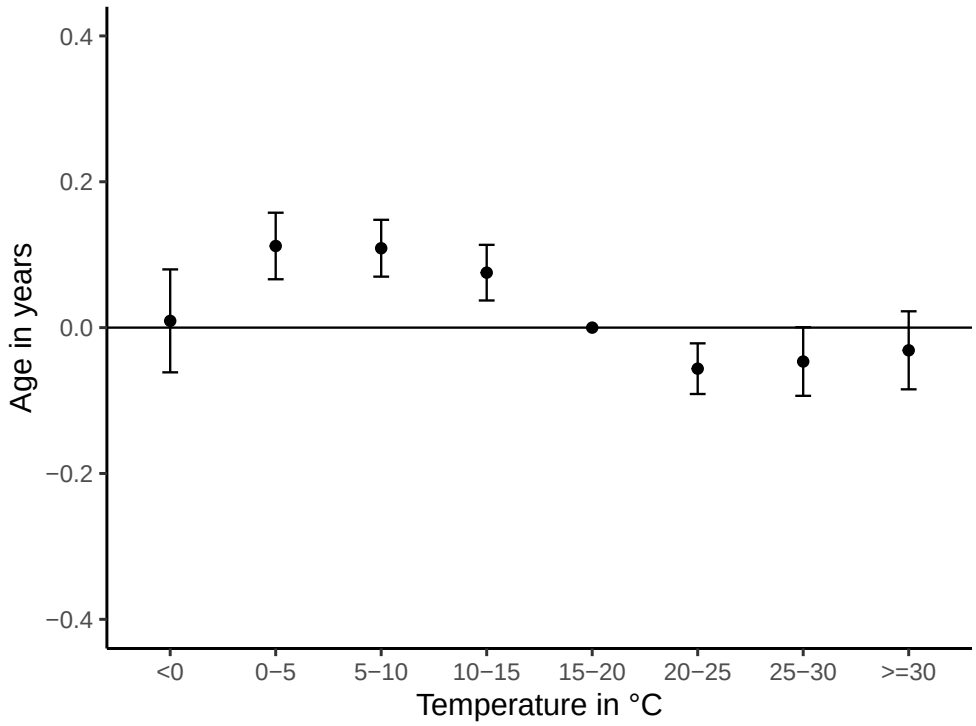
Notes: The figure reports coefficient estimates from variants of Equation (1) estimated separately by hospital ownership type. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.7: Temperature Exposure and Hospital-Acquired Dehydration Excluding Admissions with Prior Heat Exposure



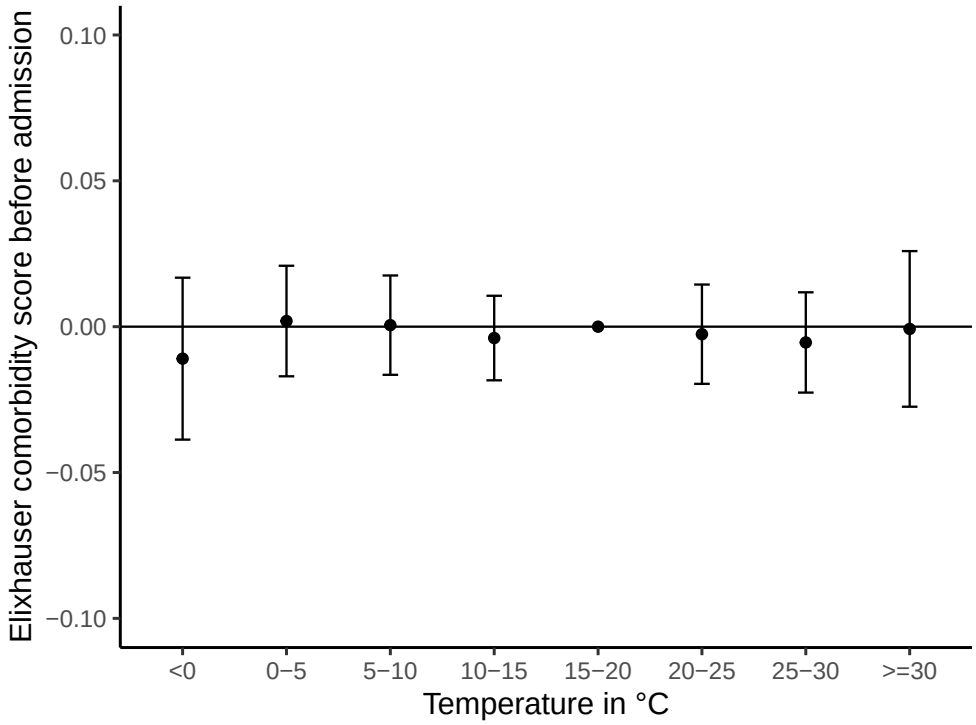
Notes: The figure reports coefficient estimates from variants of Equation (1) that exclude admissions with recent extreme heat exposure before or at admission. The specification labeled "0" excludes admissions with extreme heat on the admission day. The specification labeled "0–1" excludes admissions with extreme heat on the admission day or the previous day. The specification labeled "0–2" excludes admissions with extreme heat on the admission day or either of the two previous days. Extreme heat is defined as a daily maximum temperature above 30°C. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. All specifications include patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.8: Temperature Exposure and Patient Age at Admission



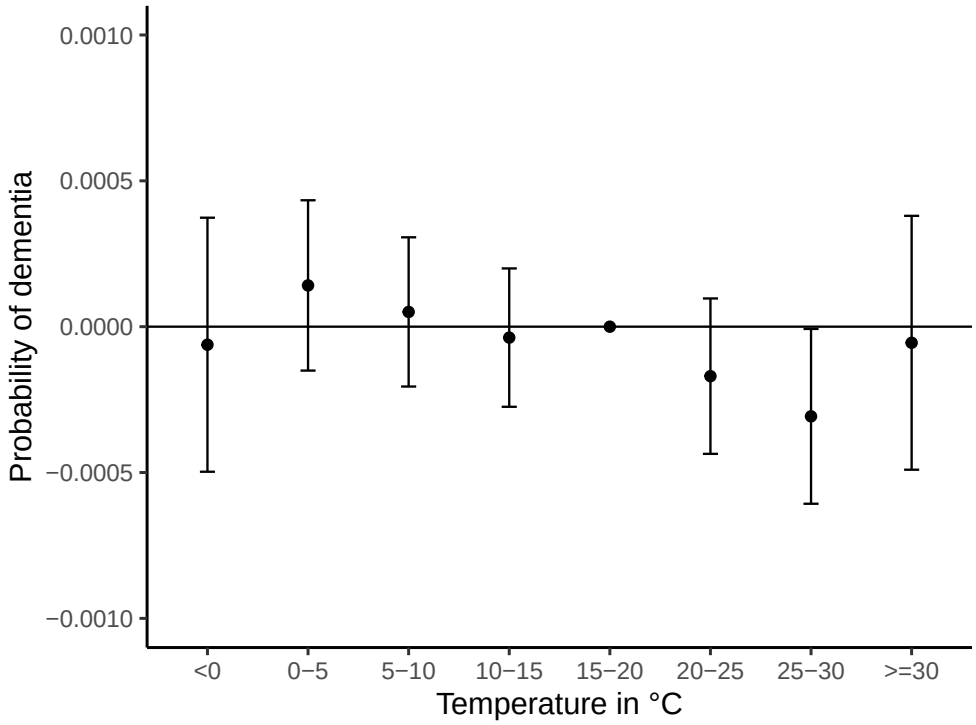
Notes: The figure reports coefficient estimates from a balancing test using Equation (1), where the dependent variable is the patient's age at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. The specification includes hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.9: Temperature Exposure and Pre-Admission Comorbidities



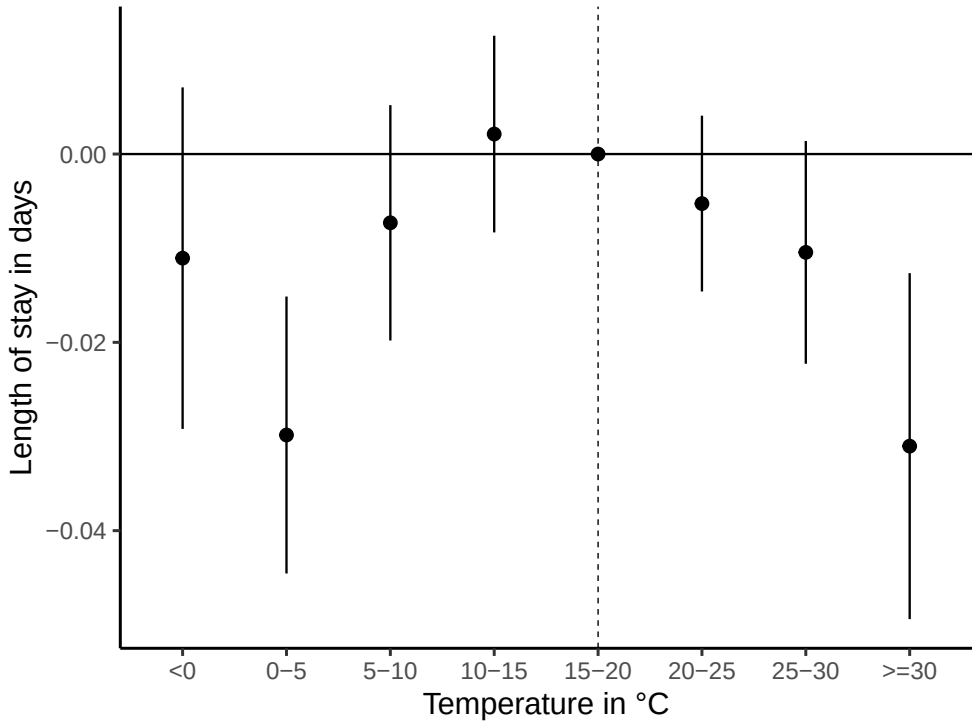
Notes: The figure reports coefficient estimates from a balancing test using Equation (1), where the dependent variable is the patient's Elixhauser comorbidity score measured in the year prior to admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. The specification includes hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.10: Temperature Exposure and Dementia Diagnosis



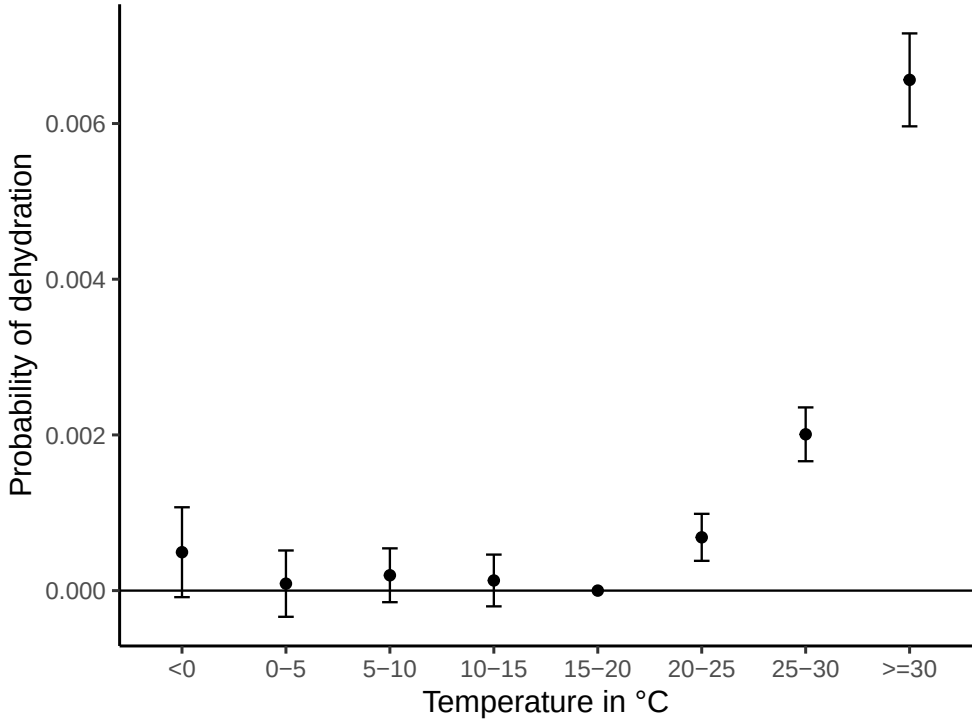
Notes: The figure reports coefficient estimates from a balancing test using Equation (1), where the dependent variable is an indicator equal to one if the patient has a dementia diagnosis in the year prior to admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. The specification includes hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.11: Admission-Day Temperature and Length of Stay



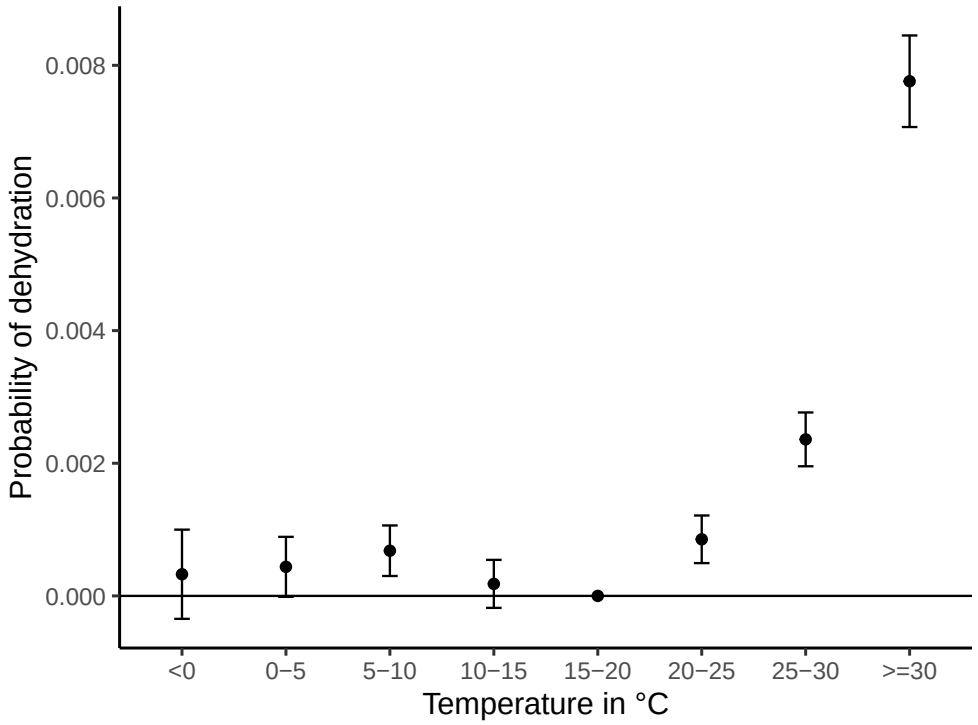
Notes: The figure reports coefficient estimates from a specification using length of stay, measured in days, as the dependent variable. Temperature exposure is measured using the daily maximum temperature on the day of admission. The reference category is 15–20°C. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.12: Temperature Exposure and Hospital-Acquired Dehydration with Length-of-Stay Fixed Effects



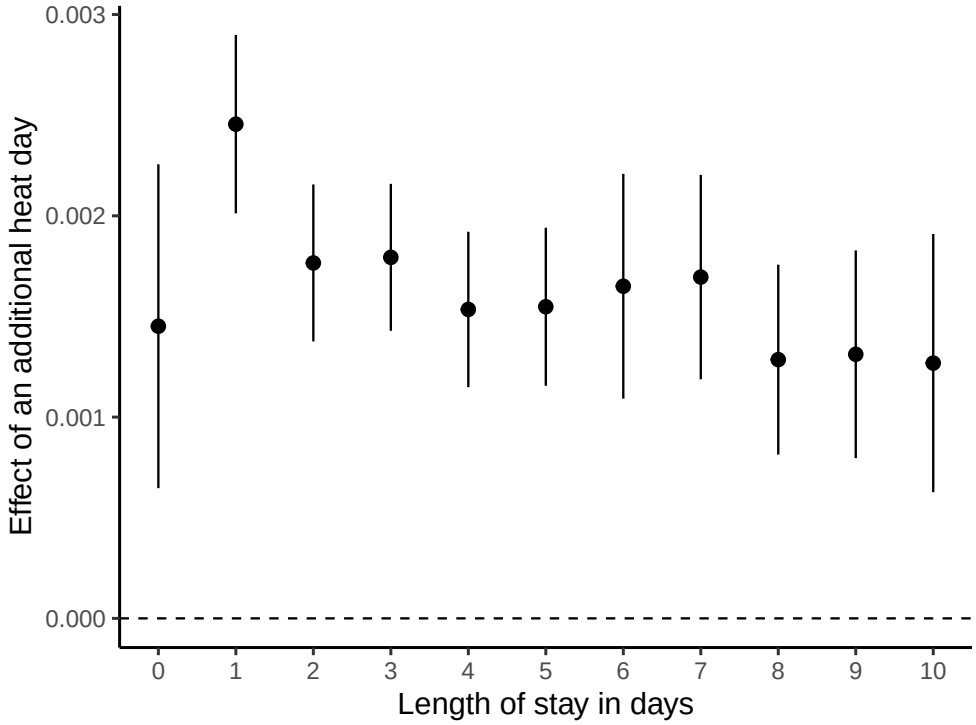
Notes: The figure reports coefficient estimates from a variant of Equation (1) that additionally includes fixed effects for each length-of-stay duration. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.13: Temperature Exposure During First Three Days of Admission and Hospital-Acquired Dehydration



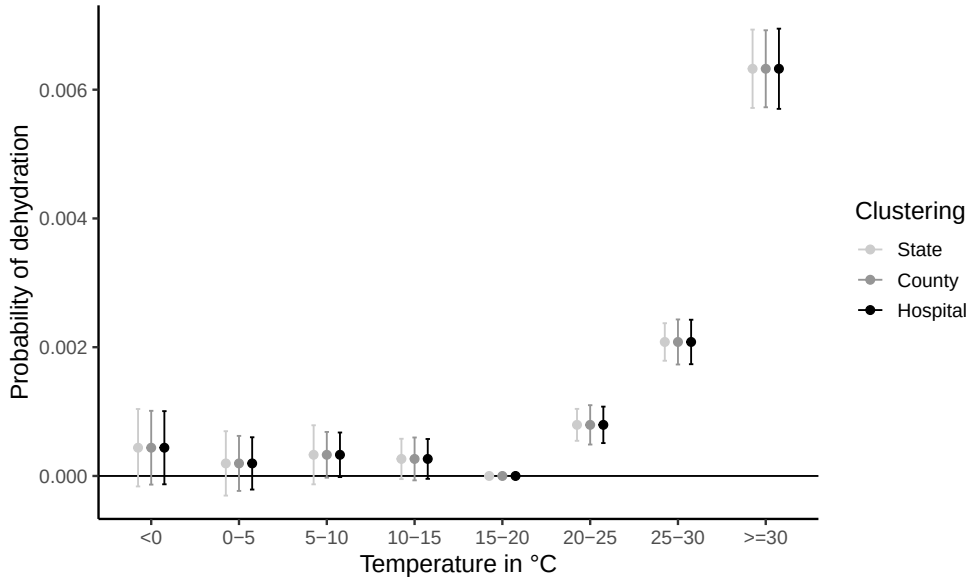
Notes: The figure reports coefficient estimates from Equation (1), where the temperature exposure is measured over the first three days of admission only and the sample is restricted to stays of at least three days. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Each coefficient shows the percentage point change in risk of hospital-acquired dehydration of an additional day in bin b relative to the reference bin $15 - 20$°C on the first three days of admission. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.14: Effect of an Additional Hot Day by Length of Stay



Notes: The figure reports coefficient estimates separately by realized length of stay. Temperature exposure is measured as the number of inpatient days in each daily maximum temperature bin rather than as the share of inpatient days. The reference category is 15–20°C, such that the reported coefficients capture the effect of an additional day above 30°C relative to an additional day in the reference category. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. The sample is restricted to stays of ten days or fewer, which account for approximately 80 percent of admissions. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. Each specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are clustered at the county level.

Figure B.15: Robustness of Main Results to Alternative Clustering



Notes: The figure reports coefficient estimates from Equation (1) to demonstrate robustness to alternative geographic clustering choices. The dependent variable is an indicator equal to one if dehydration is recorded during the hospital stay among patients without dehydration coded at admission. Temperature exposure is measured as the share of inpatient days in each daily maximum temperature bin. The reference category is 15–20°C. Coefficients are reported in probability units; a coefficient of 0.01 corresponds to 1 percentage point. The specification includes patient controls, pre-admission comorbidity controls, hospital fixed effects, primary diagnosis fixed effects, year-by-month fixed effects, day-of-week fixed effects, and holiday indicators. Vertical bars indicate 95 percent confidence intervals. Standard errors are re-estimated at the hospital, county, and state levels.