Ambient Temperature and the Risk of Hospital-Acquired Infections*

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Abstract

This study estimates how short-run exposure to extreme temperatures affects hospital-acquired infections (HAIs). Using German administrative health data (2005–2023) linked to local weather, I exploit quasi-random daily temperature variation during the first three days of admission. I find that extreme heat significantly increases HAI risk: each day $\geq 30°$C raises infection probability by 0.06 percentage points (1.43 percent), while extreme cold reduces it. These effects are concentrated among vulnerable patients, high-risk procedures, smaller hospitals, and historically cooler regions. These findings highlight a critical clinical channel through which climate change impacts healthcare systems.

Keywords: Heat; Hospital-acquired infections; Inpatient Healthcare; Climate change
JEL Codes: I10, I11, Q51

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1 Introduction

Climate change is reshaping the conditions under which economic and social life unfolds, with human health among its most consequential dimensions. Rising global temperatures have already contributed to increased mortality (Deschênes & Greenstone, 2011), reduced economic productivity, and growing healthcare expenditures (Carleton & Hsiang, 2016), with wide-ranging economic consequences (Burke et al., 2015). Extreme heat events, in particular, are projected to increase substantially in frequency, duration, and intensity across Europe over the coming decades (Rousi et al., 2022). Understanding how and why these shifts translate into measurable health and healthcare costs is therefore a central question at the intersection of environmental and health economics—and one with direct implications for how healthcare systems prepare for a future under the impact of climate change.

A substantial economics literature documents the health consequences of temperature shocks. Deschênes and Greenstone (2011) provide foundational evidence that short-run temperature fluctuations affect mortality in the United States, with effects concentrated among the elderly and during summer months. Karlsson and Ziebarth (2018) show for Germany that extreme temperatures increase both mortality and healthcare utilization across a broad range of conditions, and White (2017) documents the dynamic relationship between temperature and morbidity, showing that heat increases emergency department visits and associated healthcare costs, with effects that persist and accumulate in the days following a temperature shock. Taken together, this literature has established that temperature shocks generate substantial demand-side pressure on healthcare systems: they bring more patients through the door and raise overall utilization. Yet while the demand side of healthcare has received considerable attention, the supply side—the quality and conditions of care delivered once patients are admitted—remains comparatively underexplored.

This paper addresses that gap. I argue that temperature shocks affect not only healthcare demand but also the supply of inpatient care, by altering the conditions under which hospitals provide treatment. I use hospital-acquired infections (HAIs)—infections that develop during and are attributable to a hospital stay—as my primary measure. HAIs are among the most frequent and costly complications of inpatient care, with an estimated 4.3 million cases annually across European hospitals (ECDC, 2024) and around 10,000 to 20,000 associated deaths per year in Germany alone (Zacher et al., 2019). Crucially, a substantial share of these infections—approximately 30 percent—is considered preventable through adherence to hygiene protocols and effective care organization (Richter-Kuhlmann, 2012, Walger et al., 2013). This preventability is what makes HAIs a meaningful outcome to analyze in inpatient care: HAI incidence is sensitive to both biological factors—including temperature-sensitive pathogen dynamics and patient immune responses—and to care processes such as hygiene compliance and staff behavior. This makes them a suitable outcome for studying how ambient temperature affects inpatient care. Prior economic work on the supply side has already shown that extreme heat increases hospital admissions and that the resulting congestion and capacity constraints worsen patient outcomes, including through early discharge and excess mortality (Aguilar-Gomez et al., 2025). Other research using data from China finds that hospitals mitigate potential adverse effects through adjustments in the medical workforce, with no negative effects of temperature fluctuations on length of stay or mortality (W. Wu et al., 2025). I extend this research by examining a clinically

important outcome that is less severe than mortality, more directly linked to care processes, and partly preventable—and by providing novel large-scale evidence on how ambient temperature affects this dimension of inpatient care.

Several non-mutually exclusive channels plausibly connect ambient temperature to inpatient HAIs. On the supply side, a large literature documents that heat impairs cognitive performance, increases fatigue, and reduces the precision of task execution (Berg et al., 2015, Heyes & Saberian, 2019, Seppänen et al., 2006). If medical staff experience heat-related performance decrements, adherence to infection prevention protocols—hand hygiene, sterile technique, device management—may deteriorate at the margin, with direct consequences for HAI risk. A second supply-side channel operates through congestion: extreme heat increases hospital admissions (Aguilar-Gomez et al., 2025, Karlsson & Ziebarth, 2018), raising workload per staff member and potentially crowding out the time-intensive processes that infection prevention requires (Walger et al., 2013). On the patient side, heat-induced physiological stress may impair immune responses and wound healing, particularly among older and clinically vulnerable patients (Cheng et al., 2019, Witt et al., 2015). Finally, ambient temperature may directly affect pathogen dynamics: warmer conditions are associated with increased bacterial prevalence and altered skin microbiome composition—though the precise biological and behavioural pathways through which temperature affects HAI risk remain poorly understood (Anthony et al., 2017, 2018, Manian, 2016, McBride et al., 1977, Schwab et al., 2014). These channels may reinforce one another, amplifying the overall effect of temperature on HAI risk.

To identify the effect of temperature on HAI risk, I combine individual-level administrative health insurance data covering 41.5 million inpatient cases from 2005 to 2023 with high-resolution weather data from the German Weather Service. The empirical strategy exploits day-to-day variation in local temperature at the first three days of admission within hospitals, controlling for detailed hospital and time fixed effects. In addition, I utilize patient-specific, clinically relevant characteristics such as primary diagnosis as well as pre-admission morbidity to account for weather-related differences in patient composition and ensure comparisons across patients admitted for similar conditions and with a similar health status.

The results show that extreme heat significantly increases the risk of HAIs. Each additional day with maximum temperatures of at least 30°C during the first three days of hospitalization raises the probability of an HAI by 0.06 percentage points—a 1.43 percent increase relative to the mean. Exposure to extreme cold (<0°C), by contrast, reduces infection risk. These small, but precisely estimated effects are concentrated among older and clinically vulnerable patients and among hospitalizations involving procedures with elevated baseline infection risk, such as catheterization and joint replacement. Analysis by infection type shows the results are primarily driven by urinary tract infections (UTIs). At the hospital level, effects are stronger in smaller hospitals and in regions historically less exposed to high temperatures, consistent with limited adaptation capacity. Stratifying by hospital-specific workload reveals no systematic differences across low- and high-congestion weeks, suggesting that observable capacity constraints are unlikely to be the primary driver. Similarly, stratifying hospitals by a hospital-specific HAI-risk score reveals no systematic differences in the effects.

A back-of-the-envelope calculation suggests that heat-induced HAIs generate additional hospital costs of up to 10 million Euro per year in Germany under current climate conditions. Under projected increases in the frequency of extreme heat days, these costs could rise to approximately

18 million Euro annually by 2060. These numbers represent a modest fraction of system-wide spending on inpatient care of around 102 billion Euro in 2024 (GKV-Spitzenverband, 2026).

This paper makes three contributions. First and most centrally, it provides novel large-scale causal evidence that ambient temperature affects the conditions under which inpatient care is provided. While prior economic work on the supply side has shown that extreme heat generates hospital congestion that worsens outcomes through early discharge and excess mortality (Aguilar-Gomez et al., 2025), I show that temperature affects a clinically meaningful inpatient outcome—HAI risk—that is less severe than mortality, directly linked to care processes, and partly preventable. This shifts the focus from capacity strain to a margin that becomes increasingly policy-relevant as the frequency of extreme heat days rises. Second, I contribute to the broader literature on temperature and health, which documents substantial effects of extreme heat on health and healthcare demand (Karlsson & Ziebarth, 2018, White, 2017). I show that temperature shocks directly affect a particularly vulnerable population in terms of outcomes other than mortality. Third, I complement epidemiological studies documenting seasonal and temperature-related variation in HAIs (Aghdassi et al., 2019, Anioke et al., 2025, Anthony et al., 2017, 2018, Damonti et al., 2023, Duscher et al., 2018, Eber et al., 2011, Froschauer et al., 2021, Schwab et al., 2014, 2020, Y. Wu et al., 2023). This paper provides causal evidence based on large-scale, patient-level administrative data and within-hospital daily temperature variation rather than aggregate seasonal correlations.

The findings have direct policy implications. Germany, like many European countries, faces increasing exposure to extreme heat, while adaptation of hospital infrastructure remains incomplete; for example, only a minority of hospitals report air-conditioned patient rooms (Filser & Levsen, 2022). Much of the existing literature has found heat primarily as a driver of increased healthcare demand and capacity strain. The results presented here show that temperature shocks affect clinically meaningful inpatient outcomes describing the supply side of healthcare. Heat therefore has implications not only for the volume of care delivered, but also for the conditions under which care is provided and for patients' recovery processes during hospitalization. Climate adaptation in the hospital sector—including infrastructure, cooling capacity, and organizational responses—may thus play an important role in safeguarding patient safety and maintaining optimal care environments under rising temperatures.

The remainder of the paper is structured as follows. Section 2 provides medical background on HAIs. Section 3 describes the data sources. Section 4 outlines the empirical strategy. Section 5 presents the results, including robustness and heterogeneity analyses as well as an overview of mechanisms and a back-of-the-envelope cost estimation. Section 6 concludes.

2 Medical Background on Hospital-Acquired Infections

HAIs, also referred to as nosocomial infections, are infections that occur in direct connection with an inpatient hospital stay (RKI - Robert Koch Institut, 2016). An infection is classified as hospital-acquired if it was neither present nor incubating at the time of admission. Operationally, infections are considered hospital-acquired if symptoms first appear on or after the third day following admission (KRINKO, 2020). While HAIs can occur across a range of healthcare settings, this paper focuses exclusively on the inpatient hospital setting.

HAIs are frequent and clinically significant complications of inpatient care. In Germany, it is estimated that between 400,000 and 600,000 patients acquire an HAI each year, with approximately 10,000 to 20,000 associated deaths (Gastmeier et al., 2010, Geffers & Gastmeier, 2010, Zacher et al., 2019). Beyond mortality, HAIs complicate treatment and increase treatment costs (Arefian et al., 2016, Dietrich et al., 2017, Roberts et al., 2010, Walger et al., 2013). The associated economic costs are substantial: annual treatment costs are estimated at approximately 1.5 billion Euro in Germany and seven billion Euro across the European Union (Dietrich et al., 2017). At the individual case level, a hospitalization with an HAI incurs estimated additional costs of between 5,000 and 10,000 Euro compared to an equivalent stay without infection (Arefian et al., 2016). HAIs therefore represent both a patient safety issue and a measurable component of inpatient care.

HAIs may arise from endogenous pathogens originating from the patient's own microbiota or from exogenous pathogens transmitted within the hospital environment (Augurzky et al., 2021, Gastmeier et al., 2010, Geffers & Gastmeier, 2010). Exogenous transmission occurs through contact with healthcare personnel, visitors, contaminated surfaces, or medical devices (Augurzky et al., 2021, Gastmeier, 2012).

Risk factors for HAIs include patient characteristics such as age and pre-existing conditions, as well as intervention-related factors including invasive devices (e.g., catheters) and impaired wound healing (Augurzky et al., 2021, Gastmeier, 2012).

Because in-hospital transmission plays a central role, infection risk is closely linked to hygiene practices, staff behavior, and organizational conditions. The medical literature emphasizes that a substantial share of nosocomial infections is preventable. Approximately 30 percent of exogenously caused infections are considered avoidable through effective and consistently implemented preventive measures (Augurzky et al., 2021, Dietrich et al., 2017, Walger et al., 2013). Prevention relies heavily on adherence to hygiene protocols, including hand hygiene, protective equipment, and proper management of invasive devices.

While patient vulnerability and invasive procedures contribute to infection risk (Dietrich et al., 2017), organizational and staffing conditions are also central determinants. Because transmission frequently occurs via healthcare personnel (Gastmeier, 2012), compliance with hygiene standards depends on staff workload, time constraints, and institutional oversight. Staffing levels, workload, and care organization are associated with infection incidence (Walger et al., 2013). In this sense, HAIs can be interpreted as an outcome sensitive to both clinical complexity and the effective functioning of care processes.

HAIs are common, partly preventable outcomes that depend not only on patient characteristics but also on hygiene compliance, staffing conditions, and organizational processes. Their definition relative to admission timing (KRINKO, 2020) allows infections to be attributed to in-hospital exposure, while their documented prevention potential (Dietrich et al., 2017, Walger et al., 2013) underscores the role of hospital-level practices. These features make HAIs a suitable outcome for analyzing how external factors that affect working conditions and care processes may translate into measurable changes in inpatient care.

3 Data

3.1 Administrative Health Data

The primary data source consists of administrative health insurance records from one of Germany's largest statutory health insurers, covering approximately nine million individuals between 2005 and 2023, corresponding to more than ten percent of the German population. The dataset includes 41.5 million inpatient cases and contains detailed information on admission and discharge dates, diagnoses (ICD-10-GM), procedures (classified by the German procedure classification system OPS), and patient characteristics such as age and sex. Hospital characteristics, including location, bed capacity, and ownership type, are merged from administrative German hospital quality reports.

3.2 Weather Data

Hospital admissions are matched to high-resolution weather data from HOSTRADA, a 1 km^2 gridded dataset provided by the German Weather Service (DWD) (Krähenmann et al., 2018). Daily maximum temperature and humidity are assigned to each hospital-day based on geographic location. I add raster data on air pollution ($PM_{2.5}$) created from satellite images by Shen et al. (2024) as an additional optional control variable.

3.3 Sample Restrictions

For the final sample, I first exclude transfers and special admission categories, dropping 6 million observations. Following Augurzky et al. (2021), the analysis is restricted to inpatient cases with a minimum length of stay of three days, retaining 5.6 million cases. Infections are classified as hospital-acquired if symptoms first appear on or after the third day of hospitalization (KRINKO, 2020). The three-day minimum stay is therefore necessary to align the empirical design with these surveillance standards, given that I do not observe the precise timing of diagnoses. This restriction limits potential misclassification arising from infections already present or incubating at admission. To further reduce this likelihood, I additionally exclude cases with infectious principal or admission diagnoses, removing a further 3.8 million observations (see Table A.1).

After applying these restrictions, the final sample consists of 25.8 million inpatient cases across approximately 2,000 hospitals.

3.4 Definition of Hospital-Acquired Infections

Hospital-acquired infections are identified using secondary diagnosis codes. Following Augurzky et al. (2021)[1], an HAI is defined as the co-occurrence of at least one infection diagnosis and a corresponding pathogen or trigger code (see Table A.2). The ICD-10 code A04.7 (Clostridioides difficile enterocolitis) qualifies as an HAI without requiring an additional pathogen code. The combination of the sample restrictions and the use of secondary diagnosis codes provides a conservative approximation of hospital-acquired infections.

[1]This report on the German hospital sector utilizes a selection of ICD-10-GM diagnoses composed by healthcare professionals.

3.5 Descriptive Statistics

Table 1 presents summary statistics for the final sample. The average patient is 59 years old, 61 percent are female, and the mean length of stay is nine days. The incidence of hospital-acquired infections is 4.2 percent, slightly lower but consistent with national estimates of 4.9 percent (Aghdassi et al., 2024). Figure A.1 shows that there is a sufficient share of admissions happening on days of extreme daily temperatures. Based on previous literature exploring the relationship between ambient temperature and health, I expect the largest effects to occur at extreme daily temperatures (Aguilar-Gomez et al., 2025, White, 2017). Approximately six percent of admissions occur on days below 0°C or above 30°C. Figure 1 illustrates the spatial distribution of 2,027 German hospitals alongside the annual frequency of extreme temperature events averaged over the 2005–2023 period. The left panel depicts the mean number of days below 0°C, while the right panel shows the mean number of days above 30°C. As evident from the maps, there is a broad geographical distribution of hospitals experiencing significant variation in climate exposure.

Table 1: Descriptive Statistics

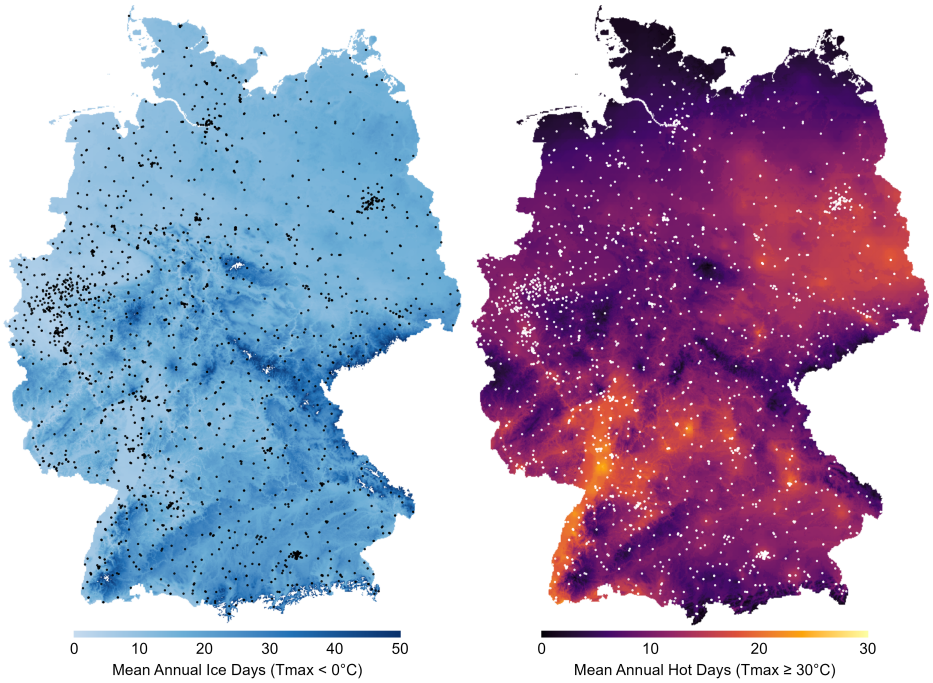
	Mean	SD
Length of stay (days)	9.0068	12.4910
Inpatient cost (EUR)	4,693	8,194
Age (years)	59.0680	23.8786
Pre-admission cost (EUR)	4,828.0	12,499.9
Hospital beds	547.1597	468.7876
	Share	
Hospital-acquired infection	0.0422	
Female	0.6114	
Emergency admission	0.4015	
In-hospital death	0.0180	
Charlson comorbidity		
0	0.7063	
1–2	0.0218	
3–4	0.0200	
≥ 5	0.2519	

Notes: Sample size is $N = 25{,}822{,}015$.

To assess whether day-to-day temperature variation is accompanied by systematic changes in patient composition, I compare observable characteristics across admissions occurring on mild (15–20°C) versus extreme heat ($\geq$ 30°C) and extreme cold (<0°C) days. Prior literature documents that hospital admission volumes can respond to temperature shocks, potentially inducing compositional changes in hospitalized patients (Aguilar-Gomez et al., 2025, Karlsson & Ziebarth, 2018, W. Wu et al., 2025). Figure A.2 reports standardized mean differences between hospitalizations across these temperature bins, following Imbens and Rubin (2015). Almost none of the observable characteristics—including age, sex, pre-admission comorbidity, procedure risk index, and inpatient spending one year prior to admission—differ by more than 0.1 standardized mean differences across temperature categories. The only noticeable difference is

the binary indicator for a holiday on the day of admission, which is consistent with this balancing check not fully accounting for seasonality combined with a low number of public holidays during summer months. Overall, these patterns suggest that day-to-day temperature variation is not systematically associated with differences in the observable composition of patients admitted to hospital.

Figure 1: Temperature and hospital distribution in Germany



Notes: The maps show the mean number of annual ice days ($T_{max} < 0°$C, left) and hot days ($T_{max} \geq 30°$C, right) across Germany. White and black dots represent the locations of the 2,027 hospitals included in the analysis.

4 Empirical Strategy

I estimate the effect of ambient temperature on the probability of HAIs by exploiting high-frequency variation in local temperature at the time of admission within hospitals. The outcome variable Y_{iht} is an indicator equal to one if patient i, admitted to hospital h on day t, develops an HAI during the stay.

The treatment variable captures short-run temperature exposure during the first three days of hospitalization. Let $T_{iht}(b)$ denote the number of days of the first three days of hospitalization during which the daily maximum temperature falls into bin b.

Related studies using panel data often measure exposure as the number of days in each temperature bin over a predefined observation window, such as the period between survey waves (Albanese et al., 2025). In the hospital setting, however, using exposure over the full length of stay would mechanically link temperature exposure to infection-induced changes in length of stay. A regression of HAI risk on length of stay shows that—based on the model in Equation 1—an additional day in hospital significantly increases risk of getting an HAI by 0.46 percentage points. Restricting attention to the early phase of hospitalization avoids this concern and ensures that temperature exposure is predetermined with respect to the occurrence of HAIs. Focusing on the first three days also reflects clinical practice as diagnostic and procedural interventions

are typically concentrated in the early phase of hospitalization. I apply the same logic when conditioning on specific treatments only in the early phase of hospitalization in my heterogeneity analysis in Section 5.

Ambient temperature is modeled flexibly using 5°C bins, consistent with the literature on temperature and health (Aguilar-Gomez et al., 2025, Deschênes & Greenstone, 2011). The reference category corresponds to temperatures between 15°C and 20°C. The estimating equation is:

$$Y_{iht} = \sum_{b \in \mathcal{B} \setminus \{15\text{–}20\}} \beta_b T_{iht}(b) + \gamma' X_{iht} + \alpha_h + \delta_d + \lambda_{ym} + \varepsilon_{iht}, \tag{1}$$

where X_{iht} includes age, sex, day-of-week as well as holiday indicators and pre-admission comorbidity categories constructed from diagnoses recorded in the year prior to hospitalization. The fixed effects α_h absorb time-invariant hospital characteristics, δ_d capture primary diagnosis fixed effects at the three-digit ICD-10 level, and λ_{ym} are year-by-month fixed effects.

Year-by-month fixed effects absorb common seasonal patterns in infection risk and temperature that have been documented in epidemiological research (Aghdassi et al., 2019, Schwab et al., 2020), ensuring that identification relies on short-run deviations from typical seasonal trends. The inclusion of detailed, clinically meaningful and patient-specific diagnosis fixed effects and pre-admission comorbidity measures ensures that comparisons are made across patients admitted for similar conditions and with comparable underlying health status, taking into account that ambient temperature may affect the composition of admissions. Under the assumption that residual temperature variation within hospital-by-diagnosis cells is uncorrelated with unobserved determinants of infection risk, the coefficients β_b capture the effect of additional exposure to temperature bin b relative to the reference category.

The model is estimated using ordinary least squares. Standard errors are clustered at the two-digit ZIP code level to account for spatial correlation in temperature shocks.

As a check on the identifying assumption, I analyze potential effects of temperature on both patient composition and treatment selection. Specifically, I use the model proposed in Equation 1 and estimate the impact of temperature on patient composition based on multiple observables, including constructed variables. For this purpose, I exclude the variables I test for from the set of control variables. First, Figure A.3 suggests no clinically meaningful effect of temperature on patient age or pre-admission comorbidity within the baseline specification. Most importantly, for the extreme temperature bins, there are no significant differences compared to the baseline category of 15–20°C for either age or patient comorbidity. While there are statistically significant effects on patient age for medium-to-low temperatures (in the 0° to 15°C bins), the magnitude is small at up to 0.04 years per day of ambient temperature. Taken together, these results suggest that the observable composition of admissions does not vary with short-run temperature fluctuations conditional on the controls. Second, I examine whether ambient temperature affects the baseline infection risk of the treatments received by patients after admission. Because specific inpatient procedures and surgeries are associated with particularly high baseline risks of HAIs, systematic differences in treatment composition across temperature conditions could bias the estimated temperature effects. I address this concern by first testing whether exposure to extreme temperatures affects the probability of receiving specific high-risk treatments during the first three days of hospitalization. Specifically, I use indicators for early catheterization—a

procedure known to carry a high risk of HAI (Gastmeier, 2012)—and for hip or knee replacement as outcome variables. Figure A.4a shows no evidence that extreme temperatures affect the probability of catheterization. Figure A.4b likewise reports null effects for the probability of hip and knee replacement. To provide a broader assessment, I also use a baseline infection-risk index[2] constructed from treatments performed during the first three days of hospitalization as an outcome variable. As shown in Figure A.5, temperature has no systematic effect on this index. Moreover, physicians' treatment decisions may depend on unobservable patient characteristics. Therefore, the null results from these treatment-related balancing checks are consistent with comparable patient composition across temperature conditions in terms of unobservables.

I further conduct a range of robustness checks to assess the stability of the estimates. These include (i) more granular four-digit primary diagnosis fixed effects; (ii) alternative time fixed effects; (iii) additional weather and environmental controls such as humidity and fine particulate matter ($PM_{2.5}$); (iv) controlling for a procedure-specific infection risk index based on procedures performed during the first three days of hospitalization; (v) excluding emergency admissions to reduce risk of treatment selection; (vi) alternative clustering levels; (vii) exclusion of the COVID-19 years; (viii) excluding admissions with prior extreme temperatures; and (ix) including stays of less than three days. Across specifications, the estimated temperature effects remain stable in magnitude and statistical significance.

5 Results

5.1 Main Results

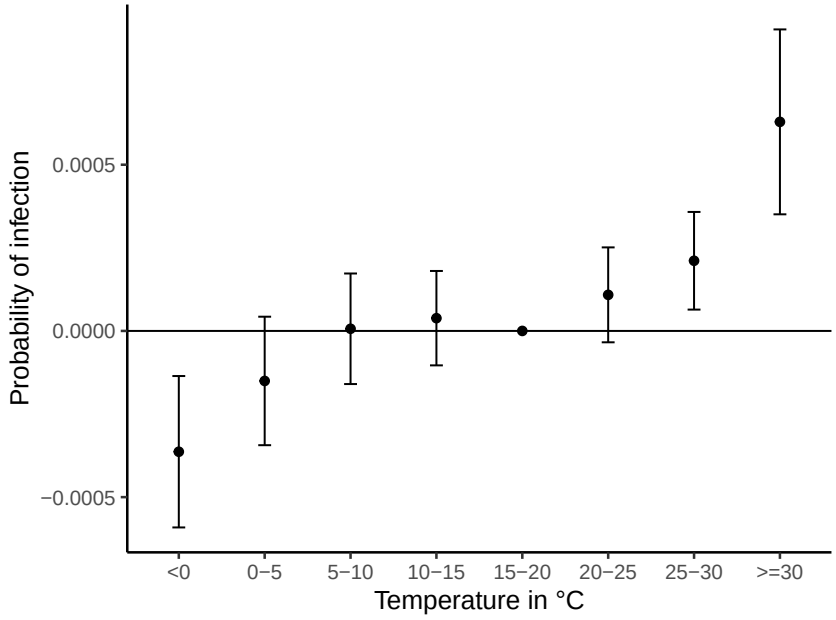
Figure 2 presents the estimated effects of temperature exposure during the first three days of hospitalization on the probability of hospital-acquired infection. Coefficients are expressed relative to the reference category of 15–20°C and represent the change in infection probability caused by one additional day of exposure to a given temperature bin.

Exposure to extreme heat significantly increases infection risk. Each additional day with maximum temperatures of at least 30°C during the first three days of hospitalization raises the probability of a hospital-acquired infection by 0.06 percentage points. Relative to the mean infection rate of 4.2 percent, this corresponds to an increase of approximately 1.43 percent. Therefore, a patient who experiences extreme heat on the day of admission and the two subsequent days faces an overall HAI risk of approximately 4.4 percent. Elevated but less extreme temperatures (25–30°C) also increase infection risk, although the magnitude is smaller. In contrast, exposure to extreme cold (maximum temperature below 0°C) reduces infection probability by 0.03 percentage points, corresponding to approximately 0.7 percent relative to the mean.

The overall pattern is increasing in temperature and aligns with epidemiological evidence documenting higher infection rates during warmer periods (Aghdassi et al., 2019, Damonti et al., 2023, Schwab et al., 2020). Building on this previous work, which primarily focuses on the aggregated and seasonal effects of HAI, my model specification captures short-run deviations in local temperatures. In general, my results indicate an almost linear relationship between ambient

[2]To predict the index I estimate a logit model consisting of the full set of three-digit OPS procedures (around 200) and time invariant controls on a sample of 1 million observations to predict a risk index of acquiring a hospital-acquired infection. I apply this model to my full sample to predict the risk index for every hospitalization.

Figure 2: Estimated effects of ambient temperature on risk of hospital-acquired infection



Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin 15–20°C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

temperature and risk of HAI similar to results in the epidemiological literature (Anthony et al., 2017) or the relationship of temperature and hospitalizations in Aguilar-Gomez et al. (2025).

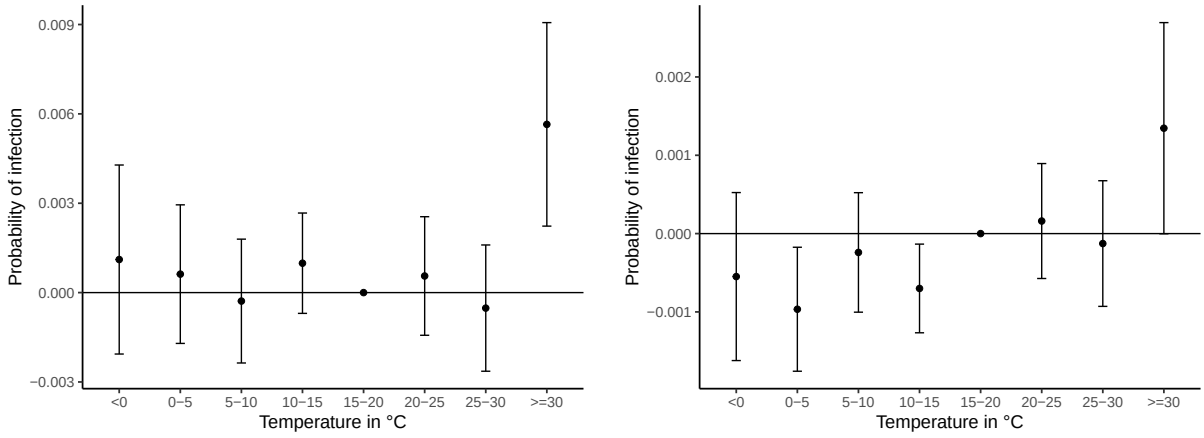
The individual-level effect is small in absolute as well as relative terms. A patient exposed to one additional extreme heat day during the first three days of hospitalization faces an infection probability of approximately 4.26 percent, compared to 4.2 percent under mild temperatures—a difference of 0.06 percentage points.

To translate the estimated effect into absolute terms, I combine the estimates with national hospitalization data. The average hospitalization in Germany experiences approximately 0.09 extreme heat days during the first three days of admission, given an annual average of 11.1 heat days in Germany in 2025 (Umweltbundesamt, 2025) and a uniform distribution of admissions across the year. Multiplying the per-day effect of 0.0006 by this average exposure and applying it to the 17.5 million inpatient cases recorded in Germany in 2024 (Statistisches Bundesamt, 2025) yields an estimate of roughly 945 additional heat-induced HAI cases per year under current climate conditions. To put this number into perspective, Germany recorded 695 cases of tick-borne encephalitis in 2024 (Deutsches Ärzteblatt, 2026). Despite this comparable incidence, tick-borne encephalitis is treated as a major public health threat: infections are subject to mandatory reporting, and vaccinations in designated risk areas are fully covered by statutory health insurance.

I also estimate the effect by treatment type. I condition the sample by treatments performed during the first three days of hospitalization before an infection is defined as an HAI to circumvent conditioning on a procedure caused by an HAI. Specifically, I analyze catheterizations (OPS 8-831) and hip and knee replacements (OPS 5-321 and 5-322). Catheterizations are well known for their high risk of HAIs and the relation of risk of surgical site infection to seasonality and ambient temperature has been researched for hip and knee replacements in epidemiological

literature before (Anthony et al., 2018, Damonti et al., 2023, Schwab et al., 2014). The risk of HAI in patients undergoing this type of catheterization is 17.6 percent compared to 4 percent in the rest of the sample. The overall share of catheterization on the first days of admission is 1.6 percent. Figure 3a shows that the effect of additional days of heat is significantly higher in cases with a performed catheterization. The estimated effect of an additional day of extreme heat is around 0.53 percentage points (3.1 percent). The effect of extreme cold, on the other hand, shows no significant results in this sub-sample. I find similar results for patients undergoing a joint replacement of their hip or knee (Figure 3b). While the baseline risk of HAI in this replacement sample is 3.1 percent compared to 4.3 percent in the rest of the sample, the estimated effect of an additional day of extreme heat is 0.13 percentage points (4.2 percent), though this result is only statistically significant at the 90 percent level. Notably, both the absolute and relative effects of extreme ambient heat for these specific treatment groups are substantially larger than the average effect across the full patient population. While the full sample exhibits an absolute increase of just 0.06 percentage points (a relative increase of roughly 1.4 percent) per extreme heat day, the relative heat penalty jumps to 3.1 percent for catheterizations and 4.2 percent for joint replacements. The negative effects for extreme cold do not show for these samples. This contrast highlights that patients undergoing invasive procedures are disproportionately vulnerable to temperature-driven infection risks.

Figure 3: Estimated effects by different treatment types



(a) Catheterization

(b) Joint replacement

Notes: This figure illustrates the estimated effect of an additional day in bin b relative to the reference bin 15–20 °C on the first three days of admission on HAI risk for patients being treated with a catheterization and joint replacement on the first three days of admission. HAI risk for cases with catheterization treatments is 17.6 percent and 3.1 percent for cases with joint replacements. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

5.2 Robustness Checks

I conduct a range of robustness analyses to assess the stability of the baseline specification in Equation 1.

First, I apply the model with additional covariates (Figure B.1). In a first step, I add patient specific controls. These include a procedure-specific infection risk index based on procedures performed during the first three days of hospitalization (see Section 4 for details on the index). The

procedure risk index captures heterogeneity in baseline infection risk associated with treatment intensity accounting for potential differences in patient composition or heat related differences in treatment while avoiding post-treatment bias by restricting attention to procedures performed before infections are classified as hospital-acquired. In a second step, I add local spatial controls such as humidity and fine particulate matter ($PM_{2.5}$). Finally, I add even more detailed patient-level controls containing fully saturated age-by-sex fixed effects. Across these specifications, the estimated heat effects remain stable in magnitude and statistical significance.

Second, I vary the fixed-effects structure (Figure B.2). Adding day-of-the-year fixed effects and state-by-year fixed effects, similar to specifications used in Aguilar-Gomez et al. (2025), does not materially change the estimates. Results are also robust to including saturated hospital-by-year-month fixed effects as done in W. Wu et al. (2025).

Third, I increase the granularity of primary diagnosis fixed effects. Figure B.3 shows that replacing three-digit ICD-10 fixed effects with four-digit codes leaves the results largely unchanged. Using only two-digit codes produces slightly noisier but qualitatively similar estimates.

Fourth, I assess sensitivity to alternative clustering levels (Figure B.4). Because temperature shocks are spatially correlated, I estimate standard errors at different geographic aggregation levels. Statistical significance remains robust across clustering choices.

Fifth, I exclude emergency admissions across temperature bins and re-estimate my model excluding cases with emergency admission (around 10 million observations). Changes in patient composition at extreme heat are partly caused by additional emergencies (Aguilar-Gomez et al., 2025, Karlsson & Ziebarth, 2018, White, 2017, W. Wu et al., 2025). Excluding these cases reduces the probability of unobservable selection since the remaining cases are those with elective or planned hospitalizations. Figure B.5 shows that the results remain robust even with the significantly reduced sample size and reduced risk of selection.

Sixth, excluding the COVID-19 years 2020–2022 does not materially alter the estimates (Figure B.6), indicating that the results are not driven by pandemic-related hospital dynamics.

Seventh, a potential concern is that the observed increase in HAI risk is driven by cumulative exposure to heatwaves prior to hospitalization rather than ambient temperature during the stay. Patients may be admitted already weakened by prior heat exposure, confounding the effect of the hospital environment with their pre-existing physiological strain. To address this, I iteratively exclude cases exposed to extreme heat for one to three days prior to admission. As shown in Figure B.7, the point estimates remain virtually unchanged compared to the baseline model. Although the confidence intervals widen—a mechanical consequence of the serial correlation of local temperatures and the reduced sample size—the stability of the coefficients confirms that short-run temperature exposure during the hospital stay independently drives the increase in infection risk.

Finally, a potential concern is that extreme temperatures might affect the probability of a patient remaining in the hospital for at least three days—for instance, due to heat-induced early mortality or expedited discharges during periods of high congestion. This could endogenously alter the composition of the sample at risk for an infection. To ensure the main findings are not driven by this sample attrition, I re-estimate the model including all hospital admissions regardless of their length of stay (adding around 5 million observations). Patients discharged before day three mechanically cannot develop a recorded hospital-acquired infection. By keeping them in the sample with an outcome of zero, I impose the most conservative possible assumption:

that every heat-induced early exit would have remained completely infection-free had their stay been prolonged. As Figure B.8 shows, even in this unconditional sample, the effect of extreme heat remains positive and statistically significant. This confirms that the results are robust to the potential competing risks of early exit.

5.3 Heterogeneity

Figure 4 presents heterogeneity analyses across patient and hospital characteristics.

Heterogeneity by age. To examine heterogeneous effects of temperature on the risk of HAI, I stratify the admissions by different age-groups. My results show that the heat effect is concentrated among older patients (Panel 4a). Patients younger than 45 show no statistically significant response to extremely low as well as high temperature, whereas patients above 45 experience progressively larger increases in infection risk. This pattern is consistent with age being a well-established risk factor for HAIs (Gastmeier, 2012) and older individuals being vulnerable to heat (Karlsson & Ziebarth, 2018). The absence of detectable effects among younger patients suggests that temperature shocks do not uniformly deteriorate healthcare outcomes, but instead interact with underlying patient vulnerability. This pattern is consistent with mechanisms operating through physiological susceptibility and heightened clinical risk among older patients holding constant the cause of treatment.

Heterogeneity by sex. When stratifying by sex, I find no statistically significant differences in effect sizes, with point estimates for extreme heat being slightly larger for men (Panel 4b).

Heterogeneity by procedure specific baseline risk. It is well established that HAI risk varies by treatment and surgery type (Rodriguez-Acelas et al., 2017). As shown previously in Figure 3, the effect size of temperature differs significantly for patients undergoing catheterization and joint replacements. Given the high dimensionality of potential treatment combinations during an inpatient stay, I additionally examine treatment heterogeneity based on the baseline HAI risk of procedures performed during the first three days of hospitalization. To do this, I utilize a procedure-specific infection risk index (detailed in Section 4) to stratify the sample into terciles (Panel 4c). The heat effect is heavily concentrated among cases in the highest tercile of baseline procedural risk, while low-risk procedures exhibit little to no response. Because the risk index is constructed from procedures performed prior to the HAI classification window, this heterogeneity reflects an interaction between early treatment-related vulnerability and temperature exposure. These results indicate that temperature shocks amplify existing clinical infection risks rather than affecting all hospitalizations uniformly.

Heterogeneity by infection type. To better understand the clinical drivers of the main result, I decompose the aggregate HAI definition into four mutually exclusive categories based on the ICD-10 codes from Table A.2: UTIs (N-codes), respiratory infections (J-codes), surgical site infections (T-codes), and other infections (remaining codes). Figure B.9 shows that the heat-induced increase in HAIs is almost entirely driven by UTIs. For an additional day of extreme heat, the risk of a UTI increases significantly, while the point estimates for respiratory and surgical site infections remain close to zero and statistically insignificant. This concentration of

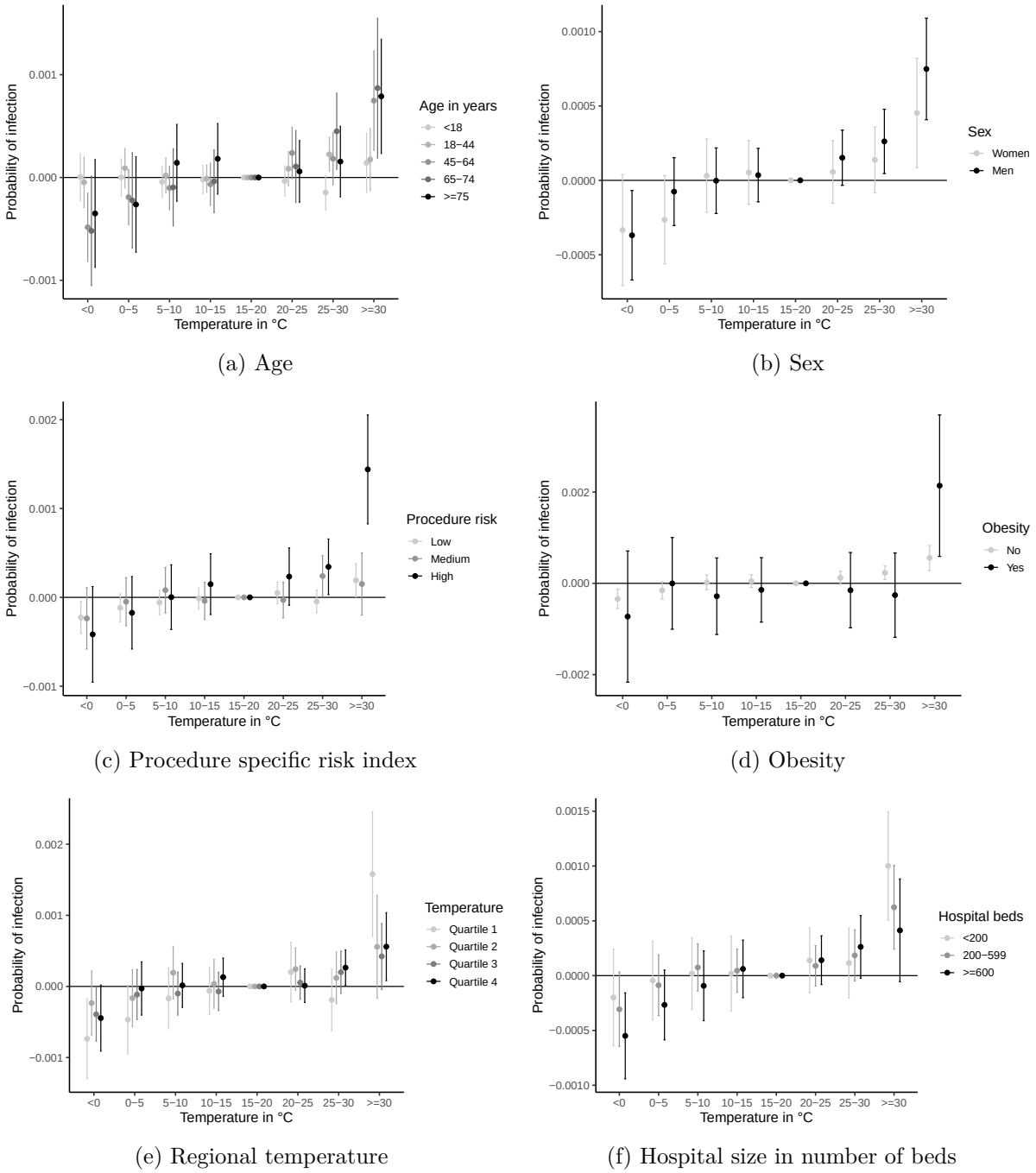
the effect in UTIs is consistent with both biological and operational mechanisms. Gram-negative bacteria, the primary cause of hospital-acquired UTIs, exhibit strong seasonality and have been shown to proliferate more rapidly at higher ambient temperatures (Eber et al., 2011, Schwab et al., 2014). Furthermore, UTIs are highly sensitive to the quality of inpatient nursing care, particularly regarding the use of urinary catheters—a known primary risk factor (Nguyen-Van-Tam et al., 1999).

Heterogeneity by obesity. To further examine patient-side vulnerability as a channel, I stratify the sample by whether patients carried a pre-admission diagnosis of obesity, identified from diagnoses recorded in the year prior to hospitalization. Figure 4d shows that patients with a pre-admission obesity diagnosis exhibit substantially larger heat effects than the remaining sample. This pattern is consistent with the physiological literature documenting that obesity impairs thermoregulation and is a risk factor for infections (Falagas & Kompoti, 2006, Speakman, 2018). The result reinforces the interpretation that patient-side vulnerability is an important pathway through which temperature affects inpatient infection risk.

Heterogeneity by hospitals. Finally, I explore heterogeneity at the hospital level. Panel 4e shows that heat effects are larger in hospitals located in regions with historically lower average maximum temperatures. This pattern is consistent with differences in adaptation or exposure to extreme heat across regions. Panel 4f shows that smaller hospitals (fewer than 200 beds) exhibit stronger heat-related increases in infection risk than larger institutions. Patients in smaller hospitals have a somewhat lower baseline HAI incidence (3.7 percent) than those in medium-sized (4.2 percent) or large hospitals (4.6 percent). The larger absolute heat effect combined with a lower baseline therefore implies an even more pronounced increase in relative infection risk in smaller institutions. Larger heat effects in smaller hospitals may reflect differences in infrastructure or organizational capacity to adapt to short-run temperature shocks. Unfortunately, the data does not allow direct observation of these channels. To check whether the observed heat effects are concentrated in hospitals with systematically higher baseline infection risk, I estimate a version of equation 1 excluding the temperature bins and extract hospital fixed effects, which capture each hospital's residual infection rate net of patient composition and seasonal variation. I then stratify hospitals into terciles based on this hospital-specific HAI-risk score. Figure B.10 shows no systematic differences across terciles: hospitals with a high baseline infection propensity do not exhibit larger heat effects than those with a low baseline rate. This suggests that the heat effects documented in this paper are not concentrated in hospitals that are generally more susceptible to infections, but are broadly present across institutions regardless of their underlying infection and work environment.

Taken together, the heterogeneity patterns consistently indicate that temperature effects are concentrated where clinical or institutional vulnerability is greatest. Neither observable capacity constraints nor institutional baseline infection risk levels appear to be the primary driver of the estimated effects, pointing instead toward limited adaptation capacity and patient-side vulnerability as the more plausible explanations.

Figure 4: Estimated effects of ambient temperature on risk of hospital-acquired infection by different subsamples



(a) Age

(b) Sex

(c) Procedure specific risk index

(d) Obesity

(e) Regional temperature

(f) Hospital size in number of beds

Notes: This figure illustrates the estimated effect of an additional day in bin b relative to the reference bin $15 - 20$°C on the first three days of admission on risk of hospital-acquired infection by different subsamples. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

5.4 Back-of-the-Envelope Cost Implications

To illustrate the economic magnitude of the estimated heat effect, I combine the reduced-form increase in infection risk with published estimates of the incremental cost of an HAI.

An additional day with maximum temperature $\geq 30°C$ during the first three days of hospitalization increases HAI risk by 0.06 percentage points, i.e. $\Delta p = 0.0006$. The literature estimates additional inpatient costs of 5,000 to 10,000 Euro per HAI case in Germany (Arefian et al., 2016). The expected cost increase per case and heat day is therefore:

$$\Delta \text{Cost}_{\text{case, heat day}} = 0.0006 \times (5{,}000\text{–}10{,}000) \approx 3\text{–}6 \text{ Euro}.$$

On average, there were 11.1 days of heat in 2025 in Germany (Umweltbundesamt, 2025). The average hospitalization experiences 0.09 extreme heat days during the first three days of admission. With 17.5 million inpatient cases in Germany in 2024 (Statistisches Bundesamt, 2025), this implies:

$$17.5 \text{ million} \times 0.09 \times (3\text{–}6) \approx 4.7\text{–}9.5 \text{ million Euro per year}.$$

This calculation captures only the additional HAI-related inpatient costs arising from extreme days of heat. To provide an illustrative projection, I scale the estimate proportionally with the expected increase in the annual number of heat days. The German Environment Agency projects an increase of about 5 to 10 additional heat days by 2060 under a high-emissions scenario (van Rüth et al., 2023). If the probability that a hospitalization's first three days include extreme heat increases proportionally with the annual frequency of heat days, the annual cost range of 4.7–9.5 million Euro scales by a factor of $(11.1+\Delta)/11.1$, with $\Delta \in \{5, 10\}$. This yields projected yearly costs of approximately 6.9–18.0 million Euro. These projections abstract from adaptation and changes in hospital volume. Total German statutory health insurance expenditure on inpatient care amounted to approximately 102 billion Euro in 2024 (GKV-Spitzenverband, 2026). The heat-induced HAI costs estimated here thus represent a modest fraction of system-wide inpatient spending.

5.5 Mechanisms

This section discusses potential mechanisms through which short-run exposure to extreme ambient temperature during the first days of hospitalization may affect the risk of HAIs. Several non-mutually exclusive channels are plausible. These operate through (i) staff performance and hygiene compliance, (ii) congestion and organizational strain, (iii) patient vulnerability, and (iv) temperature-sensitive pathogen dynamics.

Staff performance and hygiene compliance. HAIs are closely linked to adherence to hygiene protocols and the careful execution of clinical procedures (Gastmeier, 2012). Even small deviations in hand hygiene, sterile technique, or device management can increase transmission risk. A broad literature documents that high temperatures impair cognitive performance and task execution. Experimental and observational evidence shows that heat stress increases fatigue and physiological strain among surgical teams (Berg et al., 2015, Palejwala et al., 2023, Ward

et al., 2021) and reduces productivity and decision quality in cognitively demanding settings (Heyes & Saberian, 2019, Seppänen et al., 2006).

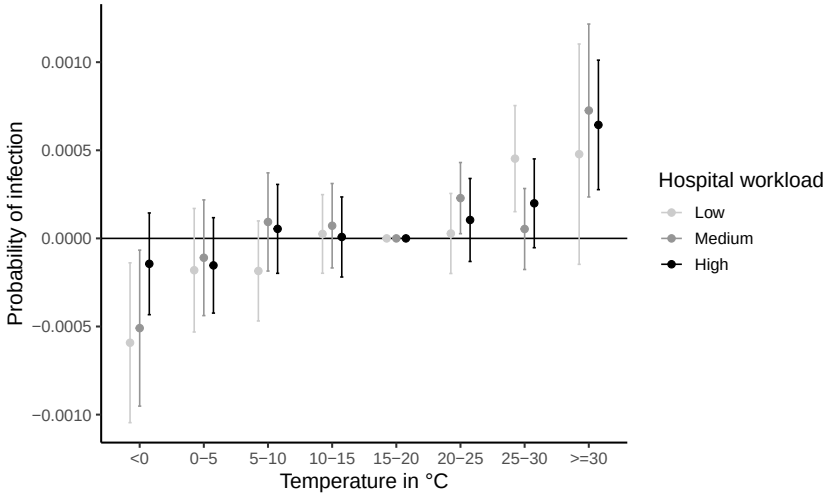
Although operating rooms are typically climate-controlled, many patient wards in Germany are not (Filser & Levsen, 2022). If extreme heat reduces attention margins or increases fatigue of medical staff, this may translate into lower effective compliance with infection prevention protocols.

Congestion and organizational strain. A second mechanism operates through temperature-induced demand shocks. Extreme heat increases hospital admissions, particularly for cardiovascular and respiratory conditions (Aguilar-Gomez et al., 2025, Karlsson & Ziebarth, 2018). Such surges can strain capacity and increase workload per staff member. Aguilar-Gomez et al. (2025) document that heat-related admission spikes worsen patient outcomes through congestion effects, while W. Wu et al. (2025) show that hospitals in China increase staffing due to congestion from temperature shocks.

Hygiene compliance and infection prevention are time-intensive processes. Under higher workload, adherence may deteriorate at the margin with high patient-to-staff ratios being a risk factor of HAIs (Walger et al., 2013). Because in-hospital transmission frequently occurs via healthcare personnel (Gastmeier, 2012), congestion provides a direct organizational pathway linking temperature shocks to infection risk.

To evaluate congestion as a potential pathway of how temperature may affect HAIs, I apply an additional heterogeneity analysis. I calculate the number of admissions by each hospital-week combination using my full dataset of over 41.5 million cases. I then split each hospital-week into terciles of high, medium and low within-hospital admission volume. Using my main sample, I then re-estimate my model for each tercile. My results in Figure 5 show that there are no systematically larger heat effects in busier weeks, suggesting that observable case-volume congestion is unlikely to be the primary driver of the results. Viewed alongside the larger impacts observed in smaller hospitals (see Figure 4f), these null results suggest that the vulnerability of smaller institutions stems from differences in baseline structural resilience rather than acute crowding.

Figure 5: Estimated effects of ambient temperature on risk of hospital-acquired infection by hospital workload



Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Patient vulnerability and clinical risk. Temperature may also affect infection risk through patient-side mechanisms. Heat exposure can impair thermoregulation, increase dehydration risk, and exacerbate cardiovascular and respiratory stress, particularly among older individuals (Cheng et al., 2019, Witt et al., 2015). Hospitalized patients are medically vulnerable by definition. Heat-related physiological stress may weaken immune responses or slow wound healing, thereby increasing susceptibility to infection following invasive procedures.

The heterogeneity results (see Section 5.3) align with this interpretation. Heat effects are concentrated among older patients, patients with a history of obesity and among hospitalizations involving procedures with elevated baseline infection risk. In contrast, younger patients exhibit no detectable response. This pattern suggests that temperature shocks interact with underlying clinical vulnerability rather than uniformly deteriorating care quality across all cases.

Temperature-sensitive pathogen dynamics. Finally, a direct biological mechanism may operate through temperature-dependent pathogen proliferation. Epidemiological studies document higher rates of surgical site infections and bloodstream infections during warmer periods (Aghdassi et al., 2019, Damonti et al., 2023, Schwab et al., 2020). While the underlying mechanisms are not well understood, warmer conditions are associated with increased prevalence of certain bacteria, particularly gram-negative pathogens and a general change in the skins microbiome (Anthony et al., 2017, 2018, Manian, 2016, McBride et al., 1977, Schwab et al., 2014). Higher ambient temperatures may increase environmental microbial load or affect colonization dynamics, raising baseline exposure risk. Given that gram-negative bacteria are primary drivers of UTIs, these biological pathways are highly consistent with the empirical results in Figure B.9, which suggest that UTIs are a leading contributor to the observed temperature-HAI relationship. Although some hospital environments are partially climate-controlled, ambient temperature may still influence microbial conditions.

Interpretation. These mechanisms are not mutually exclusive and likely interact. Extreme heat may simultaneously increase environmental pathogen load, reduce staff performance, and heighten patient susceptibility. The results provide suggestive support for a multifactorial interpretation. On the patient side, effects are highly concentrated among clinically vulnerable individuals, specifically older patients, those with a history of obesity, and those undergoing high-risk procedures. On the supply side, while short-run fluctuations in hospital workload do not appear to drive the results, the concentration of effects in smaller hospitals and colder regions suggests that structural constraints—such as a lack of climate-control infrastructure or lower organizational resilience—play a critical role. While the available data do not allow for a perfect isolation of channels, the results indicate that temperature shocks operate through a combination of physiological patient vulnerability and structural supply-side constraints, potentially amplified by temperature-sensitive pathogen dynamics.

6 Conclusion

This paper estimates the effect of short-run exposure to ambient temperature during hospitalization on the risk of HAIs, a clinically important and partly preventable outcome that is widely interpreted as an indicator of inpatient care quality. Using individual-level administrative health insurance data from Germany covering 2005–2023 and linking hospital admissions to high-resolution local weather data, I exploit quasi-random day-to-day variation in temperature during the first three days of hospitalization within hospitals. This design isolates short-run temperature exposure from aggregate seasonal patterns and avoids mechanical links between infection risk and length of stay.

I find that extreme heat significantly increases the risk of hospital-acquired infections. Each additional day with maximum temperatures of at least 30°C during the first three days of hospitalization raises the probability of an HAI by 0.06 percentage points, or 1.43 percent relative to the mean. In contrast, extreme cold reduces infection risk. These effects are small in absolute terms, but they are precisely estimated, robust across a wide range of alternative specifications, and economically meaningful given the frequency, preventability, and cost of HAIs.

The effects are concentrated among patients with greater underlying vulnerability. Heat-related increases in infection risk are strongest among older patients, patients with a history of obesity, and among hospitalizations involving procedures with elevated baseline infection risk. Analyses by infection type show that the effects are primarily driven by UTIs. Estimates are particularly large for catheterization and joint replacement treatments. At the hospital level, the effects are stronger in smaller hospitals and in regions historically less exposed to high temperatures, consistent with differences in structural resilience. By contrast, I find no systematic differences when stratifying by hospital-specific workload, providing little evidence that observable capacity constraints are the main driver of the results.

The results also imply non-trivial economic costs. A back-of-the-envelope calculation suggests that heat-induced HAIs generate additional inpatient costs of roughly 4.7 to 9.5 million Euro per year in Germany under current climate conditions. Under projected increases in the frequency of extreme heat days, these costs could rise to approximately 6.9 to 18.0 million Euro annually by 2060, abstracting from adaptation.

Overall, the findings highlight an additional channel through which climate change may affect healthcare systems. Much of the existing literature has emphasized that extreme heat raises healthcare demand and can strain hospital capacity. The evidence presented here shows that temperature shocks affect a clinically important outcome that is less severe than mortality, more directly linked to care processes, and partly preventable. As heat events become more frequent and more intense, adaptation in the hospital sector—including infrastructure, cooling capacity, and organizational measures to maintain infection prevention standards—may play an important role in protecting patient safety and maintaining healthcare quality.

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Supplemental Appendix

A Descriptives

Table A.1: Excluded Principal, Admission, or Referral Diagnoses

ICD-10 Code	Description
A00–B99	Certain infectious and parasitic diseases
I33.0	Acute and subacute infective endocarditis
J09–J18*	Influenza and pneumonia
J20*–J22	Other acute lower respiratory infections
J36	Peritonsillar abscess
J44.0	COPD with acute lower respiratory infection
J69.0	Pneumonitis due to food and vomit
J80.0	Adult respiratory distress syndrome (ARDS)
J86.9	Pyothorax without fistula
K12.2	Cellulitis and abscess of mouth
K35*	Acute appendicitis
K57.2	Diverticulosis of large intestine with perforation and abscess
K63.1	Perforation of intestine (nontraumatic)
K65.0	Acute peritonitis
K75.0	Liver abscess
K80.1	Calculus of gallbladder with cholecystitis
K80.3	Calculus of bile duct with cholangitis
K81.0	Acute cholecystitis
K83.0	Cholangitis
L02*	Cutaneous abscess, furuncle and carbuncle
L03*	Cellulitis
L89.2	Pressure ulcer, stage 3
M00–M03	Infectious arthropathies
M46.4	Discitis, unspecified
M60.0	Infective myositis
M72.6	Necrotizing fasciitis
M86*	Osteomyelitis
N30*	Cystitis
N34*	Urethritis
N39.0	Urinary tract infection, site not specified
N45.9	Orchitis and epididymitis without abscess
T81.4	Infection following a procedure, not elsewhere classified
T82.7	Infection due to cardiac/vascular device or graft
T83.5	Infection due to genitourinary prosthetic device
T84.5	Infection due to joint prosthesis
T84.6	Infection due to internal fixation device
T85.7	Infection due to other internal prosthetic device
T87.4	Infection of amputation stump

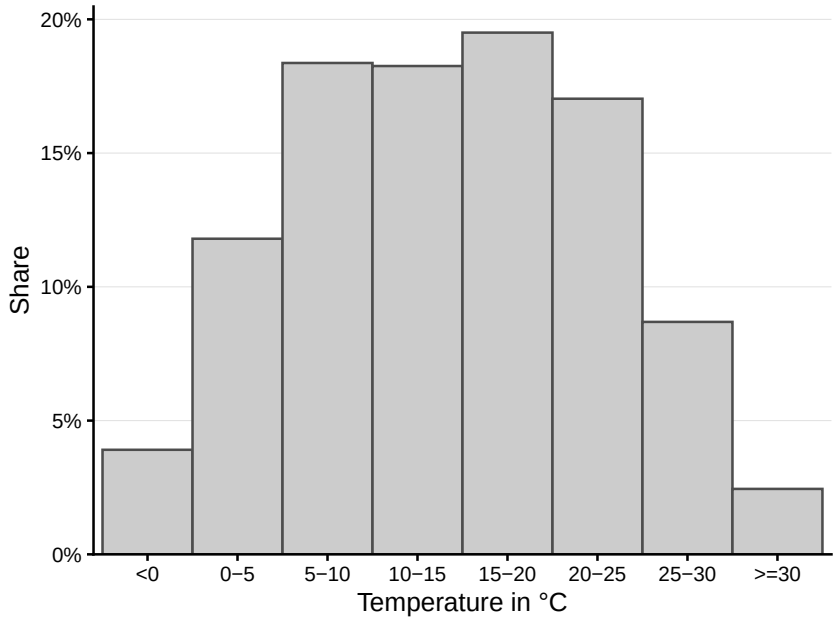
Notes: Asterisks (*) indicate that all subcategories are included. Based on Augurzky et al. (2021).

Table A.2: Definition of a hospital-acquired infection based on secondary diagnoses

Disease Diagnosis		Pathogen / Trigger Code	
ICD-10	Description	ICD-10	Description
A41.*	Other sepsis	B95.*	Streptococci and staphylococci
J13	Pneumonia due to *Streptococcus pneumoniae*	B96.*	Other specified bacterial agents
J14	Pneumonia due to *Haemophilus influenzae*	R65.0	SIRS of infectious origin without organ failure
J15.*	Bacterial pneumonia, not elsewhere classified	R65.1	SIRS of infectious origin with organ failure
J16.*	Pneumonia due to other infectious agents, NEC	T80.2	Infection following infusion, transfusion, or injection
J18.*	Pneumonia, organism unspecified		
L03.*	Cellulitis		
M86.*	Osteomyelitis		
N30.0	Acute cystitis		
N39.0	Urinary tract infection, site not specified		
T81.4	Infection following a procedure, NEC		
T83.5	Infection due to genitourinary prosthetic device		
T87.4	Infection of amputation stump		

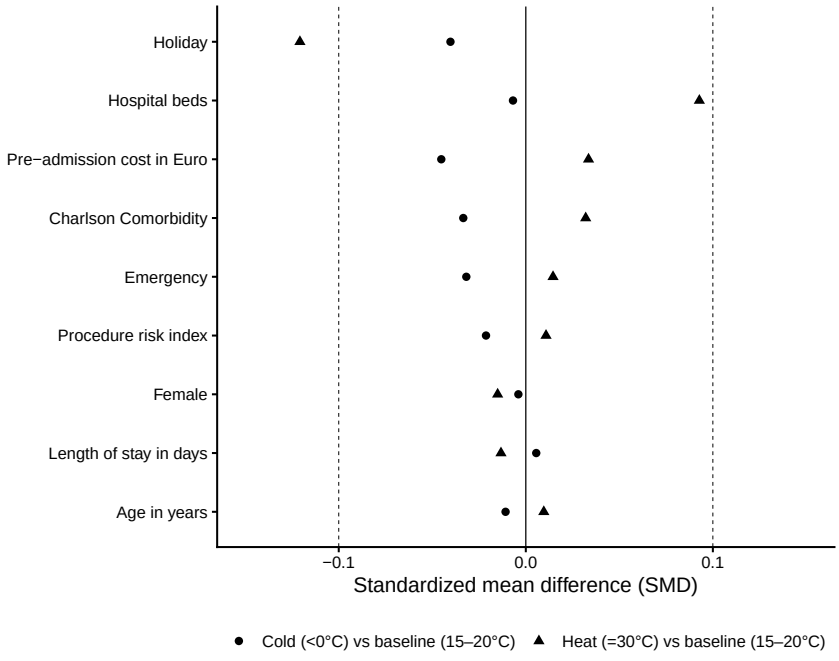
Notes: A nosocomial infection is defined as the co-occurrence of at least one disease diagnosis (left panel) and one pathogen code (right panel) in the secondary diagnoses. The ICD-10 code A04.7 (Clostridioides difficile enterocolitis) qualifies as a nosocomial infection without requiring an additional pathogen code. Asterisks (*) indicate inclusion of all subcategories. Based on Augurzky et al. (2021).

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



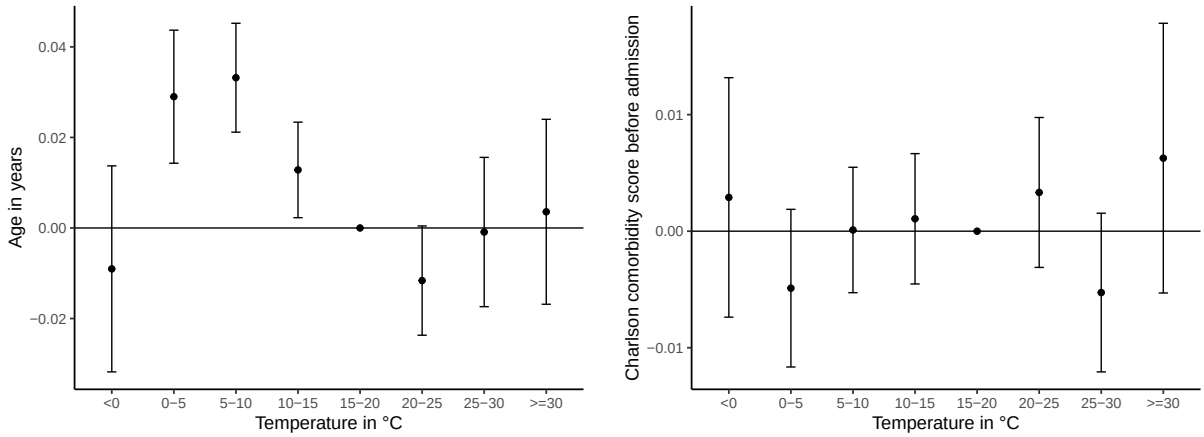
Notes: The figure shows the distribution of daily maximum temperature across hospital-days in the estimation sample. The vertical axis reports the share of hospital-days in each temperature bin.

Figure A.2: Standardized mean differences across temperature bins



Notes: This figure shows normalized differences following Imbens and Rubin (2015) between hospitalizations on days with maximum temperature between$15 - 20$°C and hospitalizations on days with extreme heat ($\geq$30°C, $N = 679{,}601$) and cold (<0°C, $N = 879{,}964$).

Figure A.3: Balancing: estimated effects of ambient temperature on different observable characteristics

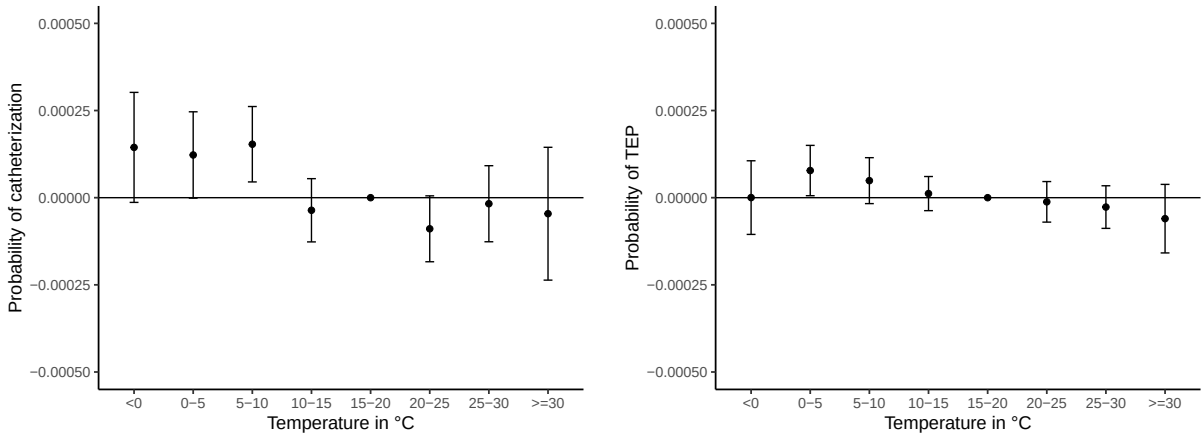


(a) Age in years

(b) Charlson comorbditiy score

Notes: This figure illustrates the estimated effect of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission on different observable characteristics. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

Figure A.4: Estimated effects of ambient temperature on treatment probability of catheterization and TEP

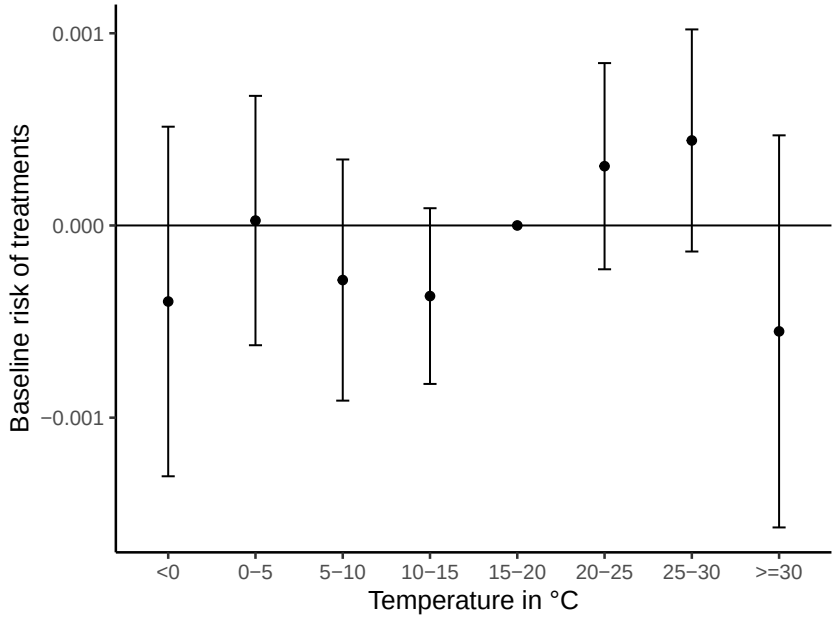


(a) Catheterization

(b) Joint replacement

Notes: This figure illustrates the estimated effect of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission on probability of being treated with a catheteriztation and TEP. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

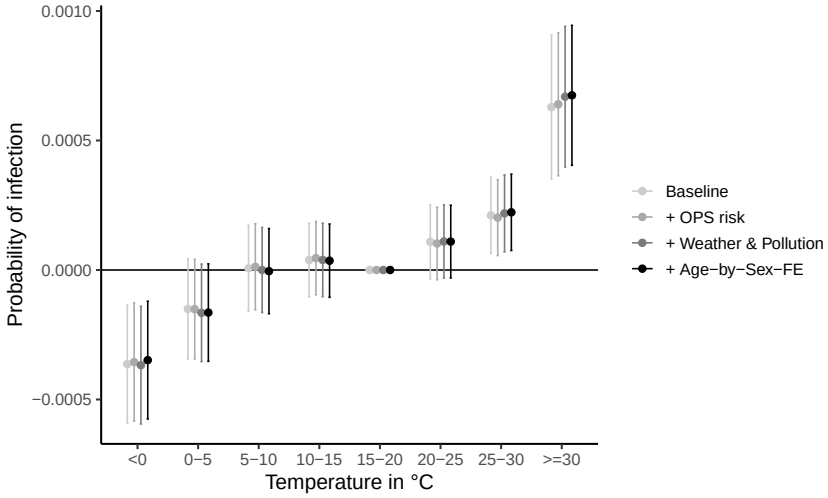
Figure A.5: Estimated effects of ambient temperature on baseline risk of treatments.



Notes: This figure illustrates the estimated effect of an additional day in bin b relative to the reference bin $15 - 20^{\circ}$C on the first three days of admission on the baseline infection risk of treatments performed during the first three days of hospitalization. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

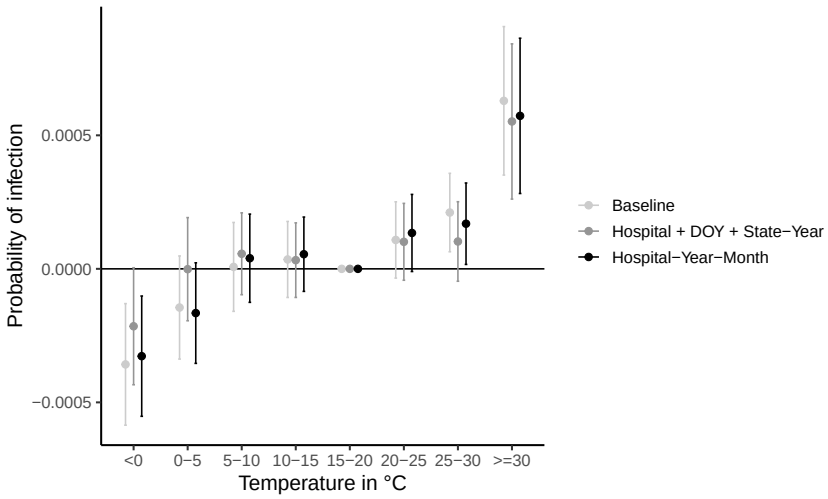
B Additional Analyses

Figure B.1: Estimated effects of ambient temperature on risk of hospital-acquired infection varying model specifications



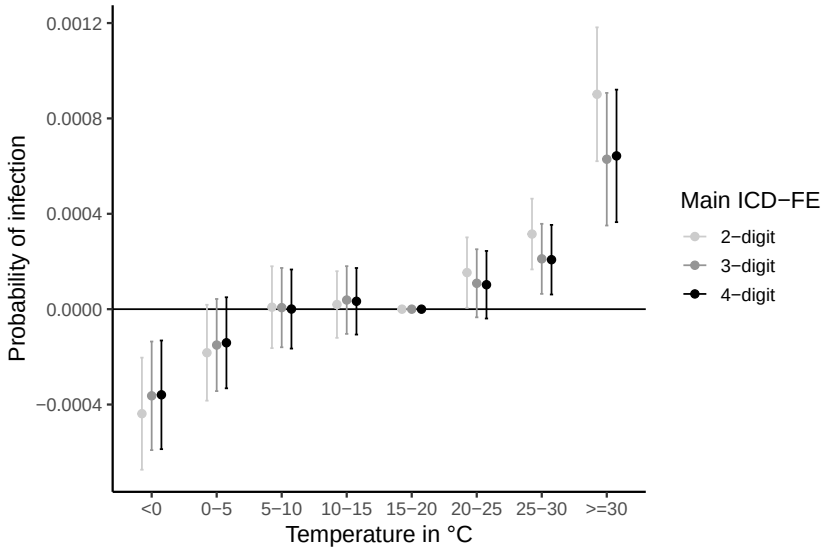
Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Figure B.2: Estimated effects of ambient temperature on risk of hospital-acquired infection with different fixed effects specifications



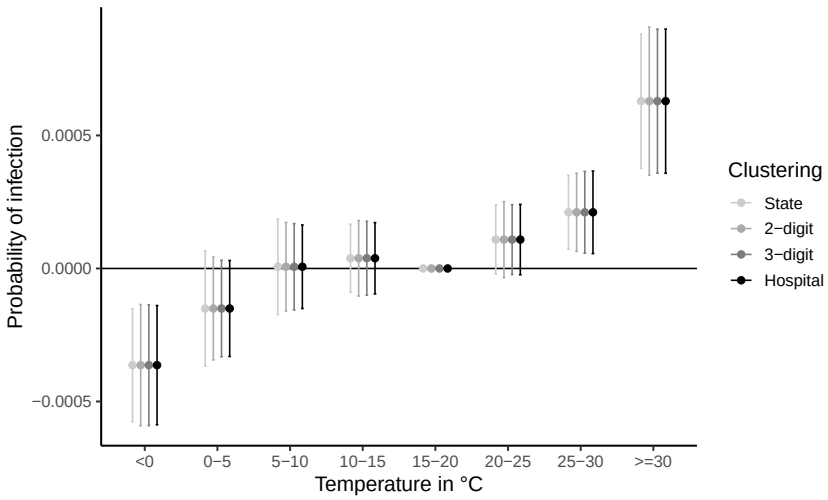
Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Figure B.3: Estimated effects of ambient temperature on risk of hospital-acquired infection with varying primary diagnosis controls.



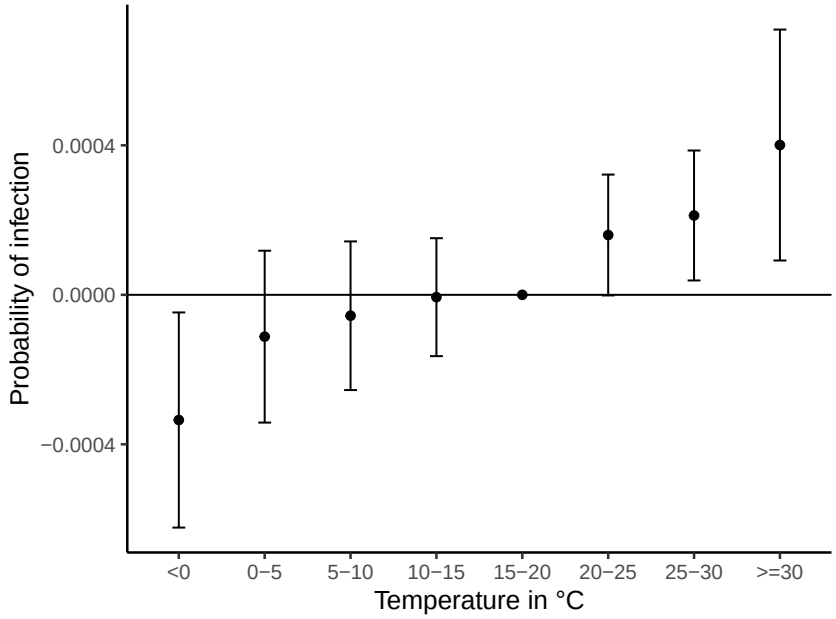
Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Figure B.4: Estimated effects of ambient temperature on risk of hospital-acquired infection with varying level of clustering



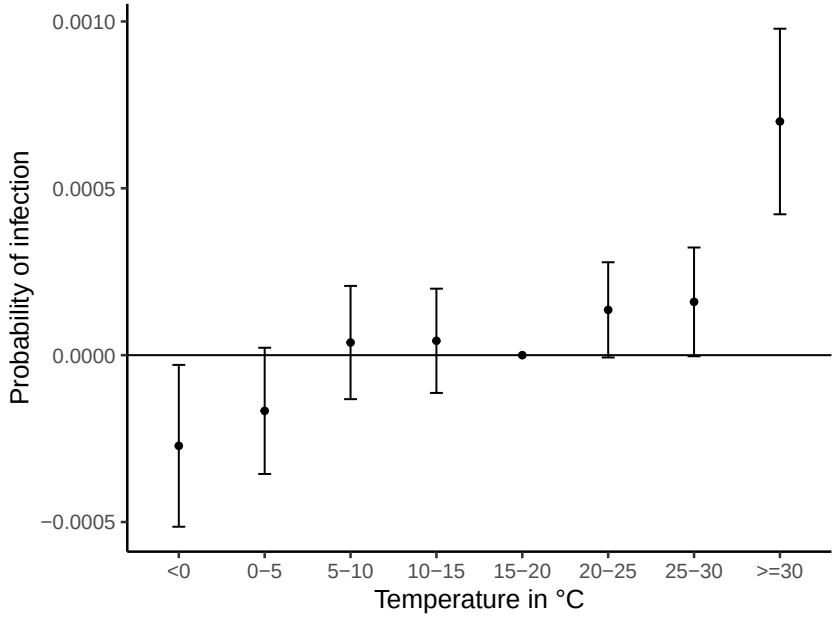
Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Figure B.5: Estimated effects of ambient temperature on risk of hospital-acquired infection excluding emergency admissions



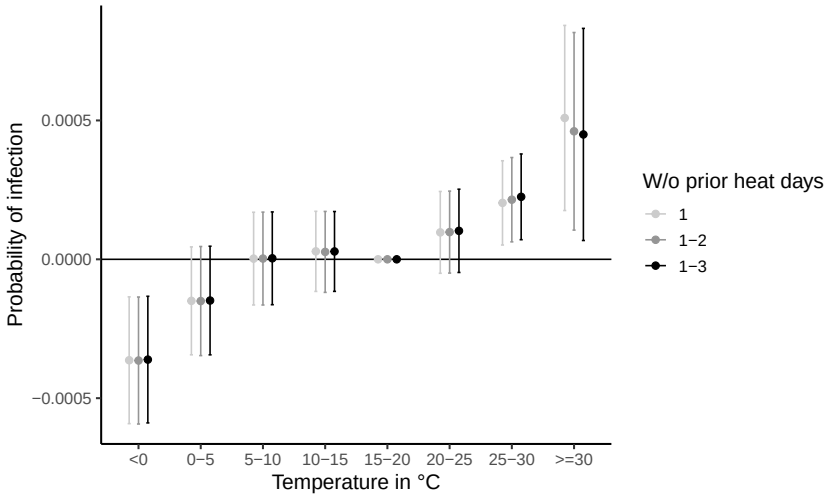
Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Figure B.6: Estimated effects of ambient temperature on risk of hospital-acquired infection excluding years 2020 to 2022.



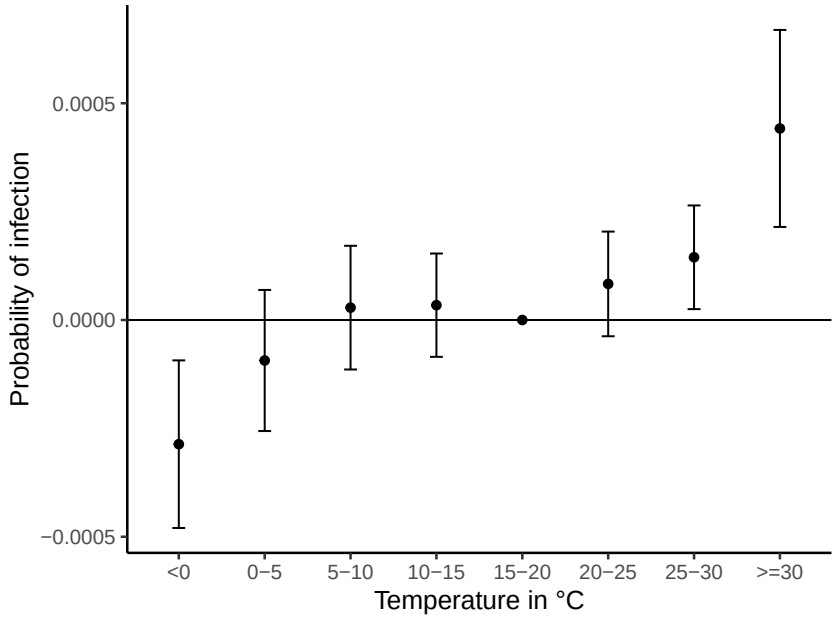
Notes: This figure is based on a sample excluding the years of COVID-19 pandemic 2020 to 2022. It illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.

Figure B.7: Estimated effects of ambient temperature on risk of hospital-acquired infection including only cases without prior heat days



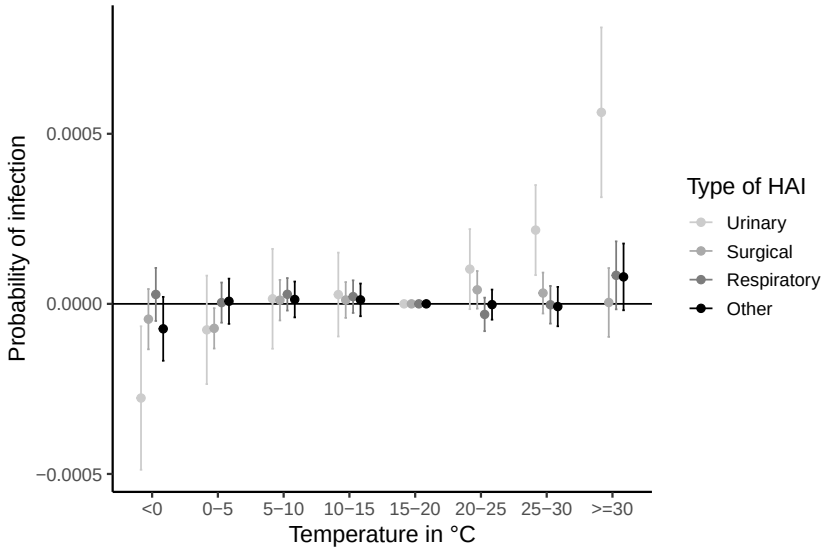
Notes: This figure is based on a sample excluding cases with days of ambient temperature $\geq 30°$C prior to admission. It illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

Figure B.8: Estimated effects of ambient temperature on risk of hospital-acquired infection including stays of less than 3 days



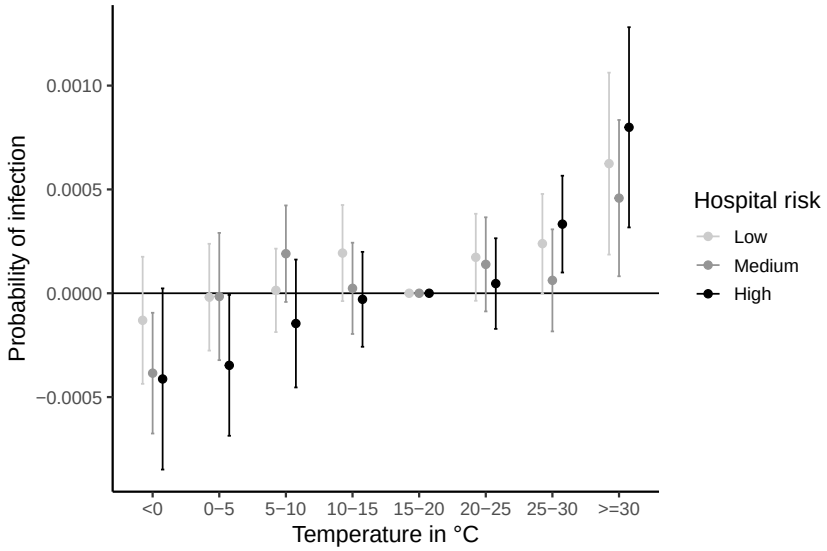
Notes: This figure is based on a sample including admissions with a length of stay of less than 3 days. It illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20°$C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

Figure B.9: Estimated effects by type of hospital-acquired infection



Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin 15–20°C on the first three days of admission by type of infection. Based on diagnosis shown in Table A.2 the respiratory category includes ICD-Codes J*, urinary N* and surgery T*. Whiskers represent 95% confidence intervals. Standard errors are clustered at the two-digit ZIP-code level.

Figure B.10: Estimated effects of ambient temperature on risk of hospital-acquired infection by hospital-specific HAI-risk



Notes: This figure illustrates the estimated percentage point change in risk of hospital-acquired infection of an additional day in bin b relative to the reference bin $15 - 20$°C on the first three days of admission. Whiskers represent 95% confidence intervals. Standard errors are clustered on two-digit-zip-code level.