Heterogenous impacts of climate change on morbidity

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Abstract

This paper examines the effect of temperature on emergency department (ED) visits using administrative data covering 50% of the Hungarian population and 3.52 million ED visits from 2009 to 2017. The results show that ED visit rates increase when average temperatures exceed 10°C, primarily driven by mild cases that do not result in hospitalization. Higher humidity amplifies the heat effect, which is also stronger following consecutive hot days. The findings further indicate that the impacts of climate change – both present and future – are substantial. Between 2009 and 2017, 0.66% of the ED visits were attributed to temperature changes relative to the period 1950–1989. Furthermore, by the 2050s, compared to the first 15 years of the 21st century, the annual ED visit rate is projected to rise by 1.24%–1.70%, depending on the climate scenario. A heterogeneity analysis reveals that the effects of high temperatures and the future impacts of climate change are disproportionately greater in lower-income districts, areas with lower general practitioner density, and among younger adults.

JEL codes: I10, I14, I18, Q54

Keywords: temperature; climate change; morbidity; emergency department visits; heterogeneous impacts

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1. Introduction

Over the past couple of decades, a substantial body of literature has been produced on the impact of climate change on human health. However, most of the research has focused on mortality (Barreca et al., 2016; Barreca, 2012; Carleton et al., 2022; Cohen and Dechezleprêtre, 2022; Conte Keivabu et al., 2024; Deschênes and Greenstone, 2011; Deschênes and Moretti, 2009; Hanlon et al., 2021; Heutel et al., 2021; Otrachshenko et al., 2018, 2017), while our knowledge regarding morbidity is considerably more limited. The studies that have focused on morbidity in general have mostly examined either hospital admissions (Agarwal et al., 2021; Karlsson and Ziebarth, 2018; Masiero et al., 2022; Rizmie et al., 2022) or emergency department (ED) visits (Gibney et al., 2023; Gould et al., 2024; Mullins and White, 2019; Sun et al., 2021; White, 2017), with a few exceptions that have studied other indicators, for example primary health care visits (Fritz, 2022). Regarding mortality, existing studies broadly agree that both extreme cold and extreme heat increases the risk of death (although the effects on cause-specific mortality rates may differ). However, in terms of morbidity, the findings are mixed: some papers reported a linear relationship (the higher the temperature, the larger the morbidity) (Fritz, 2022; Gould et al., 2024; Mullins and White, 2019), while others found rather a tilted J- or U-shaped pattern (Agarwal et al., 2021; Gibney et al., 2023; Karlsson and Ziebarth, 2018; White, 2017).

Although the existing literature provides some evidence on the effect of temperature on morbidity, it rarely addresses how these findings can be "translated" into the impacts of climate change. The literature offers little insight into what changes can be expected in the future as a result of a warming climate or how the warming experienced to date has already affected morbidity. It is particularly important to note that the morbidity impacts that have already occurred are largely overlooked, even though climate change is not only a future concern but is already happening (Dessler, 2022; Sippel et al., 2020). Furthermore, even among the papers that have made future projections, many rely on a single climate model (Agarwal et al., 2021; Fritz, 2022; White, 2017). This approach, however, fails to account for climate uncertainty, and may consequently provide misleading inputs for decision-makers (Burke et al., 2015). A notable exception is the paper by Gould et al. (2024), which uses data from 33 global climate model simulations to project future morbidity burdens of climate change.

It is important to note that many questions remain unanswered about the heterogeneity of the temperature effects and the impacts of climate change. While several studies have examined differences in temperature effects by gender and age, other important dimensions are missing from the existing literature. For instance, how do these effects vary by income level? How does the availability and quality of primary health care shape the relationship between temperature and morbidity? Furthermore, no studies have quantified the heterogeneity of climate change impacts across different societal subgroups.

In this paper, I use Hungarian administrative data on 3.52 million emergency department visits in outpatient care between 2009 and 2017, high-resolution meteorological data, and temperature projections from thirty-one climate models to study the effect of temperature on ED visits, and to project the impacts of climate change.

As an East-Central European country, Hungary lies at the intersection of different climatic zones, with its climate influenced by both continental and oceanic patterns (Mezősi, 2017). Summers are typically hot, while winters are cold. Despite its small size, Hungary exhibits non-negligible spatial variation in temperature and precipitation.

From a European perspective, Hungary ranks among the poorest in terms of population health, with a low number of doctors and nurses per capita and below-average health spending as a share of GDP (Jagger et al., 2008; OECD/European Commission, 2024; Olsen and Dahl, 2007; Welsh et al., 2021). Hungarians not only have a shorter life expectancy than most Europeans but also spend a larger proportion of their lives in poor health. This health disadvantage may make them more vulnerable to heat-related illnesses and diseases.

Hungary has a tax-funded universal healthcare system, almost all individuals are covered by compulsory health insurance, and, as a general rule, medical care is free of charge. Emergency departments are typically accessible 24 hours a day for patients with serious, life-threatening conditions, acute pain, and urgent medical needs. Patients may be transported by the National Ambulance Service, referred by a general practitioner (GP), or may walk in without a referral. In the event of a high patient volume, patients arriving with non-serious, mild symptoms may be required to wait for treatment. Alternatively, they may be referred to a primary care clinic or their GP following a triage assessment. Following the completion of the necessary medical examinations, tests, and treatment, patients may be referred to a hospital ward or another healthcare facility for the necessary specialist care, or they may be discharged to their homes.

This paper employs a flexible approach that avoids imposing restrictive functional forms, allowing for the exploration of a nonlinear relationship between temperature and ED visits. Using daily data, eight temperature categories are defined to represent different daily mean temperatures from below −5°C to above 25°C. The effect of daily mean temperature is estimated on the ED visit rate for the day of exposure and the subsequent 10 days. The baseline specification includes controls for precipitation, humidity, day-of-year and day-of-week indicators, as well as district-by-year-by-month fixed effects. The inclusion of district-by-year-by-month fixed effects ensures that effects of temperature are identified from the variation in daily temperatures within a given district and a given month.

I find that a day with an average temperature above 25°C increases the ED visit rate by 4.65 additional ED visits per 100,000 people on the day of exposure and the subsequent 10 days, relative to a daily mean temperature of 5-10°C. This means that the total number of ED visits over an 11-day period is increased by 1.60% following a hot (>25°C) day. The effect of a slightly less hot day (with an average temperature between 20-25°C) is 1.09%, while the effects of days with average temperatures between 15-20°C and 10-15°C are 0.54% and 0.31%, respectively. These effects are primarily driven by mild cases not resulting in hospitalization. Colder temperature categories below 5-10°C have no significant effects.

This paper also examines the moderating effect of humidity on heat-related ED visits. As higher humidity impairs the human body's ability to cool through sweating, it is important to explore the role of humidity to better understand the potential effects of heat stress. I find that the effect of a day with an average temperature above 25°C on the ED visit rate under high humidity conditions is 5.61 ED visits per 100,000 people (a 1.93% increase in relative terms). By comparison, under low humidity conditions, the effect is smaller, with an increase of 4.04 ED visits per 100,000 persons (an increase of 1.39%).

Additionally, this study also explores the effect of heatwaves (prolonged periods of extreme heat) on ED visits. Climate change is projected to lead to more frequent and longer-lasting heatwaves (Perkins-Kirkpatrick and Lewis, 2020; Rousi et al., 2022; Russo et al., 2017), and there is growing evidence that heatwaves has strong effects on various outcomes, including economic growth, mortality, sleep or fertility (Hajdu, 2024a, 2024b; Miller et al., 2021; Otrachshenko et al., 2018). I also find that the effect of prolonged heat stress is stronger. The cumulative effect of a day with an average temperature of >25°C when it is preceded by at least four other >25°C days is 5.91 ED visits per 100,000 people (a 2.03% increase), while the effect of a >25°C day that is not preceded by at least four other hot days is 4.38 ED visits per 100,000 people (a 1.50% increase).

Based on the temperature changes observed between 1950–1989 and 2009–2017, I estimate that a total of 46,800 excess ED visits occurred between 2009 and 2017, representing 0.66% of all ED visits during this period. This reflects the burden of climate change already being experienced. Furthermore, I also estimate the impact of future warming. Using results from thirty-one climate models, I project a 1.24% increase in the annual ED visit rate under the SSP2-4.5 climate scenario (a "middle-of-the-road" scenario) and a 1.70% increase under the SSP5-8.5 scenario (a worst-case scenario) by the 2050s.

Beyond these average effects, this study reveals substantial heterogeneity. Higher temperatures have stronger effects on individuals residing in districts with lower income levels. Consequently, the projected impact of climate change is 30-35% higher in low-income districts than among individuals living in middle-income or higher-income districts.

The quality and availability of primary health care, measured by the density of general practitioners, also shapes the relationship between temperature and ED visits. In districts with high GP density, heat-induced increases in ED visits are smaller than in areas with low GP density. As a result, the projected impacts of climate change are 35–50% greater in low GP density districts.

The largest differences are observed between age groups. An important finding is that the effects of hot temperatures decrease considerably with advancing age, and these differences are reflected in the markedly different impacts of climate change. The projected impact on ED visits is over four times higher for the 18-44 age group than for those 65 years and older, and more than one and a half times higher than for the 45-64 age group.

This study makes several important contributions to the literature. First, it analyzes the effects of temperature on morbidity in an East-Central European country, a region previously underrepresented in research. Most of the existing studies have focused on the USA (Gould et al., 2024; Mullins and White, 2019; Sun et al., 2021; White, 2017) or Western European countries (Gibney et al., 2023; Karlsson and Ziebarth, 2018; Masiero et al., 2022; Rizmie et al., 2022), with limited research available for other regions, aside from a few exceptions like Indonesia (Fritz, 2022) or China (Agarwal et al., 2021). Second, this paper provides projections of the impact of climate change, incorporating both climate uncertainty and the uncertainty in the relationship between temperature and morbidity – aspects often overlooked in prior studies. I also show that the impacts of climate change are not only a distant concern but are already influencing our lives today, with a measurable impact on ED visits from 2009 to 2017. Third, this paper explores the heterogeneity in the temperature effects and the future impacts of climate change, an important consideration for designing effective public policies. While many previous studies have focused on understanding age- and sex-specific heterogeneity in the effects of different temperatures (e.g., extreme cold or hot), this study goes a step further by summarizing these temperature effects into a single measure – the impact of climate change – to illustrate how different societal groups will be affected by a warming climate. In examining heterogeneity, I also focus on dimensions that have not yet been addressed in the literature. Fourth, I examine how humidity moderates the effect of heat and how prolonged exposure to heat intensifies the effects on morbidity; two important aspects that have received little attention from the previous papers.

2. Data

2.1. ED visits

The empirical analysis utilized an individual-level administrative panel database from the Databank of the HUN-REN Centre for Economic and Regional Studies, which covers a randomly selected 50% of the Hungarian population in 2003 (Sebők, 2021). The database spans from 2003 to 2017, but the analysis was restricted to the period between 2009 and 2017 due to the unavailability of health-related data before 2009. The dataset includes detailed records for all outpatient care visits, categorized by type of care provided, enabling the identification of emergency department (ED) visits. For each visit, key patient characteristics (age, sex, and district of residence) and the ICD-10 code of the principal diagnosis were recorded. This allowed for the calculation of daily ED visit rates by district of residence (number of ED visits per 100,000 persons), as well as age-, sex-, and diagnosis-specific rates. In addition, inpatient care data enabled a distinction between severe and mild ED cases. Severe cases were defined as ED visits followed by a hospital stay on the same day or the next, while mild cases were those not followed by immediate hospitalization.[1]

The sample was restricted to individuals aged 18 and over. The final dataset comprised 647,539 observations (197 districts multiplied by 3,287 days).

Fig. 1 provides a summary of the ED visits data. A total of 3.52 million ED visits were observed between the years 2009 and 2017.[2] Over these nine years in Hungary, the mean number of daily ED visits per 100,000 persons increased from approximately 20 to over 30.[3] The district-level averages for the period 2009-2017 demonstrate considerable spatial heterogeneity, with the lowest values below 10 ED visits per day per 100,000 persons and the highest values above 50. Injuries (including poisoning, and certain other external causes) accounted for approximately 32% of visits, while diseases of the circulatory, digestive, and respiratory systems represented 13%, 12%, and 8%, respectively. The remaining diagnostic

[1] For 1 January 2009 and 31 December 2017, the severity of the ED visits cannot be defined. In the former case, new hospital stays cannot be identified due to the lack of data for 2008. In the latter case, due to the lack of data for 1 January 2018, the hospital stays for the day following the ED visit are not known.

[2] Note that this represents only half of all the ED visits in outpatient care in Hungary, as the data covers 50% of the population.

[3] The increase is probably partly due to the opening of new EDs in several locations during this period with EU funding. The increasing number of GP vacancies (Papp et al., 2019) may also have contributed to the increase in ED visits. However, during the same period, the number of ED visits increased significantly not only in Hungary but also in California, for example (Gould et al., 2024).

categories each accounted for 5-6% or less. Table 1 also reveals that approximately 18% of the ED visits are followed by hospitalization (severe cases).[4]

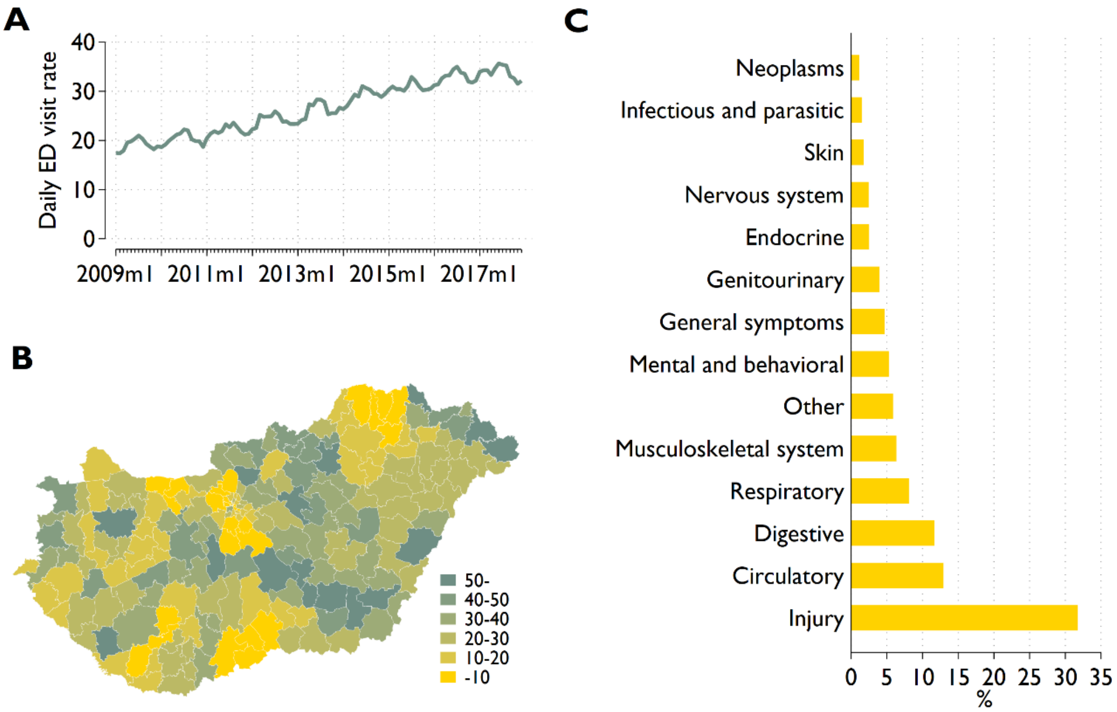

Fig. 1. Temporal trend, geographic variability, and disease type distribution of daily ED visit rates

Notes: (A) Country-level averages of daily ED visit rates by month. The country-level values are calculated as the weighted average of the district-level values. The average number of populations over the years 2009-2017 is used as each district's weight. (B) Average daily ED visit rates from 2009–2017. (C) Distribution of ED visits by diagnosis (defined by ICD-10 codes). Neoplasms: C00-97, D00-48, Infectious and parasitic: A00-99, B00-99, Skin and subcutaneous tissue: L00-99, R20-23, Nervous system: G00-99, R25-29, Endocrine: E00-90, Genitourinary: N00-99, R30-39, General symptoms: R50-69, Mental, behavioral: F00-99, R40-49, Musculoskeletal: M00-99, Respiratory: J00-99, R05-09, Digestive: K00-93, R10-19, Circulatory: I00-99, R00-04, Injury: S00-99, T00-98, Other: D50-89, H00-95, O00-99, P00-96, Q00-99, R70-99, V00-99, W00-95, X00-99, Y00-98, Z00-99, U00-99.

2.2. Weather

The meteorological data were derived from the European Climate Assessment & Dataset project (Cornes et al., 2018). The E–OBS 30.0e dataset (The ECA&D Project Team, 2024) provides information on the daily mean, minimum and maximum temperatures, relative humidity, and precipitation from 1950. The data are provided at a spacing of 0.1° × 0.1° in

[4] Table A1 (Supplementary Materials) shows the ED visit rates by age, sex, and the districts' income level.

regular latitude/longitude coordinates. The gridded weather data were aggregated to the district-by-day level by averaging the weather observations from the four grid points closest to each of the 197 district seats.

To estimate nonlinear temperature effects, eight temperature categories were constructed based on daily mean temperatures. These categories were as follows: ≤−5°C, −5–0°C, 0–5°C, 5–10°C, 10–15°C, 15–20°C, 20–25°C, and >25°C. In the analysis sample, 4.3% of the days have an average temperature >25°C, while 2.7% have an average temperature ≤−5°C (Table 1). However, there are some non-negligible variations in the annual number of days with an average temperature >25°C and ≤−5°C across different years and districts (Figure A1, Supplementary Materials).

To gain further insight into the effects of heat stress, additional indicators for heatwave days and hot days with high and low humidity levels were created. Heatwave days were defined as those days with an average temperature >25°C that are preceded by at least four other >25°C days. Under this definition, non-heatwave hot days are those with an average temperature >25°C where the preceding four days were not all above 25°C days. High-humidity hot days were defined as days with relative humidity above 60% and an average temperature >25°C, while low-humidity hot days were defined as >25°C days with relative humidity below 60%.

Table 1. Descriptive statistics

Variable	Mean	SD	Min	Max	N
Daily ED visit rate	26.50	21.85	0.00	228.42	647,539
Daily ED visit rate					
Severe cases	4.72	7.04	0.00	136.61	647,145
Mild cases	21.78	19.16	0.00	204.81	647,145
Daily mean temperature (°C)					
≤−5	0.027	0.163	0	1	647,539
−5 to 0	0.088	0.283	0	1	647,539
0 to 5	0.154	0.361	0	1	647,539
5 to 10	0.176	0.381	0	1	647,539
10 to 15	0.166	0.372	0	1	647,539
15 to 20	0.196	0.397	0	1	647,539
20 to 25	0.149	0.357	0	1	647,539
>25	0.043	0.202	0	1	647,539
>25°C days					
Heatwave day	0.010	0.098	0	1	647,539
Non-heatwave day	0.033	0.179	0	1	647,539
>25°C days					
High humidity	0.016	0.126	0	1	647,539
Low humidity	0.027	0.161	0	1	647,539

Notes: Population-weighted figures. Unit of observations: district-by-day.

2.3. District-level characteristics

To analyze heterogeneity by income and an indicator of primary health care quality, district-level average annual pre-tax income per capita and the number of general practitioners per 100,000 inhabitants were merged to the dataset. Data on total pre-tax income, the number of GPs, and total population at the district level were drawn from the National Regional Development and Spatial Planning Information System (TEIR). These figures were used to calculate district-level average annual pre-tax income per inhabitant (in 2023 HUF) and GP density for the years 2009–2017.

Three income categories were created based on population-weighted thresholds. The first category includes the poorest districts, comprising 25% of the population, where the average annual pre-tax income per capita ranged from 0.80 to 1.21 million HUF (in 2023 prices) during 2009–2017. The second category consists of the richest districts, also accounting for 25% of the population, with incomes ranging from 1.76 to 2.69 million HUF. The third category represents middle-income districts, covering the remaining (middle) 50% of the population, with incomes between 1.22 and 1.75 million HUF.

Similarly, to capture the quality of primary health care, districts were divided into three groups based on the average number of GPs per 100,000 inhabitants during 2009–2017. The first group represents districts with low GP density (ranging from 33.3 to 44.8 GPs per 100,000 inhabitants) and includes 25% of the population. The second (medium density) group covers districts with 44.8 to 56.0 GPs per 100,000 inhabitants, comprising 50% of the population. The third group consists of districts with 56.0 to 86.8 GPs per 100,000 inhabitants, also accounting for 25% of the population.

Figure A2 (Supplementary Materials) shows the geographical heterogeneity of income levels and the GP density.

2.4. Climate change

The projections regarding future temperatures were derived from the most recent release of the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) database (Thrasher et al., 2022). This dataset provides projections of daily temperature and humidity for the period 2015-2100 and retrospectively simulated historical data for the period 1950-2014. The projections are based on output from Phase 6 of the Climate Model Intercomparison Project (CMIP6) and have a spatial resolution of $0.25° \times 0.25°$. In this analysis, projections from thirty-one climate models[5] under two climate change scenarios (SSP2-4.5 and SSP5-8.5) were considered. The SSP2-4.5 scenario is often described as a "middle-of-the-road" scenario. It assumes the implementation of climate protection measures, although a decline in CO2 emissions only occurs after the mid-21st century, and the increase in the CO2 concentration stops only in the last decades of the century (O'Neill et al., 2016). In contrast, the SSP5-8.5 scenario represents a worst-case scenario, assuming high levels of greenhouse gas emissions and a fossil fuel-based development trajectory, with a sharply increasing CO2 concentration during the 21st century.

To project the future impact of climate change, changes in the temperature distribution by climate model were calculated for 2050-2059 using 2000-2014 as a baseline period. In the first step, daily temperature data for Hungary were calculated by averaging the mean temperature for each day over the grid points within the borders of Hungary. Subsequently, the annual distribution of the eight temperature categories described above was determined for the 2050s and compared to the temperature distribution of the baseline period:

$$\Delta \mathrm{T}_{\mathrm{ol}}^{\mathrm{j}} = \mathrm{T}_{\mathrm{ol}}^{\mathrm{j},2050-2059} - \mathrm{T}_{\mathrm{ol}}^{\mathrm{j},2000-2014} \tag{1}$$

where *o* stands for the SSP scenario and *l* stands for the climate model. The variable T denotes the annual number of days when the daily mean temperature falls into temperature category *j*.

The previously introduced E-OBS 30.0e dataset was also used to calculate the change in the temperature distribution between the periods of 1950–1989 and 2009–2017. This is the warming experienced to date that already affects of our life. First, the number of days falling into the eight temperature categories (≤−5°C, −5–0°C, …, >25°C) was calculated for each year between 2009 and 2017, and these distributions were compared with the average temperature distribution during the period 1950–1989:

$$\Delta \mathrm{T}^{\mathrm{j,y}} = \mathrm{T}^{\mathrm{j,y}} - \mathrm{T}^{\mathrm{j},1950-1989} \tag{2}$$

where the variable T denotes the number of days per year in year *y* (2009, … , 2017) when the daily mean temperature falls into temperature category *j*.[6] In this calculation, daily mean temperature for Hungary is determined by averaging the temperature at the grid points falling within the boundaries of the country.

[5] ACCESS-CM2, ACCESS-ESM1-5, CanESM5, CESM2, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, CNRM-CM6-1, CNRM-ESM2-1, EC-Earth3, EC-Earth3-Veg-LR, FGOALS-g3, GFDL-CM4-gr1, GFDL-CM4-gr2, GFDL-ESM4, GISS-E2-1-G, HadGEM3-GC31-LL, IITM-ESM, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, KACE-1-0-G, MIROC6, MIROC-ES2L, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, NorESM2-LM, NorESM2-MM, TaiESM1, UKESM1-0-LL.

[6] To deal with the effects of leap years, each temperature distribution has been converted to 365-day years.

Fig. 2 illustrates the observed and projected changes in the temperature distribution. Panel A presents the temperature distributions for the periods 1950–1989 and 2009–2017, based on the E-OBS 30.0e dataset, while Panel B shows the distributions for 2000–2014 and 2050–2059, using the average projections from the 31 climates models in the NEX-GDDP-CMIP6 database. (Detailed projections from each climate model are provided in Figure A3 of the Supplementary Materials.) The data indicate substantial warming in the recent decades. For instance, the number of days with a mean temperature >25°C increased from 4.07 per year in 1950–1989 to 13.7 days in 2009–2017. The climate models project that this trend will intensify further in the coming decades.

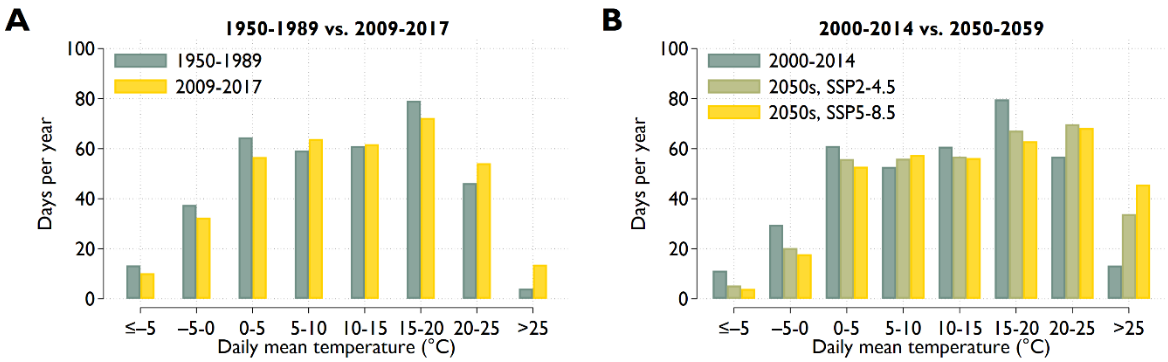

Fig. 2: Changes in temperature distributions: 1950–1989 vs. 2009–2017 and 2000–2014 vs. 2050–2059

Notes: Each distribution assumes a 365-day long year. (B) The averages of the 31 climate models are used.

3. Methods

3.1. The temperature-ED visit relationship

The effect of temperatures on ED visit rates was derived by estimating the following equation:

$$M_{rt} = \sum_j \sum_{b=0}^{10} \beta_b^j T_{r(t\text{-}b)}^j + \sum_k \sum_{b=0}^{10} \gamma_b^k P_{r(t\text{-}b)}^k + \sum_l \sum_{b=0}^{10} \delta^l H_{r(t-b)}^l + \rho_{rym} + \theta_{md} + dow_t + \varepsilon_{rt} \quad (3)$$

where M is the ED visit rate in district *r* at time *t* (year *y*, month *m*, day *d*). T stands for the temperature categories (≤−5°C, −5–0°C, 0–5°C, 5–10°C, 10–15°C, 15–20°C, 20–25°C, >25°C). In the analysis, the temperature category with a daily mean temperature of 5–10°C serves as the reference category. P denotes the amount of precipitation (0 mm, 0−2 mm, 2−5 mm, 5−10 mm, over 10 mm), while H stands for the relative humidity (≤50%, 50–60%, 60–70%, 70–80%, 80–90%, >90%). District-by-year-by-month fixed effects (ρ) account for unobserved location-by-time-specific factors that influence the ED visit rate. Time-invariant seasonality and the effect of fixed-date holidays were captured by dummies for the day of the year (θ). Finally, dummy variables denoting the day of the week were also included to control for the weekly pattern of morbidity (dow).

The coefficient β^j represents the effect of a day when the daily mean temperature falls into temperature bin *j* on the ED visit rate (relative to a day with a mean temperature of 5–10°C). To examine the temporal dynamics of the temperature-ED visit rate relationship, it is allowed that the ED visits rate at time *t* is influenced by both the contemporaneous weather (b=0) and weather in the previous 10 days (b = 1, …, 10). Furthermore, it is also important to note that the β_b coefficients can be interpreted as the effects of temperature at time *t* on the ED visit rate after *b* days (Stock and Watson, 2015). This implies that the sum of the β coefficients ($\beta_0 + \beta_1 + \ldots + \beta_{10}$) represents the 11-day cumulative effect of temperature at time *t*, which is the focus of this paper.

From a simplified perspective, this empirical specification derives the effect of temperature by comparing the ED visit rate on a day with a colder temperature in a given district, year, and month with the ED visit rate on another day with a warmer temperature in the same district, year, and month. This comparison is then repeated for ED visit rates on the subsequent days to obtain the effects of lagged temperatures.

The regressions were weighted by the mean adult population of each district over the period 2009–2017, and standard errors were clustered at the district level. For the estimations, STATA package *reghdfe* was used (Correia, 2017). When examining heterogeneity, separate regressions were estimated for each group.

3.2. The impacts of climate change

To estimate the impact of climate change on ED visits by the 2050s, the sum of the temperature coefficients derived from Eq. (3) was multiplied by the projected temperature changes estimated by Eq. (1). The uncertainty in the relationship between temperatures and ED visits was accounted for by bootstrapping the β coefficient estimates (50 times, sampling with replacement). This means that a projection is calculated as follows:

$$\Delta \mathrm{M}_{\mathrm{sol}} = \sum_{\mathrm{j}} \sum_{\mathrm{b}=0}^{10} \beta_{\mathrm{bs}}^{\mathrm{j}} \, \Delta \mathrm{T}_{\mathrm{ol}}^{\mathrm{j}} \tag{4}$$

where ΔM is the change in the ED visit rate due to climate change, *s* represents the bootstrap sample, *o* denotes the SSP scenario, and *l* stands for the climate model. A total of 1,550 potential projections were analyzed for each SSP scenario, encompassing both climate and regression uncertainty. The findings are presented in terms of changes relative to the annual ED visit rate for the period between 2009 and 2017. In the analysis of heterogeneous effects, the corresponding age-, sex-, and income-specific temperature coefficients were employed.

A similar method was used to estimate the impact of climate change on the number of ED visits for each year from 2009 to 2017:

$$\Delta M^{y} = \sum_{j} \sum_{b=0}^{10} \beta_{b}^{j} \, \Delta T^{j,y} \tag{5}$$

where ΔM represents the change in the ED visit rate due to climate change in year *y* (2009, … , 2017). The temperature coefficients (β) were obtained from Eq. (3), while the temperature changes between 1950–1989 and 2009–2017 (ΔT) were calculated using Eq. (2). The estimated impacts on the ED visit rate was then converted into the total number of visits, assuming a total population of 8.1 million adults in Hungary.

4. Results

4.1. The relationship between temperature and the ED visit rate

The relationship between temperature and emergency department visits is summarized in Panel A of Fig. 3. The estimated cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days (219.5). Thus, these values represent the percentage change in the number of ED visits for a given temperature on the exposure day and over the following 10 days.

Relative to a daily mean temperature of 5-10°C, the influence of colder temperatures on the ED visit rate on the day of exposure and the subsequent 10 days is not significant. However, higher temperatures do have a significant and non-negligible effect. The 11-day cumulative effect of a day with an average temperature above 25°C is 1.60%, roughly 4.65 additional ED visits per 100,000 persons. The cumulative effect of a day with an average temperature between 20-25°C is slightly lower, with an estimated 1.09% (3.19 ED visits per 100,000 persons), while the effects of days with average temperatures between 15-20°C and 10-15°C are 0.54% (1.57 ED visits per 100,000 people) and 0.31% (0.89 ED visits per 100,000 people), respectively. These values indicate that the effect of temperatures in the upper part of the distribution is approximately linear.

Panel B of Fig. 3 shows that the heat-induced increase in the ED visit consists almost entirely of mild cases that do not result in hospitalization. Following the hottest days, mild cases increase by 1.84% (4.42 ED visits per 100,000 persons), whereas severe cases increase by only 0.46% (0.24 ED visits per 100,000 persons). Moreover, unlike mild cases, severe cases appear to be unaffected by other warmer days above the reference category. However, on the coldest days, severe cases increase by 1.07% (0.56 ED visits per 100,000 persons).

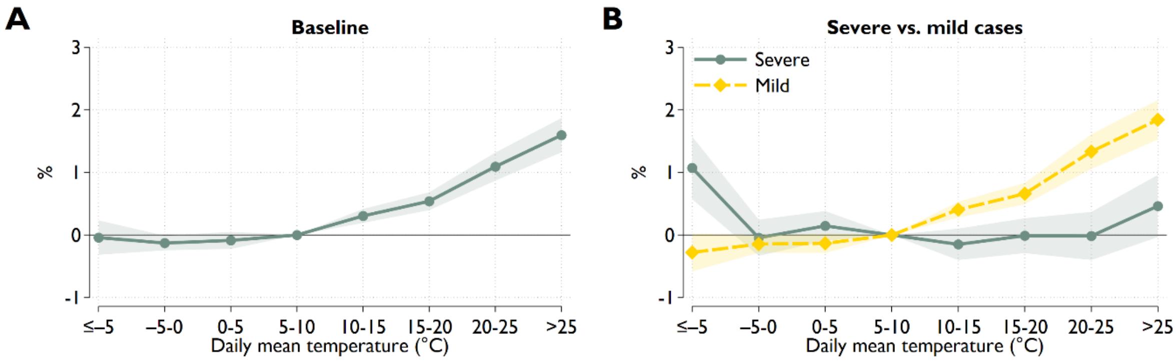

Fig. 3: The cumulative effects of temperatures on ED visits

Notes: (A) Baseline relationship. (B) Estimates for severe and mild cases. Cumulative effects for lags 0-10. The cumulative coefficients are expressed as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over an 11-day period. In Panel B, the respective ED visit rates are used to calculate the percentage effects. Shaded areas represent 95% confidence intervals. The effects are compared to a day with a mean temperature of 5–10°C. The model includes district-by-year-by-month, day-of-the-year, and day-of-the-week fixed effects. Precipitation and relative humidity are controlled for. The regressions are weighted by the mean adult population of each district over the period 2009–2017. Standard errors are clustered by district.

The effects shown above are cumulative effects over 11 days. Figure A4 (Supplementary Materials) reveals that the largest effects across all temperature categories are observed on the day of exposure, with half or more of the cumulative effect occurring within the first day. For the two highest temperature categories, ED visit rates are also increased in the following few days. In contrast, for the other temperature categories there is minimal difference between the cumulative effects at lag 0 and, for example, lag 7. However, the effects of the coldest temperatures at later lags appear to have the opposite effect compared to the effect at lag 0, with their 11-day cumulative effect reaching zero.

Since the choice of 10 lags is somewhat arbitrary, Figure A5 (Supplementary Materials) demonstrates that the results remain consistent when using 7 or 13 lags instead of 10 (in addition to the contemporaneous temperature). For accurate comparison, the estimated results in this case are not expressed as percentage effects, but shown in absolute values. Additionally, the inclusion of an extended lag structure (lags 11–29) has no apparent impact on the baseline estimates. Over this additional 19-day period, the effects for all temperature categories are not significantly different from zero (Figure A6, Supplementary Materials).

The pattern of the temperature's effect on ED visits for most diagnosis groups is broadly similar to that observed for all visits (Figure A7, Supplementary Materials). However, there are some differences. Heat appears to exert a negligible or slightly negative effect on ED visits for diseases of the nervous, circulatory, and respiratory systems. In contrast, above-average heat-induced increases are observed for endocrine and metabolic diseases, injuries, diseases of the skin and subcutaneous tissue, and general symptoms. In these cases, the cumulative effect of a day with an average temperature above 25°C is around 3% or more. Furthermore, cold reduces or does not affect ED visits for almost all diagnosis groups. The only exception is the category of injuries (which also includes poisoning and certain other consequences of external causes), where the effect is large and positive.

To rule out the possibility that unmeasured seasonal factors drive the results, a falsification test was performed. In this estimation, the weather variables were replaced by temperature, precipitation, and humidity observations exactly one year later. Since emergency department visits cannot be affected by future weather (the impossibility of backward causation), zero temperature coefficients are expected in this specification. This is precisely what was found; the estimated effects are small and usually statistically insignificant (Figure A8, Supplementary Materials).

A series of additional sensitivity tests provided further confirmation of the conclusion drawn from the baseline specification (Figure A9, Supplementary Materials). Replacing the district-by-year-by-month fixed effects with county-by-year-by-month and separate district fixed effects has no considerable impact on the results. Moreover, this was also the case when the more restrictive district-by-year-by-week fixed effects were included. In this latter specification, the temperature variability within a given district, year, and calendar week was leveraged. The baseline pattern of the temperature effects was also replicated when daily maximum or minimum temperatures were used, precipitation and humidity were excluded, three lags of the dependent variable were included, or a Poisson pseudo maximum likelihood (PPML) regression was estimated (Correia et al., 2020).

Since the appropriate level(s) for clustering the standard errors is not entirely clear, alternative clustering methods were applied, demonstrating that the conclusions remain unchanged (Figure A10, Supplementary Materials). The statistical significance was unaffected even when more conservative clustering methods were used.

The baseline pattern of the estimated temperature effects was also obtained for temperature categories with a 2°C range, with the lowest category representing a mean temperature of ≤−8°C and the highest category representing a mean temperature of >28°C

(Figure A11, Supplementary Materials). No significant difference was observed between the effects of temperature categories below 10°C. However, above 10°C, an almost linear relationship was observed between temperature and ED visits, with a higher ED rate consistently observed in warmer temperatures.

The observation that as heat stress intensifies, so too does the emergency department visits, was supported by the results of the analysis of the heat-humidity interaction (Table 2). The effect on the ED visit rate is more pronounced when hot temperatures (>25°C) are accompanied by higher humidity levels than when they are accompanied by lower humidity levels. In the former case, the estimated cumulative effect is 1.93% (5.61 ED visits per 100,000 people), while in the latter case, it is 1.39% (4.04 ED visits per 100,000 persons). Moreover, it is also important to note that the effect of prolonged heat stress on morbidity appears to be considerably stronger (Table 3). The cumulative effect of a day with an average temperature of >25°C when it is considered a heatwave day (preceded by at least four other >25°C days) is 2.03% (5.91 ED visits per 100,000 people), while the impact of a >25°C day that is not considered a heatwave day is 1.50% (4.38 ED visits per 100,000 people).

Table 2. Heat-humidity interaction

Daily mean temperature (°C)	(1)
≤−5°C	−0.04 (0.14)
−5-0°C	−0.13 (0.06)*
0-5°C	−0.09 (0.07)
5-10°C	ref. cat.
10-15°C	0.30 (0.06)**
15-20°C	0.53 (0.07)**
20-25°C	1.06 (0.11)**
>25°C	
low humidity	1.39 (0.14)**
high humidity	1.93 (0.18)**

Notes: Cumulative effects for lags 0-10. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days. The model includes district-by-year-by-month, day-of-the-year, and day-of-the-week fixed effects. Precipitation and relative humidity are controlled for. The regressions are weighted by the mean adult population of each district over the period 2009–2017. Standard errors are clustered by district. * p<0.05, ** p<0.01

Table 3. The effect of heatwave days

Daily mean temperature (°C)	(1)
≤−5°C	−0.04 (0.14)
−5-0°C	−0.13 (0.06)*
0-5°C	−0.09 (0.07)
5-10°C	ref. cat.
10-15°C	0.30 (0.06)**
15-20°C	0.54 (0.07)**
20-25°C	1.10 (0.11)**
>25°C	
non-heatwave day	1.50 (0.16)**
heatwave day	2.03 (0.22)**

Notes: Cumulative effects for lags 0-10. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days. The model includes district-by-year-by-month, day-of-the-year, and day-of-the-week fixed effects. Precipitation and relative humidity are controlled for. The regressions are weighted by the mean adult population of each district over the period 2009–2017. Standard errors are clustered by district. * $p<0.05$, ** $p<0.01$

4.2. Heterogeneities in the temperature effects

The subsequent analysis examines the heterogeneities in the temperature effects, estimating how these vary by sex, age, district-level income, and GP density. The percentage effects are calculated using group-specific means of the ED visit rate.

No substantial difference is observed in the temperature effects between women and men (Panel A of Fig. 4). For example, the effect of a day with an average temperature above 25°C is 1.68% for women and only slightly lower (1.51%) for men. Similar minimal differences are found across most other temperature categories.

In contrast, notable differences emerge across age groups, at least for the warmer temperatures (Panel B of Fig. 4). The effects of the warmer temperature categories decrease considerably with advancing age, whereas the effects of colder temperatures vary only to a more limited extent. The 11-day cumulative effect of a day with an average temperature above 25°C is 2.31%, 1.61%, and 0.65% for the youngest (18-44 years old), middle (45-64 years old), and oldest (65 years old or older) age groups, respectively. Importantly, these differences are reflected not only in percentage effects but also in absolute terms: the heat-related increase in ED visits is much larger for the youngest age group (5.77 ED visits per 100,000 persons) compared to the middle-aged (4.35 ED visits per 100,000 persons) and the oldest generation (2.70 ED visits per 100,000 persons). Large differences are also observed for the 20-25°C temperature category.

Panel C of Fig. 4 summarizes the relationship between temperature and ED visits across three income groups: the low-, middle-, and high-income districts. The results show that the effects of higher temperature categories tend to weaken with increasing income. For exposure to temperatures above 25°C, the effects are 1.82% in the low-income districts, 1.56% in the middle-income districts, and 1.39% in the high-income districts. Similarly, for the 20-25°C temperature category, the effects are 1.35%, 1.08%, and 0.79%, respectively. In contrast, the effects of the coldest temperature category show some variation but appear unrelated to income levels.

Panel D of Fig. 4 explores the relationship between temperature effects and the quality of primary health care, proxied by the number of GPs per 100,00 inhabitants. Generally, in districts with high GP density, the effects of warmer temperature categories are lower than in districts with medium or low GP density. The effect of a >25°C day is 1.39% in high GP density districts, compared to 1.65% and 1.55% in districts with medium and low GP density, respectively. The differences are even more pronounced for the 20-25°C temperature category, with effects of 0.54%, 1.19%, and 1.30%, respectively.

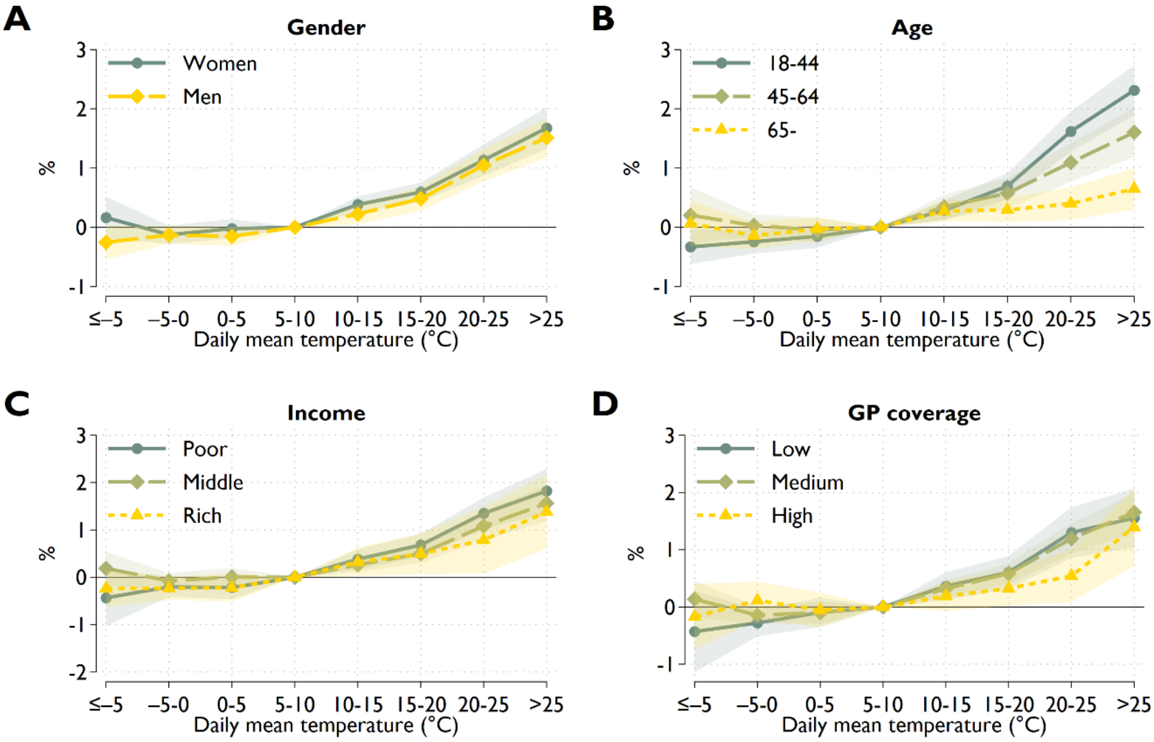

Fig. 4: Heterogeneity in the effects of temperature

Notes: Cumulative effects for lags 0-10. The cumulative coefficients are expressed as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total (group-specific) ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. Standard errors are clustered by district.

4.3. The impact of climate change, 2009-2017

Fig. 5 illustrates the impact of temperature changes observed between 1950–1989 and 2009–2017 on the total number of ED visits in Hungary. The calculations are based on Eq. 5, assuming a total population of 8.1 million adults in Hungary. The figure presents the cumulative number of excess ED visits over the nine-year sample period, revealing a clear, steadily increasing trend. Each year shows a varying number of excess visits due to shifts in the temperature distribution relative to 1950–1989. By the end of the period, the total number of excess ED visits reaches approximately 46,800 (95% CI: 39,300–54,200). This figure exceeds the annual patient volume of an average rural emergency department (Varga et al., 2017), and accounts for 0.66% of all ED visits from 2009 to 2017.

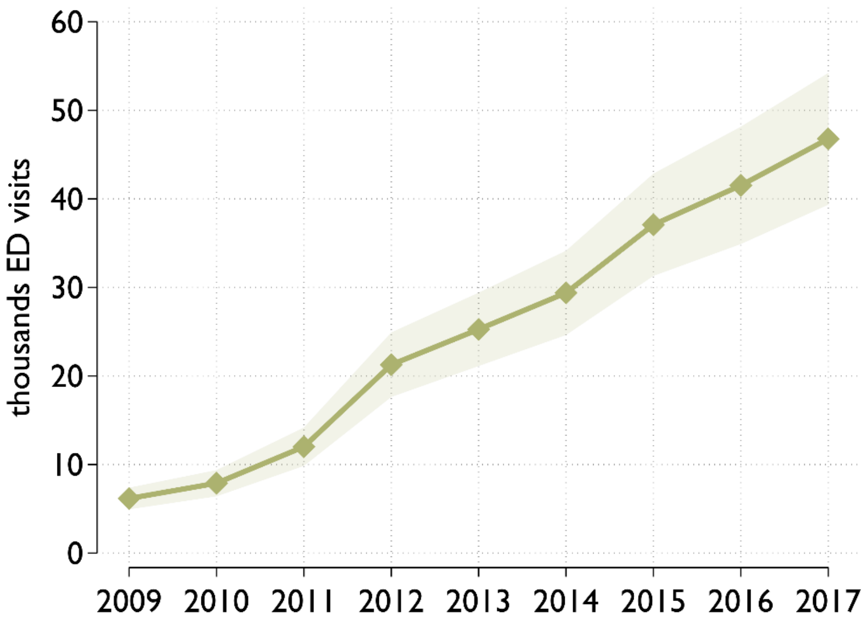

Fig. 5: The impact of climate in 2009-2017

Notes: The cumulative number of excess ED visits due to temperature changes. Changes in the temperature distribution are calculated as the difference between the period of 1950–1989 and each year from 2009–2017. The impacts are calculated assuming a total population of 8.1 million adults in Hungary. Shaded areas represent 95% confidence intervals.

4.4. The impact of climate change, 2050s

The future morbidity burdens of climate change were examined for the 2050s under the assumption that the relationship between ED visits and temperatures will be the same in the future as was observed between 2009 and 2017. By combining the projected temperature changes between 2000–2014 and 2050–2059 from thirty-one climate models with the estimated temperature coefficients (see Eq. 4), I found that the average projection suggests an increase of 1.24% (95% CI, 0.54%–2.84%) in annual the ED visit rate under the SSP2-4.5 climate scenario and an increase of 1.70% (95% CI, 0.70%–3.47%) under the SSP5-8.5 scenario (Fig. 6, Panel A). These percentage changes represent an increase of 119.6 (95% CI, 52.1–274.8) and 164.5 (95% CI, 68.1–335.3) ED visits per 100,000 persons per year under the SSP2-4.5 and SSP5-8.5 scenarios, respectively.

The latest baseline population projection from Eurostat (EUROPOP2023) indicates that the Hungarian adult population will be approximately 7.6 million by the mid-2050s. Based on this figure, the total morbidity burden due to climate change for Hungary in the 2050s is estimated to be approximately 91,000 additional ED visits under the SSP2-4.5 scenario and approximately 125,000 additional ED visits under the SSP5-8.5 scenario. It is important to note that the climate change-induced additional ED visits will not be distributed uniformly across the year. Nearly 50% of the increase is projected to occur during the summer months, slightly over 25% during autumn, and approximately 20% during spring, while the ED visits during the winter months are expected to remain almost unaffected (Fig. 6, Panels B and C).

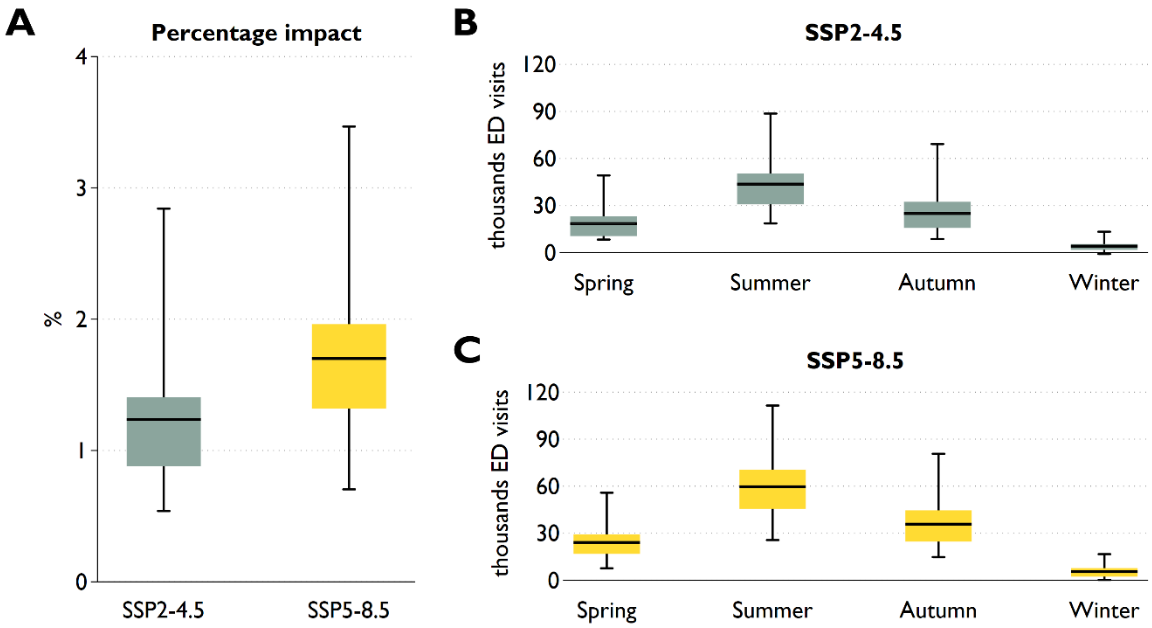

Fig. 6: The impact of climate change in the 2050s on ED visits

Notes: (A) The percentage impact of climate change on the annual ED visit rate. (B) and (C) Change in the total number of ED visits in the 2050s by season assuming a population of 7.6 million adults in Hungary. The impacts are calculated using changes in the temperature distribution between the periods of 2050–2059 and 2000–2014. The black horizontal lines indicate the mean of the projections, the boxes are the interquartile ranges, and the whiskers show the middle 95% of the projections.

4.5. Climate change heterogeneity

Although the impacts described above highlight the societal consequences of climate change as a whole, it remains unclear which groups will bear the greatest burden. To address this, the subsequent analysis utilizes the group-specific temperature effects across the entire temperature distribution (see Fig. 4) and calculates the projected impacts of climate change for the 2050s, disaggregated by sex, age, district-level income, and GP density. Table 4 summarizes these projections, presenting the averages.

As shown earlier, the temperature effects for men and women are virtually identical. Consequently, the projected impacts of climate change also do not differ between the sexes. For example, under the SSP5-8.5 scenario, the average projected increase in the annual ED visit rate is 1.71% for women and 1.69% for men.

The large differences in the temperature effects across age groups (Fig. 4) are mirrored in the projected climate change impacts. The percentage increase in the ED visit rate due to climate change is more than four times greater for the 18–44 age group and more than one and a half times greater for the 45–64 age group compared to the 65+ age group. Under the SSP5-8.5 scenario, the projected increase in the annual ED visit rate is 2.61% for the youngest age group, 1.53% for the middle age group, and 0.63% for the oldest age group.

Income disparities are also not negligible in the projected impacts of climate change. The average projections show that the effect on individuals living in the poorest districts is about 35% larger than for those in the richest districts and about 30% larger than for those in the middle-income districts. For instance, under the SSP5-8.5 scenario, the average of the projections on the annual ED visit rate is 2.07% for the low-income districts, 1.59% for the middle-income districts, and 1.55% for the high-income districts.

Similarly, the calculations indicate that districts with lower GP density will experience a larger increase in the ED visits due to changing climate. Under the SSP5-8.5 scenario, the average projected increase is 1.86% for the low GP density districts, 1.72% for the middle GP density districts, and 1.37% for the high GP density districts.

Table 4. Average projected impacts of climate change on the ED visit rate

	Climate scenario	
	SSP2-4.5	SSP5-8.5
Sex		
Women	1.24%	1.71%
Men	1.23%	1.69%
Age		
18-44	1.91%	2.61%
45-64	1.10%	1.53%
65-	0.45%	0.63%
Income category		
Poor	1.53%	2.07%
Middle	1.15%	1.59%
Rich	1.11%	1.55%
GP density		
Low	1.40%	1.86%
Medium	1.26%	1.72%
High	0.93%	1.37%

Notes: Percentage impacts of climate change on the annual ED visit rate in the 2050s. The impacts are calculated using changes in the temperature distribution between the periods of 2050–2059 and 2000–2014.

5. Conclusions

This study, using high-quality administrative data on emergency department visits in Hungarian outpatient care from 2009 to 2017, demonstrated that ambient temperature has a substantial effect on morbidity. A day with an average temperature above 25°C was found to result in a 4.65-visit increase per 100,000 individuals on the day of exposure and the subsequent 10 days, relative to a daily mean temperature of 5-10°C. This represents a 1.6% increase, expressed as a percentage of the sample average of the total ED visit rates over 11 days. The effects of the other temperature categories above the reference temperature were also positive, showing a consistent pattern: the higher the temperature, the stronger its effect on ED visits. It is also shown that the temperature-induced increases are primarily driven by mild cases; ED visits that are not followed by hospitalization. The results regarding the moderating effect of humidity and the impact of consecutive hot days suggest that the stronger the heat stress, the greater the effect on morbidity. In contrast, colder temperatures below the reference category (5-10°C) were found to have no substantial effects on ED visits.

Comparing the results with other studies is challenging due to variations in time scales (daily, weekly or monthly data), outcome variables, the choice of temperature metrics (minimum, maximum or mean), reference temperature, and the inclusion and treatment of lagged effects. Additionally, differences in climate and health care systems across countries or regions may influence the findings.

Despite these challenges, the estimated effect of heat in this study aligns reasonably well with findings from other studies on ED visits. When comparing these results, it is important to consider how the percentage (relative) effects are computed, specifically the reference value against which the effect is calculated. For example, it makes a difference whether the benchmark is the average number of ED visits per day, per week or even per month. Gould et al. (2024) report that in California, one additional day with a daily maximum temperature above 34°C increases the monthly ED visit rate by nearly 0.4%. Sun et al. (2021), using U.S. data and accounting for lagged effects up to five days, found that ED visits are 7.8% higher (expressed as a percentage of daily ED visits) when the daily maximum temperature exceeds 34.4°C. Similarly, White (2017) reported that in California, a day with an average temperature above 80°F (~26.7°C) increases ED visits by 5.1% over a 31-day period (expressed relative to the average daily ED visit rate). Gibney et al. (2023) report that in England, hot temperatures increase weekly ED visits by approximately 7.5% over a four-week period. Across these studies, the observed effects are typically concentrated within the first one or two weeks following high temperatures, with later lags showing little to no effect. Re-expressing these findings relative to the total ED visit rate over one- or two-week periods would make most of them broadly comparable to the results of this study.

In contrast, the estimated effects of cold temperatures vary considerably across studies. Some, such as Gould et al. (2024) and Sun et al. (2021), report that ED visits decrease during cold weather compared to mild temperatures. Others, such as White (2017), observe the opposite, while Gibney et al. (2023), consistent with this paper, find no significant effect of cold temperatures on ED visits. However, the present study also highlights some important heterogeneity. Mild and severe cases respond differently to cold temperatures. While ED visits that do not result in hospitalization slightly decrease with exposure to cold temperatures, the number of severe cases increases significantly. Since mild cases constitute the majority of total ED visits, the overall effect is practically zero.

The observed temperature effects and projected temperature changes of this paper imply that by the 2050s (compare to the period 2000–2014), the annual ED visit rate will increase by 1.24% under the SSP2-4.5 climate scenario (corresponding to 119.6 ED visits per 100,000 people per year), and by 1.70% under the SSP5-8.5 scenario (equivalent to 164.5 ED visits per 100,000 people per year). Nearly 50% of the increase is projected to occur during the summer months. At the same time, climate change is already having a measurable impact on ED visits today. During the sample period, 2009–2017, 46,800 ED visits (0.66% of all ED visits) were attributed to changes in the temperature distribution compared to 1950–1989.

Beyond these average effects, substantial heterogeneities were observed. Individuals residing in districts with lower income levels appear to experience greater adverse effects when exposed to high temperatures. By the 2050s, the projected increase in ED visits due to climate change in low-income districts is estimated to be 30–35% higher than in middle-income or higher-income districts. This disparity may be partially attributed to inadequate insulation and limited access to air-conditioning in low-income areas, as well as a higher prevalence of outdoor occupations more directly exposed to extreme weather conditions.

Furthermore, temperature-induced increases in ED visits are significantly smaller in districts with a high density of general practitioners compared to those with low GP density. As a result, the projected impacts of climate change are 35–50% greater in districts with low GP density. These findings indicate a substitution relationship between emergency care and primary care services. General practitioners may effectively manage and treat many heat-related health issues, which, as shown in this study, are primarily milder cases, thereby reducing the demand for emergency treatment.

The largest differences, however, were observed across age groups. As age increases, the effect of temperature decreases substantially, a finding consistent with some other studies (Gould et al., 2024; Sun et al., 2021; White, 2017). As a result, by the 2050s, the projected impact of climate change on ED visits is more than four times larger for the youngest age group compared to the oldest age group.

These findings mean that policymakers need to develop strategies to mitigate the effects of climate change on morbidity. For example, it could be important to implement heat warning systems that provide information to those most vulnerable in order to help them avoid the adverse effects of heat. Local authorities may need to open cooling stations where people can spend the hottest hours. The results also show that it is not always easy to predict which social groups will be most affected by the impacts of climate change. For instance, in the case of health impacts, it is easy to assume that the older population, who tend to be in poorer health, will suffer most of the consequences. This may be true for health impacts such as mortality. However, when it comes to ED visits, we have seen that the impacts are more pronounced for the younger generations. The results also suggest that more easily accessible GP care may reduce the overload on emergency care during heatwaves. By coordinating and properly planning the different modes and levels of care, treatment efficiency and patient satisfaction may be increased. Finally, it is perhaps also worth noting that humanity would be best served not by trying to mitigate the effects of climate change, but by trying to limit climate change itself and keep it to as low a level as possible. While it is important to prepare for the potential impacts, this does not mean that the best decision is to focus our limited resources on this alone. As many of the potential impacts of climate change are unforeseen, it may be worthwhile to adopt a strategy that aims to avoid having to face these potentially catastrophic effects by limiting future warming of the climate.

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Supplementary Materials

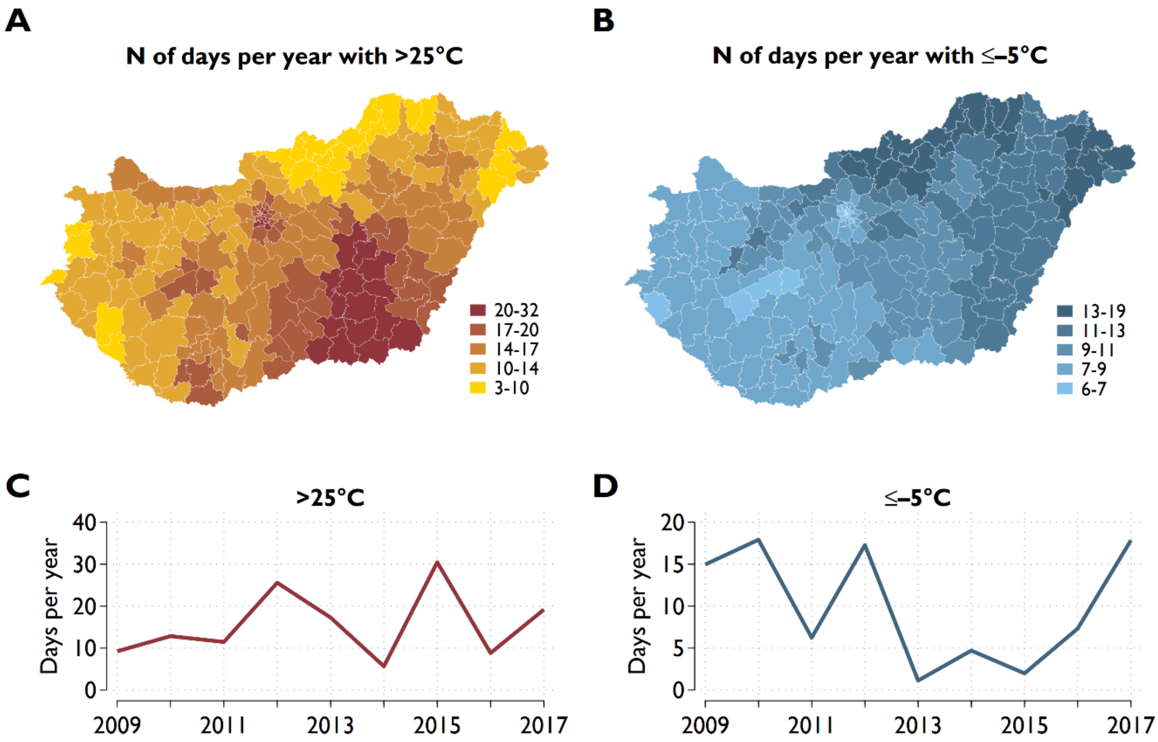

Figure A1. Temperature differences across years and districts

Notes: (A) District-level averages of the annual number of days with an average temperature >25 °C for 2009–2017. (B) District-level averages of the annual number of days with an average temperature ≤−5 °C for 2009–2017. (C) Country-level averages of the number of days per year with an average temperature >25 °C. (D) Country-level averages of the number of days per year with an average temperature ≤−5 °C. The country-level values are calculated as the weighted average of the district-level values. The average number of populations over the years 2009-2017 is used as each district's weight.

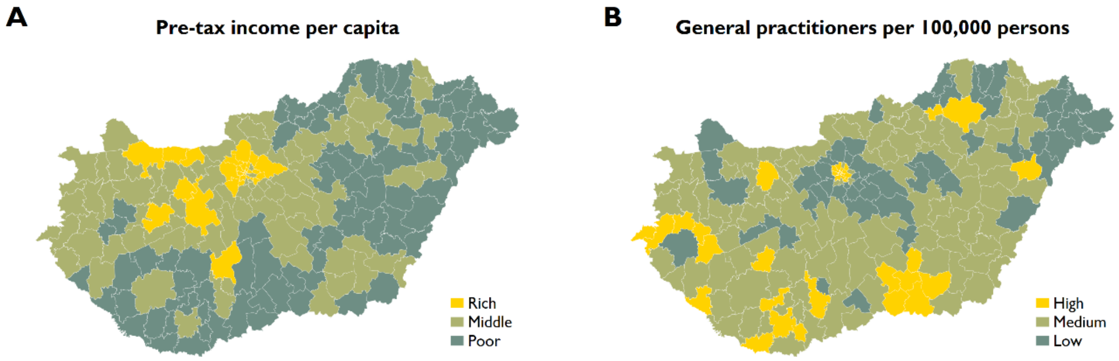

Figure A2. Income differences and GP density across districts

Notes: (A) Rich = richest 25%, middle = middle 50%, poor = poorest 25%. (B) High = highest 25%, medium = middle 50%, low = lowest 25%. Population-weighted shares. Based on the average annual pre-tax income per capita and the average number of general practitioners per 100,000 persons for the years 2009-2017.

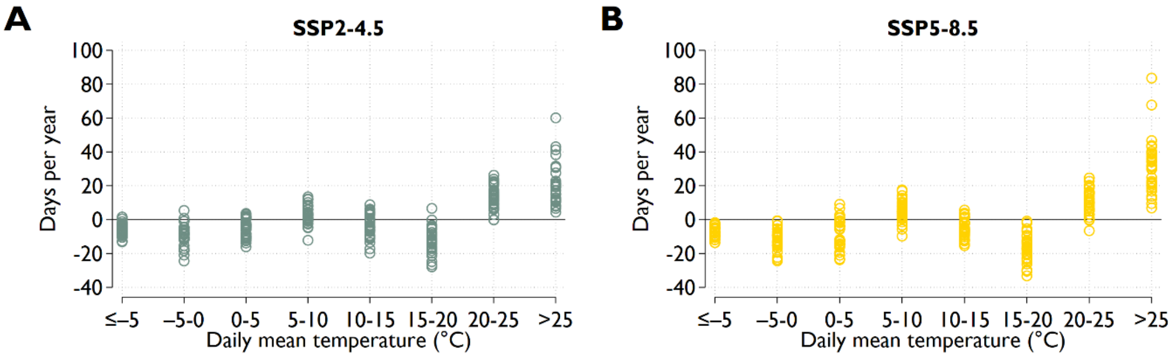

Figure A3. Projected temperature changes between the periods 2050-2059 and 2000-2014

Notes: Each circle shows the projections of one of the thirty-one climate models.

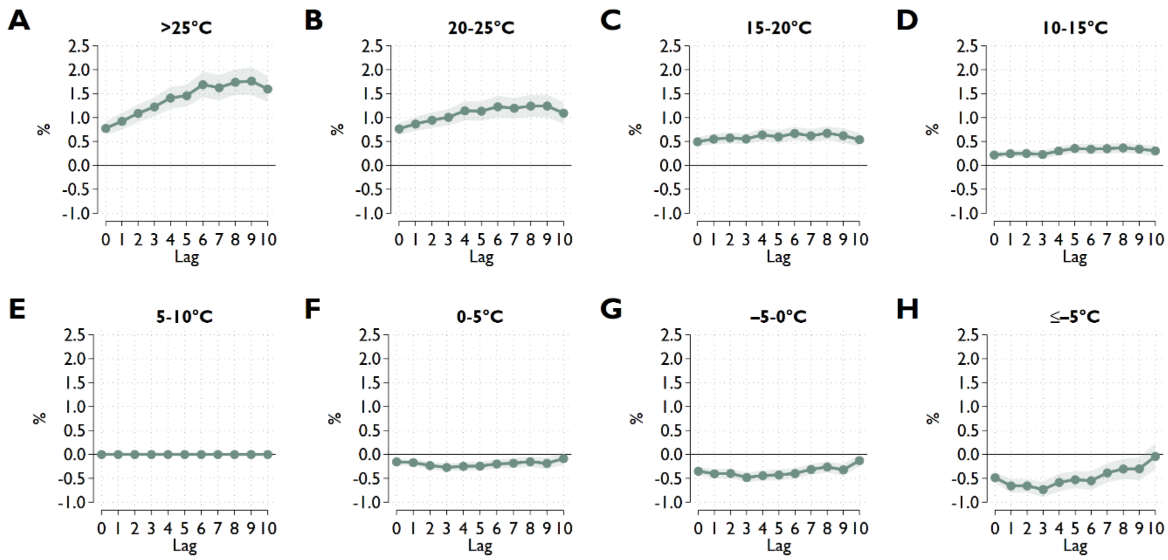

Figure A4. Cumulative effects by lag

Notes: The point estimates represent the cumulative effect for a given temperature category up to the corresponding lag. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. Standard errors are clustered by district.

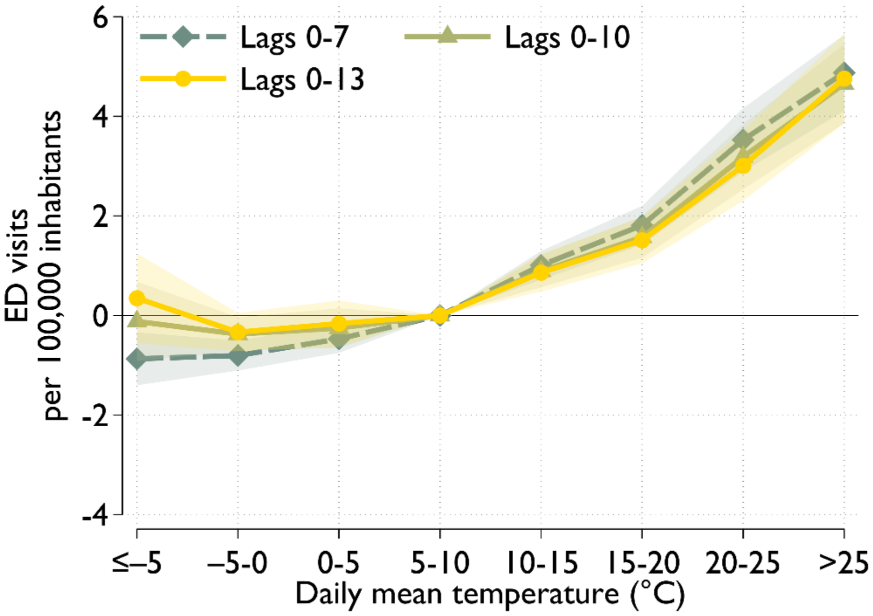

Figure A5. Temperature effects using different number of lags

Notes: Cumulative effects over 8, 11 or 14 days. Shaded areas represent 95% confidence intervals. The effects are compared to a day with a mean temperature of 5–10°C. Standard errors are clustered by district.

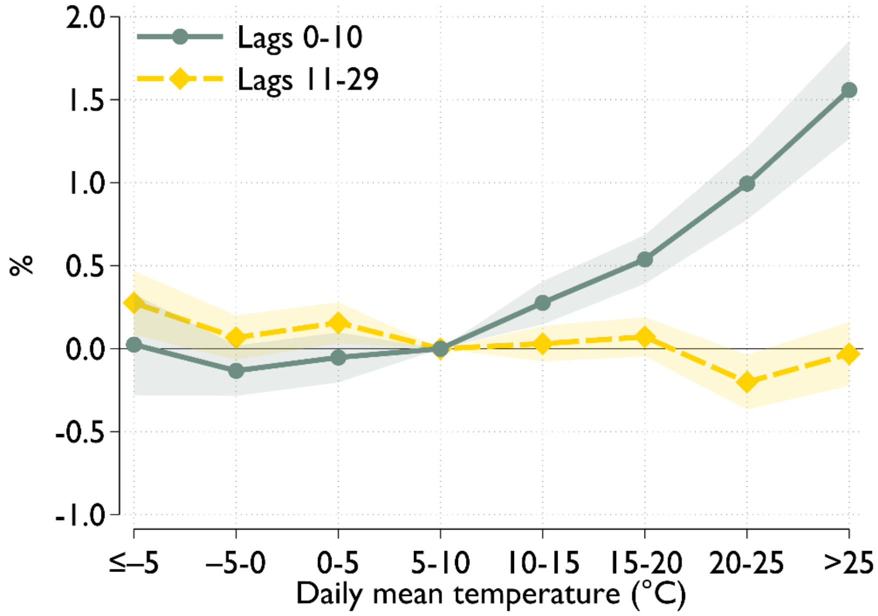

Figure A6. Cumulative effects for lags 0-10 and lags 11-29

Notes: The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 (lags 0-10) or 19 days (lags 11-29). Shaded areas represent 95% confidence intervals. The effects are compared to a day with a mean temperature of 5–10°C. Standard errors are clustered by district.

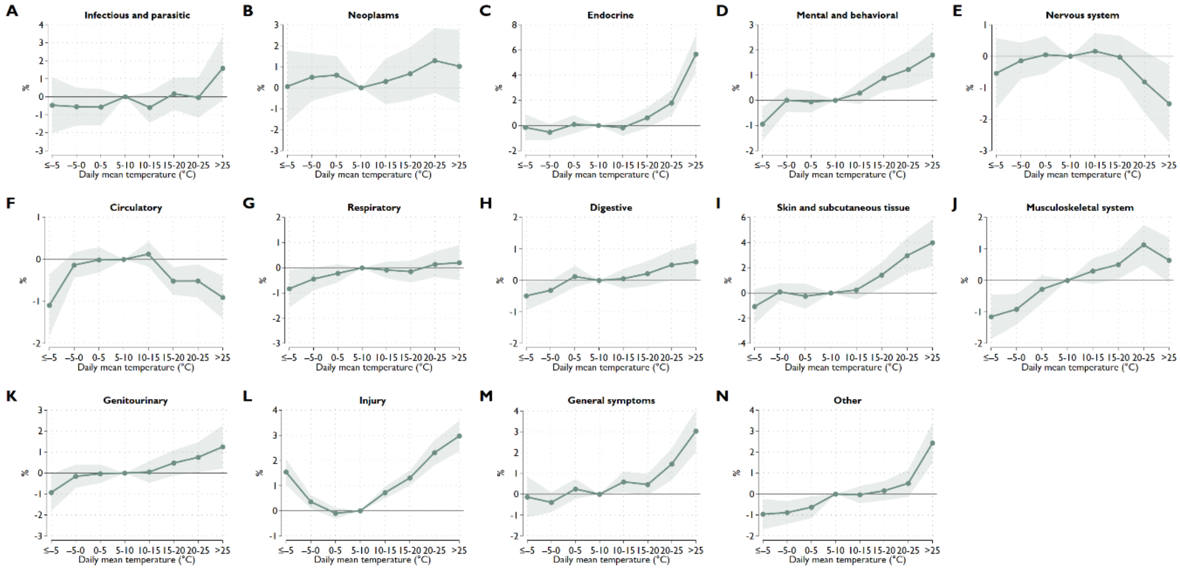

Figure A7. Temperature effects by diagnosis category

Notes: The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. The effects are compared to a day with a mean temperature of 5–10°C. Standard errors are clustered by district. The diagnosis categories are defined by ICD-10 codes. Infectious and parasitic: A00-99, B00-99, Neoplasms: C00-97, D00-48, Endocrine: E00-90, Mental, behavioral: F00-99, R40-49, Nervous system: G00-99, R25-29, Circulatory: I00-99, R00-04, Respiratory: J00-99, R05-09, Digestive: K00-93, R10-19, Skin and subcutaneous tissue: L00-99, R20-23, Musculoskeletal: M00-99, Genitourinary: N00-99, R30-39, Injury: S00-99, T00-98, General symptoms: R50-69, Other: D50-89, H00-95, O00-99, P00-96, Q00-99, R70-99, V00-99, W00-95, X00-99, Y00-98, Z00-99, U00-99.

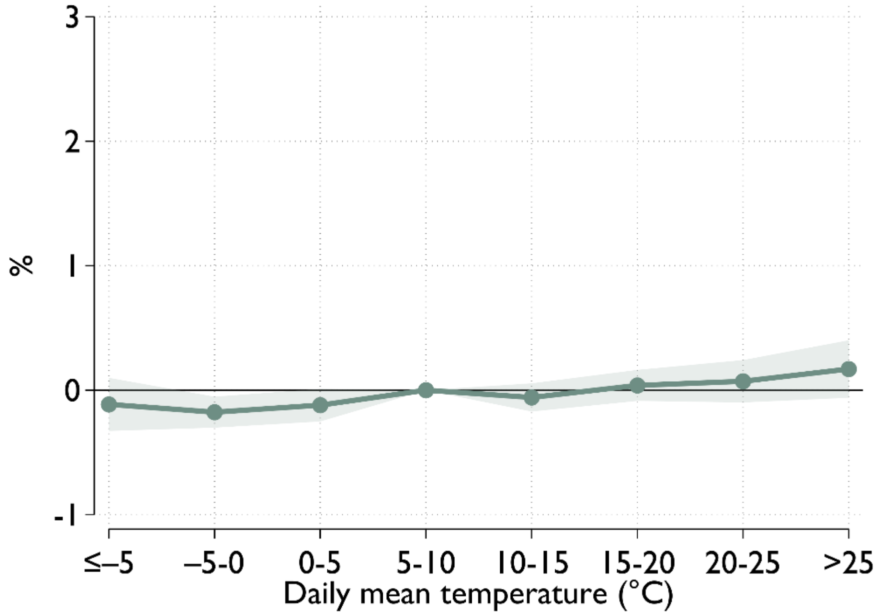

Figure A8. Falsification test with future temperatures

Notes: Cumulative effects for lags 0-10. Based on temperatures measured one year later. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. The effects are compared to a day with a mean temperature of 5–10°C. Standard errors are clustered by district.

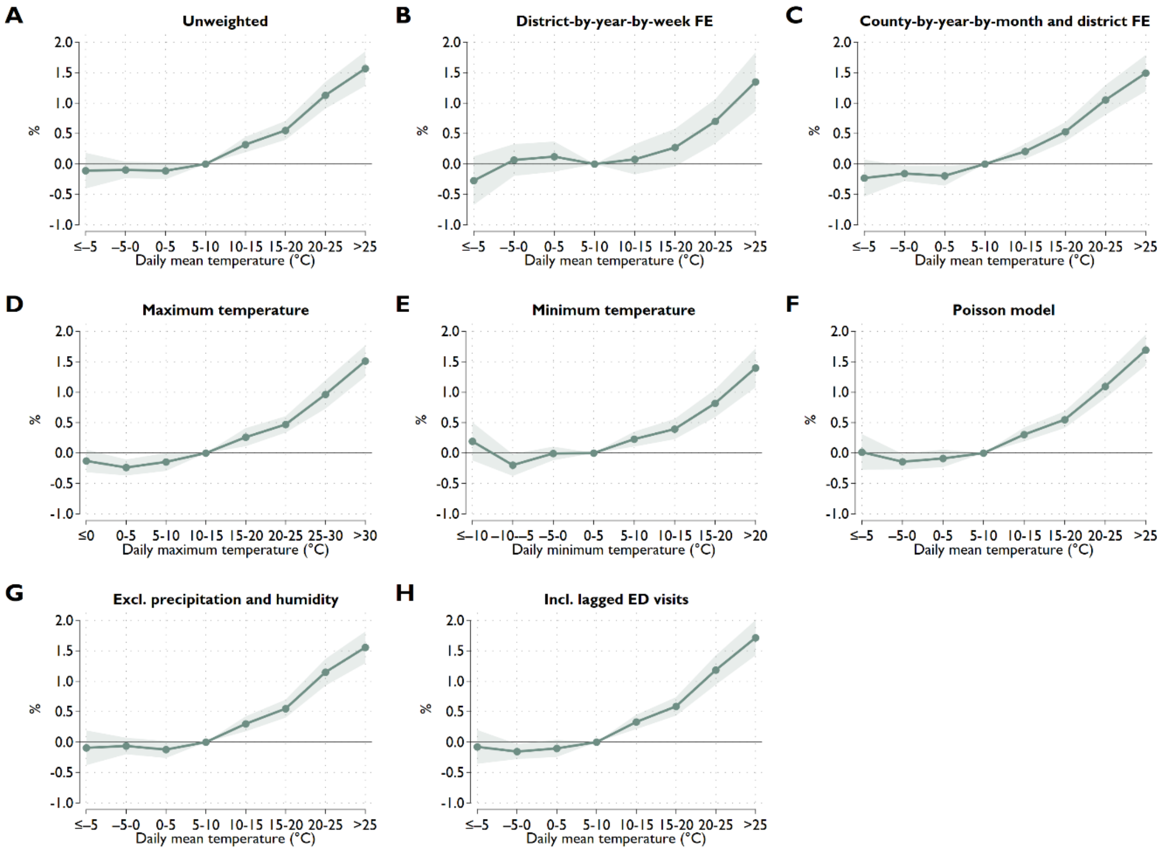

Figure A9. Sensitivity tests

Notes: Cumulative effects for lags 0-10. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. Standard errors are clustered by district.

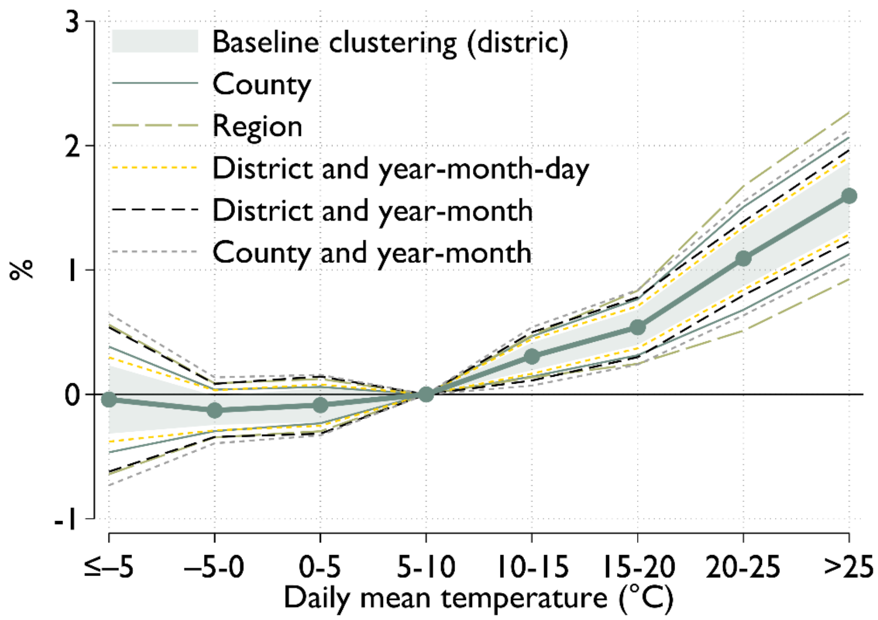

Figure A10. Alternative clustering methods

Notes: Cumulative effects for lags 0-10. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sample average of the total ED visit rates over 11 days.

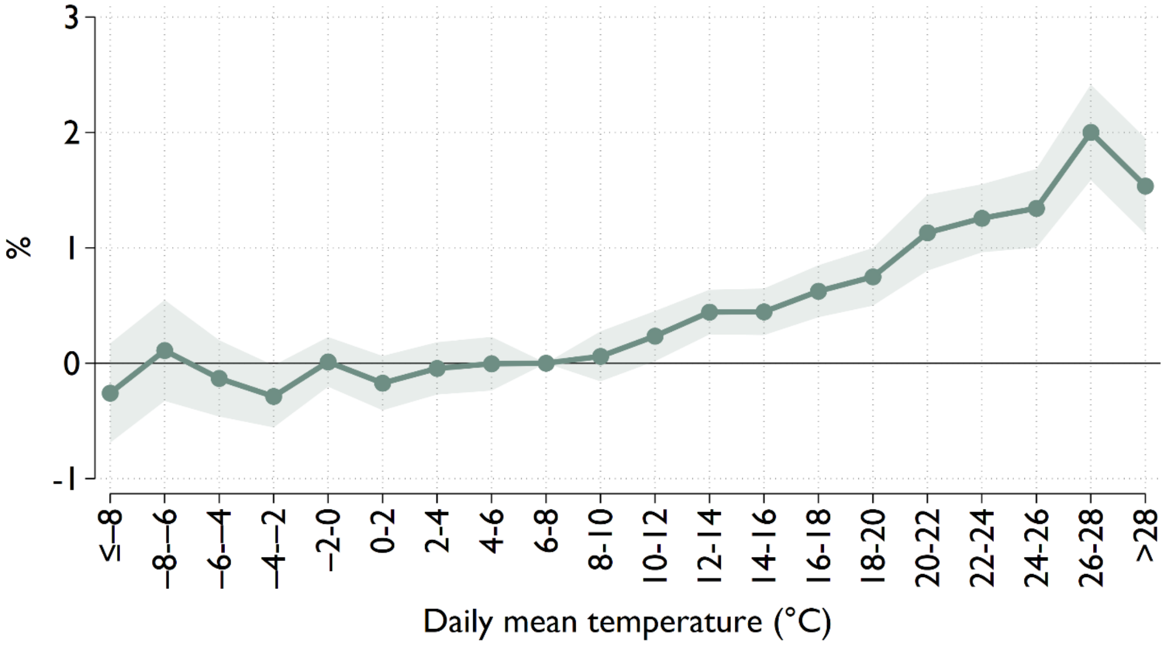

Figure A11. The cumulative temperature effects using 2°C-wide temperature categories

Notes: Cumulative effects for lags 0-10. The cumulative coefficients are presented as percentage effects, calculated by dividing the sum of the temperature coefficients by the sum of the daily ED visit rates over an 11-day period. Shaded areas represent 95% confidence intervals. The effects are compared to a day with a mean temperature of 6–8°C. Standard errors are clustered by district.

Table A1: ED visit rates by subgroups

	Mean	SD
Age		
18-44	22.7	22.5
45-64	24.6	26.0
65-	37.8	40.5
Sex		
Women	25.6	23.7
Men	27.5	25.8
Income category		
Poor	27.1	23.2
Middle	29.4	22.6
Rich	19.5	16.5
GP density		
Low	25.1	20.4
Medium	28.7	22.8
High	20.1	18.8

Notes: Population-weighted figures. Unit of observations: district-by-day.