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Heterogenous impacts of climate change on morbidity

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ABSTRACT
This paper examines how temperature affects emergency department (ED) visits, using administrative data covering 50% of the Hungarian population and comprising 3.52 million outpatient visits from 2009 to 2017. Days with an average temperature above 25°C increase the ED visit rate by 4.65 visits per 100,000 people over an 11-day period (1.60% increase), compared to days with a mean temperature of 5–10°C. The effects of other warmer temperature categories are similarly positive, while colder temperatures show no significant impact. Higher humidity intensifies the heat effect, which is also stronger following consecutive hot days. Between 2009 and 2017, 46,800 ED visits (0.66% of total visits) were attributed to changes in the temperature distribution relative to 1950–1989. Furthermore, by the 2050s, compared to the early decades of the 21st century, the annual ED visit rate is projected to increase by 1.24%–1.70%, depending on the climate scenario. The future impacts of climate change are 30–40% stronger in low-income districts and disproportionately affect younger adults aged 18–44, who face over four times the impact compared to individuals aged 65 and older.

JEL codes: I10, I14, I18, Q54
Keywords: temperature; climate change; morbidity; emergency department visits, heterogeneous impacts

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Az éghajlatváltozás morbiditásra gyakorolt heterogén hatásai

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ÖSSZEFOGLALÓ

A tanulmány a hőmérséklet sürgősségi betegellátó osztályok (SBO) betegforgalmára gyakorolt hatását vizsgálja egy, a magyar lakosság 50%-át lefedő és 3,52 millió járóbeteg-látogatást tartalmazó adminisztratív adatbázis felhasználásával 2009 és 2017 között. A 25°C feletti átlaghőmérsékletű napok, a 5-10°C-os átlaghőmérsékletű napokhoz képest, 4,65 látogatással növeli a SBO-k betegforgalmát 100 000 lakosra vetítve a meleg hőmérsékletnek való kitettség napján és a következő 10 nap alatt (ami 1,60%-os növekedést jelent). A többi melegebb hőmérsékleti kategória hatása ehhez hasonlóan pozitív, míg a hidegebb hőmérsékletek esetében nem mutatható ki jelentős hatást. A magasabb páratartalom fokozza a hőség hatását, valamint a forró napok hatása is erősebb, ha egymást követő forró napok előzik meg őket. A 2009 és 2017 közötti években 46 800 SBO látogatás tulajdonítható a hőmérséklet 1950-1989 közötti időszakhoz képesti növekedésének. Ez az összes ED-látogatás 0,66%-át teszi ki ebben az időszakban. Továbbá, a 21. század első évtizedeihez képest a 2050-es évekre az éves SBO-látogatások száma – éghajlati forgatókönyvtől függően – 1,24%-1,70%-kal fog növekedni. Az éghajlatváltozás jövőbeli hatásai 30-40%-kal erősebbek az alacsony jövedelmű járásokban, és aránytalanul nagy mértékben érintik a 18-44 év közötti korosztályt, akik esetében több mint négyszer nagyobb a hatás, mint a 65 éves és idősebbek körében.

JEL: I10, I14, I18, Q54

Kulcsszavak: hőmérséklet; éghajlatváltozás; morbiditás; sürgősségi betegellátás; heterogén hatások

Heterogenous impacts of climate change on morbidity

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Abstract

This paper examines how temperature affects emergency department (ED) visits, using administrative data covering 50% of the Hungarian population and comprising 3.52 million outpatient visits from 2009 to 2017. Days with an average temperature above 25°C increase the ED visit rate by 4.65 visits per 100,000 people over an 11-day period (1.60% increase), compared to days with a mean temperature of 5–10°C. The effects of other warmer temperature categories are similarly positive, while colder temperatures show no significant impact. Higher humidity intensifies the heat effect, which is also stronger following consecutive hot days. Between 2009 and 2017, 46,800 ED visits (0.66% of total visits) were attributed to changes in the temperature distribution relative to 1950–1989. Furthermore, by the 2050s, compared to the early decades of the 21st century, the annual ED visit rate is projected to increase by 1.24%–1.70%, depending on the climate scenario. The future impacts of climate change are 30–40% stronger in low-income districts and disproportionately affect younger adults aged 18–44, who face over four times the impact compared to individuals aged 65 and older.

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Acknowledgments

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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; Burke et al., 2018; Carleton et al., 2022; Cohen and Dechezleprêtre, 2022; Conte Keivabu et al., 2024; Deschênes and Greenstone, 2011; Deschênes and Moretti, 2009; Gasparrini et al., 2015; Gould et al., 2024; Hanlon et al., 2021; Heutel et al., 2021; Karlsson and Ziebarth, 2018; Masiero et al., 2022; Otrachshenko et al., 2018, 2017; Vicedo-Cabrera et al., 2021), while our knowledge regarding morbidity is considerably more limited. The studies that have focused on morbidity 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 provides 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. The morbidity impacts that have already occurred are almost entirely ignored by the literature, 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 have used only 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. However, there are no studies that quantify social heterogeneity with respect to the impacts of climate change on morbidity.

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 morbidity, and to project the impacts of climate change. 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.

Using daily data, a nonlinear relationship between temperature and the ED visit rate is estimated by applying temperature categories representing 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, indicators of day-of-year, day-of-week, and district-by-year-by-month fixed effects. The inclusion of district-by-year-by-month fixed effects means 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. 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 considerably 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 5.61 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.

However, beyond these average effects, this study identifies substantial heterogeneity. Higher temperatures have stronger effects on people living in districts with lower income levels, and consequently, the projected impact of climate change is 30-40% higher in low-income districts than among individuals living in middle-income or higher-income 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 impact of climate change 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. Third, this paper explores heterogeneity in the future impacts of climate change, an important consideration for designing effective public policies. While many previous studies have focused on understanding 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. 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

The empirical analysis was based on the individual-level administrative panel database of the Databank of the HUN-REN Centre for Economic and Regional Studies, covering 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 administrative dataset contains comprehensive data on each outpatient care visit, classified according to the type of care provided. This has enabled the identification of all emergency department (ED) visits. For each visit, some patient characteristics (age, sex, district of residence) and the ICD-10 code of the principal diagnosis were observed. Thus, in addition to the calculation of daily ED visit rates by district of residence (number of ED visits per 100,000 persons), age-, sex-, and diagnosis-specific rates were calculated. The sample was restricted to individuals aged 18 and over. The final dataset comprised 647,539 observations (197 districts multiplied by 3,287 days).

Figure A1 (Supplementary Materials) provides a summary of the ED visits data. A total of 3.52 million ED visits were observed between the years 2009 and 2017.[1] Over these nine years in Hungary, the mean number of daily ED visits per 100,000 persons increased from approximately 20 to over 30.[2] The district-level averages for the period 2009-2017 demonstrate

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

[2] 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 contributedto 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).

considerable spatial heterogeneity, with the lowest values below 10 ED visits per day per 100,000 persons and the highest values above 50.[3] 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 categories each accounted for 5-6% or less.

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 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 A2, 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%.

The E-OBS 30.0e dataset was also used to calculate the impact of climate change on ED visits during the sample period (2009-2017). 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:

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

$$\Delta T^{j,y} = T^{j,y} - T^{j,1950-1989}, y = 2009, \ldots, 2017 \quad (1)$$

where the variable T denotes the number of days per year when the daily mean temperature falls into temperature category j.[4] 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.

To examine heterogeneity by income, district-level average annual pre-tax income per capita was merged to the dataset. The National Regional Development and Spatial Planning Information System (TEIR) contains data on the total settlement-level pre-tax income and total population, allowing for the calculation of average annual pre-tax income per capita at the district level for the years 2009-2017 (in 2023 HUF). Three income categories were then created using population-weighted thresholds. In the first category, 25% of the population residing in the poorest districts is included, while the second category comprises 25% of the population residing in the richest districts. In the third category, the remaining 50% of the population, living in middle-income districts, is included. Figure A3 (Supplementary Materials) shows the geographical heterogeneity of income levels.

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 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
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.

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

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° × 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:

$$\Delta \mathrm{T}_{\mathrm{ol}}^{\mathrm{j}} = \mathrm{T}_{\mathrm{ol}}^{\mathrm{j},2050-2059} - \mathrm{T}_{\mathrm{ol}}^{\mathrm{j},2000-2014} \tag{2}$$

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. Figure A4 (Supplementary Materials) summarizes the projections.

3. Methods

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

$$\mathrm{M}_{\mathrm{rt}} = \sum_{\mathrm{j}} \sum_{\mathrm{b}=0}^{10} \beta_{\mathrm{b}}^{\mathrm{j}} \mathrm{T}_{\mathrm{r(t-b)}}^{\mathrm{j}} + \sum_{\mathrm{k}} \sum_{\mathrm{b}=0}^{10} \gamma_{\mathrm{b}}^{\mathrm{k}} \mathrm{P}_{\mathrm{r(t-b)}}^{\mathrm{k}} + \sum_{\mathrm{l}} \sum_{\mathrm{b}=0}^{10} \delta^{l} \mathrm{H}_{\mathrm{r(t-b)}}^{\mathrm{l}} + \rho_{\mathrm{rym}} + \theta_{\mathrm{md}} + \mathrm{dow}_{\mathrm{t}} + \varepsilon_{\mathrm{rt}} \tag{3}$$

[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.

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 and year-by-month levels (two-way clustering). For the estimations, STATA package *reghdfe* was used (Correia, 2017).

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. (2). 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:

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

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 determine the impact of climate change on the number of ED visits for each year in 2009-2017 using outputs from Eq. (1) and Eq. (3):

$$\Delta M^{y} = \sum_{j} \sum_{b=0}^{10} \beta_{b}^{j} \, \Delta T^{j,y}, y = 2009, \ldots, 2017 \tag{5}$$

where ΔM represents the change in the ED visit rate due to climate change in year *y* (2009, … , 2017). The impacts on the ED visit rates were then converted to the number of visits, assuming a total population of 8.1 million adults in Hungary.

4. Results

4.1. The historical relationship between temperature and the ED visit rate

The relationship between temperature and emergency department visits is summarized in Fig. 1. 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.

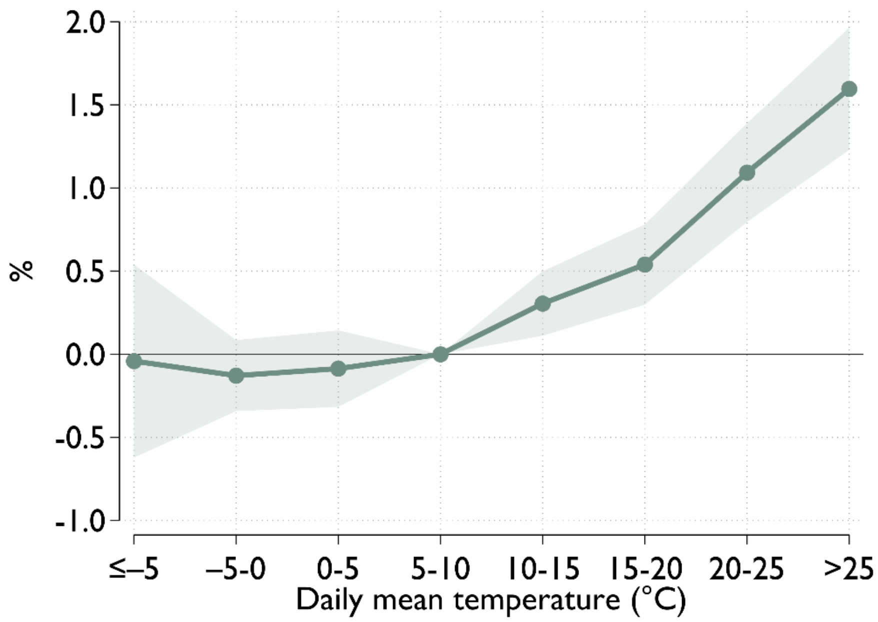

Fig. 1: The cumulative effects of temperatures on ED visits

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. 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 and year-by-month.

The largest effects across all temperature categories are observed on the day of exposure (Figure A5, Supplementary Materials), 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. Furthermore, the inclusion of lags 11-29 has no apparent impact on the baseline estimates. The effects over an additional 19-day period are not significantly different from zero for either temperature category (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 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, or a Poisson pseudo maximum likelihood (PPML) regression was estimated (Correia et al., 2020). Finally, alternative clustering methods of the standard errors yielded unchanged main conclusions (Figure A10, Supplementary Materials).

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% (5.61 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 (0.29)
−5-0°C	−0.13 (0.11)
0-5°C	−0.09 (0.12)
5-10°C	ref. cat.
10-15°C	0.30 (0.10)**
15-20°C	0.53 (0.12)**
20-25°C	1.06 (0.15)**
>25°C	
low humidity	1.39 (0.20)**
high humidity	1.93 (0.21)**

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 and year-by-month. * $p<0.05$, ** $p<0.01$

Table 3. The effect of heatwave days

Daily mean temperature (°C)	(1)
≤−5°C	−0.04 (0.29)
−5-0°C	−0.13 (0.11)
0-5°C	−0.09 (0.12)
5-10°C	ref. cat.
10-15°C	0.30 (0.10)**
15-20°C	0.54 (0.12)**
20-25°C	1.10 (0.15)**
>25°C	
non-heatwave day	1.50 (0.22)**
heatwave day	2.03 (0.30)**

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 and year-by-month. * $p<0.05$, ** $p<0.01$

4.2. The impact of climate change, 2009-2017

Fig. 2 shows how the temperature changes observed between 1950–1989 and 2009–2017 impacted the total number of ED visits in Hungary. The figure depicts the cumulative number of excess ED visits over the nine years of the sample period. A clear and steadily increasing trend can be observed, with each year showing a varying number of excess ED visits due to changes in the temperature distribution compared to 1950-1989. At the end of the period, the total number of excess ED visits reaches approximately 46,800 (95% CI, 36,200–57,400). This figure is significantly higher than the annual patient volume of an average rural emergency department (Varga et al., 2017), and represents 0.66% of all ED visits in 2009-2017.

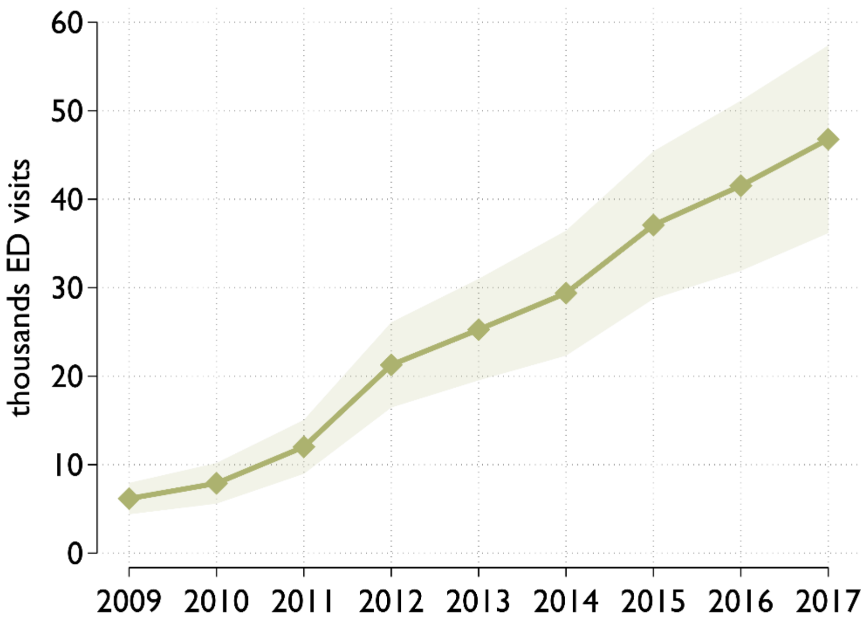

Fig. 2: The impact of climate in 2009-2017

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.

4.3. The future impact of climate change

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 from thirty-one climate models with the estimated temperature coefficients, 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. 3, 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. 3, Panels B and C).

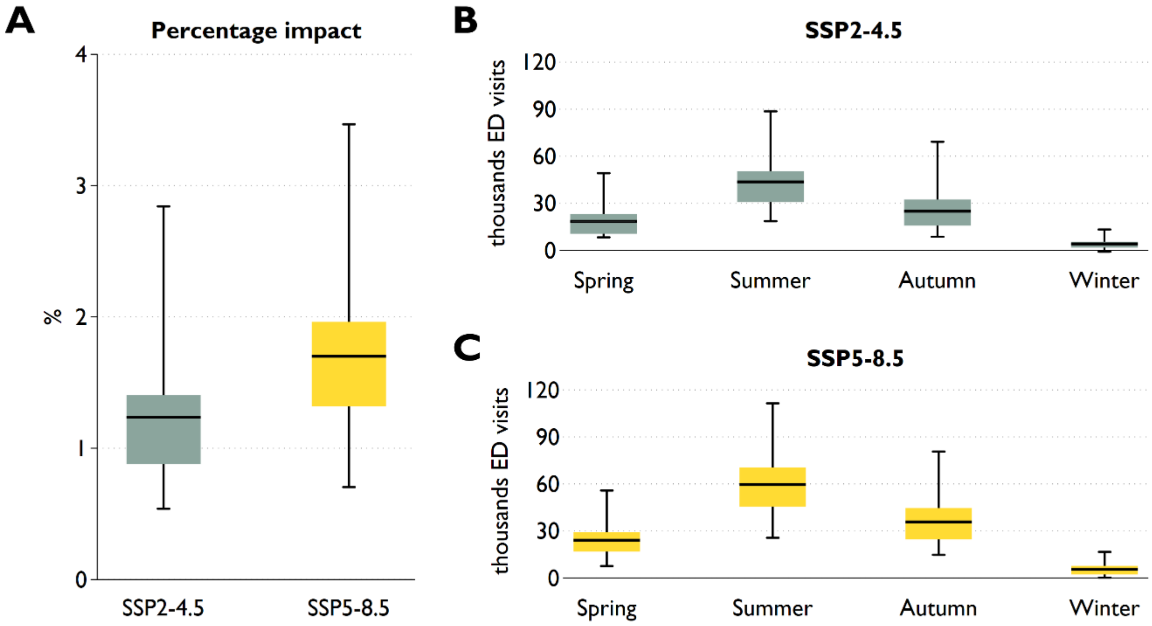

Fig. 3: The impact of climate change in the 2050s on the annual ED visits

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.

4.4. Heterogeneity by age, sex, and district-level income

Although the impacts described above showed the consequences of climate change for society as a whole, it remains unclear which groups will bear the greatest burden. To address this, the subsequent analysis calculates the impacts by district-level income, sex, and age, thus revealing the extent of inequality in the impacts of climate change. The percentage impacts were calculated using the group-specific means of the ED visit rate.

Panel A of Fig. 4 summarizes the relationship between temperature and ED visits for three distinct population groups: the 25% of the individuals residing in the poorest districts, the 25% residing in the richest districts, and the remaining middle 50%. It can be observed that the effect of the higher temperature categories weakens with income. Additionally, there is some difference in the effect of the coldest temperature category, but it seems to be uncorrelated with the income levels. These differences imply that the projected impact of climate change is stronger for the poorest 25% than for the richest 25% and the middle 50% (Fig. 4 Panels B and C). The average projections show that the effect on individuals living in the poorest districts is 35–40% larger than for those residing in the richest districts and slightly more than 30% larger than for those residing in the middle-income districts, under both climate scenarios. For example, under the SSP5-8.5 scenario, the average of the projected impact on the annual ED visit rate is 2.07% for the poor (95% CI, 0.89%–4.03%), 1.59% for the middle-income group (95% CI, 0.64%–3.23%), and 1.55% for the rich (95% CI, 0.58%–3.33%).

The analysis of the effect of temperature among women and men reveals no substantial difference in the effect of temperatures (Fig. 5). Consequently, the impact of climate change does not differ between men and women. The average of the projections under the SSP5-8.5 scenario is 1.71% (95% CI, 0.68%–3.50%) for women and 1.69% (95% CI, 0.71%–3.34%) for men.

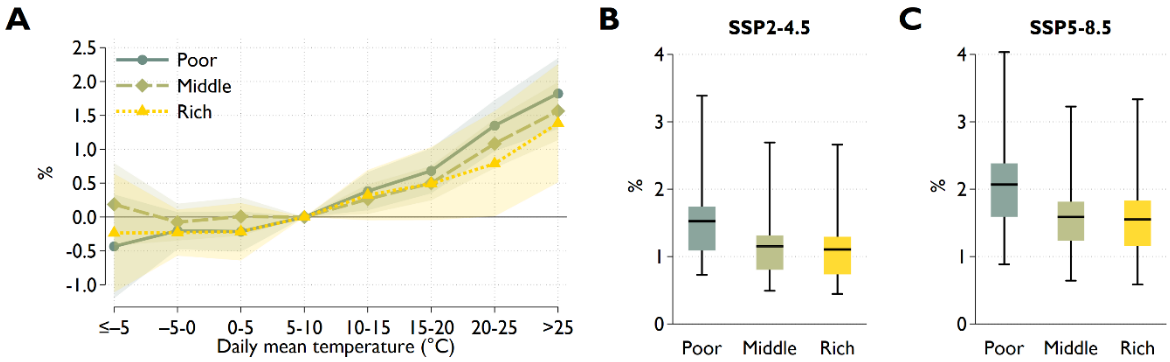

Fig. 4: The effects of temperatures and the impacts of climate change by district-level income

Notes: (A) The relationship between temperature and the ED visit rate in 2009-2017. 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 (income-specific) ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. Standard errors are clustered by district and year-by-month. (B) and (C) The projected impact of climate change (for the 2050s) on the annual ED visit rate. 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.

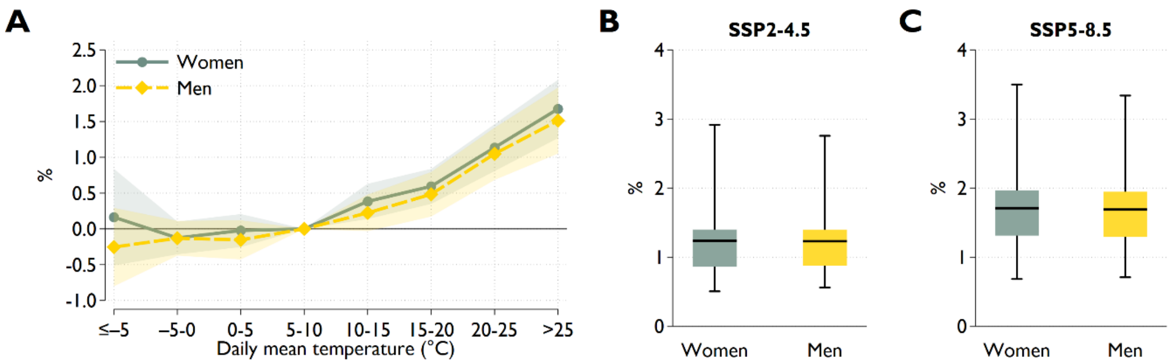

Fig. 5: The effects of temperatures and the impacts of climate change by sex

Notes: (A) The relationship between temperature and the ED visit rate in 2009-2017. 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 (sex-specific) ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. Standard errors are clustered by district and year-by-month. (B) and (C) The projected impact of climate change (for the 2050s) on the annual ED visit rate. 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.

The most notable differences are observed between age groups. The effects of the higher temperature categories decrease considerably with advancing age, whereas the effects of colder temperatures vary only to a more limited extent (Fig. 6, Panel A). The cumulative effect of a day with an average temperature above 25°C is 2.31%, 1.61%, and 0.65% for the youngest, middle, and oldest age groups, respectively. Note, however, that not only the percentage effects show large differences, but also the "absolute" effects are much larger for the youngest age group (5.77 ED visits per 100,000 persons) than for the middle-aged (4.35 ED visits per 100,000 persons) or the oldest generation (2.70 ED visits per 100,000 persons).

These differences are reflected in the markedly different impacts of climate change by age. Based on the mean of the projections, the percentage impact of climate change on the ED visit rate 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 than for the 65+ age group (Fig. 6, Panels B and C). Under the SSP5-8.5 scenario, the annual ED visit rate is projected to increase by 2.61% (95% CI, 1.10%–5.18%) in the youngest age group, by 1.53% (95% CI, 0.58%–3.23%) in the middle age group, and by 0.63% (95% CI, 0.18%–1.42%) in the oldest age group.

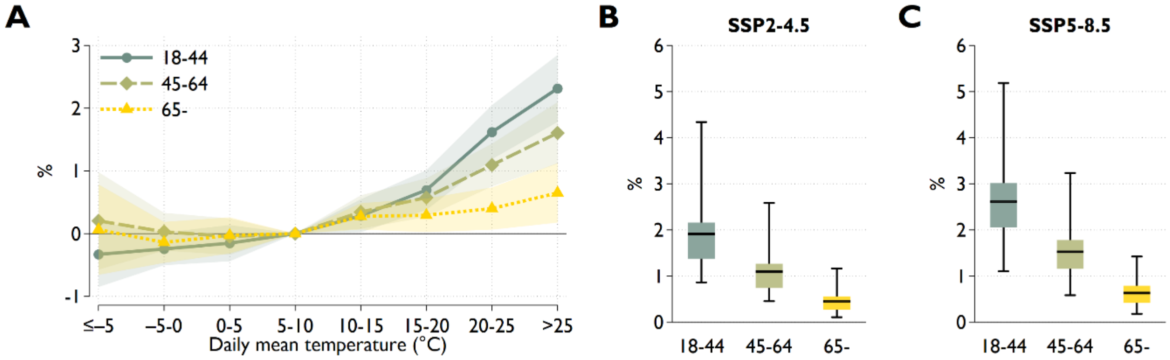

Fig. 6: The effects of temperatures and the impacts of climate change by age

Notes: (A) The relationship between temperature and the ED visit rate in 2009-2017. 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 (age-specific) ED visit rates over 11 days. Shaded areas represent 95% confidence intervals. Standard errors are clustered by district and year-by-month. (B) and (C) The projected impact of climate change (for the 2050s) on the annual ED visit rate. The impacts are calculated using changes in the temperature distribution between the periods of 2050-2059 and 1990-2014. 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.

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. The results regarding the moderating effect of humidity and the impact of consecutive hot days also 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 effect on ED visits.

The observed temperature effects and projected temperature changes imply that by the 2050s, 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. However, climate change is already having a measurable impact on ED visits today. During the sample period, 2009-2017, 46,800 ED visits were attributed to changes in the temperature distribution compared to 1950-1989, representing 0.66% of all ED visits during this period.

Beyond these average effects, substantial heterogeneities were identified. People residing in districts with lower income levels seem to experience greater adverse effects when exposed to high temperatures. The projected increase in ED visits due to climate change for them by the 2050s is 30-40% higher than those for individuals residing in middle-income or higher-income districts. However, the largest differences were observed across age groups. As age increases, the effect of temperature decreases. Consequently, the projected impact of climate change by the 2050s is more than four times larger for the youngest age group than for 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. 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

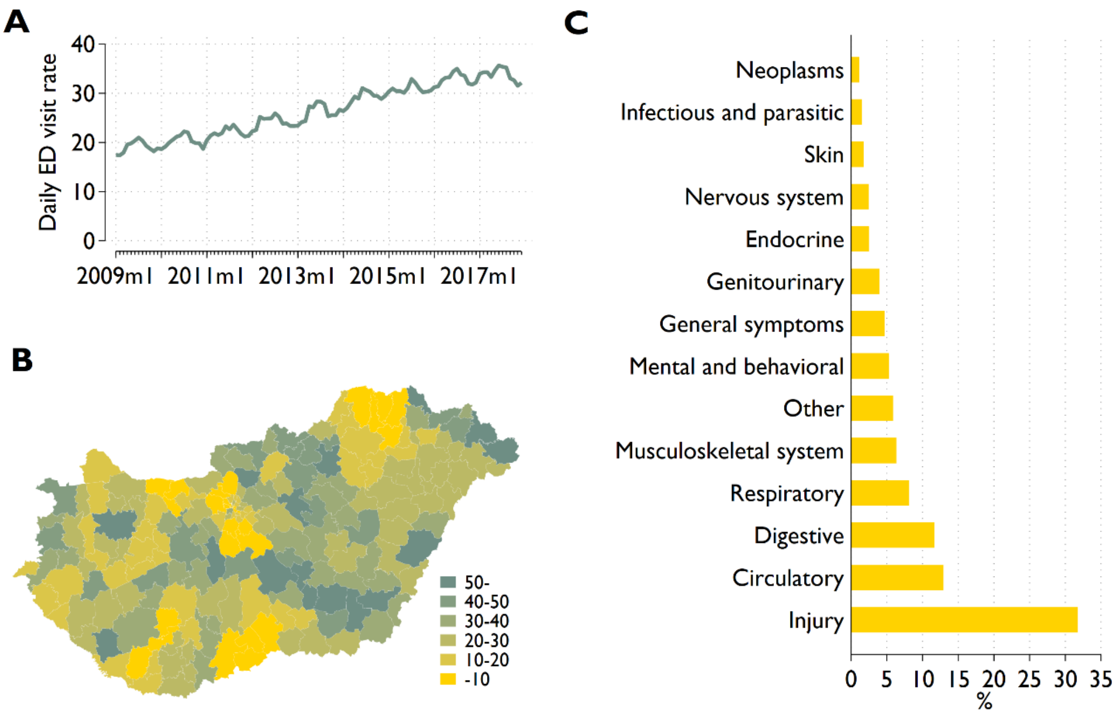

Figure A1. Temporal trend, geographic variability, and disease type distribution of daily ED visit rates

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.

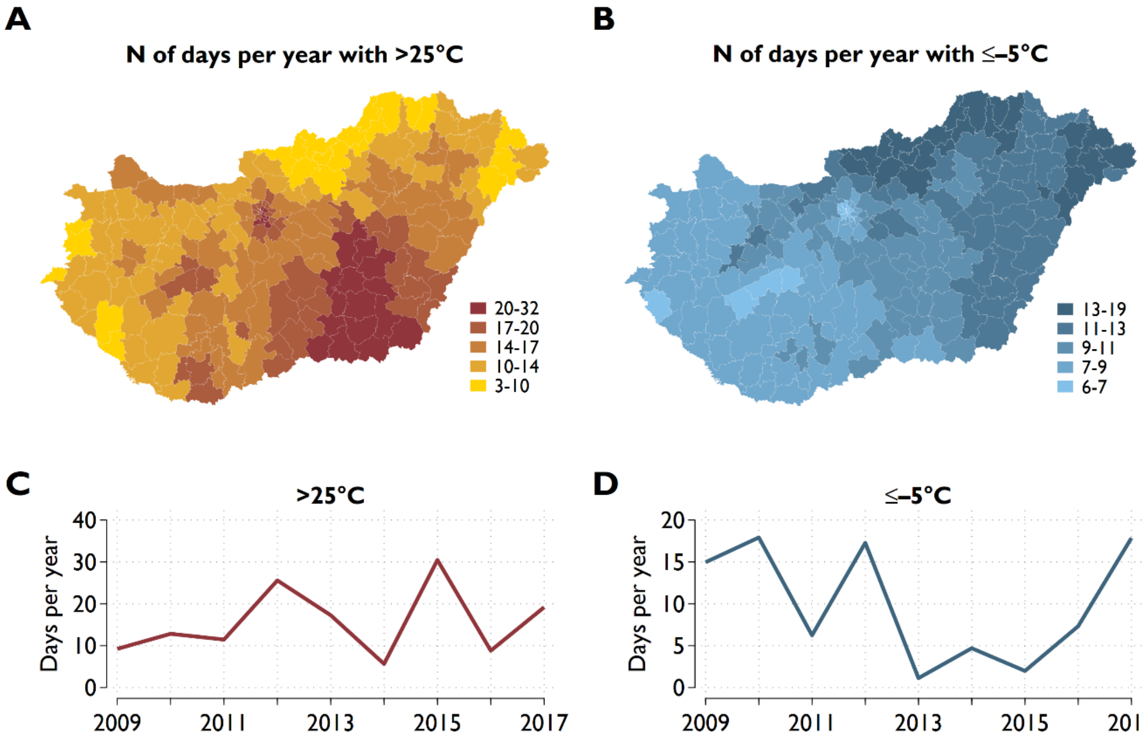

Figure A2. Temperature differences across years and districts

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.

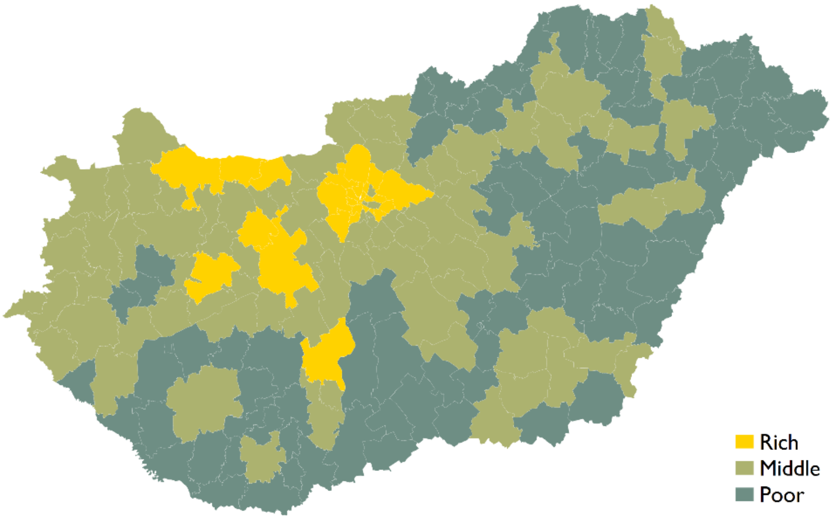

Figure A3. Income differences across districts

Notes: Rich = richest 25%, middle = middle 50%, poor = poorest 25%. Population-weighted shares. Based on the average annual pre-tax income per capita for the years 2009-2017.

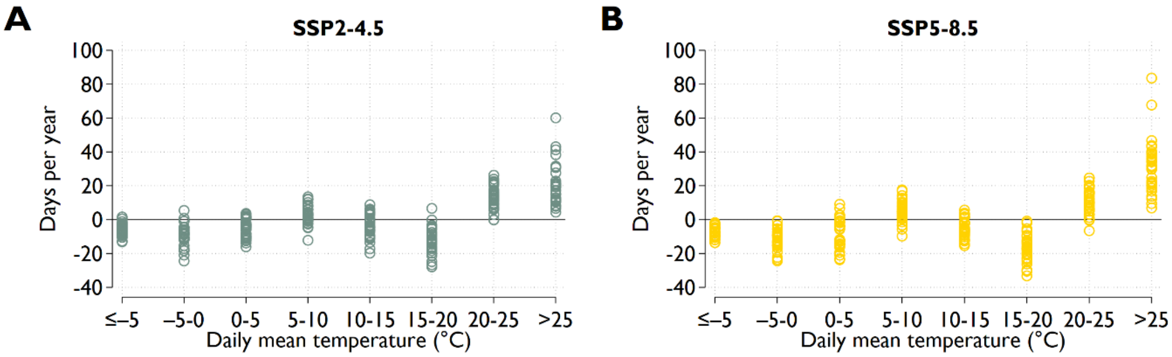

Figure A4. Projected temperature changes between the periods 2050-2059 and 2000-2014

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

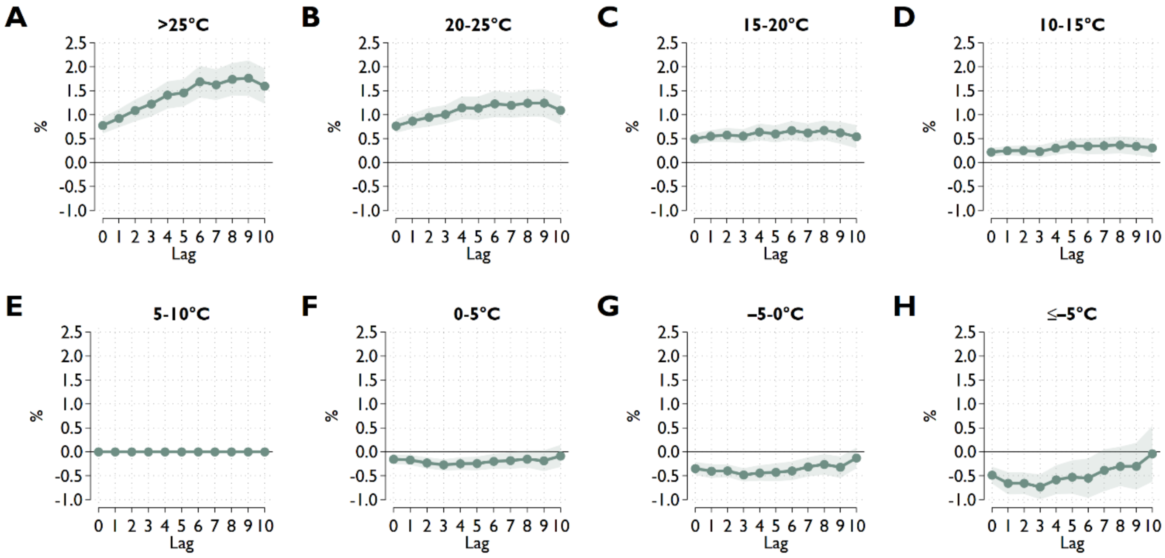

Figure A5. Cumulative effects by lag

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 and year-by-month.

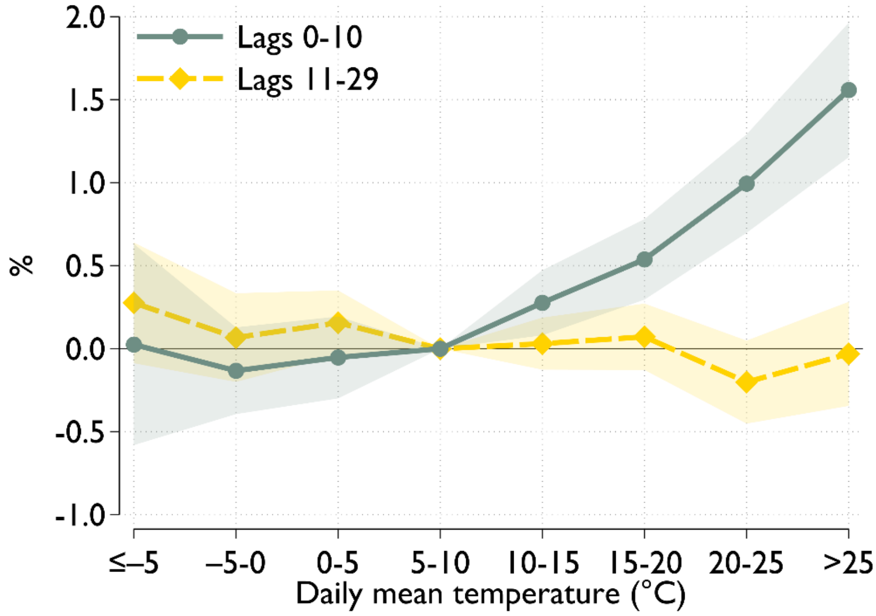

Figure A6. Cumulative effects for lags 0-10 and lags 11-29

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 and year-by-month.

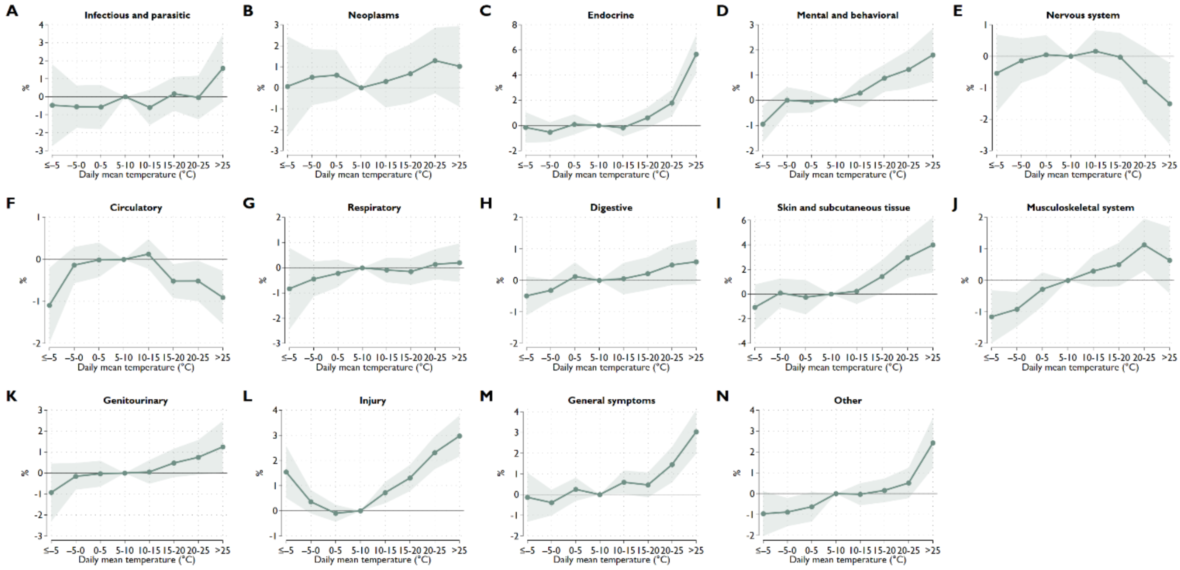

Figure A7. Temperature effects by diagnosis category

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 and year-by-month. 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.

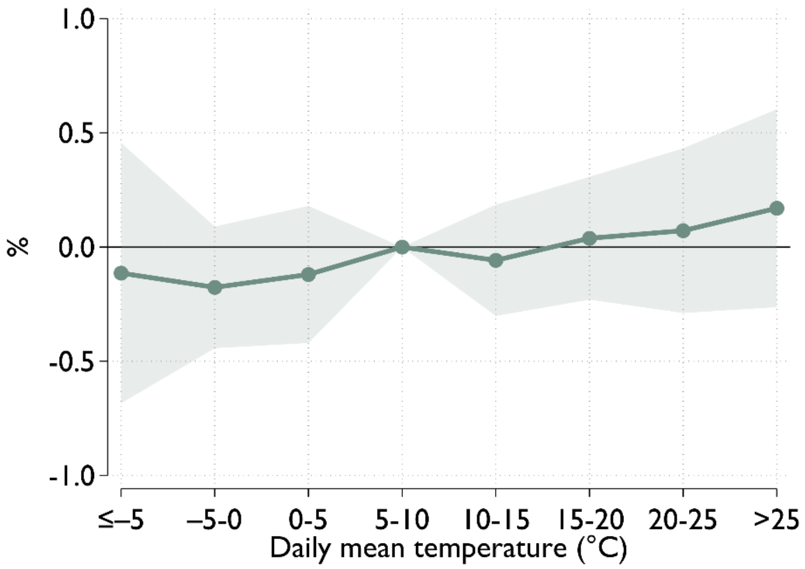

Figure A8. Falsification test with future temperatures

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 and year-by-month.

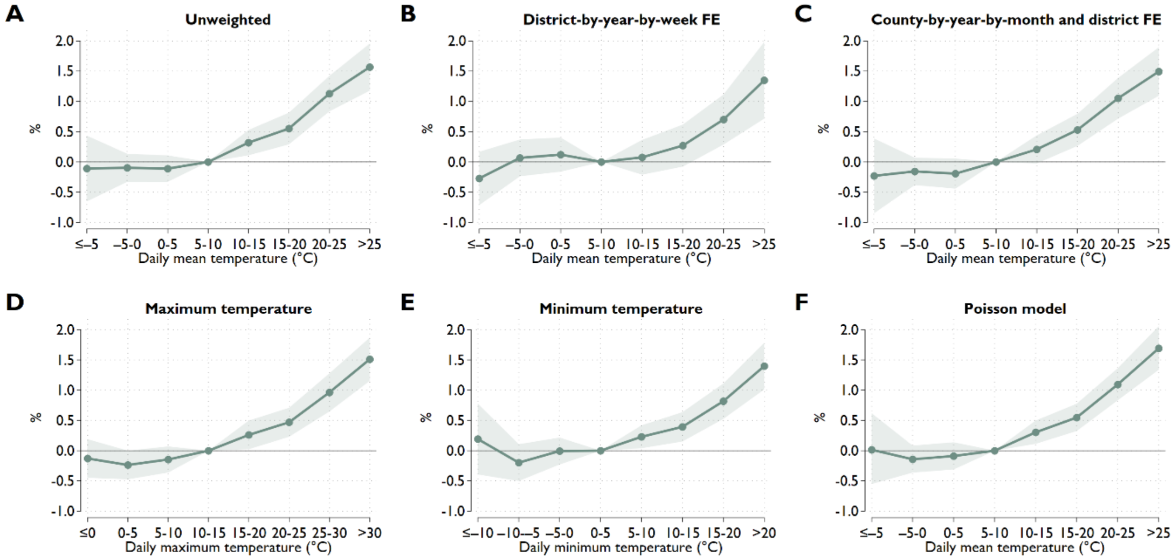

Figure A9. Sensitivity tests

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 and year-by-month.

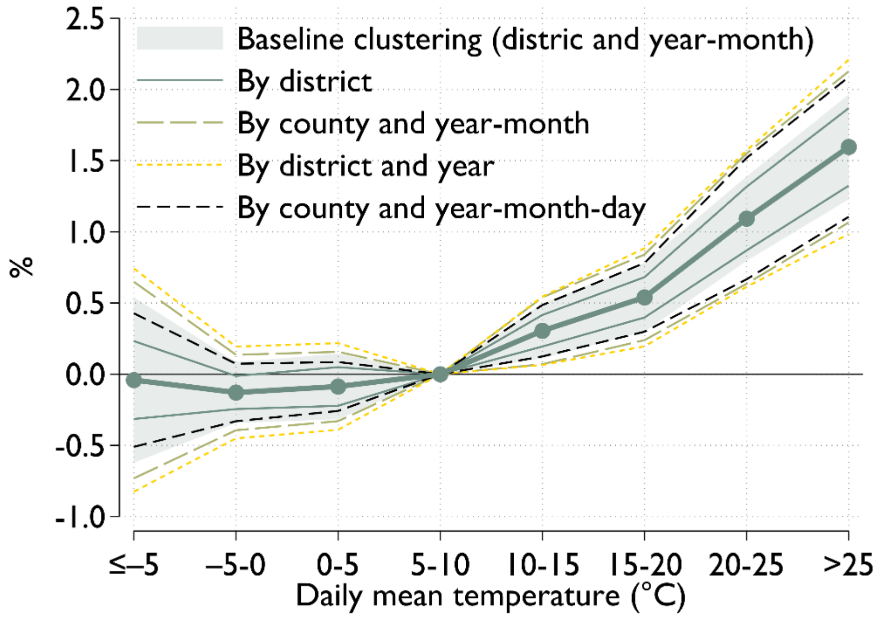

Figure A10. Alternative clustering methods

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.

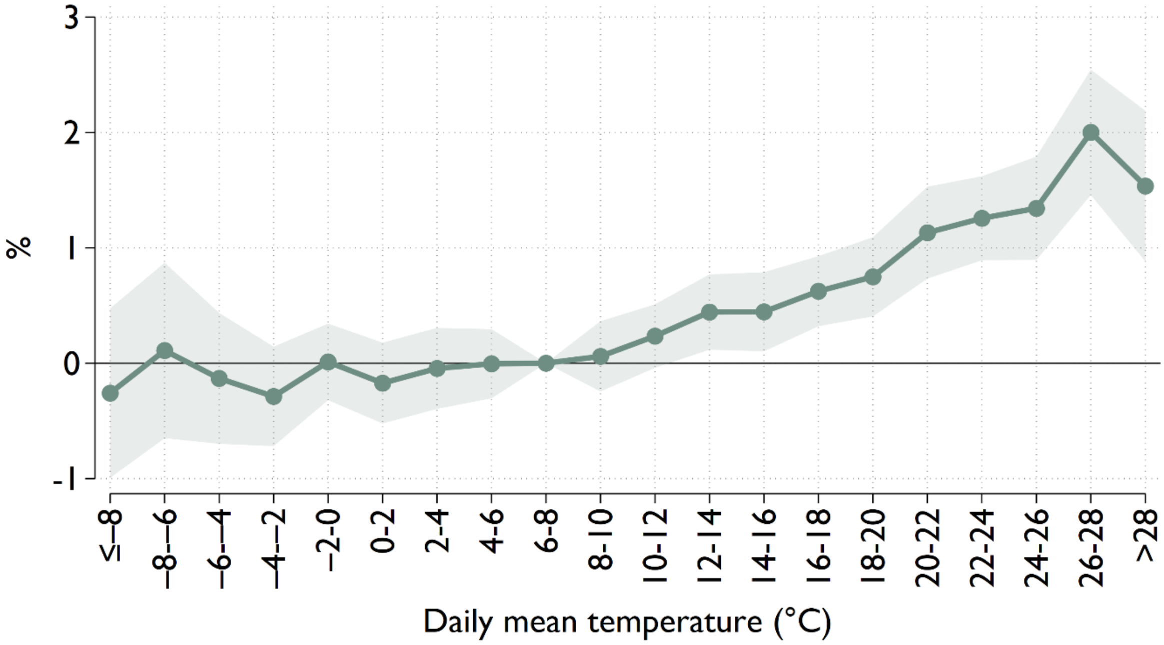

Figure A11. The cumulative temperature effects using 2°C-wide temperature categories

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 and year-by-month.

Table A1: ED visit rates by age, sex and districts' income category

	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

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