Demographic Change Under Climate Change: Projecting the Future Health(Care) Burden From Heat Waves in the Metropolitan Area of Vienna, Austria

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Abstract

Extreme weather events such as heat waves are expected to become more frequent and intense as a consequence of global warming. No doubt, this will affect the health and well-being of all populations, including those in regions with moderate climates like Central Europe. Using spatiotemporal meteorological data and an exhaustive administrative database on all hospital admissions from 2009 to 2018 in the metropolitan area of Vienna, Austria, we model the relationship between thermal hazards and hospitalizations. Differentiating by age, sex, socioeconomic status, and degree of urbanization allows us to account for the effects of demographic dynamics, heterogeneity, and agglomeration effects when projecting the future burden of urban heat on health and healthcare. To the best of our knowledge, no other study to date considers climate effects on health in conjunction with the differential vulnerability of the exposed population in an urban environment.

1 Introduction

Global warming is anticipated to contribute to more frequent, intense extreme weather events, including heat waves, cold spells, heavy precipitation, and droughts. Thermal hazards in regions with historically moderate climates such as Central Europe increasingly affect the well-being of the local population. In the Austrian city of Vienna, heat days (i.e. days with a maximum temperature of ≥ 30° and a minimum temperature of > 18°) were rare events in the 1960s and 70s at an average of 8.9 days per year. By contrast, half a century later, this number has almost tripled to an average of 25.4 heat days per year between 2010 and 2020.

These changing climatic conditions pose serious threats to human health. For example, direct exposure to extreme heat conditions can lead to exhaustion, dehydration, hyperthermia, heat strokes, and exacerbate cardiovascular problems (González-Alonso et al. 2008; Michelozzi et al. 2009; Crandall and González-Alonso 2010; Kenny et al. 2010). Indeed, the *Lancet Commission on Health and Climate Change* warns that "climate change is a medical emergency" (Watts et al. 2015).

In recent years, the relevance of research in this field has increased dramatically because of accelerated climatic change. However, financial austerity due to the 2008 economic crises has led to reduced public health spending in European countries, which creates strains for health management and healthcare provision. Therefore, to ensure the long-term sustainability of healthcare provision, it is imperative to consider future challenges such as changes in morbidity that lead to increased climate-induced hospital admissions.

While there is ample evidence on vulnerability to mortality from temperature extremes, there are relatively less studies that focus on morbidity. Understanding the impact of future climatic conditions on illnesses is important because early and appropriate interventions can prevent premature death. Likewise, given that the impact of climate change is not distributed evenly across population subgroups and locations (Muttarak et al. 2016), it is essential to investigate demographic differentials and spatial heterogeneity in health vulnerability to temperature extremes. Such knowledge is useful for forecasting the vulnerability of future societies (Lutz and Muttarak 2017). Studies that comprehensively analyze demographically differentiated vulnerability to temperature extremes at a refined geographical scale and project into the future are scarce. By exploiting postal code-level administrative database on all hospital admissions in the metropolitan area of Vienna, Austria, this study investigates how temperature anomalies affect hospitalization of different population subgroups and explores how this pattern varies by socioeconomic characteristics of the areas on a small scale. Based on the empirical evidence, we project future health vulnerability to climate change for the city of Vienna using machine learning techniques (Striessnig et al 2019).[1]

Our contribution to this pressing health and climate issue thus comprises three main components. First, we use rich historical data to study the relationship between extreme temperature events and health within the context of social and structural characteristics. We investigate the relative impact of increased average temperature and extreme heat on the healthcare demand for inpatient services. Accounting for population dynamics, we then study the differential impact of heat by age group, gender, and urban–rural residence. While literature on the impact of temperature extremes on mortality is abundant, there is relatively little evidence on morbidity. In particular, our focus on demographic differentials allows for identifying vulnerable subgroups of the population that public health interventions and policy planning may need to target. Second, our study focuses on small geographic units, which enables us to capture spatial heterogeneity at the postal code level in terms of climatic conditions, socioeconomic composition, and built infrastructure. Because of localized climate effects, the scale of this research provides a closer look at how the degree of human vulnerability and ability to respond and adapt to a changing climate varies considerably across geographical locations—even within the same city. Our analysis identifies vulnerable hotspots both in terms of exposure and adaptive capacity for policy planning. Third, we use these empirical findings to project the future number of hospitalizations, and hence the expected strain on the public healthcare system, under different climate and population scenarios (SSPs). To our knowledge, our study is among the first to combine population and climate projections using individual-level and small-area data.

[1] The projection component is a work in progress. Results are not included in this draft.

2 Previous Literature on Differential Vulnerability

Research about extreme temperatures and health only gained traction after the 2003 European heat wave killed an estimated 30,000 to 70,000 people, most of whom were older adults, including approximately 15,000 people in France (De Bono et al. 2004; Robine et al. 2008; García-Herrera et al. 2010). This event portrayed an urgent image of a looming global health issue on a warming planet with an aging population. Since then, a growing body of work has focused on mitigating vulnerability in specific groups, such as the elderly, immigrants, or people in high-risk occupations. Differential vulnerability is a product of demographic differences in physiological susceptibility, hazard exposure, and socioeconomic and psychosocial factors that influence risk perceptions and the capacity to respond. Different demographic groups have varying degrees of susceptibility to extreme temperatures due to physiological differences in their ability to thermoregulate heat and cold. These functions are necessary for the body to maintain its core temperature of about 36.5–38.5°C and carry out biophysical functions. Exceeding these bounds triggers physiological responses to correct the body's core temperature (Moran and Mendal 2002; Sessler 2008); however, as it deviates from a healthy range, the risk of death or injury increases significantly (Moran and Mendal 2002).

Age-wise, biophysical vulnerability to extreme heat is highest amongst the oldest and youngest population groups: Infant vulnerability to extreme temperatures reflects their undeveloped immune, respiratory, and thermoregulatory systems as well as their inability to care for themselves (Xu et al. 2012; Kakkad et. al 2014; Xu et al. 2017). An additional characteristic unique to infants is their larger surface-area-to-volume ratio, which heightens the risk of heat-related illnesses and mortality (Kakkad et al. 2014; Xu et al. 2017). As people age, reduced thermoregulatory functions inhibit the body from adjusting its internal temperature while reducing individual perceptions of external temperature changes. Common medications for age-related illnesses further compromise thermoregulation (Conti et al. 2007; Abrahamson et al. 2008) and dehydration can cause harmful drug concentration levels and an increased risk of adverse effects (Nordon 2009). Additionally, the age-related loss of ability to accomplish activities of daily living can impede otherwise simple adaptations such as moving somewhere cooler, drinking water, or contacting someone for help (Abrahamson et al. 2008; Conti et al. 2007; Foroni et al.). Finally, underlying medical conditions commonly linked to increased risks of illness, hospitalization, or death in the general population include cardiovascular and psychiatric disorders (Semenza et al. 1999; Stafoggia et al. 2006), diabetes and renal diseases (Semenza et al. 1999), substance abuse disorders and alcoholic cirrhosis (Semenza et al. 1999; Hansen et al. 2008; Cusack et al. 2011).

Apart from biological distinctions, demographic and socioeconomic characteristics also influence social and behavioral patterns as well as the ability to prepare for, respond to, and cope with extreme events. While risk perception is fundamental in driving behavioral responses, disaster research notes that individuals often lack the ability to properly calculate risk and respond appropriately (Paton and Johnston 2001). For example, the elderly may not identify as "old" or appreciate how their age or medical conditions increase their risk of heat-related illness (Sheridan 2007; Abrahamson et al. 2008; Bittner and Stößel 2012). Likewise, highly educated individuals not only tend to have better risk perception, but they are also better prepared for extreme weather events and emergencies (Muttarak and Pothisiri 2013; Pichler and Striessnig 2013; Hoffmann and Muttarak 2017). Such demographically differentiated vulnerability points to how changing demographic structures and compositions can thus modify the degree of health vulnerability to extreme weather events.

Indeed, the empirical evidence widely shows that older adults are especially vulnerable to extreme heat, as demonstrated by emergency department, hospitalization, and mortality data from studies in different regions. Because high temperatures may exacerbate chronic illnesses, all-cause hospitalizations and emergency department visits have also been shown to increase during extreme heat (Basagaña et al. 2011; Gronlund et al. 2014; Hess et al. 2014). While older adults seem to be at a heightened vulnerability for experiencing medical conditions including cardiovascular, respiratory, renal illnesses as well as heat stroke and dehydration, children and infants are especially prone to dehydration and electrolyte imbalances (Kovats and Hajat 2008; Knowlton et al. 2009).

There is also substantial spatial heterogeneity in health vulnerability to extreme temperatures and the geographical unit of analysis further influences its analysis and results. For example, Gronlund et al.'s (2014) study of hospital admissions amongst older American adults found significant variation between five broad climate zones, as well as within zones. Although hotter climate zones showed higher overall levels of cause-specific hospitalizations, this same pattern was not present when comparing each zone's largest city. This points towards urban–rural differences in heat impacts, vulnerability, hospital accessibility, and heat warning systems. Whether regions with moderate climates will face greater burdens under changing climatic conditions than historically hotter places remains unclear. Findings from Canada (Stapleton et al. 2013), the United States (Knowlton et al. 2009), France, and Italy (Ogg 2005) suggest that a lack of acclimatization in temperate regions may explain increased levels of hospitalization amongst older adults. Conversely, Åström et al.'s (2013) age-stratified projections for European countries show that Southern Europe will see the greatest increase of heat-related respiratory hospital admissions (RHA), while Eastern Europe will see the lowest. However, the authors note that their models may underestimate future temperatures because of uncertainties and a bias towards past events.

The demographically and spatially differentiated vulnerability described above implies that future changes in population composition and spatial distribution will have implications on future vulnerability to heat extremes. Just like the consequences of global warming are not equally experienced across the world, different demographic groups are affected differentially by climate extremes due to their varying levels of exposure, sensitivity, and adaptive capacity (Edenhofer et al. 2014).

When estimating and projecting the future impact of extreme heat on health and healthcare systems, two long-term demographic trends deserve particular attention. First, structural changes in the population composition are adding pressure to already-strained healthcare systems. Although, urban population growth in places like Vienna is likely to rejuvenate urban age structures, the absolute number of older people continues to grow as the Baby Boomer generation ages. Second, increased urbanization and population density heighten population exposure to climate risks (Seto et al. 2011). By 2050, the projected global share of people living in cities will rise from about 55% to 68% (UN DESA 2018). During hot summer months, the urban heat island effect impacts densely populated urban places because temperatures in built-up areas exceed those in the surrounding countryside.

Furthermore, urban population growth and the associated increase in economic activity and traffic intensity also change the urban land cover. The built infrastructure in urban environments, particularly in the absence of green spaces, often exacerbates the effects of extreme heat and the urban heat island. Cities within moderate climate zones that have not previously been exposed to and lack experience with heat waves of similar frequency and intensity may therefore be more vulnerable to future temperature extremes of increasing intensity.

Vienna is considered one of Europe's most rapidly growing cities and the entire metropolitan region continues to grow, both in terms of population size and economic activity. At the same time, over the next thirty years the share of the Viennese population aged 75 and older is projected to increase in each of its 23 districts (MA 23 2014), ranging from 8.4% in Hietzing to 115.6% in Donaustadt, with a mean increase of 55.7% for all districts. While the migration of young adults to the city will somewhat temper this process by keeping high-density, inner districts relatively "younger," low-density, suburban districts will continue to get older. One feature of aging populations and changes to family structure is the increased share of people living alone. In 2012, 384,079 (22.1%) Viennese households were occupied by a single person, of which 29% were inhabited by persons aged 65 or older. Most (73.7%) of these `person elderly households were occupied by women, which reflects their longer life expectancies (Statistik Austria 2012). By 2043, an estimated 477,265 (22.6%) Viennese households will be occupied by a single person, of which 35.7% will be single-person elderly households. 72% of these will be female. Increased social isolation from living alone makes older female adults particularly vulnerable to temperature extremes because of a lack of social support and assistance (Kim et al. 2020). Planning for healthcare services thus needs to account for these changing demographic structures and living arrangements while anticipating future climate risk.

3 Research Design, Data, and Methods

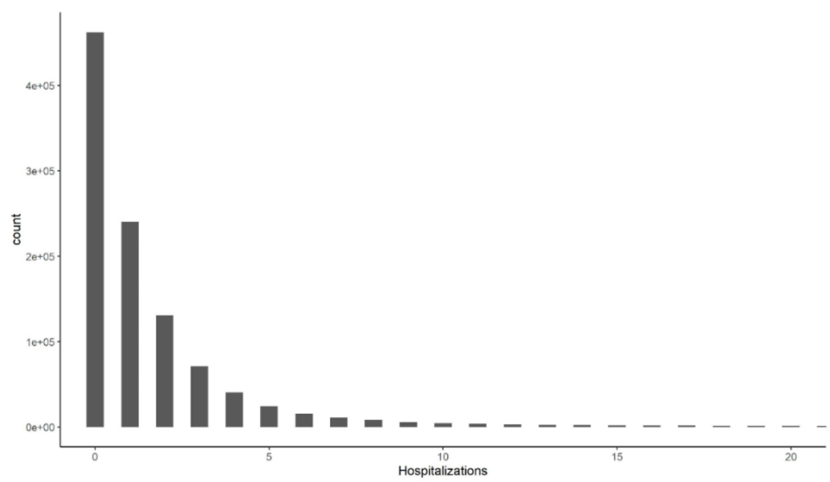
Our assessment of the future impact from extreme temperatures on morbidity comprises three separate steps. The first step entails econometric analyses of historical data to identify the empirical relationship between meteorological events and hospital admissions at the postal code level. The second step generates projections of future population exposure to heat extremes at the municipality level based on a machine learning algorithm (regression trees) describing past spatial shifts in age-structured populations. Finally, the third step combines the information derived from the previous two steps to create projections of future hospital admissions under various exogenous meteorological scenarios for Austria.

3.1 Step 1: Estimating the Impact of Past Heat Extremes on Hospital Admissions

The first econometric analysis employs three datasets about hospital admissions, meteorological indicators, and the population characteristics of Vienna and the surrounding, mostly rural region of Lower Austria. This area covers approximately 20,000 km^2 and has a total population of roughly 3.5 million, of which 1.9 million live in the City of Vienna (415 km^2). Between 2009 and 2018, residents from these two regions were admitted to a hospital more than 8.6 million times.

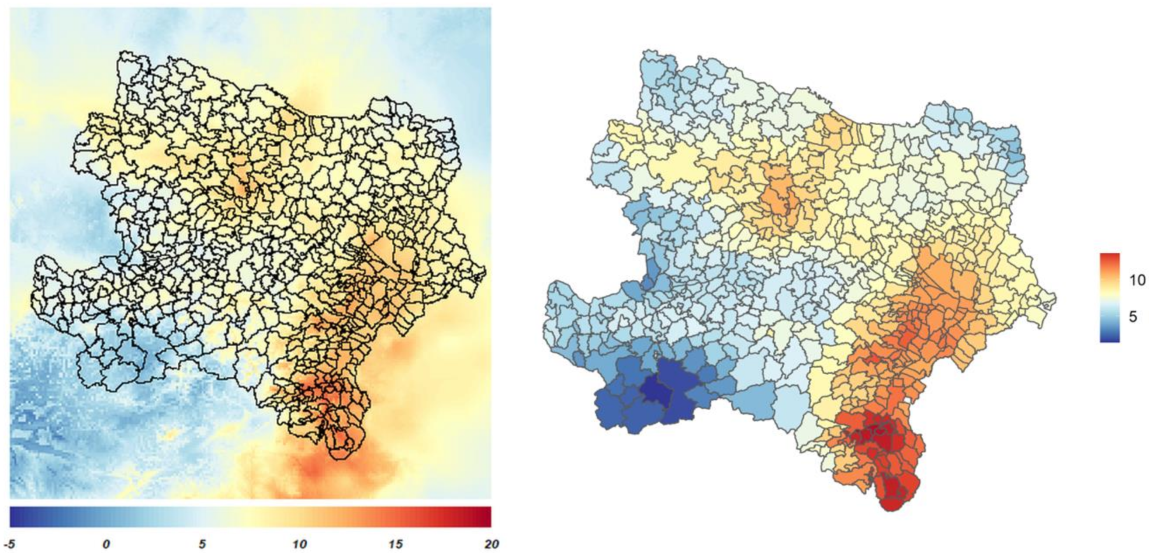
Detailed information about each hospital admission was collected by the Association of the Austrian Social Insurance Funds (*Dachverband der österreichischen Sozialversicherungsträger*, DVB). This administrative dataset includes information about each hospitalization's primary and secondary diagnosis (ICD-10), date of admission and discharge, reason for discharge, patient characteristics such as age group, sex, and residential postal code, as well as the admitting institution's hospital code. Figure 1 depicts a count histogram showing the daily hospitalizations per postal code from 2009 to 2018 that we include in our model. The average daily hospitalizations among the 653 postal codes in our study area ranged from 3.31 in 2018 to 3.83 in 2017, while the maximum number of single-day hospitalizations ranged from 195 in 2018 to 250 in 2015. For more details, see Table A1 in the Appendix.

Figure 1: Count histogram of daily hospitalizations per postal code, 2009–2018



Our second dataset provides daily, model-based meteorological information derived from weather stations in and around Vienna. The data was provided by the Austrian weather service (*Zentralanstalt für Meteorologie und Geodynamik*, ZAMG) and includes indicators such as minimum, maximum, and mean temperature, as well as humidity and precipitation, at the 1x1 km grid level. For our statistical models, we matched geo-referenced patient postal code information from the DVB data with these grid-level data to extract the weather conditions that patients were exposed to prior to admission, assuming that they were at or near their place of residence. As population density cannot be derived at the postal code level (the postal codes do not necessarily pertain to geographically consistent areas), we further aggregated the grid-level data to the municipality level via spatial aggregation and proxied postal code density according to their municipality. For example, Figure 2 shows how this aggregation looks on a day where a wide range of maximum temperatures occur across the study area.

Figure 2: Daily maximum temperature 2 m above the ground at grid (left) and municipality level (right)



We next used the meteorological data to construct four key temperature measures for our modelling: These capture the maximum temperature on a given day at the postal code's geolocation, if it was a heat day (with a maximum temperature above 30°C and a minimum temperature above 18°C), if it was part of a heat episode (consisting of at least three consecutive heat days), and the number of heat days during the past seven days.

Demographic and socioeconomic data at the postal code level were obtained from the Austrian Statistical Office. The data include information on population sizes between 2009 and 2019 by age group, population density, and sex distribution, as well as information about the local population's educational background and employment status for the most recent year (2019). This information allows us to investigate the differential impact of heat extremes given the socioeconomic characteristics of the population that resides under a specific postal code.

After merging these three datasets by postal code and day, we applied panel data methods to identify the effect of temperature extremes on hospital admissions. The panel structure allows us to control for region, year, month, and weekday fixed effects, thus removing the potentially biasing influence of confounding, time-invariant regional factors, weekend effects, seasonalities, and common time trends over the years. To avoid the confounding influence of increased morbidity related to cold spells, we restricted our analysis to May through September when sub-zero temperatures are unlikely and heat waves can occur.

We used the aggregate number of daily hospital admissions for residents of a given postal code as the main outcome variable and disregarded diagnoses. Because this variable is highly right-skewed (Figure 1), Poisson models were applied. The number of hospitalizations (count variable H) per population was regressed across different climatic variables (T) at the postal code (i)/daily level (dmy) using postal code fixed effects (μ_i) and controlling for year (Y), month (M), and weekday (W).

$$E(H_{idmy} | X_{idmy}) \equiv h(X_{idmy})$$

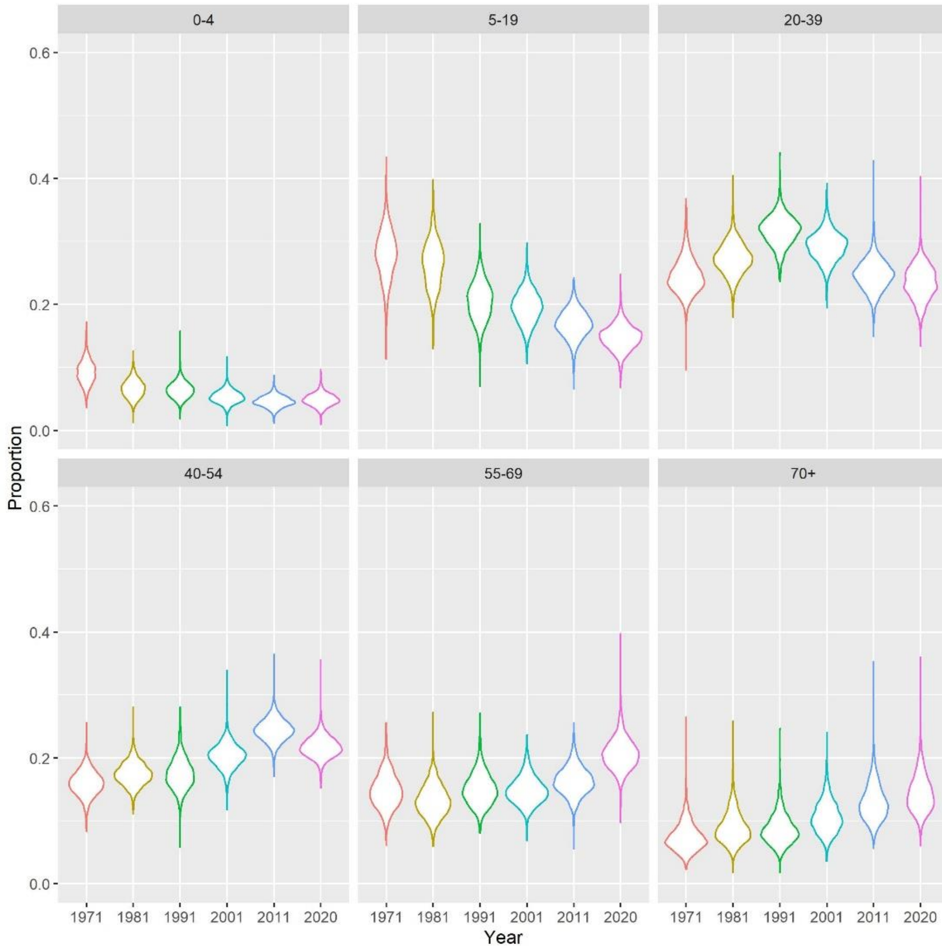
$$\log h(X_{idmy}) = \beta_0 + \log P_{iy} + \beta_1 T_{idmy} + \sum \beta_2 \mathbf{1}[Y{=}{=}y] + \sum \beta_3 \mathbf{1}[M{=}{=}m] + \sum \beta_4 \mathbf{1}[W{=}{=}w] + \mu_i$$

Temperature variables reflect the maximum temperature on a given day, if the day was a heat day, if it followed a heat episode (*dmy*, *dmy -1*, *dmy -2*, *dmy -3*, *all > 30°C*), and the number of heat days in the past seven days. Additionally, all models control for the average level of precipitation on day *dmy*. We also ran separate regressions for the different age and sex groups to account for differential risk patterns. These models also formed the basis of our projections in Step 3, which account for the differential temperature risks according to age and sex groups. Moreover, interaction models were used to explore the extent to which contextual background influences temperature effects and to help capture underlying differential vulnerabilities to heat stress. This comprises education (percent of population with at least secondary education), employment status (percent employed), as well as population density.

3.2 Step 2: Estimating Spatial Drivers to Project Age-Structured Populations

The second part of the analysis draws on three different data sources. The primary dataset is the Austrian Population Census, which was conducted in 10-year intervals until 2001, after which it was replaced by a registry-based system. Data from 1971 onward are available from the Austrian Statistical Office and comprise age- and sex-structured population data at the municipality level. As the municipality structure has changed over time, the data were harmonized according to the administrative boundaries for 2020. Figure 3 displays the age-specific proportions of the municipality population between 1971 and 2020.

Figure 3: Age-specific proportions of the municipality population per year. Vienna and Lower Austria, 1971–2020



These historical patterns informed the construction of a machine learning (regression tree) model to project future age-structured populations at the municipality level. To date, Austria lacks such sub-national population projections. A key obstacle to producing small-scale, long-term spatial projections of demographic characteristics is the difficulty of applying conventional demographic approaches to such spatial and temporal scales. The cohort-component approach is currently the dominant method for population projections (Burch 2018). However, it is challenging to apply it sub-nationally, because it requires both sufficient base-year data and future assumptions about demographic rates for each of the spatial units to be projected.

To produce spatially detailed future projections of heterogeneous populations in spite of these obstacles, researchers have recently developed alternatives to the conventional cohort-component approach. Hauer (2019) projected US county-level populations and different demographic structures by extrapolating rates of change in each sub-population before scaling the size of all population sub-groups up or down to match a given target projection at the national level. However, this approach does not allow for spatial variation in outcomes between national scenarios, making it more suitable for shorter time horizons. A simpler scaling method has been used for Europe by Terama et al. (2017).

However, their approach to downscaling the national-level age structure from cohort-component projections to the sub-national level does not allow for changes over time in the relative age distribution across regions.

Our regression tree approach offers a promising alternative to the conventional process-based approach. As shown by Striessnig et al. (2019), regression trees can capture the complex empirical patterns observed at the US county level. By relying on a non-parametric model, regression trees can also capture non-linear relationships and interactions (Kuhn and Johnson 2013), such as those between age structure and population change. Moreover, regression trees enable greater interpretability compared to other approaches such as bagging, random forests, or boosting, all of which involve creating multiple trees that are combined into a single consensus prediction.

Based on historically observed patterns in age structure and municipality characteristics, the model uses separate "tree branches" during training to empirically identify variables that best describe the various age profiles. Age groups were modeled using separate trees because they are dominated by different drivers. The dependent variable in each tree is change over time in the age-specific share of the population at the municipality level (*m*) relative to the same change at the provincial level (*p*):

$$\Delta \text{ relative share} = (\text{share}_{t,m} - \text{share}_{t-10,m}) \ / \ (\text{share}_{t,p} - \text{share}_{t-10,p}) \ . \ s$$

The set of potential predictor variables includes temporally lagged shares of all age groups for up to three periods in the past, neighborhood variables that account for potential spatial autocorrelation, and various geographical metrics. To rule out linear dependence among these predictors, we conducted a collinearity investigation for each tree. We trained our model based on predicted changes in the most recently observed decade (2011–2020) and validated the training model based on the 2001–2011 experience.

We first grew a large tree on the training data for each age group using recursive binary splitting. Using the Classification And Regression Tree (CART) algorithm, a binary split was performed at each splitting node, minimizing the sum of squared errors. To avoid overfitting, cost complexity pruning was applied to obtain a sequence of best subtrees for the tuning parameter *a*. This parameter determines the tradeoff between tree size and goodness of fit, with larger values of *a* leading to smaller trees. Repeated 10-fold cross-validation allowed us to tune and validate the trees by selecting the level of *a* that minimizes the average error. Finally, the different tree branches separated municipal age-related characteristics that could lead to different changes in the outcome variable.

For the projections, the different regression trees were applied decade-by-decade from 2020 to 2050 to jointly create future age compositions at the municipality level. Summing up the projected population shares in the different age groups can lead to small deviations from 1. To prevent these small deviations from accumulating over periods, we additionally constrained the results at the end of each time step. This was done according to existing projections at larger spatial scales by applying iterative proportional fitting. The existing projections are from (1) the Austrian Statistical Office, which provides age patterns at the provincial level (*Länder*, i.e. Vienna vs. Lower Austria), as well as (2) from grid-level (1x1km) projections of total population counts according to the Shared Socioeconomic Pathways (SSPs). The SSPs are a set of five qualitative narratives for century-scale, global developments (O'Neill et al. 2014) that have been translated into quantitative population projections at the national level (KC and Lutz 2017) and disaggregated to the grid level (Bryan Jones and O'Neill 2016; B. Jones, O'Neill, and Gao 2020). Three central SSPs were matched with the available provincial projection scenarios from the Austrian Statistical Office, given that they share similar assumptions regarding the drivers of population change: SSP1 corresponds to the "low life expectancy variant" (*Niedrige Lebenserwartungsvariante*), SSP2 to the "main scenario" (*Hauptszenario*), and SSP3 is comparable to the "aging scenario" (*Alterungsszenario*). For our projection model, we aggregated the gridded projection results to the municipality level to obtain total population targets.

3.3 Projecting Future Hospital Admissions Considering Climate and Population Change

Finally, Step 3 combines the age-specific population projections from Step 2 with the model estimated in Step 1 to project hospital admissions according to future changes to demographic composition and the climatic circumstances to which the population will be exposed. The spatial disaggregation of the SSPs will allow us to evaluate the effect of three different socioeconomic scenarios, i.e. the population exposed to future heat extremes, on future hospital admissions. The socioeconomic effect needs to be distinguished from the effect caused by global warming. Thus, we rely on detailed climate projections created specifically for the Austrian context by the Climate Change Centre Austria (CCCA) to complete this exercise. The ÖKS15 database provides model-based information on the evolution of various climate parameters, including those used in our Step 1 econometric model, under various climate scenarios. All daily metrics are available up until 2100 at a 1x1 km grid. For the purpose of our projections, we aggregate grid-level information to the municipality level under two contrasting scenarios: a business-as-usual scenario (RCP8.5) and a climate-protection scenario (RCP4.5). Additionally, we utilize the entire collection of regional climate projections (total: 13) for each temperature measure to observe the magnitude of future temperature change signals in our research area.

4 Results

First, results from the baseline models show that there is a significant association between (extreme) temperature and daily hospitalizations in Vienna and Lower Austria. Next, the preliminary results about the interaction effects between socio-demographic variables and heat point towards a significantly higher vulnerability for lower-educated populations. Finally, the differential impact of heat on different age and sex groups indicates increased effects on the population above 70 years.

4.1 Baseline Models: Temperature Impacts on Hospitalizations

In the Appendix, Table 2 shows the preliminary results from the Poisson estimations. To explore the effects of different heat measures on the number of daily hospitalizations, separate regressions were run for each temperature variable described in Section 3.2. Coefficient estimates were omitted for year, month, and weekday, as well as precipitation for better readability. The results from Model 1 show that, indeed, the number of hospitalizations significantly increased by 1.3% on days where the temperature exceeded 30°C compared to days below that threshold. The same is true when using a continuous explanatory variable, *maximum heat*. A 1°C increase was significantly associated with a 0.8% increase in hospitalizations per day. Surprisingly, a heat wave (defined as at least three consecutive days exceeding both a 30°C maximum temperature and 18°C minimum) was not significantly related to the number of hospitalizations on a given day (Model 3). In Model 4, the explanatory variable is the number of heat days within the past eight days (including the current day), which shows a significantly positive effect on the number of hospitalizations per population, although the coefficient is somewhat smaller than for the other temperature variables.

4.2 Socioeconomic and Demographic Drivers of Temperature Impacts

As outlined in Section 2, heat vulnerability varies between socio-demographic groups. To test whether this holds true for Austria with its relatively generous welfare system, we interacted the different heat measures of heat with the shares of low-educated and unemployed, as well as the population density for each postal code. Tables A3 to A5 in the Appendix show the full regression results, while Figure 4 below depicts the main and interaction effects that the heat variables have on the share of the low-educated population, wherein the dots represent the point estimates and the whiskers represent the 95% confidence intervals. This clearly shows that the higher the share of low-educated people residing in one area, the stronger the effects of heat on the number of hospitalizations are. Unexpectedly, the exact opposite is true for the unemployed share, while population density does not seem to affect heat vulnerability at all in our dataset (for details, see Appendix tables). These results persist when the number of hospitalizations is regressed across the socio-demographic indicators that interacted with the heat measures within each given model (see Figure 5 below).

Figure 4: Dot-whisker plot of interaction effects between heat measures and low education

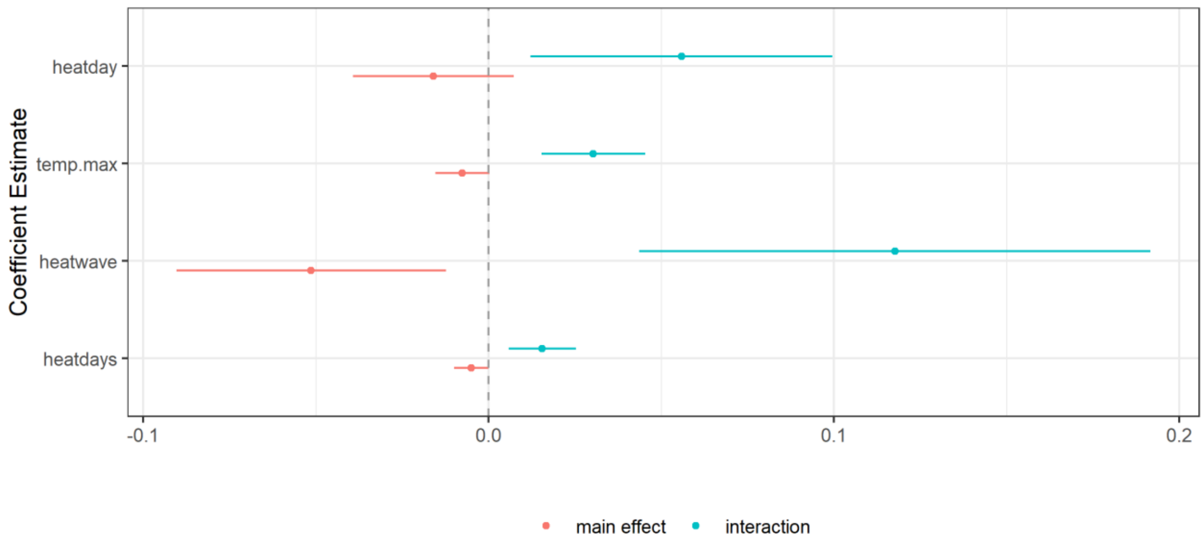
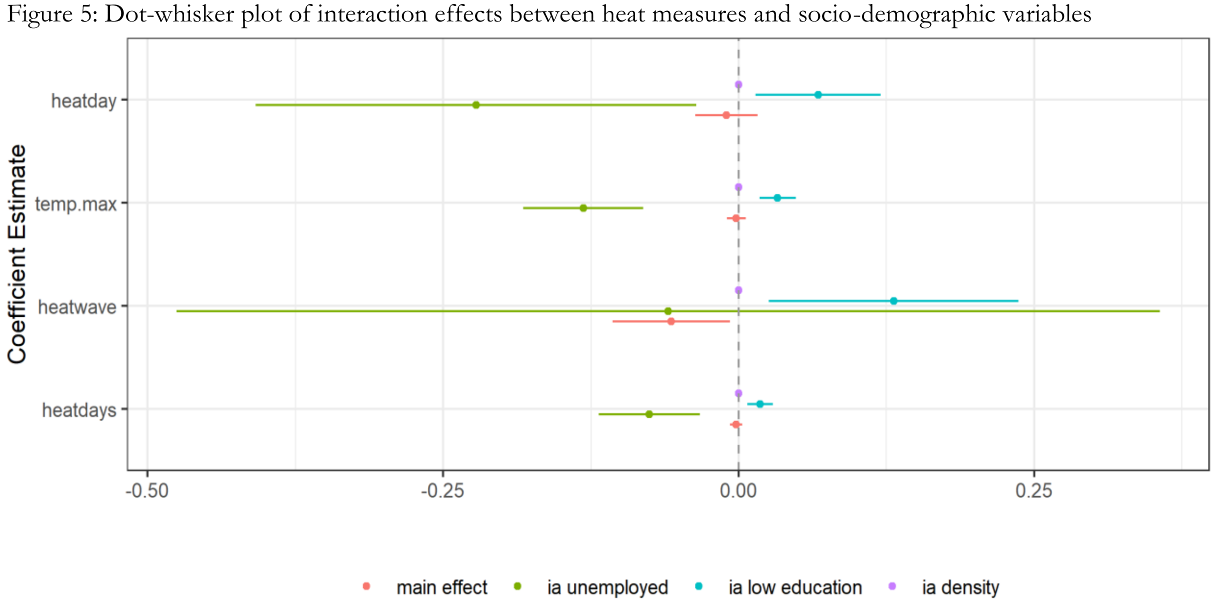


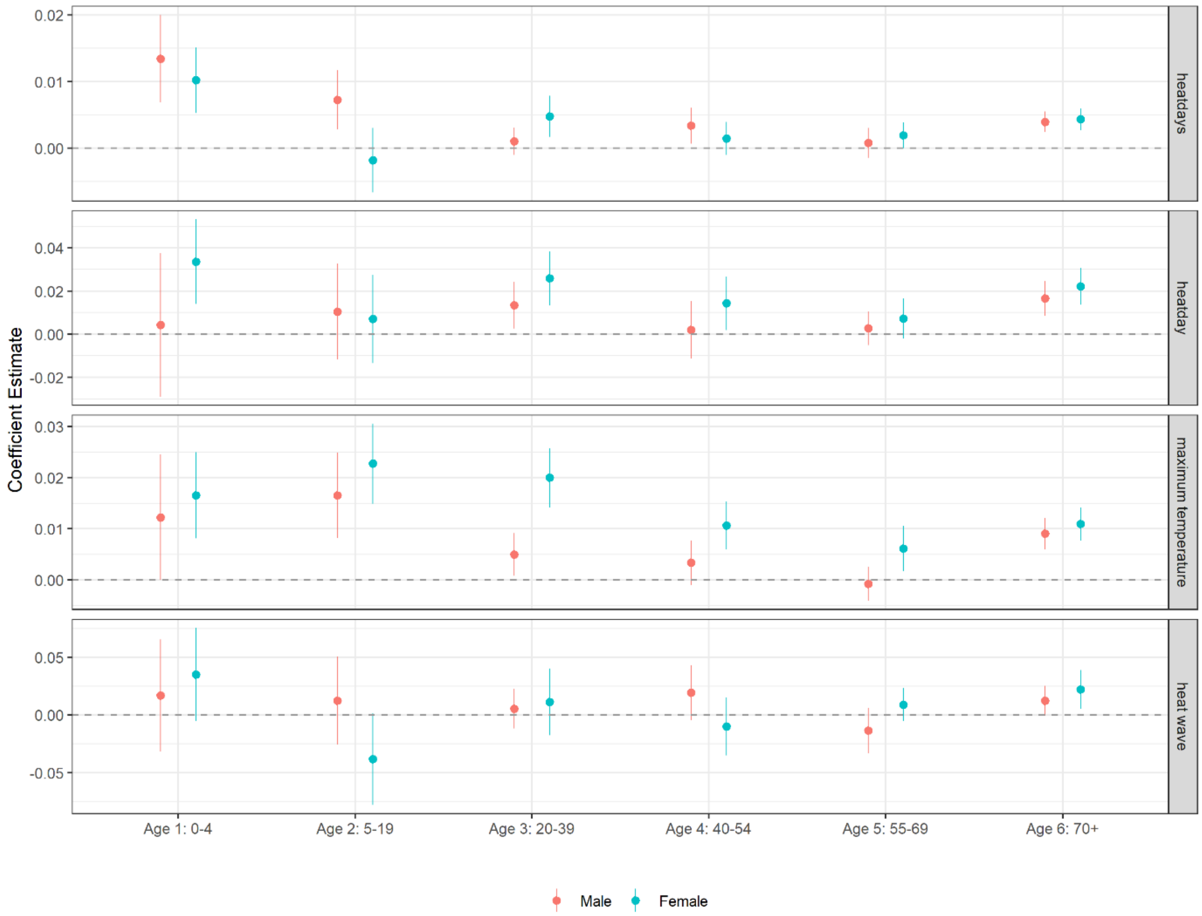
Figure 5: Dot-whisker plot of interaction effects between heat measures and socio-demographic variables



4.3 Differential Temperature Impacts by Age and Sex

The preliminary results from the age- and sex-specific models indicate that the significance of the heat indicators in terms of daily hospitalizations depends on the selected indicator (see Tables A6 to A11 in the Appendix). A notable exception is in the oldest age group—above 70 years (see Table A11 in the Appendix). Hospitalizations for this age group are significantly affected by heat, independent of the climate measure, while the younger age groups are mostly affected by the number of heat days and maximum temperature during a day. Unlike findings from previous literature, our female sample does not show higher vulnerability than the male one. However, the model does not control for potential comorbidities or behavioral aspects that might drive these results. Figure 6 depicts a summary of all age- and sex-specific coefficients with 95% confidence intervals for the different heat measures used.

Figure 6: Dot-whisker plot of standardized coefficients by age and sex



5 Discussion and Conclusion

The findings from our preliminary analysis are fairly consistent in that hospitalization numbers rise as heat days, the number of consecutive heat days, and maximum temperature increase. In particular, a clear pattern emerges when investigating the interactions between different heat measures and socioeconomic characteristics of a given area at the postal code level. Hospitalizations increase alongside the rise in extreme temperatures across all climate measurements, particularly for the postal code areas with a higher share of individuals with a lower level of education. In fact, it is these areas that are vulnerable to heat extremes while hospitalizations do not necessarily increase in more educated areas. This finding is in line with observations from previous literature that education provides a protective effect against the adverse consequences of climate change, possibly by equipping individuals with a better capacity to prepare for and respond and adapt to the climatic shocks (Lutz et al. 2014; Muttarak and Lutz 2014).

Interestingly, and somewhat perplexing, we also found that postal code areas with higher shares of unemployment showed decreased hospitalizations under extreme heat. We expected to see the opposite, since unemployment is associated with a lower capacity to cope with and adapt to climatic shocks. However, this finding illustrates a complex and unique characteristic of being unemployed in Austria. For instance, generous unemployment benefit may deter an individual from taking on low-paid or undesirable jobs that may likewise increase their vulnerability to heat. Hence being unemployed does not necessarily imply a disadvantaged economic status. Likewise, the unemployment rate for the younger age group (aged 15 to 24) has been consistently higher than for older groups and the national average over the past 25 years (Statistik Austria 2021). Therefore, postal code areas with higher shares of unemployment may also reflect higher share of younger individuals living in that area. Furthermore, some literature argues that the relationship between economic downturn and health can be procyclical, i.e. health improves during the times of economic crisis because individuals have more time to pursue healthy lifestyles (Haaland and Telle 2015; Ballester et al. 2019). We plan to further explore the definition and the composition of the unemployed population in our data.

With respect to demographically differentiated vulnerability to extreme temperatures, the age differentials display a bimodal pattern where hospitalizations are particularly high for the very young (aged 0 to 4) and older age group (aged 70 and above). This finding reflects both the lower physiological ability to thermoregulate body temperature among these age groups as well as lower autonomy to cope with temperature extremes. Regarding sex differences, our results do not show a clear sex disparity in vulnerability to heat extremes.

In the subsequent analyses, we will perform population projections by age at the municipality level. The results from this exercise combined with the presented results from the econometric analysis will be used to project future health vulnerability given different climate and socioeconomic scenarios.

6 Appendix

Table A1: Summary statistics – total hospitalizations per postal code area per day

Year	mean	sd	min	max	sum
2009	3.79	12.66	0	235	877,606
2010	3.80	12.80	0	221	881,065
2011	3.79	12.82	0	222	878,071
2012	3.79	13.03	0	220	881,084
2013	3.75	13.00	0	241	869,374
2014	3.75	13.17	0	225	871,608
2015	3.75	13.24	0	250	869,845
2016	3.81	13.57	0	225	886,520

2017	3.83	13.80	0	246	887,605
2018	3.31	11.10	0	195	766,786

Table A2: Effects of different heat measures on the number of hospital admissions per population

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population			
Heatday (dummy)	0.0130*** (0.0016)			
Maximum temperature		0.0084*** (0.0007)		
Heat wave (dummy)			0.0073 (0.0049)	
Heatdays				0.0031*** (0.0004)
Fixed Effects:				
Postal code	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes
Pseudo R2	0.79916	0.79917	0.79916	0.79907
Log-Likelihood	-1,402,084.1	-1,402,031.2	-1,402,109.4	-1,402,078.1
BIC	2,813,257.3	2,813,137.7	2,813,308.0	2,813,231.5

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: All models are Poisson models, using population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A3: Effects of interactions between different heat measures and share of low educated on the number of hospital admissions per population

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population			
Heatday (dummy)	-0.0160 (0.0119)			
Heatday (dummy) x low education share	0.0558* (0.0223)			
Maximum temperature		-0.0076. (0.0040)		
Maximum temperature x low education share		0.0303*** (0.0076)		
Heat wave			-0.0514** (0.0199)	
Heat wave x low education share			0.1176** (0.0378)	
Heatdays				-0.0050* (0.0025)
Heatdays x low education share				0.0155** (0.0050)
Fixed Effects:				
Postal code	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes
Observations	1,062,891	1,062,891	1,062,891	1,062,891
Pseudo R2	0.79916	0.79917	0.79916	0.79916
Log-Likelihood	-1,402,077.4	-1,402,013.5	-1,402,100.7	-1,402,064.6

BIC	2,813,257.8	2,813,116.0	2,813,304.5	2,813,218.4

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A4: Effects of interactions between different heat measures and share of unemployed on the number of hospital admissions per population

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population			
Heatday (dummy)	0.0217*** (0.0043)			
Heatday (dummy) x unemployment share	-0.1550* (0.0627)			
Maximum temperature		0.0147*** (0.0014)		
Maximum temperature x unemployment share		-0.1172*** (0.0252)		
Heat wave			-0.0091 (0.0115)	
Heat wave x unemployment share			0.2564* (0.1443)	
Heatdays				0.0067*** (0.0009)
Heatdays x unemployment share				-0.0636*** (0.0143)
Fixed Effects:				
Postal code	Yes	Yes	Yes	Yes

Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes
Pseudo R2	0.79916	0.79917	0.79916	0.79916
Log-Likelihood	-1,402,081.3	-1,402,016.4	-1,402,107.6	-1,402,066.0
BIC	2,813,265.7	2,813,135.8	2,813,318.2	2,813,235.0

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A5: Effects of interactions between different heat measures and population density on the number of hospital admissions per population

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population			
Heatday (dummy)	0.0164*** (0.0022)			
Heatday (dummy) x density	-7.15e-7* (3.02e-7)			
Maximum temperature		0.0105*** (0.0009)		
Maximum temperature x density		-5e-7*** (1.2e-7)		
Heat wave			0.0095 (0.0071)	
Heat wave x density			-3.46e-7 (6.46e-7)	
Heatdays				0.0044***

				(0.0005)
Heatdays x density				-2.75e-7*** (7.32e-8)
Fixed Effects:				
Postal code	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes
Pseudo R2	0.79916	0.79917	0.79916	0.79916
Log-Likelihood	-1,402,079.9	-1,402,015.4	-1,402,108.7	-1,402,063.2
BIC	2,813,262.7	2,813,147.6	2,813,334.4	2,813,243.4

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A6: Effects of different heat measures on the number of hospital admissions per population for age group 0 to 4 years and both sexes

	Female age 0–4				***Male age 0 –4***			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population							
Heatday (dummy)	0.0042 (0.0169)				0.0336*** (0.0100)			

Maximum temperature		0.0023*				0.0030***		
		(0.0012)				(0.0008)		
Heat wave (dummy)			0.0168				0.0350*	
			(0.0248)				(0.0207)	
Heatdays				0.0135***				0.0102***
				(0.0033)				(0.0025)
Fixed Effects:								
Postal code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,047,744	1,047,744	1,047,744	1,047,744	1,052,793	1,052,793	1,052,793	1,052,793
Pseudo R2	0.41127	0.41128	0.41127	0.41131	0.43483	0.43484	0.43482	0.43484
Log-Likelihood	-124,723.6	-124,721.2	-124,723.4	-124,714.4	-155,228.9	-155,226.5	-155,231.3	-155,225.3
BIC	258,388.3	258,383.5	258,387.9	258,369.9	319,443.6	319,452.7	319,462.2	319,436.4

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A7: Effects of different heat measures on the number of hospital admissions per population for age group 5 to 19 years and both sexes

	Female age 5–19				*Male age 5–19*			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population							
Heatday (dummy)	0.0104 (0.0113)				0.0070 (0.0104)			
Maximum temperature		0.0031*** (0.0008)				0.0043*** (0.0007)		
Heat wave (dummy)			0.0124 (0.0195)				-0.0384* (0.0203)	
Heatdays				0.0073** (0.0023)				-0.0018 (0.0025)
Fixed Effects:								
Postal code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,057,842	1,057,842	1,057,842	1,057,842	1,061,208	1,061,208	1,061,208	1,061,208
Pseudo R2	0.39332	0.39334	0.39332	0.39333	0.39719	0.39723	0.39719	0.39719
Log-Likelihood	-212,758.0	-212,750.0	-212,758.3	-212,753.5	-231,409.6	-231,391.3	-231,407.8	-231,409.5
BIC	434,574.3	434,544.3	434,561.0	434,551.3	471,893.4	471,856.7	471,889.9	471,893.2

Table A8: Effects of different heat measures on the number of hospital admissions per population for age group 20 to 39 years and both sexes

	Female age 20–39				*Male age 20–39*			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population							
Heatday (dummy)	0.0134* (0.0055)				0.0258*** (0.0063)			
Maximum temperature		0.0009* (0.0004)				0.0037*** (0.0005)		
Heat wave (dummy)			0.0054 (0.0087)				0.0115 (0.0148)	
Heatdays				0.0010 (0.0011)				0.0048** (0.0016)
Fixed Effects:								
Postal code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208
Pseudo R2	0.56923	0.56923	0.56923	0.56923	0.47912	0.47915	0.47911	0.47912
Log-Likelihood	-453,142.9	-453,143.1	-453,145.9	-453,145.6	-290,424.8	-290,407.7	-290,429.7	-290,426.1
BIC	915,360.0	915,360.5	915,365.9	915,365.4	589,923.8	589,889.6	589,933.7	589,926.5

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A9: Effects of different heat measures on the number of hospital admissions per population for age group 40 to 54 years and both sexes

	Female age 40–54				*Male age 40–54*			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population							
Heatday (dummy)	0.0020 (0.0067)				0.0143* (0.0063)			
Maximum temperature		0.0006 (0.0004)				0.0020*** (0.0004)		
Heat wave (dummy)			0.0194 (0.0121)				-0.0100 (0.0129)	
Heatdays				0.0034* (0.0014)				0.0014 (0.0013)
Fixed Effects:								
Postal code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,062,891	1,062,891	1,062,891	1,062,891	1,061,208	1,061,208	1,061,208	1,061,208
Pseudo R2	0.55895	0.55895	0.55895	0.55895	0.51191	0.51192	0.51191	0.51191
Log-Likelihood	-404,093.4	-404,092.4	-404,091.9	-404,090.1	-390,363.1	-390,355.6	-390,365.2	-390,365.0
BIC	817,276.0	817,273.8	817,273.0	817,269.3	789,786.4	789,771.5	789,804.6	789,804.2

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A10: Effects of different heat measures on the number of hospital admissions per population for age group 55 to 69 years and both sexes

	Female age 55–69				*Male age 55– 69*			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population							
Heatday (dummy)	0.0028 (0.0040)				0.0072 (0.0048)			
Maximum temperature		-0.0001 (0.0003)				0.0012** (0.0004)		
Heat wave (dummy)			-0.0134 (0.0099)				0.0090 (0.0073)	
Heatdays				0.0008 (0.0011)				0.0019* (0.0010)
Fixed Effects:								
Postal code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,062,891	1,062,891	1,062,891	1,062,891	1,061,208	1,061,208	1,061,208	1,061,208
Pseudo R2	0.60003	0.60003	0.60003	0.60003	0.57028	0.57029	0.57028	0.57029
Log-Likelihood	-466,528.7	-466,528.8	-466,527.9	-466,528.6	-514,350.5	-514,345.9	-514,351.0	-514,349.9

BIC	942,146.6	942,146.7	942,144.8	942,146.4	1,037,789.0	1,037,780.0	1,037,790.1	1,037,787.8

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

Table A11: Effects of different heat measures on the number of hospital admissions per population for age group 70 and above and both sexes

	Female age 70and above				***Male age 70 and above***			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Dependent Variable: Total hospitalizations per population							
Heatday (dummy)	0.0165*** (0.0042)				0.0221*** (0.0043)			
Maximum temperature		0.0091*** (0.0016)				0.0109*** (0.0017)		
Heat wave (dummy)			0.0122* (0.0067)				0.0222** (0.0086)	
Heatdays				0.0039*** (0.0008)				0.0044*** (0.0008)
Fixed Effects:								
Postal code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208	1,061,208
Pseudo R2	0.63423	0.63423	0.63422	0.63423	0.56760	0.56760	0.56759	0.56759

Log-Likelihood	-676,629.3	-676,619.2	-676,637.2	-676,627.0	-610,413.0	-610,404.5	-610,421.9	-610,414.7
BIC	1,362,332.9	1,362,312.7	1,362,348.6	1,362,328.2	1,229,914.0	1,229,897.0	1,229,931.8	1,229,917.5

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

All models are Poisson models with population number as offset and year, month, weekday, and postal code as fixed effects. Standard errors are clustered at the postal code level. Sample restricted from May through September, and models control for precipitation.

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