DISCUSSION PAPER

Discussion paper 40/2021

Roberto Astone, Maria Vaalavuo

Climate change and health: Consequences of high temperatures among vulnerable groups in Finland

Global warming has increased the likelihood of heat waves also in high latitude regions not accustomed to high temperatures. This has made the evaluation of potential human health consequences and need for adaptation in the health care sector more urgent. In this study, we examine the effects of high temperatures on morbidity and mortality in Finland. Individual level data for the total population on hospital visits, causes of death, demographic and socioeconomic information as well as daily weather data are used to study outcomes at the municipality-month level over a span of 20 years. Panel data linear regression methods are utilized alongside high-dimensional fixed effects minimizing confounding variation. Analysis is conducted by age groups with special emphasis on the elderly population, as well as for specific elderly risk groups identified in previous literature. We also differentiate both morbidity and mortality effects cause-specifically with a broad set of different discharge diagnosis groups and the most common causes of death. The models show a clear increase in the number of acute all-cause and cause-specific hospital visits as well as all-cause and cause-specific mortality that disproportionately affect the elderly population. We also find some evidence that heat-waves might affect certain vulnerable population groups more intensely. The evidence can be used in identifying vulnerable groups as extreme heat waves are expected to become more frequent and intense. The study has been financed by the Academy of Finland and it is part of the project "Climate change and Health: Adapting to Mental, Physical and Societal challenges" (CHAMPS).

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Abstract

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Keywords: Climate change, heat waves, temperature, mortality, morbidity

Tiivistelmä

Roberto Astone, Maria Vaalavuo
Ilmastonmuutoksen terveysvaikutukset: korkeiden lämpötilojen vaikutus haavoittuviin ryhmiin Suomessa. Terveyden ja hyvinvoinnin laitos (THL).
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Ilmastonmuutos on lisännyt lämpöaaltojen todennäköisyyttä myös Suomessa, jossa kuumiin olosuhteisiin ei olla totuttu. Tämä on tehnyt terveysvaikutuksien arvioinnin ja terveydenhuoltojärjestelmän valmistautumisen entistä tärkeämmäksi. Tässä tutkimuksessa käytettiin yksilötason dataa sairaalakäynneistä, kuolleisuudesta ja perustiedoista sekä päivittäistä säädataa 20 vuoden ajalta lämpösairastavuus- ja lämpökuolleisuustarkasteluissa kunta-kuukausitasolla. Metodina käytimme lineaarista regressiota hyödyntäen kiinteitä vaikutuksia, jotka minimoivat havaitsemattomien sekoittavien tekijöiden vaikutuksia. Analysoimme lopputulemia erikseen ikäryhmittäin sekä diagnoosi- ja kuolinsyyryhmittäin. Analysoimme erikseen ikääntyneen väestön keskuudessa niitä ryhmiä, jotka aiempi kirjallisuus on tunnistanut riskiryhmiksi. Tuloksemme näyttävät, että kuolleisuus ja erikoissairaanhoidon käynnit lisääntyivät selkeästi lämpimien päivien lukumäärän kasvaessa. Vaikutukset ovat useimmiten voimakkaampia ikääntyneessä väestössä. Tuloksemme osoittavat, että kuolleisuus on suurempaa aiemman kirjallisuuden osoittamissa riskiryhmissä. Tuloksiamme voidaan käyttää potentiaalisten riskiryhmien tunnistamiseen Suomessa, jossa lämpöaallot ovat yleistymässä ja voimistumassa. Tutkimus on saanut rahoitusta Suomen akatemialta ja on osa tutkimushanketta ”Psyykkinen ja fyysinen terveys sekä yhteiskunnalliset haasteet ilmastonmuutokseen sopeutumisessa” (CHAMPS).

Avainsanat: ilmastonmuutos, lämpöaallot, terveys, kuolleisuus

Contents

1. Introduction

According to the latest report by the Intergovernmental Panel on Climate Change (IPCC, 2021), we are on course towards global warming of 1.5ºC, in relation to 1850-1900, in the next two decades. Changes in global mean temperatures have disproportionate effects on the frequency of rare events such as extreme heat waves. For example, the report projects that extreme heat events which, in the period 1850-1900, occurred once in 1 10 years, are currently likely to occur 2.8 times more often and become hotter than before. Such changes are significant for our daily lives and necessitate preparedness in the health care sector to protect public health. The effects of heat waves on health due to thermal stress and thermoregulation are well documented in existing research. The most prominent effects are increases in cardiovascular, renal, respiratory and diabetes related hospitalization and mortality (WHO, 2013). Research focusing on specific heat waves, such as the 2003 heatwave in Europe, shows that the death toll attributable to the heat wave exceeded 70,000 people (Robine et al., 2008).

There is also evidence of adverse effects of heat waves in Finland despite its northerly location. The impacts of the 2003 heatwave in Europe and the 2010 heatwave in Russia were both experienced in Finland too, with 200 and 300 excess deaths reported, respectively (Kollanus and Lanki, 2013). Näyhä (2005) reported 800 excess deaths from the exceptionally warm summer of 1972. These figures are still small in relation to the annual mortality and in relation to cold effects in Finland (Näyhä, 2007). However, this is likely to change in the future. For example, Kim et al. (2018) project that the mean duration of a heat wave with mean temperatures above +20ºC is projected to grow in Finland from 6.1 days per year up to 9.4 days.[1] In addition, winter temperatures in Finland are projected to rise even faster than summer temperatures, shifting the temperature hazard towards the summer period (Ruosteenoja et al., 2016).

In this article, our principal aim is to examine effects of temperature on human health in Finland, by first establishing the overall effect on the whole population and then on different sub-groups of the population and to identify groups most at risk of severe health consequences. We analyse the effects of temperature on health care use and mortality during summer months using rich individual level register data on the total population administered by the Finnish Institute for Health and Welfare and Statistics Finland.

Studies on heat-related mortality already exist, including for the Nordic countries, but few utilise individual level data and fewer still also analyse hospital visits. We believe that including hospital visits helps us get a broader view of the health effects of heat, since, as we learn from our results, different diagnosis categories often emerge when looking at hospital visits and mortality. A large panel data set spanning 20 years gives statistical power and the high granularity of the data enables the use of accurate daily measurements of weather variables in all municipalities, ruling out non-acute hospital visits and studying heterogeneity in heat effects between different groups of interest such as age groups, socioeconomic groups and groups with relevant pre-existing medical conditions by performing analyses separately for these subgroups. We find mortality effects of similar magnitudes reported by previous literature, and elevated morbidity in terms of acute hospital visits due to heat exposure, respiratory illness, renal illness and diabetes.

Due to the plausible growth in excess mortality and morbidity attributable to heat, studies on how to adequately prepare for rising temperatures and temperature shocks are increasingly important. Identifying vulnerable groups facing the largest risk is part of the preparedness of the health care system. The elevated burden on health care systems and greater health care expenditure caused by these events justifies studying the heterogeneous effects of temperature among different groups of people, and the evidence can guide how to best allocate resources to mitigate these effects. The degree to which

[1] Prediction calculated using ERA-interim reanalysis data and RCP4.5 intermediate future climate scenario

individuals or households are able to adapt their behavior to heat exposure in the short term is a major determinant of mortality and morbidity. The ability is also likely to vary across population groups that present different vulnerabilities to begin with. Several studies report a significantly higher risk of hospitalization and mortality for elderly people and infants, related to both heat waves and cold spells, compared to the prime-age group (Hajat et al., 2014, Knowlton, 2008, Nitschke et al., 2011, Sherbakov et al., 2018). Ageing population typical to the Nordic countries is thus another factor aggravating the effects of heat waves in Finland.

2. Previous literature

There exist multiple direct and indirect channels through which climate and climate change may affect human health. Examples range from effects on diseases, destructive weather events, droughts, and mental health. In this article, we are interested in the direct effects of changes in the daily outdoor temperature on the human physiological health. Several studies have examined this relationship also in Finland (Kollanus and Lanki, 2013; Kollanus et al., 2021; Ruuhela, 2018; Ruuhela et al., 2017). In general, researchers have not reached consensus on the precise causal relationships and the magnitude of the effects. The differences in statistical methods, local demographics, local health care systems and data availability could help to explain the differences. The threshold temperature at which health effects start to emerge also varies geographically, as mortality is at its lowest point often around the local most frequent temperature (Yin et al., 2019). We have concentrated on reviewing literature that attempts to find causal effects of temperature on health outcomes and literature focusing on developed countries.

A common method in climate economics literature is to use panel data fixed effects models (e.g., Barreca (2012), Deschenes and Greenstone (2011), Mullins and White (2019)) that utilize broad data in both temporal and spatial dimension and compare random variation in temperatures to the variation of different outcomes of interest. When comparing time series data on weather variables and health outcomes, effects of many confounders are excluded by design, since most variables influencing health are not correlated with daily temperature. Natural exogeneity, or the randomness of short-term weather variation also means that validity 3 is not threatened by issues common to causal analyses such as reverse causality. There remain some potential confounders that are important to consider in analysing heat effects, such as humidity and air pollution. These variables could have a common temporal pattern with temperature, and therefore confound the association with temperature and health.

Fine particulate matter is a type of air pollution which has the biggest impact on human health. Fine particles and their health effects have been studied extensively. For example, Deryugina et al. (2019) found that similarly to temperature, fine particulate matter also disproportionately affects the elderly population. Carder et al. (2008) and Rainham and Smoyer-Tomic (2003) studied the interactions between air pollution and temperature in Scotland and Toronto, respectively. They both showed that the evidence on the interaction between air pollution and temperature is inconclusive.

Fine particle levels in Finland are commonly low, and the peaks are concentrated in the early spring when street dust levels are high (FMI, 2013). We restrict our empirical analysis in the period from May to September and, consequently, avoid the early spring period when the fine particle pollution peaks due to road dust. The panel fixed effects method used in this article, more thoroughly explained in the method section, will also mitigate possible confounding of pollution fluctuation between months by taking into account the level differences in outcomes between months. Ozone is another form of pollution which has the second highest impact on health after fine particles. The climate in Finland is not favourable for ozone formation and therefore the ozone levels in Finland are relatively low and very rarely exceed the healthy levels (FMI, 2021). For these reasons, we are confident in our choice to not include air pollution measures in our empirical models.

Humidity alongside high temperatures is known to affect human capability to withstand heat stress by hindering the body's ability to evaporate heat energy. Barreca (2012) studied the effect of temperature and humidity on mortality rates in the U.S. in the years 1973-2002 and predicted that annual mortality rates would decrease in the cold and dry areas where the cold-season mortality effects dominate and increase in the hot and humid areas where the hot-season mortality dominates. Barreca's main findings are that three additional days per month above 90ºF (approx. 32ºC) result in a 0.54 excess deaths per 100,000 inhabitants, and three additional days between the humidity levels 16 and 18 g/kg causes an increase of 0.22 deaths per 100,000 inhabitants. Low humidity levels in interaction with cold weather also increase mortality, plausibly due to easier transmission of influenza. He concluded that humidity alongside temperature is an important predictor of mortality in the U.S. and not including humidity generates biased results for the hot and humid regions due to the geographical and temporal differences in the relationship between temperature and humidity.

There is evidence that temperature effects are delayed in time and health effects of temperature exposure accumulate (e.g., Gronlund et al. (2014)). Several studies have also reported that heat effects are rather immediate and persist 3-5 days, while cold effects persist for longer periods, up to 15 days (Gasparrini and Armstrong, 2010, Peterson et al., 2008, Yang et al., 2012). Therefore, daily level analyses often contain some kind of lag structure for temperature. Common methods in the field of environmental epidemiology are distributed lag models (DLM), notably the distributed lag nonlinear models (DLNM). Developed by Armstrong (2006), DLNM is adapted from DLM to include the estimation of nonlinear exposure effects. The method models the exposure-response association in two dimensions using separate functions for the lag dimension and the predictor itself. Gasparrini et al. (2012) studied temperature related cause-specific mortality in the UK between years 1993-2006 using the DLNM method. They found that all-cause mortality rises by 2.1 percent for each day with a temperature above the 93rd percentile of region-specific yearly temperatures. More than half of the measured mortality was attributable to cardiovascular and respiratory diseases.

Another reason to include the lag-dimension is to take into account the so-called harvesting/displacement effect common to temperature-mortality analyses. Harvesting takes place when there is a peak in the number of deaths as an immediate response to the exposure to high temperature, and this is compensated partially by a reduction in the number of deaths following the exposure. Harvesting effect consists mainly of individuals that are extremely vulnerable and whose deaths are preponed by any slight additional physical stress, in this case, heat. According to some studies, the initial mortality increases during heat waves are largely driven by the harvesting effect (Deschenes and Moretti, 2009), and are offset by a subsequent fall in mortality in the following periods. Therefore, harvesting needs to be considered when analyzing the causal effects of heat.

Deschênes and Greenstone (2011) study the temperature-mortality relationship in the U.S. during years 1968-2002 by using a panel data fixed effects model. They divide the daily temperature measures into 10 bins, each with a width of 10ºF. Then, they explain the annual all-cause mortality using the number of days in each temperature bin during a year, including county and state-by-year fixed effects. They find that one additional day over 90ºF (approx. 32ºC) raises the annual age-adjusted all-cause mortality rate by 0.11 percent relative to a moderately warm day of 60ºF-70ºF which is a modal bin used as a reference. They also report elevated risk for the elderly population and infants, while no other heterogeneous effects were examined.

There is evidence that some attributes, or combinations of them, that might lead to an elevated risk of heat vulnerability. One of the risk groups is elderly population living alone (Vandentorren et al., 2006). Not having anybody to take care of oneself might cause symptoms of heat exposure to remain unattended or decrease the use of simple preventive measures such as staying hydrated or opening the windows. History of dementia-related illness is another potential contributor to the risk of heat-related mortality and morbidity. For example, based on their results from Stockholm, Rocklov et al. (2014) argue that dementia might explain 5 a significant part of heat related mortality among the elderly population.

In addition, people with low incomes might be less able to adapt to high temperatures, such as investing in air conditioning or moving locations. However, there is surprisingly little evidence on elevated heat vulnerability of groups in lower socioeconomic positions, especially from the developed countries. Gouveia et al. (2003) found only little evidence that the socioeconomic position of individuals modifies the temperature-mortality relationship in Brazil (risk is elevated only among the most deprived groups in Sao Paulo). A city-level study from the U.S. showed that a 10 percent increase in the poverty level modified the temperature-mortality association (on the warm side of the temperature distribution) by 4.3 percent (Curriero et al., 2002).

Heat affects health through different physiological mechanisms and the magnitude of the effects is likely to vary across disease groups. Moreover, people with certain pre-existing conditions might be more susceptible to heat-related health effects, while healthy individuals are less likely to be affected. According to previous studies, hospital visits related to asthma are elevated during heat waves (Soneja et al., 2016), and people who have been diagnosed with asthma are more susceptible to morbidity during heat waves (Khalaj et al., 2010). Diabetes has also been reported to decrease the ability to endure heat stress and elevate the risk of negative health consequences in this population group (e.g., Vallianou et al. (2020), Xu et al. (2019)). Some studies have also shown that temperature affects cardiovascular health outcomes and causes elevated risk of morbidity and mortality among individuals having pre-existing cardiovascular illness (Semenza et al., 1996).

3. Data and research design

3.1 Data

We use register data on the use of specialized health care (HILMO) administered by the Finnish Institute for Health and Welfare, data on causes of death and data on individuals' socioeconomic status (FOLK) administered by Statistics Finland, and daily weather data administered by the Finnish Meteorological Institute. Individual level data are merged by using an encrypted ID code unique to each individual. Health outcomes are connected to the individual's municipality of residence and the local weather. The data are then aggregated to the municipality-day and municipality-month level to form a panel dataset to be used in the empirical analyses.

The data span from 1998 to 2017 but only the summer months from May to September are included. This is done to keep the emphasis on heat effects, and it allows us to disregard some of the stronger seasonality in 6 the outcomes taking place between seasons, such as the overall decline of morbidity in the summer compared to the winter. As stated earlier, this also mitigates the possible confounding effects of road dust, a major component of harmful air pollution in the early spring. Since municipality borders change across time due to municipal mergers, we fix the municipality areas to the ones of 2015 throughout the data. Some spatial accuracy is lost by doing this, since some weather data are disregarded and replaced with measurements from the parent municipality.

3.2 Outcome variables: hospital visits and mortality

All health care services in Finland are divided into primary health care and specialized health care. The health care data used in this article consist of public sector specialized care visits due to better data availability and comparability. Our data cover around half of all the outpatient visits in the public sector as there were 10.8 million outpatient visits in the specialized care compared to 9.9 million outpatient visits in the primary health care during the year 2019 (Kyrolä and Järvelin, 2020; Puroharju et al., 2020). The data include primary symptom diagnosis codes corresponding to the International Classification of Diseases 10th edition (ICD-10) to distinguish between diagnosis groups and a variable to distinguish between acute and other hospital visits.

We are interested in two outcome variables: hospital visits and mortality. As strong long- and shortterm seasonality can be observed for all hospital visits due to holiday seasons and the fact that planned visits concentrate on weekdays, we include only acute visits that present less seasonality. Longer term seasonality is taken into account also by the use of fixed effects that restrict only the inter-month variation into the analysis.

The hospital visits are analysed cause-specifically in diagnoses which are selected based on existing evidence (Bogdanovic et al., 2013; Kovats et al., 2004). The following ICD-10 diagnoses are chosen for the analysis: all cardiovascular diseases (I00-I99), respiratory diseases (I60-I69), selected renal diseases (N00-N39), dementia (F00-F03), psychiatric disorders (F04-F99) and diabetes related diagnoses (E10-E14). Respiratory illness with codes J60-J79 is excluded due to it being caused by inhalation of inorganic substances, inorganic dust or chemicals. In addition, hyperthermia (T67) and exposure to excessive natural heat (X30), are included and classified under the category ”heat exposure”. Hospital visits are also restricted to acute visits only. Examining acute visits results in a firmer exposure-response link since acute visits are more likely to be directly connected with the weather outcomes of the same day.

Mortality and morbidity analysis is conducted first for all causes, followed by cause-specific analysis. The heat-mortality mechanism is not easily visible in the cause of death data. For example, deaths are very rarely registered as being directly caused by heat. In addition, the data contain a primary cause of death, an immediate cause of death and 4 contributing causes of death. We determine the cause-specific 7 deaths in our data by using both the primary and immediate causes of death. We consider separately two of the most common causes of death: cardiovascular causes (I00-I99) and respiratory causes (I60-I69). All outcomes are calculated per 100,000 population, using yearly population estimates calculated from the FOLK data. Summary statistics on the average monthly mortality and hospital visit counts for the study period are presented in tables 1 and 2. The definitions of vulnerable groups are detailed in the following section.

Table 1: Average monthly mortality rates per 100,000 population (May-September of 1998-2017)

	Age group			
	0-64	65-74	75-84	85 and above
Whole population				
All cause mortality	18.6	137.1	366.1	1078.2
Respiratory	1.7	21.8	79.2	265.3
Cardiovascular	4.9	53.7	167.6	553.9
Low-income elderly population				
All cause mortality	.	.	916.0	1622.6
Elderly population living alone				
All cause mortality	.	.	294.0	797.8
Elderly with pre-ex. cardiovascular conditions				
All cause mortality	.	.	539.2	1187.4
Elderly with pre-ex. asthma				
All cause mortality	.	.	434.3	903.6
Elderly with pre-ex. Alzheimer or dementia				
All cause mortality	.	.	546.9	868.0
Elderly with pre-ex. diabetes				
All cause mortality	.	.	710.0	1096.3
Elderly with pre-ex. mental or behavioral illness				
All cause mortality	.	.	436.6	747.7

Table 2: Average monthly acute hospital visits per 100,000 population (May-September of 1998-2017)

	Age group			
	0-64	65-74	75-84	85 and above
Whole population				
All acute hospital visits	1188.8	2413.1	4438.0	6842.5
Heat exposure	2.75	15.6	37.5	76.3
Respiratory diagnoses	84.4	198.9	395.4	611.1
Cardiovascular diagnoses	67.8	516.1	1069.8	1718.7
Diabetes diagnoses	13.4	26.7	45.0	51.5
Renal diagnoses	25.6	87.3	230.5	507.9
Psychiatric diagnoses	138.3	109.7	154.4	247.5
Alzheimer & dementia diagnoses	0.56	19.7	107.7	242.0
Low-income elderly population				
All cause mortality	.	.	6201.9	8440.1
Elderly population living alone				
All cause mortality	.	.	4474.4	7122.4
Elderly with pre-ex. cardiovascular conditions				
All acute hospital visits	.	.	10960	14092
Elderly with pre-ex. asthma				
All acute hospital visits	.	.	13327	17958
Elderly with pre-ex. Alzheimer or dementia				
All acute hospital visits	.	.	11508	11782
Elderly with pre-ex. diabetes				
All acute hospital visits	.	.	14655	15616
Elderly with pre-ex. mental or behavioral illness				
All acute hospital visits	.	.	13040	14607

3.3 Demographic and socioeconomic data

Annual data describing individuals' basic information is provided by Statistics Finland. Variables selected for use are the municipality number for the place of residence, year, unique personal identifier, age, sex, disposable income, living arrangement and a family identifier code. Since the data don't include observations for individuals' year of death, this information is extrapolated from the previous year in case the individual dies. In our analyses, hospital visits and mortality are analysed separately for four age groups 0-64, 65-74, 75-84, and 85+.

A low-income indicator is based on equivalised family disposable income, which is a measure taking into account paid taxes and received social transfers. The OECD modified equivalence scale (OECD, 2009) was used to take into account the size and composition of the household: the sum of the family disposable income is divided by a weighted sum of family members. The first adult of the household is weighted by 1, all following adults by 0.5 and children under 14 by 0.3. Each year, the first quintile of the income distribution (the poorest 20 percent of the population) is defined as having low income. We have also created a dummy variable which takes on the value 1 if the individual is living alone, based on the living arrangement variable.

Data on hospital visits and ICD-10 codes are also used to create indicators on pre-existing medical conditions for each individual. Pre-existing conditions are identified based on an indicator variable that has a value of 1 if an individual has had any acute or non-acute hospital visits during the past 5 years in different diagnosis categories. In these analyses, first 5 years of the data are therefore omitted.

The diagnoses of interest in determining pre-existing conditions are diabetes, cardiovascular disease, asthma, dementia and Alzheimer's disease and psychiatric diagnoses.

3.4 Independent variables: weather data

Weather data are obtained from the Finnish Meteorological Institute (FMI) and the variables selected for use are the municipality number, date, daily mean temperature and relative humidity. To focus on the effects of extreme heat that is expected to increase due to ongoing climate change, we concentrate on the months from May to September in this article, excluding albeit important health effects of cold in Finland.

We have chosen to use daily mean outdoor temperature as the main predictor in the models. The temperature for each municipality in the dataset is calculated based on spatially averaging from the FMI's 10km x 10km gridded dataset. Compared to several studies in which temperature is calculated by averaging between the daily minimum and maximum temperatures, FMI measures are more accurate and less prone to measurement error, as daily mean temperature is calculated by averaging from up to 8 daily measures. This is especially important in Finland where there is large variation in the day length.

The relationship between temperature and health outcomes is often found to be U-shaped, where negative health outcomes occur at both ends of the yearly temperature distribution. Drawing a linear relationship between continuous temperature and health outcomes is likely to result in a decrease in negative health outcomes given a rise in temperature, since most of the daily average temperatures in Finland are below 14ºC, or what the minimum mortality temperature (MMT) in Finland is estimated to be (Ruuhela, 2018), and since the mortality effects of cold dominate in Finland (Näyhä, 2007). Therefore, it is important to specifically identify effects of extreme heat and to take into account the nonlinear effects of temperature.

Independent variable binning is a tool to easily model nonlinear effects and is used in several climate economics papers studying the temperature-morbidity effect (Barreca, 2012, Mullins and White, 2019, Otrachshenko et al., 2017). Binning independent variables into discrete categories reduces variation but, in turn, parameters are estimated separately for each category, enabling the modelling of nonlinear effects. The downside of the reduction in variation is smaller the larger the data is. Aforementioned studies use several decades of daily observations, and our article uses 20 years of daily measures restricted to five of the warmest months. Upsides of data binning instead of, for example, fitting a specific polynomial function into the data is that no assumptions of 10 the functional form relationship between the variables are needed. The association is determined freely by the data.

Following the example of Barreca (2012), Mullins and White (2019), Otrachshenko et al. (2017), we categorize temperature into 10 bins in our analyses. Figure 1 shows these bins and the average distribution of days per month in each bin in the sample. The temperature is truncated so that the days in the lowest bin form about 0.5 percent of the municipality-days in the sample and the highest bin about 0.1 percent. The small proportion of days below 1ºC and over 25ºC is due to the varying climate in the whole of Finland, as the warmest days are mostly seen in the south and the coldest days only in the north. Figure 2 illustrates the spatial distribution of the number of days in the highest two temperature bins.

The literature is inconclusive on which measurement best proxies the heat stress felt by humans and thus, is the most appropriate in analyzing the health effects. Barnett et al. (2010) assess the quality between measurements such as mean, minimum and maximum temperature with and without humidity, apparent temperature and Humidex-index, which is a "real feel" type of measurement which combines temperature with dew point measures into a scale. They study mortality effects of weather using a large dataset from 107 cities in the U.S. They conclude that different measures might give slightly different results, but there are no clear winners in terms of measurement accuracy. They suggest using the best available data when conducting research on the topic.

Ruuhela et al. (2017) use physiologically equivalent temperature (PET) in their study of extreme temperatures and mortality. PET is calculated by using outdoor air temperature, relative humidity, wind speed and solar radiation. One of the conclusions of the study is that using daily average temperature as a predictor is in most cases adequate and the inclusion of PET is not particularly beneficial. Since high levels of humidity are also seen in Finland during extreme weather events, and humidity is used as a predictor in several studies (Barreca et al., 2015, Barreca, 2012, Mullins and White, 2019), we test how humidity affects our main results. The measures of relative humidity, which contain a component of temperature, are converted into specific humidity (g/m3) using a conventional meteorological formula, to avoid multicollinearity in further analysis.

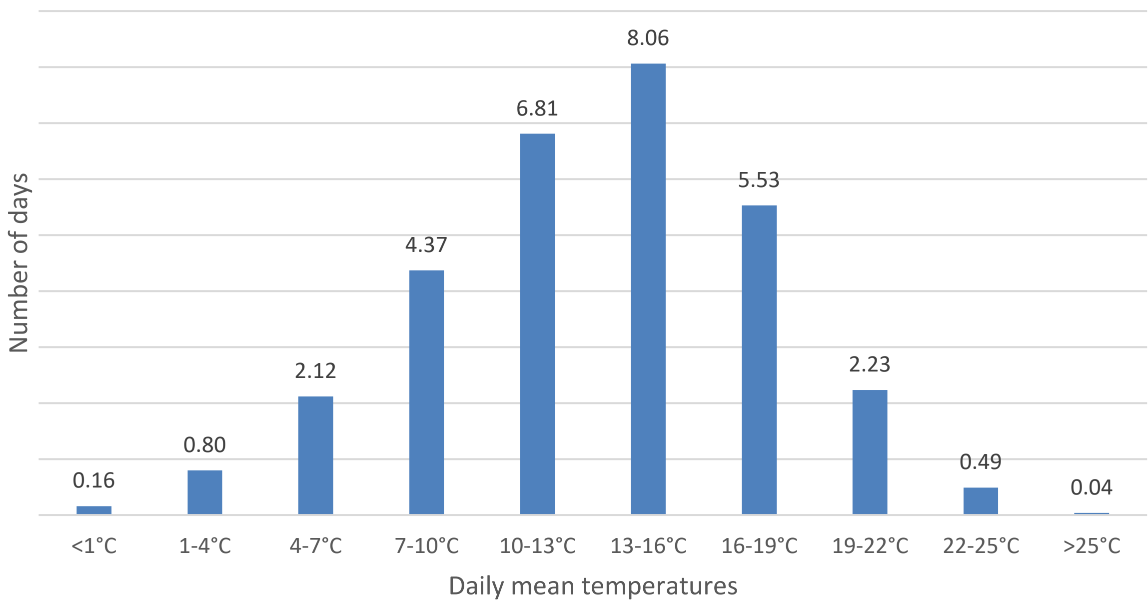
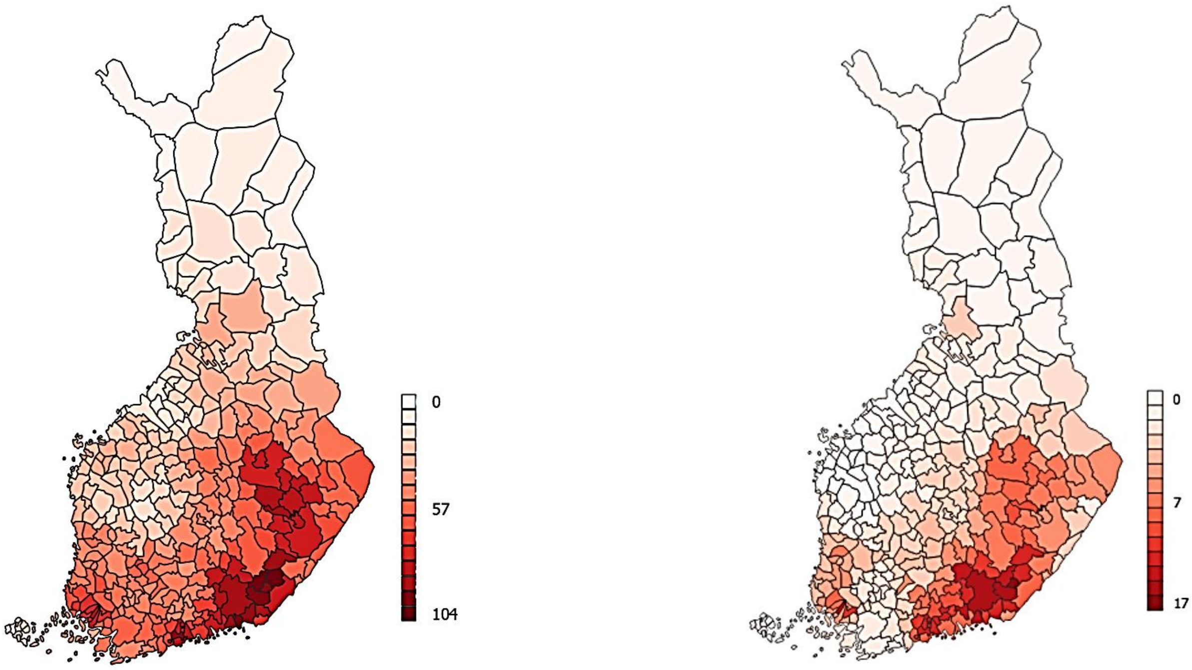


Figure 1: Average distribution of days per month in each temperature category, 1998-2017

Note: This figure represents the historical average of the monthly distribution of daily mean temperature days in all 311 municipalities in the sample, during the months May to September and years 1998-2017.



(a) Number of days between 22-25°C (b) Number of days exceeding 25°C

Figure 2: Spatial distribution of the number of days in the two highest temperature bins during the whole

Note: This figure represents the spatial distribution of days in the highest daily mean temperature categories in all 311 municipalities in the sample, including months May to September and years 1998-2017. The warmest municipalities in this figure have a day in the highest temperature category almost once per year on average, and about 5 days per year in the range 22-25ºC on average. This figure is constructed by the authors using the QGIS software.

3.5 Empirical methods

After aggregating the data to the municipality-month level, our empirical model is formalized as follows:

$$Y_{(i,m,y)} = \sum_{B} \beta_B \, T_{B_{(i,m,y)}} + \alpha_{(i,y)} + \gamma_{(m)} + \varepsilon_{(i,m,y)}$$

where Y is the monthly sum of hospital visits or mortality per 100,000 population in municipality i, month m and year y. Y is explained by the sum of days per month in each of 10 different temperature bins T(B). Temperature bin 5, which corresponds to the daily mean temperatures between 13-16ºC, is omitted as a reference category. Municipality-year level fixed effects α(i, y) take into account the differences in trends in the outcome variables between different municipalities and between different years, that could be caused for example by differing trends in the population age distribution, health, health care quality, or any other differences in trends. Month fixed effects γ(m) take into account seasonality in the outcome variables common to all municipalities, for example differences in health care use between months. Robust standard errors are clustered at the municipality level in all the regressions due to the plausible correlations between standard errors within municipalities.

Regressions are weighted using the yearly population of each municipality. Using regression weights mitigates the comparability issues between areas that are small and densely populated and areas that are large and sparsely populated by allowing areas to impact the results in relation to their population size (Dell et al., 2014). Adding weights is equivalent to multiplying each five terms in the previously formalized equation by the square root of the population size in municipality i (Dupraz, 2013). The OLS regressions are run in Stata by using the reghdfe command, which allows the easy use of high-dimensional fixed effects (Correia, 2017). We conduct the analysis also by using Poisson regression methods, firstly due to the widespread use of this method in earlier studies (Barnett et al., 2010, Curriero et al., 2002, Gasparrini et al., 2015, Gouveia et al., 2003) and secondly due to a concern that smaller municipalities might have monthly outcome counts that are Poisson distributed instead of normally distributed. The baseline results obtained using the Poisson fixed effects regressions are available in the appendix.

Lastly, we conduct a municipality-day level analysis which does not account for harvesting and lagged effects of temperature, in order to compare the two approaches. This approach is formalized as follows:

$$Y_{(i,d,m,y)} = \beta_B \, T_{B_{(i,d,m,y)}} + \alpha_{(i,y)} + \gamma_{(m)} + \varepsilon_{(i,d,m,y)}$$

In this case, Y is the sum of hospital visits or mortality per 100,000 population in municipality i, for day d, month m and year y. Y is explained by the realized category of the daily mean temperature T(B) each day. We apply the same set of fixed effects in this specification.

4. Results

4.1 Main results on all-cause hospital visits and mortality

After aggregating the data on the municipality-month level, we estimate the main effects on all acute hospital visits and on the all-cause mortality for the age groups 0-64, 65-74, 75-84, and 85+ (Tables 3 and 4). We can see that the number of days with high mean temperatures is significant and consistently positive in determining both monthly hospital visits and mortality. As expected, the effect grows stronger in older age categories and in the highest temperature bins, suggesting nonlinearity in the relationship. In Table 3 on the acute hospital visits for all causes, the point estimates imply on average a relative 14 increase of 1.4% (16.8 more visits per 100,000 population) for the age group 0-64 and 0.9% increase (63.8 more visits per 100,000 population) for the age group 85+ for an additional day per month in the highest temperature bin. We also see that cold days are even more strongly associated with hospital visits in the oldest age group and in the second age group.

In the case of mortality (Table 4), the point estimates indicate up to 2.2% increase in mortality (23.2 excess deaths per 100,000 population) in the age group 85+, for an additional day per month in the highest temperature bin. In contrast to the results on acute hospital visits, we do not find an increase in mortality in the coldest days. All marginal effects, in percentages, are visualised in Figure 3.

Table 3: Effect of an additional day in specific temperature bins on monthly acute hospital visits per 100,000 population, compared to the reference category (13-16°)

	Age group			
	<65	65-74	75-84	>84
Temp <1°C	15.39*	31.67**	15.46	84.57***
	(8.356)	(14.50)	(18.78)	(30.94)
Temp 1-4°C	3.514*	5.119	13.58**	-21.36**
	(1.961)	(3.359)	(5.668)	(10.05)
Temp 4-7°C	6.296***	8.546***	11.09***	-5.196
	(2.004)	(3.248)	(4.118)	(6.253)
Temp 7-10°C	-0.457	-0.766	1.334	-11.24***
	(0.912)	(1.489)	(2.246)	(4.267)
Temp 10-13°C	2.898***	3.251**	5.077**	-5.378
	(0.762)	(1.337)	(2.028)	(3.932)
Temp 16-19°C	0.0546	-0.549	-0.573	0.302
	(0.800)	(1.344)	(2.138)	(3.545)
Temp 19-22°C	3.605***	2.590*	2.994	6.423
	(0.764)	(1.552)	(2.236)	(4.485)
Temp 22-25°C	4.394***	4.312	5.037	15.40
	(1.427)	(3.116)	(5.359)	(9.678)
Temp >25°C	16.83***	13.87	36.11	63.84**
	(3.735)	(12.16)	(28.33)	(32.42)
N	31100	31100	31100	31100
Mean of Dep. Var.	1188.3	2406.8	4425.6	6955.2

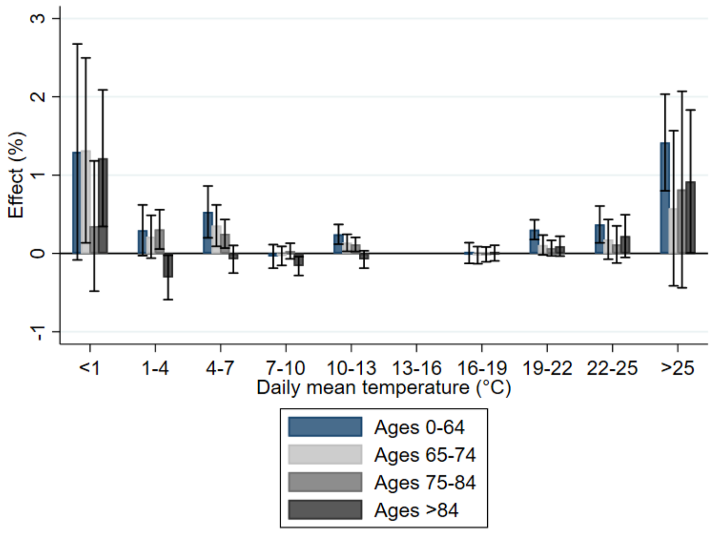
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of an additional day in specific temperature bins on monthly all cause mortality per 100,000 population, compared to the reference bin (13-16°C)

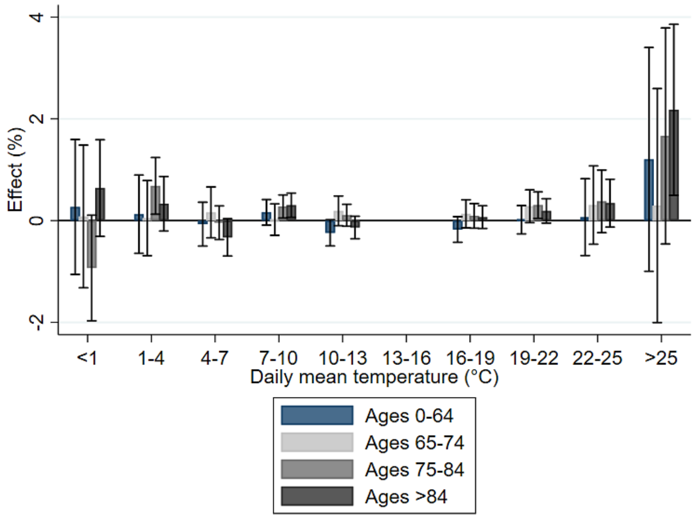
	Age group			
	<65	65-74	75-84	>84
Temp <1°C	0.0500	0.110	-3.368*	6.814
	(0.126)	(0.964)	(1.914)	(5.157)
Temp 1-4°C	0.0234	0.0672	2.470**	3.537
	(0.0729)	(0.507)	(1.027)	(2.911)
Temp 4-7°C	-0.0128	0.219	-0.147	-3.507*
	(0.0408)	(0.344)	(0.609)	(1.990)
Temp 7-10°C	0.0302	0.0273	1.006**	3.236**
	(0.0238)	(0.212)	(0.418)	(1.292)
Temp 10-13°C	-0.0445*	0.259	0.381	-1.431
	(0.0244)	(0.201)	(0.399)	(1.197)
Temp 16-19°C	-0.0322	0.181	0.340	0.736
	(0.0239)	(0.190)	(0.448)	(1.212)
Temp 19-22°C	0.00326	0.380*	1.103**	2.039
	(0.0264)	(0.222)	(0.478)	(1.304)
Temp 22-25°C	0.0125	0.413	1.367	3.656
	(0.0715)	(0.529)	(1.137)	(2.555)
Temp >25°C	0.223	0.399	6.012	23.18**
	(0.208)	(1.580)	(3.914)	(9.126)
N	31100	31100	31100	31100
Mean of Dep. Var.	18.57	134.8	361.6	1065.3

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



a) All acute hospital visits



b) All-cause mortality

Figure 3: Marginal effect of an additional day per month in a specific temperature category on the monthly

4.2 Cause-specific results

Next, we differentiate acute hospital visits and mortality cause-specifically in Figures 4 and 5. Figure 4 shows the cause-specific visits for all people above 75 years old. Hospital visits with heat exposure diagnoses (a) 17 are unsurprisingly heavily impacted with point estimates implying close to 40% increase in acute hospital visits for an additional day per month in the highest temperature bin, but in absolute numbers these visits are still rare. Other drivers behind the increase in the overall number of hospital visits seem to be visits with respiratory diagnoses and renal diagnoses (b) and diabetes, dementia and psychiatric diagnoses (c). However, according to these point estimates, visits with cardiovascular diagnoses are not elevated during heat waves (b).

On the other hand, cardiovascular causes of death seem to be the largest contributor to the all-cause mortality in Figure 5, with the point estimates implying effects of around 2-3% for an additional day in the highest temperature category. Also, deaths due to respiratory diseases are affected more than the overall mortality. When looking at the cause specific measures, it is helpful to refer to the Tables 1 and 2 in order to see the overall prevalence of each cause within different population groups.

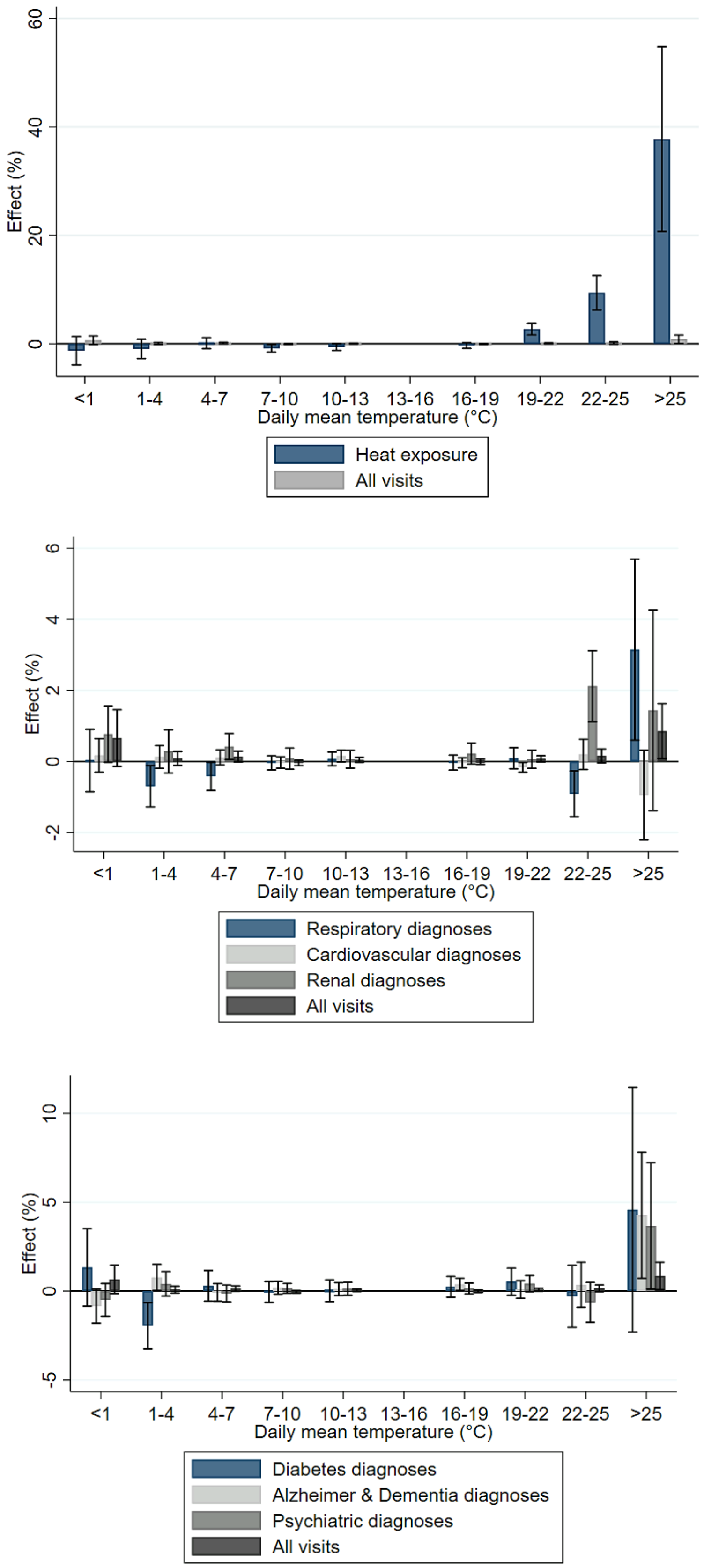


Figure 4: Effect of an additional day per month in specific temperature bins on monthly acute hospital visits, by primary cause. The sample is restricted to the elderly population (75 and older). Note that the Y-axes vary between the plots.

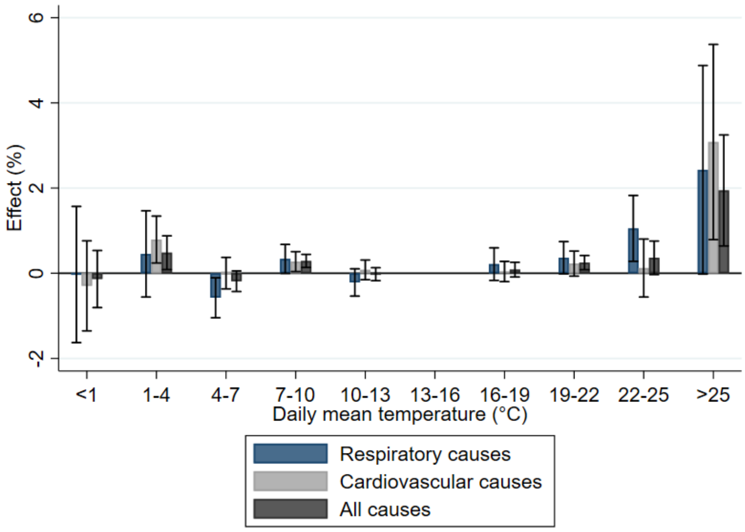
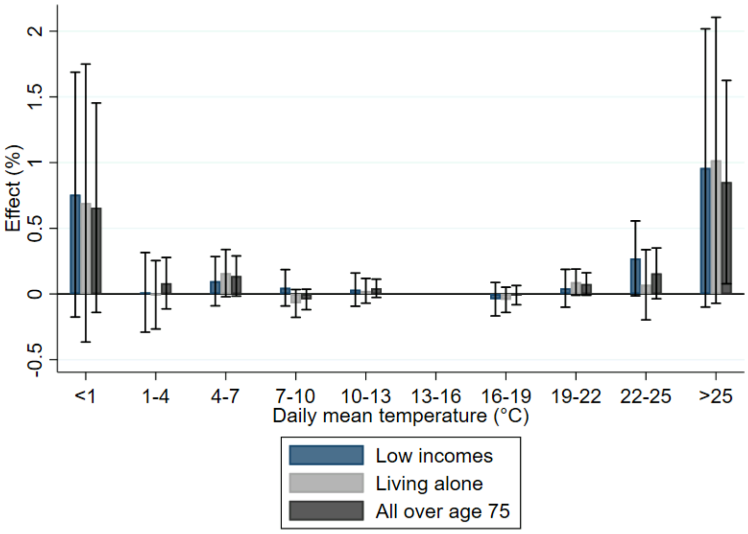


Figure 5: Effect of an additional day in specific temperature bins on monthly mortality per 100,000 population, by either primary or immediate cause. The sample is restricted to the elderly population (75 and older).

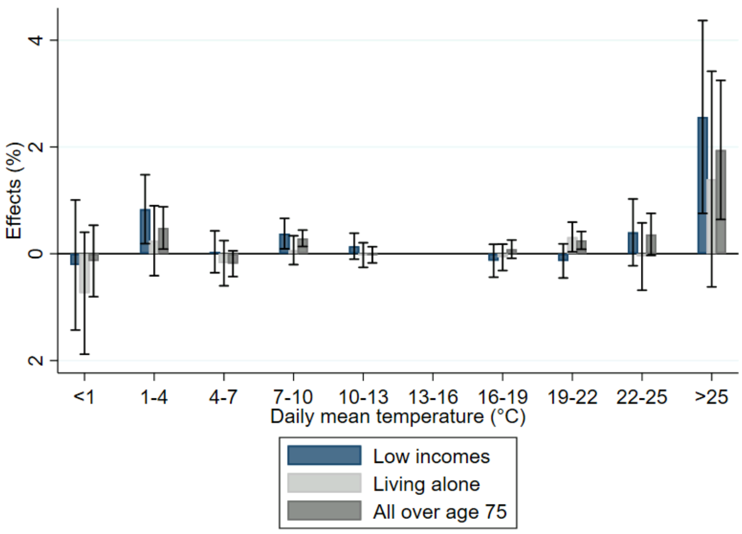
4.3 Risk groups

We move on to analyse the temperature-morbidity relationship in various population subgroups with plausibly elevated risk of negative health consequences. We start by looking at acute hospital visits and all-cause mortality in the elderly low-income population as well as in the elderly population living alone. By looking back at Table 1, we can observe that mortality among the low-income people is significantly higher compared to the whole population, but mortality among people living alone is slightly lower compared to the whole population in the three oldest age groups. We see from Figure 6 (a) that the effect of the highest temperature on acute hospital visits is slightly larger for both of these risk groups with point estimates suggesting around one percent increase, while confidence intervals are also wide. As for mortality (b), the effect is the strongest among the low-income elderly population, with an increase in mortality of more than two percent. However, against our expectation, the effect is smaller among those living alone.

As another important risk factor, we look at all acute hospital visits (Figure 7) and all-cause mortality (Figure 8) for individuals with pre-existing medical conditions retrieved from the health care use history. There are remarkably few strong effects among these risk groups. However, among those with dementia or Alzheimer, the effect on acute hospital visits is much stronger than among all individuals above 75 years old (Figure 7b). As for mortality, the point estimates are slightly higher among those with cardiovascular disease and diabetes (Figure 8a) as well as dementia or Alzheimer and psychiatric disorder (Figure 8b). However, there is some uncertainty regarding these estimates due to wide confidence intervals.

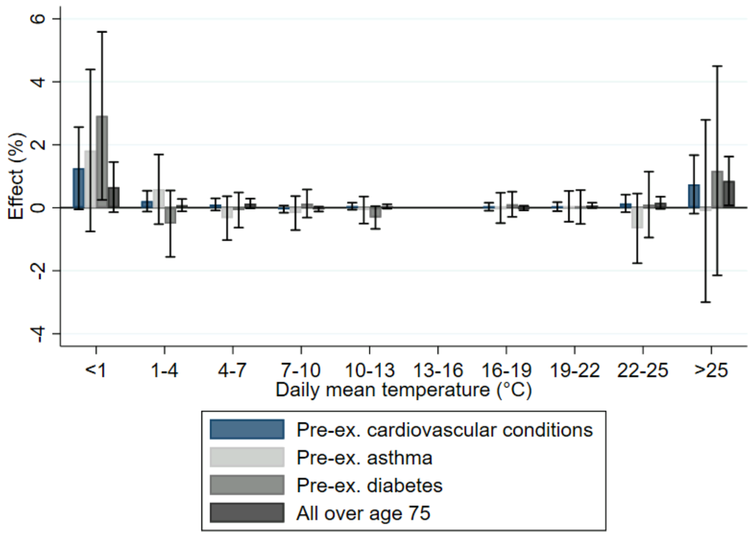


a) Acute hospital visits



b) All-cause mortality

Figure 6: Effect of an additional day per month in specific temperature bins on monthly outcomes, by risk group. The sample is restricted to the elderly population (75 and older). Note that the Y-axes vary between the plots.



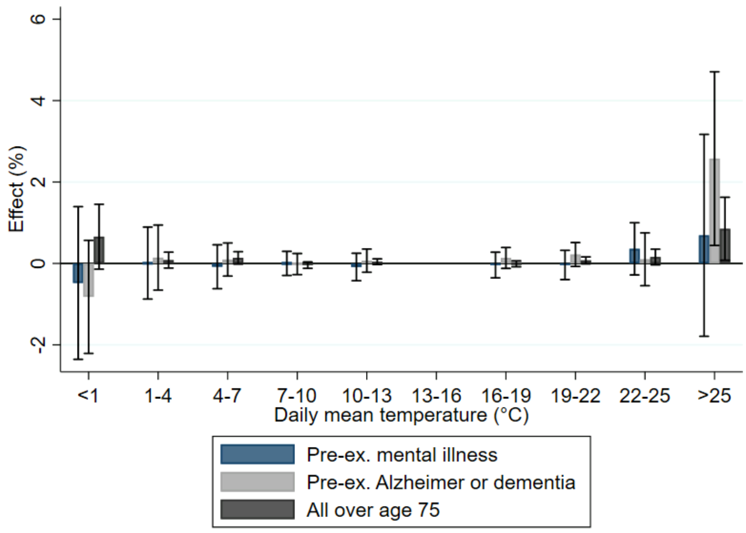


Figure 7: Effect of an additional day per month in specific temperature bins on monthly acute hospital visits, by risk group. Note that the Y-axes vary between the plots.

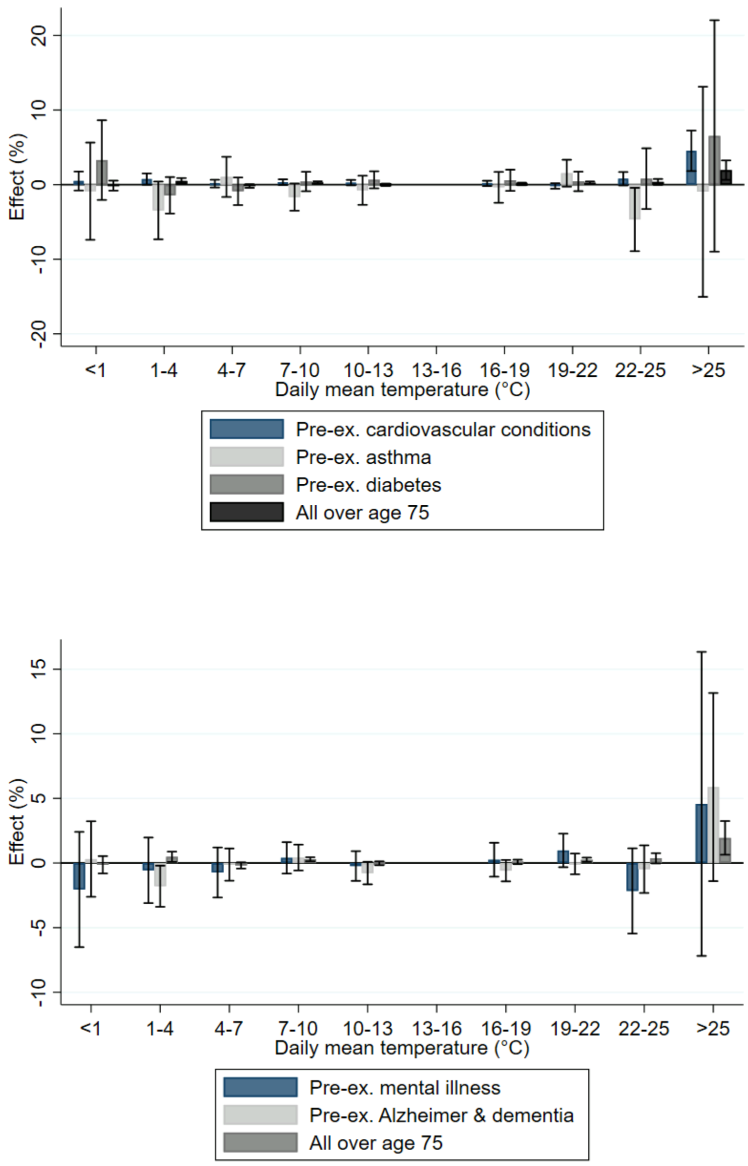


Figure 8: Effect of an additional day per month in specific temperature bins on monthly all-cause mortality, by risk group. Note that the Y-axes vary between the plots.

4.4 Municipality-day level analysis

Next, we compare the main results on the municipality-month level to results on the municipality-day level to better understand the potential harvesting effect (Tables 5 and 6). As expected, the point estimates of the daily level model imply significantly higher effects than the municipality-month level model, up to 45.2 more hospital visits per 100,000 population (an increase of 10.8%) in the age group 85+ for a daily average temperature in the highest category (Table 5). In the case of mortality, the point estimates imply up to 11.2 more deaths per 100,000 population (an increase of 32%) in the oldest age group for a daily average temperature in the highest category (Table 6). It is highly plausible that these estimates are inflated due to harvesting, as discussed in Deschenes and Moretti (2009). We believe that using the municipality-month level model is more appropriate for estimating the effects of heat as it reduces the need for considering lagged effects and the harvesting effect.

Table 5: Effect of temperature on daily acute hospital visits per 100,000 population, compared to the reference temperature category (13-16°C)

	Age group			
	<65	65-74	75-84	>84
Temp <1°C	0.509	0.567	-2.179	1.481
	(0.958)	(2.068)	(3.003)	(5.269)
Temp 1-4°C	0.426	0.109	-0.555	-4.276*
	(0.338)	(0.754)	(1.368)	(2.191)
Temp 4-7°C	0.324	-0.226	-0.241	-0.687
	(0.258)	(0.443)	(0.806)	(1.531)
Temp 7-10°C	0.603***	-0.271	-0.311	-2.290*
	(0.189)	(0.354)	(0.613)	(1.283)
Temp 10-13°C	0.313**	0.368	1.078**	0.0383
	(0.135)	(0.276)	(0.498)	(0.853)
Temp 16-19°C	0.177	0.0867	1.368***	4.912***
	(0.177)	(0.289)	(0.526)	(1.040)
Temp 19-22°C	1.454***	0.932**	3.169***	10.01***
	(0.188)	(0.438)	(0.615)	(1.700)
Temp 22-25°C	1.885***	2.464***	6.993***	17.21***
	(0.273)	(0.807)	(1.264)	(3.016)
Temp >25°C	4.280***	9.551***	15.91***	34.41***
	(0.696)	(2.545)	(4.431)	(8.605)
N	951660	951660	951660	951660
Mean of Dep. Var.	38.83	78.65	144.6	227.3

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of temperature on daily all-cause mortality per 100,000 population, compared to the reference temperature category (13-16°C)

	Age group			
	<65	65-74	75-84	>84
Temp <1°C	0.0464	0.0843	-0.397	1.773
	(0.0418)	(0.271)	(0.608)	(1.885)
Temp 1-4°C	0.0046	0.143	0.0765	0.630
	(0.0168)	(0.132)	(0.251)	(0.773)
Temp 4-7°C	-0.0006	0.0926	0.215	-0.308
	(0.0102)	(0.0731)	(0.173)	(0.551)
Temp 7-10°C	-0.0087	-0.0311	-0.0887	-0.0834
	(0.00785)	(0.0639)	(0.135)	(0.388)
Temp 10-13°C	-0.0138^{**}	0.0626	-0.0769	-0.235
	(0.00603)	(0.0478)	(0.106)	(0.330)
Temp 16-19°C	0.0185^{***}	0.103^{**}	0.0576	0.697^{**}
	(0.00641)	(0.0460)	(0.124)	(0.281)
Temp 19-22°C	0.0226^{***}	0.244^{***}	0.600^{***}	2.695^{***}
	(0.00763)	(0.0656)	(0.148)	(0.519)
Temp 22-25°C	0.0501^{**}	0.261^{*}	1.931^{***}	5.048^{***}
	(0.0200)	(0.140)	(0.317)	(0.705)
Temp >25°C	0.186^{***}	0.0116	3.608^{***}	11.15^{***}
	(0.0475)	(0.404)	(0.828)	(2.728)
N	951660	951660	951660	951660
Mean of Dep. Var.	0.607	4.404	11.82	34.81

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Robustness checks

We also present our main results by adding two effect modifiers, specific humidity and an interaction of high specific humidity and high temperature (above 13g/kg and above 22°C). First, in Figure 9 we illustrate the relationship between daily specific humidity and daily average temperature in the whole sample period. We see that the relationship is highly linear and higher specific humidity is only witnessed during warmer weather. Second, our results in table 7 show that humidity and the humidity-heat interaction play a significant role in determining the number of acute hospital visits. It is especially the humid hot days that affect hospital visits. However, when looking at the effects on all-cause mortality (Table 8), we see that humidity and the humidity-heat interaction are not statistically significant and do not alter the main results.

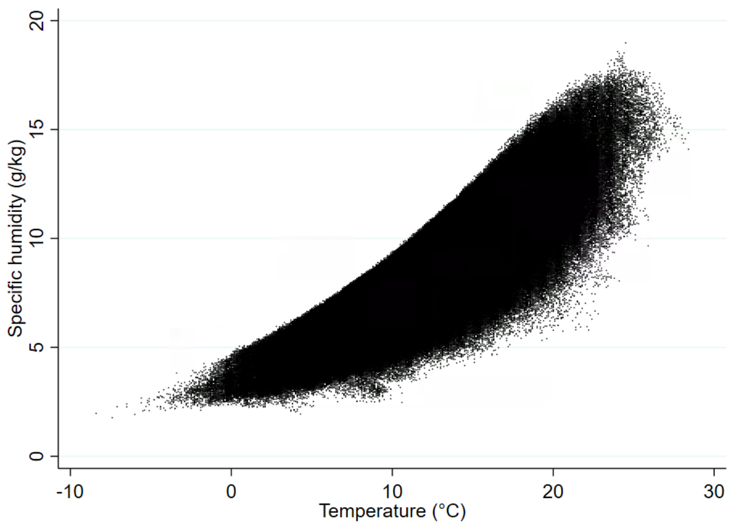


Figure 9: Humidity-temperature relationship in Finland during months May-September in 1998-2017

Table 7: Effect of an additional day in different weather-outcome categories on monthly acute hospital visits per 100,000 population

	Model 1	Model 2	Model 3
Temp <1°C	18.83*	3.305	3.602
	(9.894)	(9.928)	(9.888)
Temp 1-4°C	3.601*	-3.392	-3.105
	(2.007)	(2.530)	(2.559)
Temp 4-7°C	6.559***	4.749**	4.867**
	(2.120)	(2.209)	(2.210)
Temp 7-10°C	-0.722	-1.208	-1.164
	(0.905)	(0.909)	(0.894)
Temp 10-13°C	2.790***	2.842***	2.859***
	(0.741)	(0.811)	(0.820)
Temp 16-19°C	-0.0900	-0.133	0.0408
	(0.814)	(0.976)	(0.939)
Temp 19-22°C	3.499***	3.907***	4.955***
	(0.792)	(1.020)	(1.058)
Temp 22-25°C	4.596***	4.082*	-5.819
	(1.485)	(2.313)	(4.973)
Temp >25°C	18.68***	15.09***	-3.120
	(3.997)	(4.086)	(8.374)
Humidity <4g/kg		12.09***	11.89***
		(3.464)	(3.439)
Humidity 4-7g/kg		0.727	0.762
		(0.864)	(0.857)
Humidity 7-10g/kg		-1.750*	-1.729*
		(0.929)	(0.927)
Humidity 13-16g/kg		-2.104	-4.781***
		(1.638)	(1.418)
Humidity >16g/kg		9.356**	-1.050
		(3.637)	(3.611)
Humidity >13g/kg & Temp >22°C			18.75***
			(6.678)
Temperature	Yes	Yes	Yes
Humidity	No	Yes	Yes
Interaction	No	No	Yes
N	31100	31100	31100
Mean of Dep. Var.	1631.0	1631.0	1631.0

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effect of an additional day in different weather-outcome categories on monthly all-cause mortality per 100,000 population

	Model 1	Model 2	Model 3
Temp <1°C	0.002	0.043	0.040
	(0.201)	(0.245)	(0.245)
Temp 1-4°C	0.241*	0.253*	0.251*
	(0.125)	(0.151)	(0.151)
Temp 4-7°C	-0.086	-0.099	-0.100
	(0.068)	(0.087)	(0.088)
Temp 7-10°C	0.152***	0.129**	0.129**
	(0.050)	(0.060)	-0.06
Temp 10-13°C	-0.033	-0.059	-0.059
	(0.042)	(0.047)	(0.047)
Temp 16-19°C	0.035	0.061	0.059
	(0.047)	(0.050)	(0.049)
Temp 19-22°C	0.153***	0.212***	0.202***
	(0.052)	(0.075)	(0.077)
Temp 22-25°C	0.215**	0.305**	0.401*
	(0.102)	(0.124)	(0.214)
Temp >25°C	1.112***	1.310***	1.488**
	(0.414)	(0.436)	(0.574)
Humidity <4g/kg		0.060	0.062
		(0.148)	(0.148)
Humidity 4-7g/kg		0.072	0.071
		(0.065)	(0.065)
Humidity 7-10g/kg		0.096*	0.095*
		(0.051)	(0.051)
Humidity 13-16g/kg		-0.058	-0.031
		(0.102)	(0.111)
Humidity >16g/kg		-0.123	-0.021
		(0.367)	(0.417)
Humidity >13g/kg			-0.183
& Temp >22°C			(0.342)
Temperature	Yes	Yes	Yes
Humidity	No	Yes	Yes
Interaction	No	No	Yes
N	31100	31100	31100
Mean of Dep. Var.	1631.0	1631.0	1631.0

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusions

Deadly heat waves have alerted governments and public health officials to react to the negative health consequences of global warming (Martinez et al., 2019). Climate change has increased the likelihood of heat waves also in Finland where the population is used to mild temperatures and where cold temperatures have previously been identified as a larger risk for public health (Näyhä, 2007). The change necessitates new research to identify vulnerable groups and to adapt the health care sector to protect public health and mitigate adverse consequences.

In this article, we set out to examine the effects of high temperatures in Finland using unique register data on the total population. Employing a panel fixed effects method, we analysed the effects of temperature during summer months on acute hospital visits and mortality for all causes and cause-specifically at the municipal-month level and examined the effects in various subgroups of the population. Our contribution lies especially in studying hospital visits and mortality together as well as looking at the heterogeneous effects to identify vulnerable groups. We add to the existing literature on the heat effects in Finland with an important perspective on health care use in addition to the extreme cases of mortality. We also introduce a model widely used in climate economics but, at least to our knowledge, not yet applied to Finland or other Nordic countries.

Our results show that the highest temperatures were, as expected, associated with an increase in the number of hospital visits and excess deaths. Relative increases in acute hospital visits but not in mortality were visible for younger age groups too, perhaps indicating that working age individuals are not able to protect against heat when working or indicating vulnerability among young children. In addition, it suggests that the significance of heat effects is underestimated among working age population. Nevertheless, our main effort was to study effects in more detail among the elderly population.

The effects were strongest among the oldest population group as demonstrated by earlier literature (Deschenes and Greenstone, 2011; Deschenes and Moretti, 2009; Kollanus et al., 2021). However, against our expectations, we were mostly unable to detect an elevated risk among older people with pre-existing medical conditions, which could indicate that individuals in these groups are mostly aware of the health risks connected to heat waves and are prepared to protect themselves. Individuals with Alzheimer / dementia were one of the groups among which a higher effect on hospitalization and mortality was found during heat waves. This result is in line with previous literature (e.g., Rocklöv et al. (2014)). In addition, elderly people in the lowest income quintile were affected more strongly in terms of both mortality and acute hospital visits than 29 all persons above the age 75. This could be related to the overall worse health among low-income people or weaker opportunities to adapt to heat (e.g., access to cooled areas). Effect on acute visits was slightly higher also for those living alone compared to that of the the whole elderly population, but in terms of mortality the effect was lower.

Our results are similar in magnitude to the results of studies utilizing similar methods, to the extent the analyses are comparable. For example, Barreca (2012) estimates that three additional days above 90ºF (approx. 32ºC) result in 0.54 excess deaths per month per 100,000 population in the U.S., or a percentage effect of 0.78% when reflected against the mean mortality rate, although he controls for humidity and uses a bimonthly average of the number of temperature-days. Deschenes and Greenstone (2011) estimate that an additional day above 32ºC per year increases annual all-cause mortality by 0.11% in the U.S. Otrachshenko et al. (2017) estimate a mortality effect of 0.06% for an additional day per year above 25ºC in Russia. Our most comparable result for the all-cause mortality effect for the whole population (Table 8) ranges from 0.3% for an additional day in the range 22-25°C, and 1.5% for days above 25ºC.

In relation to other studies from Finland, our results on mortality are smaller in magnitude. For example, Ruuhela et al. (2018) find an effect on mortality of 16% at a daily mean temperature of 24ºC, using the DLNM method and daily level analysis. Kollanus et al. (2021) define heatwave as a period in which the daily average temperature exceeds the 90th percentile of that from May to August during the years 2000-2014 (about 20ºC). They find average mortality effects of 6.7% in the age group 65-74 and 12.8% during all heat wave days in the age group 75 or older. One reason for the differing results can be that these studies are based on a daily level analysis and do not explicitly take into account the harvesting effect. The results from our daily level analysis (Table 6) results are closer to these estimates, implying around 30% excess deaths depending on age groups, for a day with an average temperature above 25ºC. However, as we argue above, we believe that these results are overestimated due to the harvesting effect.

In terms of hospital visits, White (2017) find that for a day above 80ºF (26.7°C), emergency department visits rise by about 3.5% on the same day and 5.1% on total. Studies on effects on hospitalization in Finland are more difficult to find. Sohail et al. (2020) study the effect of heatwaves on cardiorespiratory hospital admissions in Helsinki by defining a heat wave using 90th and 95th percentile cutoffs for the daily mean temperature in May–August 2001–2017 and find that pneunomia admissions rise by 20.5% in the age group above 75 for heat wave days and all respiratory admissions rise especially during intense and prolonged heat waves. In comparison, we find that a day above 25°C increases the monthly acute hospital visits only by 1.1% (Table 7) and the same-day visits by up to 10.8% for the age group 85+ (results ranging from 2.9% among those aged 65 or less to up to 10.8% among the oldest age group). Monthly respiratory admissions 30 are impacted by about 3% in the age group 75 and older.

Our results show that health care services need to adapt to increasing care needs in the future. However, it is also possible that in the long-term the population is able to cope with high temperatures better. For example, Folkerts et al. (2020) found that the temperature at which mortality is at its minimum (i.e., minimum mortality temperature) has increased in the Netherlands during the study period of 1995-2017. It remains to be analysed whether the measured acclimatization is due to physiological, infrastructural, behavioral or technological adaptation. In addition, Barreca (2012) found that warmer counties in the U.S. were less susceptible to high temperatures and humidity levels compared to cold counties. Further research on the acclimatization across time and the differences in vulnerability across different parts of Finland would be valuable. Research projecting local and national health consequences of climate change and related costs in the health and social care sector is needed. At the same time, efforts should be put in studying the effectiveness of adaptation policies and interventions.

Adaptation measures can be divided into short-term adaptation such as avoiding exposure by accessing cooler areas and spaces or using air conditioning. For example, Deschenes and Greenstone (2011) predict an 11 percent annual increase in residential energy consumption in the U.S. due to individual level adaptation to high temperatures by usage of air conditioning. Long-term adaptation consists for example of migration and redesign of urban areas and construction methods. For example, Farhadi et al. (2019) examine the mitigation possibilities of urban heat island effect (UHI)[2] and find that a lot can be done to mitigate the UHI effect, for example by increasing urban vegetation cover. Another important form of adaptation takes place at the community level, and policy measures are also needed to protect public health, for example, through education, preventive health care and heat wave warning systems (Martinez et al., 2019). The gradual unfolding of climate change will also probably allow for a number of other long-term adaptation measures.

As a limitation of our study, the way in which causes of death are reported differs from the broader set of diagnoses reported in the data on hospital visits. Causes of death are more concentrated to a few common diagnoses, with the two most common diagnoses being cardiovascular and cancer diagnoses, and thus less information is available on the possibly multiple reasons leading to the death. In practice, heatrelated morbidity for some causes is not represented in the causes of death statistics and heat-related mortality for some diagnoses is not represented in the morbidity statistics. This was visible for cardiovascular diseases: mortality from these causes increased, but not hospital visits. In conclusion, multiple indicators of health outcomes should be used in studying the health effects of temperature.

[2] The occurence of elevated temperatures in urban areas due to paved surfaces, human activities and energy usage.

As another limitation, it is important to note the uncertainty related to our results due to relatively small number of hot days even in the span of 20 years.

Another concern about the causal inference in this study is the increase in travelling and the common Finnish habit of spending time at the summer cottages during the summer, which means that people are away from their home municipalities. Unfortunately, the hospital discharge register data only includes the home municipality of the individual, instead of the municipality where the visit took place. This hampers the causal analysis for obvious reasons. In addition, especially individuals with health problems might seek respite in the cooler countryside during heat waves, while individuals might be in a very unequal positions in their possibilities to escape hotter urban areas. Since this article only includes specialized care visits, there might also be some selection implications. Visits to occupational health care or private health care are not reported in our data.

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Appendix A.

Main results using the Poisson regression method. In the following regressions, the Stata command ppmlhdfe (Correia et al., 2019) is utilized. The effects on the acute hospital visits seem to be milder, but the effects on mortality are higher when using the Poisson method. It is important to note that the Poisson method did not allow for the application of municipality level population weights, which might partly explain discrepancies between the model results.

Table A1: Effect of an additional day in specific temperature bins on monthly acute hospital visits per 100,000 population, compared to the reference category (13-16°C)

	Age group			
	<65	65-74	75-84	>84
Temp <1°C	1.007***	1.008***	1.002	1.010***
	(0.002)	(0.002)	(0.003)	(0.003)
Temp 1-4°C	1.001	1.002	1.003	0.995**
	(0.001)	(0.002)	(0.002)	(0.002)
Temp 4-7°C	1.002**	1.001	1.001	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
Temp 7-10°C	1.000	1.001	1.002**	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
Temp 10-13°C	1.000	1.000	1.000	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
Temp 16-19°C	0.999	1.000	0.999	1.000
	(0.001)	(0.001)	(0.001)	(0.001)
Temp 19-22°C	1.002***	1.001	1.000	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
Temp 22-25°C	1.001	1.000	1.000	1.006**
	(0.001)	(0.003)	(0.003)	(0.003)
Temp >25°C	1.009***	1.007	1.010	1.000
	(0.004)	(0.007)	(0.007)	(0.007)
N	31090	31010	31050	31030
Mean of Dep. Var.	1326.1	2688.7	4922.0	7447.0

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effect of an additional day in specific temperature bins on monthly all cause mortality per 100,000 population, compared to the reference category (13-16°C)

	Age group			
	<65	65-74	75-84	>84
Temp <1°C	0.994	0.998	0.997	1.016**
	(0.009)	(0.009)	(0.006)	(0.007)
Temp 1-4°C	1.009	0.997	0.995	0.996
	(0.008)	(0.006)	(0.005)	(0.005)
Temp 4-7°C	1.005	0.985***	0.999	0.995
	(0.005)	(0.005)	(0.003)	(0.003)
Temp 7-10°C	1.000	1.001	1.001	1.000
	(0.003)	(0.003)	(0.003)	(0.003)
Temp 10-13°C	1.003	0.994	1.000	0.996
	(0.004)	(0.004)	(0.002)	(0.002)
Temp 16-19°C	1.004	1.003	0.999	0.999
	(0.004)	(0.004)	(0.003)	(0.002)
Temp 19-22°C	1.000	1.003	1.003	0.998
	(0.003)	(0.004)	(0.002)	(0.003)
Temp 22-25°C	1.012	0.994	0.997	1.007
	(0.008)	(0.007)	(0.006)	(0.006)
Temp >25°C	1.034	1.009	1.019	1.038**
	(0.026)	(0.024)	(0.017)	(0.016)
N	28660	28850	30035	30320
Mean of Dep. Var.	23.13	151.2	385.7	1122.6

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$