



Title	Degrees and dollars : Health costs associated with suboptimal ambient temperature exposure
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1 **Degrees and Dollars – Health Costs Associated with Suboptimal**
2 **Ambient Temperature Exposure**

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17

18 **Abstract**

19 Suboptimal ambient temperature exposure significantly affects public health. Previous studies have
20 primarily focused on risk assessment, with few examining the health outcomes from an economic
21 perspective. To inform environmental health policies, we estimated the economic costs of health
22 outcomes associated with suboptimal temperature in the Minneapolis/St. Paul Twin Cities
23 Metropolitan Area.

24 We used a distributed lag nonlinear model to estimate attributable fractions/ cases for mortality,
25 emergency department visits, and emergency hospitalizations at various suboptimal temperature
26 levels. The analyses were stratified by age group (i.e., youth (0-19 years), adult (20-64 years), and

27 senior (65+ years)). We considered both direct medical costs and loss of productivity during
28 economic cost assessment.

29 Results show that youth have a large number of temperature-related emergency department visits,
30 while seniors have large numbers of temperature-related mortality and emergency hospitalizations.
31 Exposures to extremely low and high temperatures lead to \$2.70 billion [95% empirical confidence
32 interval (eCI): \$1.91 billion, \$3.48 billion] (costs are all based on 2016 USD value, \$2016) economic
33 costs annually. Moderately and extremely low and high temperature leads to \$9.40 billion [\$6.05
34 billion, \$12.57 billion] economic costs. The majority of the economic costs are consistently
35 attributed to cold (>75%), rather than heat exposures and to mortality (>95%), rather than
36 morbidity. Our findings support prioritizing temperature-related health interventions designed to
37 minimize the economic costs by targeting seniors and to reduce attributable cases by targeting youth.

38

39 *Keywords:* climate health, climate change, extreme temperature, extreme heat, ambient exposure,
40 urban health

41

Introduction

42 Ambient temperature exposures are associated with substantial adverse health impacts involving a
43 wide range of health conditions (Analitis et al., 2008; Basu, 2009; Chen et al., 2016; Ye et al., 2011).
44 As temperature is predicted to be more variable and extreme in the future (EPA, 2016), such health
45 risks are particularly concerning (Crimmins et al., 2016). Estimates from 2006-2010 show that 1,300
46 and 670 premature deaths are related to extreme cold and heat exposure, respectively, in the United
47 States each year (Berko, Ingram, Saha, & Parker, 2014). However, these estimates are based only on
48 clinical diagnoses of temperature-related illnesses such as hypothermia and hyperthermia and known
49 to underestimate the true burden by omitting cases where ambient temperature was a contributing
50 exposure (Crimmins et al., 2016). Decision makers tasked with protecting communities from
51 environmental hazards like extreme temperatures not only need better assessments of the number of
52 individuals impacted, but the associated economic burden as well. The latter is critical as decision
53 makers attempt to allocate resources and justify budgets for environmental health planning across a
54 range of environmental hazards (e.g., air pollution) that impact communities besides extreme
55 temperature (Hutton & Menne, 2014).

56 Although the relationship between ambient temperature and population health is well
57 studied, few investigators have linked health risks to economic costs. Knowlton et al. (2011), Lin et
58 al. (2012), and Schmeltz et al. (2016) are among the few that have provided such economic
59 estimates. However, the information provided in these studies is limited, as they consider only a few
60 health outcomes for limited periods in the year. For instance, Knowlton et al. (2011) analyzed a
61 specific two-week long heat wave in California during summer 2006, despite evidence that
62 temperature-related adverse health impacts occur year-round and with considerable seasonal
63 variability (Gasparrini et al., 2015, 2016). Lin et al. (2012) and Schmeltz et al. (2016) only considered

64 hospitalizations, despite evidence that temperature impacts a wider range of health outcomes (e.g.,
65 mortality (Gasparrini et al., 2015) and emergency department visits (Saha, Brock, Vaidyanathan,
66 Easterling, & Luber, 2015; Zhang et al., 2014)). Failing to account for multiple outcomes leads to
67 underestimation of the corresponding economic burdens. These studies also provide insufficient
68 information on how the health and economic burden change over a larger range of temperature,
69 limiting the integration of temperature and health response functions into health intervention
70 planning.

71 Targeting these research gaps, we introduce a comprehensive approach to assess the health
72 economic burden associated with exposure to a range of cold and hot temperatures in the
73 Minneapolis-St. Paul Twin Cities Metropolitan Area (TCMA). We include mortality, emergency
74 department visits, and emergency hospitalizations in this analysis. The economic costs estimated
75 account for direct medical costs and productivity loss.

76 Data & Methods

77 Public Health Data

78 The Twin Cities Metropolitan Area includes seven counties (Anoka, Carver, Dakota, Hennepin,
79 Ramsey, Scott, and Washington) and has total residents of over 3 million (Minnesota Department of
80 Health, 2015). We obtained all-cause mortality (MORT) data (1998-2014) for these seven counties
81 from the Office of Vital Records, Minnesota Department of Health. All-cause morbidity data (2005-
82 2014) were collected from all emergency departments within the Minnesota Hospital Association
83 (MHA) network, available from the Minnesota Hospital Discharge Dataset (MNHDD). The
84 MNHDD contains patient claims data voluntarily submitted by members of the MHA, a trade
85 association representing Minnesota Hospitals. The Minnesota Department of Health (MDH)
86 purchases these data from MHA under a Memorandum of Understanding between MHA and

87 MDH. The morbidity dataset further breaks down to emergency department visits followed by
88 discharge (EDV) and emergency department visits followed by hospitalization (EDHSP). For this
89 analysis, we assume that patients do not stay for treatment in an emergency department for longer
90 than three days without being hospitalized, as emergency departments normally cannot
91 accommodate extended stays. Consequently, we removed 11,138 EDV records (approximately 0.2%
92 of total morbidity records) with emergency department stays longer than three days. We stratified
93 the data further by age: youth (0-19 years), adult (20-64 years), and senior (65+ years).

94 [Environmental Data](#)

95 We extracted historical hourly meteorological data for the TCMA for seven National
96 Weather Service weather stations within the TCMA on both raw data (i.e. air temperature) and
97 compound temperature indicators (i.e. heat index, wind chill index, and wet bulb global
98 temperature). We use daily maximum heat index (HI_{max}) as the ambient temperature metric, which is
99 calculated using air temperature ($^{\circ}F$) and relative humidity (%) according to the method of Rothfusz
100 (1990) for consistency with National Weather Service standards. This choice is based on
101 composition, current policy in use, time-at-exposure (e.g. few individuals are exposed when
102 minimum temperature is observed), and extensive model comparison (using different temperature
103 variables mentioned above and different statistics including daily minimum, mean, and maximum).
104 Outside of summer months, the values of HI_{max} are comparable to daily maximum air temperature
105 in the TCMA. We assumed that all individuals within the TCMA had the same exposure level at any
106 given time during the study.

107 Although not selected for the final model, we considered air pollutants during the model
108 development phase. We obtained data on ozone (O_3) and particulates with diameters equal to or
109 smaller than 2.5 micrometers ($PM_{2.5}$) from the Minnesota Pollution Control Agency for the years

110 2000 to 2010. More details on the exploratory analysis using air pollution as a potential confounder
111 are in [Supplemental Information Section 1](#).

112 [Estimating the Exposure-Response Functions](#)

113 We used a DLNM to characterize the exposure-response function between temperature and
114 population health (Gasparrini et al. 2010). This method is appropriate because there are distinct
115 temporal delays (lag λ) between the exposures and responses considered in this study (Anderson &
116 Bell, 2009). Furthermore, this study used a quasi-Poisson generalized linear model:

117
$$\ln(E(Y_t)) = \beta_0 + cb + ns(Date, df) + \beta_1 \cdot dow + \underbrace{\beta_2 \cdot holidays}_{\text{Morbidity Models Only}} \quad (1)$$

118

119 where Y_t is the daily counts of public health outcomes; cb is a cross-basis function that captures both
120 the exposure-response relationship (i.e., how different exposure levels affect human health at a given
121 time) and the lag-response relationship (i.e., how a given exposure level affects human health at
122 different time lags). We further adjusted for day of week (dow), a long term trend ($date$), holiday
123 effects ($holidays$, only for morbidity model based on the results of likelihood ratio tests). More
124 specifically, this model assumes that exposure response relationship to be a natural cubic spline with
125 three internal knots at 10th, 75th, 90th percentiles of the HI_{max} distribution. The lag-response
126 relationship is also assumed to be a natural cubic spline function. Three internal knots are equally
127 spaced through the logarithmic lag range. The maximum lag considered is 28 days in order to
128 capture the delayed effects of cold exposure (Anderson & Bell, 2009). The long-term trend is
129 assumed to be a natural cubic spline function with 8 and 7 degrees of freedom given to each year for
130 the mortality and morbidity models, respectively. Holiday effect is only significant for morbidity
131 outcomes and is adjusted for by including a binary variable that equals 1 on federal holidays and 3

132 following days and 0 on other days. These model specifications are based on extensive mode
133 comparisons using quasi-Akaike Information Criterion and Mean Absolute Errors. More details on
134 model selection can be found in the [Supplemental Information Section 2](#).

135 We calculate all risk estimates relative to reference baselines that correspond to minimum relative
136 risk (RR) (Tobías, Armstrong, & Gasparrini, 2017). This baseline is referred to as the minimum
137 effect temperature (MET) in this study for both mortality and morbidity outcomes. For RR
138 estimates, statistical significance is defined as the probability of type I error is smaller than 0.05.

139 Attributable Fraction and Attributable Cases

140 We calculate attributable fractions (AF) and attributable cases (AC) to show the percentage and
141 number of cases of the health outcomes associated with hazardous ambient temperature exposures.
142 To calculate AFs and ACs, we used a method in Gasparrini and Leone (2014). The underlying
143 assumption is a *backward* perspective – the health response at a given time t is a result of many
144 exposure events that led up to it. More specifically, AF and AC are defined as:

$$145 \quad AF_{x,t} = 1 - \exp(-\sum_{l=0}^L \beta_{x_{t-l}, l}) \quad (2)$$

$$146 \quad AC_{x,t} = AF_{x,t} \cdot Y_t \quad (3)$$

147 where x is the ambient temperature exposure level at time t ; $\beta_{x_{t-l}, l}$ is the natural logarithm of RR
148 given exposure at time $t-l$ (i.e., x_{t-l}) after l days have elapsed; N_t is daily counts of population health
149 outcomes at time t . In this study, we examined attributable risks for two temperature ranges:
150 moderate to extreme exposures, defined by the bottom and top 30% of the historical temperature
151 record (40 and 76°F, respectively); and extreme exposures, defined by the bottom and top 5% of the
152 historical temperature records (18 and 89°F, respectively). Exposure ranges are defined by percentiles
153 as opposed to absolute temperature values to sure our results are interpretable in different urban

154 climate settings. The over-arching goal is to compare the health outcomes and relevant economic
155 burdens attributable to different levels of cold and heat exposures. We examined both AF and AC
156 to identify the most vulnerable and the most affected age groups.

157 When it comes to uncertainty assessment for AF and AC, it is challenging to obtain an analytical
158 solution using the approach in Gasparrini and Leone (2014) (Graubard and Fears 2005). Therefore,
159 Monte Carlo simulations ($n = 5,000$) were used to express uncertainty as 95% empirical confidence
160 intervals (eCI).

161 Year-to-Year Variations for Cost Estimation

162 Various parameters for estimating costs, such as Cost-to-Charge Ratios (CCR), differ drastically
163 from year to year. Consequently, there is a need to explore the year-to-year variability in terms of
164 AC. This study proposes an incremental approach:

$$165 \quad AC(y)_p = \begin{cases} \sum_{i=1}^{m_y} AC_{x,t_i}, & y = 1 \\ \sum_{i=1}^{m_y} AC_{x,t_i} - \sum_{i=1}^{m_{y-1}} AC_{x,t_i}, & y > 1 \end{cases} \quad (4)$$

166 where $AC(y)_p$ denotes the point estimation of AC during year y ; m_y is the number of observations in
167 the first y years of the time series. The uncertainty around $AC(y)_p$ is assumed to depend on that of
168 $AC(y)_{p,tot}$. In other words, for each simulation result of total attributable cases ($AC_{tot,sim}$) there is an
169 annual attributable cases (AC_{sim}) defined as:

$$170 \quad AC(y)_{sim} = \frac{AC(y)_p}{AC_{tot,p}} AC_{tot,sim} \quad (5)$$

171 The results of this intermediate step are shown in [Supplemental Information Section 3](#).

172

173 Cost estimation

174 We use the Value of a Statistical Life (VSL) to estimate the total health-related costs of
175 mortality. VSL is the “societal willingness to pay for mortality risk reductions” (Kenkel, 2003) and is

176 independent of any health, demographic, or socioeconomic characteristics. The economic loss due
177 to mortality is the product of total lives lost and VSL. We convert the mean VSL estimate of \$4.8
178 million (\$1990) (U.S. EPA, 1997), which is based on a 1997 meta-analysis, to 2016 dollars (details in
179 [Supplemental Information sections 4.1.1-4.1.3](#)). We also considered several updated VSL estimates
180 (Thomson & Monje, 2015), ranging from \$5.56 to \$13.90 million (\$2016) ([Supplemental](#)
181 [Information Section 4.1.4](#)). All cost parameters and estimates in this study are in \$2016, unless
182 otherwise specified.

183 Medical cost of temperature-related morbidity depend on the number of EDVs and
184 EDHSPs that are associated with temperature exposure and the loss in productivity for extended
185 stay at the healthcare facility. To estimate the population level medical cost, we used three factors:
186 total billed charges reflected on individual emergency department records or discharge forms, cost-
187 to-charge ratio (CCR), and the professional fee ratio (PFR). CCR converts the total amount billed to
188 an amount that approximates what the medical facility receives (Levit, Friedman, & Wong, 2013). In
189 this study, total billed charges and CCR were calculated from emergency department records in the
190 TCMA and differs from year to year. PFR accounts for costs that are not facility-based, such as
191 salaries for physicians and other healthcare professionals. This study used the PFR value for EDV
192 among commercially insured individuals, 1.286, estimated by Peterson et al. (2015). Notably, PFR
193 estimates for EDHSP or for Medicaid visits do not vary substantially for other insurance types,
194 based on the same study.

195 We used the Daily Production Value (DPV) to calculate the productivity loss for the days
196 when individuals were at the healthcare facility as a result of EDV or EDHSP. Grosse et al. (2009)
197 provided the DPV estimates for 5-year age groups starting from 15-19 years using a combination of
198 factors such as average daily working hours, usual hourly compensation, daily market compensation

199 and more. The implication for this study is that the youth (0-19 years) and senior (65+ years) age
200 groups generally do not work more than 14 hours/week on average for formal market
201 compensation. The adult (20-64 years) age group tends to work 21-35 hours/week. Consequently,
202 the average DPV, weighted by age distribution, in Minneapolis (2010 U.S. Census) is \$8.74/day
203 (\$2007) for the youth, \$175.78/day (\$2007) for the adult, and \$57.12/day (\$2007) for the senior
204 populations. More details on calculation of these values are in the [Supplemental Information Section](#)
205 [4.2.](#)

206 Thus, the total cost of temperature-related morbidity can be expressed at the following:

$$\begin{aligned}\text{Morbidity Cost} &= \text{Medical Cost} + \text{Productivity Loss} \\ &= \text{Attributable EDV or EDHSP} \times \\ &\quad (\text{Total Billed Charges} \times \text{CCR} \times \text{PFR} + \text{Length of Stay} \times \text{DPV})\end{aligned}$$

207 Research involving the collection or study of existing data and if the information is recorded by the
208 investigator in such a manner that subjects cannot be identified, directly or through identifiers link to
209 the subjects, is exempt from the International Review Board approval at the Minnesota Department
210 of Health.

211 Results

212 Descriptive statistics of the study population are in [Table 1](#). Between 1998 and 2014, there were
213 301,198 deaths in the TCMA, with a majority being seniors (65+ years). The morbidity dataset
214 contains 8,117,358 records with a majority being adults (20-64 years). Among them, 17.9%
215 (1,447,793) were EDHSPs with an average hospital stay of 4.42 days.

216 In [Figure 1](#), we show the exposure-response functions for total and age group-specific daily
217 mortality and morbidity. These functions characterize the relative risk associated with each
218 temperature exposure level compared to the reference level (i.e., MET). In the total population

219 (Figure 1(a)), MET is 84°F for mortality and 71°F for EDV and EDHSP. (MET estimates in Figure
220 1(b-d) are shown in Supplemental Information Section 5). As expected, the U- or J- shapes of the
221 exposure-response functions show low health risk at moderate exposure levels. High temperatures
222 are associated with increased risk for mortality and EDV but not for EDHSP. Low temperatures are
223 associated with increased risk across all population health outcomes. Age-specific analyses reveal
224 three additional pieces of information that are important for understanding the relationship between
225 temperature and population health. First, ambient temperature exposure is associated with mortality
226 in the oldest age group (65+ years) only. Based on our results, ambient temperature exposure is not
227 associated with mortality in the two younger age groups. Thus, we do not provide the relevant
228 mortality burdens for them. Second, based on measures of morbidity, extreme heat exposures only
229 affect youth (Figure 1(b-d)). Third, moderate and extreme cold affects morbidity in all age groups.
230 Uncertainty around RR estimated here are further captured by ACs, discussed below and in
231 Supplemental Information Section 6, computed via the Monte Carlo simulation process mentioned
232 above (Gasparrini and Leone 2014).

233 Figures 2 and 3 show AFs and ACs across exposure types (cold and heat) and magnitudes
234 (moderate to extreme exposures and extreme exposures only) by age group. Mortality results,
235 marked in red, are only shown for seniors (65+ years). From 1998 to 2014, inclusive, 13,991 (6.2%)
236 deaths among seniors are attributed to moderate to extreme cold exposures and 3,444 (1.5%) to
237 extreme cold exposures. During the same period and in the same age group, 2,016 (0.9%) deaths are
238 attributed to moderate to extreme heat exposures and 1,144 (0.5%) to extreme heat exposures.

239 We analyzed EDV and EDHSP results in the same way. Youth (0-19 years) is the only age
240 group with substantial health burden associated with heat exposures. There are 23,478 [95% eCI:
241 8,751, 37,860] (1.2% [95% eCI: 0.4%, 1.9%]) cases of EDVs and 1,089 [95% eCI: 194, 1,929] (0.78%

242 [95% eCI: 0.1%, 1.4%]) EDHSPs associated with moderate to extreme heat exposures. Among
243 them, 12,079 [95% eCI: 7,512, 16,420] (0.6% [95% eCI: 0.4%, 0.8%]) EDVs and 657 [95% eCI: 102,
244 1,189] (0.5% [95% eCI: 0.1%, 0.9%]) EDHSPs are associated with extreme heat exposures. Heat
245 exposures are not associated with health burden among adults (20-64 years) or seniors (65+ years) in
246 the TCMA. Regarding cold, there are positive AFs and ACs for all health outcomes and for all age
247 groups considering moderate to extreme exposures. Given EDV, youth has the highest AF as well
248 as AC (7.03% [95% eCI: 5.9%, 8.1%], 137,622 [95% eCI: 115,749, 157,331], respectively). However,
249 the EDHSP-specific analysis shows that although the youth has the highest AF (6.6% [95% eCI:
250 2.5%, 10.3%]), seniors have the highest AC (24,252 [95% eCI: 15,750, 32,327]). The underlying
251 reason is that there are many more senior EDHSPs than youth EDHSPs. When we considered only
252 extreme cold, all estimates become smaller, as expected, and the AF and AC among senior EDV
253 cases were no longer positive; otherwise, all patterns were similar to those described above. The
254 attributable EDHSPs for youth, adult, and senior are 2,488 [95% eCI: 1,225, 3,680], 4,372 [95% eCI:
255 1,992, 6,732], and 4,445 [95% eCI: 2,319, 6,509] – their differences become smaller than that
256 considering moderate to extreme cold exposures. Overall, youth is the most vulnerable but not
257 always the most affected (measured by burden) age group. Based on EDHSP AC, seniors and adults
258 are both have higher health burden compared to the youth. Numbers used to generate [Figures 2](#) and
259 [3](#) are in [Supplemental Information Section 6](#).

260 After taking into consideration inflation and income growth, based on total AC in the 65+
261 years age group and the VSL estimated by U.S. EPA (1997), the mortality costs related to moderate
262 to extreme cold and heat exposures are \$8,119.33 million [95% eCI: \$4,158.15 million,
263 \$11,862.49million] and \$1,167.50 million [95% eCI: \$478.11 million, \$1,839.77 million] per year,
264 respectively. The mortality costs related to extreme cold and heat only are \$2,00.67 million [95%
265 eCI: \$1,152.52 million, \$2,809.77 million] and \$665.06 million [95% eCI: \$276.35, \$1,041.53 million]

266 dollars per year, respectively. Using updated VSL values of Thomson and Monje (2015) did not lead
267 to substantial changes in these estimates ([Supplemental Information Section 4.1.5](#)).

268 After taking into consideration inflation, the overall results show that the medical costs for
269 EDHSP are higher than those of EDV due to the durations of stay. In addition, the medical costs
270 due to cold exposures are higher than those of heat due to higher health burden (i.e. AC and AF).
271 Among EDVs, the largest contributor to annual medical costs is the 0-19 years age group under cold
272 exposure. This age group accounts for \$8.18 million [95% eCI: \$7.82 million, \$8.54 million] in
273 medical expenses associated with moderate to extreme cold exposures and \$2.21 million [95% eCI:
274 \$2.11 million, \$2.32 million] associated with only extreme cold exposures ([Table 2 and 3](#)). Among
275 EDHSPs, the largest contributor to annual medical costs is the 65+ year age group under cold
276 exposure, which accounted for \$37.20 million [95% eCI: \$33.48 million, \$40.85 million] in medical
277 expenses associated with moderate to extreme cold exposures and \$6.85 million [95% eCI: \$5.81
278 million, \$7.90 million] associated with only extreme cold exposures.

279 Among adults (20-64 years), productivity loss was associated with relevant EDVs and
280 EDHSPs under cold exposures. Considering moderate to extreme cold exposures among adults, the
281 annual productivity loss is \$1.63 million [95% eCI: \$1.41 million, \$1.84 million] due to EDVs and
282 \$1.93 million [95% eCI: \$1.64 million, \$2.22 million] due to EDHSPs. Considering extreme cold
283 exposures only, the annual productivity loss is \$0.29 million [95% eCI: \$0.23 million, \$0.35 million]
284 due to EDVs and \$0.46 million [95% eCI: \$0.38 million, \$0.55 million] due to EDHSPs.

285 Each year, the health burden associated with ambient temperature exposure leads to
286 economic costs of approximately \$9.40 billion [95% eCI: \$6.05 billion, \$12.57 billion] considering
287 both moderate and extreme exposures and \$2.70 billion [95% eCI: \$1.91 billion, \$3.48 billion]

288 considering only extreme exposures in the TCMA. Morbidity loss makes up roughly 0.1-2.5% of the
289 total costs depending exposure magnitude and age group.

290 **Discussion**

291

292 This study presents estimates of the health-related economic costs associated with ambient
293 temperature exposures for the TCMA – approximately \$9.40 billion annually when both extreme
294 and moderate exposures are considered. This comprehensive estimate relies on multiple criteria,
295 capturing different population health outcomes. The World Health Organization recommends the
296 use of such multi-criteria approach for estimating health-related costs associated with climate change
297 as a means of internalizing an array of external costs, enabling comparison across different
298 outcomes, and providing explicit rules for balancing a range of information (Hutton, Sanchez, &
299 Menne, 2013). Based on such multi-criteria approach, our results show that cold exposures are
300 responsible for the economic costs for the TCMA considering mortality and emergency department
301 visits. This holds true regardless of health outcome or age group. Harsh winters and freezing
302 temperatures pose serious health risks even for a well-acclimatized population. The methods
303 developed in this study demonstrate strengths that recommend its application for other jurisdictions
304 and types of environmental exposures.

305 Our findings highlight that temperature-related costs vary by age. Seniors are the only age
306 group for which extreme temperature conditions are associated with increased mortality. These
307 results are broadly consistent with Hajat et al. (2014), Dang et al. (2016), and Yang, Ou, Ding, Zhou,
308 & Chen, (2012), which demonstrate that mortality associated with ambient temperature exposure is
309 greater for persons 65 years or older compared to younger age groups. Consequently, the overall
310 mortality costs are essentially mortality costs for seniors. Factors that make seniors more vulnerable
311 to ambient temperature exposures include social isolation (Naughton et al., 2002), poverty (Basu &

312 Ostro, 2008), a high prevalence of chronic health conditions (Hajat et al., 2014), and reduced ability
313 to take preventive actions to mitigate exposures (Ebi, Mills, Smith, & Grambsch, 2006). Regarding
314 morbidity outcomes, the relative risks for youth increase more rapidly than other age groups as
315 temperature move to the extremes of both cold and heat. Cold exposures affect all three age groups,
316 consistent with the results of Cui et al. (2016) and Zhang et al. (2014). The youth age group has the
317 highest AF associated with cold exposures. Heat exposures, on the other hand, affect only the
318 youth. Regarding this particular observation, current literature provides inconsistent evidence
319 (Nitschke et al. 2007, 2011; Kingsley et al. 2015; Zhang et al. 2014). It is important to keep in mind
320 that there are many more senior EDHSP cases than youth cases. Seniors hospitalized after
321 emergency department visits likely require more intensive and extensive medical services due to co-
322 morbidities and reduced physiological capacity (Ebi et al., 2006; Hajat et al., 2014). Therefore, it is
323 plausible that seniors contribute more to medical costs even though youth are associated with higher
324 health risks of EDHSP given hazardous temperature exposure.

325 This study suggests that studies that limit to seniors *a priori*, under the assumption that other
326 age groups are not as severely impacted by ambient temperatures, may be substantially
327 underestimating the total health burden. There are a large number of individuals 0-19 years whose
328 emergency department visits are also associated with ambient temperature although few of them
329 result in death. Therefore, this study confirms that the youngest and the oldest age groups both need
330 to be considered at risk (Sarofim et al., 2016; Xu et al., 2013). With regard to public health services,
331 focusing on both the youngest and the oldest individuals appears necessary. This analysis provides
332 information for supporting strategic prioritization of different age groups in intervention programs
333 (e.g., risk communication and education). Specific application will depend on the objective of the
334 decision maker. For instance, targeting youth is justifiable when the goal is to protect the most

335 vulnerable individuals. Targeting seniors, especially when exposed to cold, may be more efficient in
336 reducing the overall economic costs.

337 The multi-criteria developed in this study is an extension of the theoretical framework in
338 Knowlton et al. (2011), with the goal of improving economic costs assessment of health risks
339 associated with ambient temperature exposure. This design accounts for various different aspects of
340 economic costs, such as medical expenses and productivity loss, simultaneous while considering a
341 single mortality or morbidity case. The overall economic costs can be considered a composite
342 indicator of impact measurement. This indicator allows for potential comparison between the public
343 health consequences of different environmental exposures, such as air pollution and extreme
344 temperature exposure, which involve multiple health outcomes and aspects of economic costs. The
345 capacity for comparison is crucial to public health decision makers with needs to prioritize at-risk
346 population and allocate scarce resources to manage different environmental exposures.

347 Although different public health outcomes are eventually summed to obtain the total
348 economic costs, it is easy to backtrack to the itemized cost criterion that contributes the most (or the
349 least) to the overall economic burden. For instance, in our study, we attribute 98% of the total
350 economic burden to mortality although the remaining 2% affects a much larger number of
351 individuals (see [Supplemental Information Section 7](#)). The theoretical framework of this study is
352 flexible. When new parameter estimates become available, cost estimates can be easily updated.

353 This study has a few limitations. With an ecological study design, the conclusions that we can
354 draw on the underlying causal mechanism are limited. The exposure measurement relies on
355 meteorological records. Future study may be able to utilize more advanced exposure measurement
356 technology to gain better insights into personal-level exposure intensity and duration. On mortality,
357 we assume VSL to be insensitive to age. This assumption is consistent with the current government

358 practices (Thomson & Monje, 2015; U.S. EPA NCEE, 2010). However, its validity and how VSL
359 vary with age are still up for debate among health economists (U.S. EPA NCEE, 2010) (Aldy &
360 Viscusi, 2007). As for morbidity, we did not include some outcomes such as non-emergent clinical
361 visits due to data access. Such outcomes could be potentially relevant to sub-optimal cold exposure,
362 given the delayed effects. Future studies should consider further expanding morbidity measures.
363 This study considers only direct productivity losses. Indirect losses such as time off work that was
364 taken by parents who need to take care of their sick children are not included in the cost function,
365 which may result in underestimation. Regarding the overall cost function, it is important to point out
366 that by adding mortality costs and morbidity costs, theoretical costs (i.e., willingness-to-pay) are
367 added to transactions that have actually occurred (i.e., medical bills). To compensate for this
368 limitation, the itemized as well as the overall costs of public health burden associated with hazardous
369 ambient temperature exposures are both provided.

370 Conclusion

371

372 This study estimates economic costs incurred by the health burden of ambient temperature
373 exposures, a particularly relevant public health threat given the shifting temperature patterns due to
374 climate change. The results can help develop effective public health interventions that target specific
375 at-risk populations and inform resources allocation. Using multiple criteria to aggregate economic
376 estimates across different age groups leads to a useful, transparent, and flexible composite indicator
377 of costs. This approach can be adopted for assessing the overall impact of other environmental
378 exposures, such as air pollution, that involve multiple health outcomes and aspects of costs.

379

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382

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384 Service (Chanhassen, Minnesota Forecast Office) and the Minnesota Pollution Control Agency in
385 acquiring the necessary data.

386

387 Abbreviations

Abbreviation	Long Form
CCR	Cost-to-charge ratio
DPV	Daily production value
DLMN	Distributed lag nonlinear model
eCI	Empirical confidence interval
EDHSP	Emergency department visits followed by hospitalization
EDV	Emergency department visits followed by discharge
EPA	Environmental Protection Agency
HI	Heat index
MDH	Minnesota Department of Health
MET	Minimum effect temperature
MM	Millions
MORT	Mortality
NWS	National Weather Service
PFR	Professional-fee ratio
RR	Relative risk
TCMA	Minneapolis – St. Paul Twin Cities Metropolitan Area
USD	U.S. dollar
VSL	Value of a statistical life

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- 512

513

Age Group (yo)	Mortality (1998-2014)			Morbidity (2005-2014)			EDHSP		
	MORT			EDV			EDHSP		
	<i>tot</i>	μ	δ	<i>tot</i>	μ	δ	<i>tot</i>	μ	δ
0-19	7,034	1	1	1,957,692	536	84	139,318	38	9
20-64	68,550	11	3	3,980,639	1,090	127	721,132	197	22
65+	225,614	36	7	720,096	197	40	587,343	161	18
All	301,198	48	8	6,658,427	1,823	210	1,447,793	396	36

514

515

516 **Table 1.** Mortality and morbidity in the Minneapolis-St. Paul Twin Cities Metropolitan Area.

517 Three population health outcomes are Mortality; EDV - Emergency Department Visits; EDHSP -

518 Emergency Department Visits followed by hospital admission. *tot* sums the total number of cases

519 for each population health outcomes over the course of 17 years for mortality and 10 years for

520 morbidity. μ - daily mean case counts; δ - daily variability measured by standard deviation.

Health Outcome	Cost Criteria	Age Group	Moderate-Extreme Cold Exposure HI_max < 30 th percentile	Moderate-Extreme Heat Exposure HI_max > 70 th percentile
			Expected Value [95% eCI]	Expected Value [95% eCI]
Mortality (MORT)	-	0-19	---	---
		20-64	---	---
		65+	8,119.33 [4,158.15, 11,862.49]	1,167.50 [478.11, 1,839.77]
Emergency Department Visit (EDV)	Medical Costs	0-19	8.18 [7.82, 8.54]	1.40 [1.15, 1.65]
		20-64	7.17 [6.25, 8.11]	---
		65+	2.54 [2.01, 3.06]	---
	Productivity Loss	0-19	0.16 [0.15, 0.16]	0.03 [0.02, 0.03]
		20-64	1.64 [1.43, 1.85]	---
		65+	0.12 [0.10, 0.15]	---
Emergency Hospitalization (EDHSP)	Medical Costs	0-19	12.81 [10.63, 14.98]	1.51 [1.11, 1.94]
		20-64	27.69 [23.53, 31.81]	---
		65+	37.20 [33.48, 40.85]	---
	Productivity Loss	0-19	0.04 [0.03, 0.05]	0.005 [0.004, 0.006]
		20-64	1.93 [1.63, 2.21]	---
		65+	0.78 [0.71, 0.86]	---
Total	-	-	8215.18 [4,908.92, 11,357.45]	1,171.47 [614.26, 1749.07]

521

522 **Table 2.** Cost estimates for each health outcomes by age groups (in million USD, \$2016)

523 attributable to moderate to extreme ambient temperature exposure.

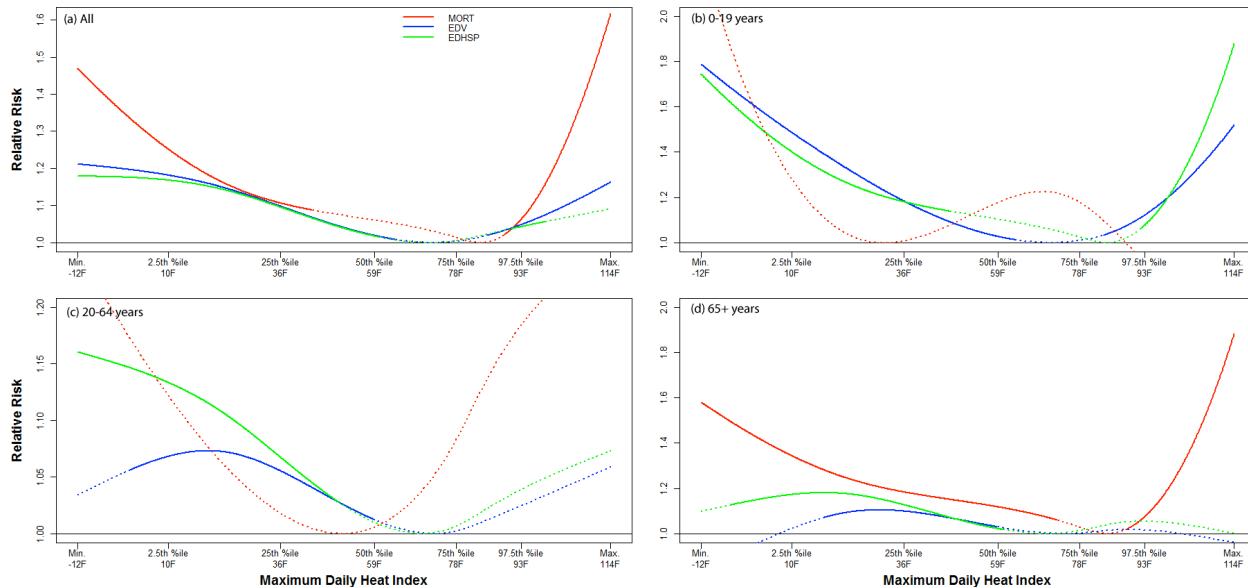
Health Outcome	Cost Group	Age Group	Extreme Cold Exposure HI_max < 5 th percentile (unit=\$MM) Expected Value [95% eCI]	Extreme Heat Exposure HI_max > 95 th percentile (unit=\$MM) Expected Value [95% eCI]
Mortality (MORT)	-	0-19	---	---
		20-64	---	---
		65+	2,005.67 [1,152.52, 2,809.77]	665.06 [276.35, 1,041.53]
Emergency Department Visit (EDV)	Medical Costs	0-19	2.21 [2.11, 2.32]	0.73 [0.65, 0.81]
		20-64	1.27 [1.00, 1.54]	---
		65+	---	---
	Productivity Loss	0-19	0.04 [0.04, 0.04]	0.01 [0.01, 0.02]
		20-64	0.29 [0.23, 0.35]	---
		65+	---	---
Emergency Hospitalization (EDHSP)	Medical Costs	0-19	3.49 [2.87, 4.13]	0.91 [0.63, 1.22]
		20-64	6.57 [5.39, 7.77]	---
		65+	6.85 [5.81, 7.90]	---
	Productivity Loss	0-19	0.01 [0.01, 0.01]	0.003 [0.002, 0.004]
		20-64	0.46 [0.38, 0.55]	---
		65+	0.15 [0.12, 0.16]	---
Total	-	-	2,033.24 [1,318.64, 2725.38]	667.61 [343.46, 993.11]

524

525 **Table 3.** Cost estimates for each health outcomes by age groups (in million USD, \$2016)

526 attributable to extreme ambient temperature exposure.

527



528

529 **Figure 1.** Exposure-response functions for each health outcome by age groups.

530 Solid lines indicate relative risks (compared to minimum effect temperature) significantly greater
 531 than 1 (p -value <0.05) and dotted lines indicate non-statistically significant results (p -value ≥ 0.05).

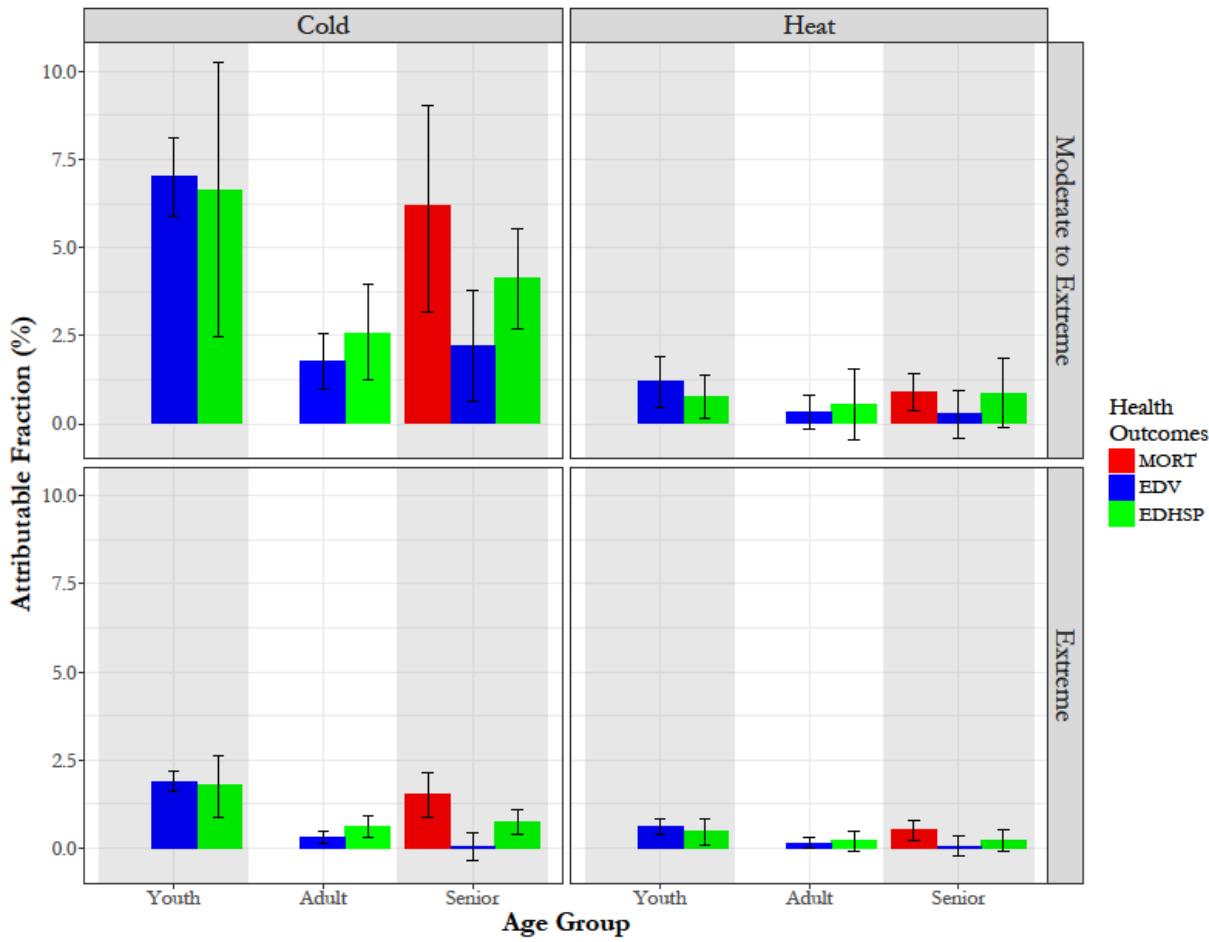
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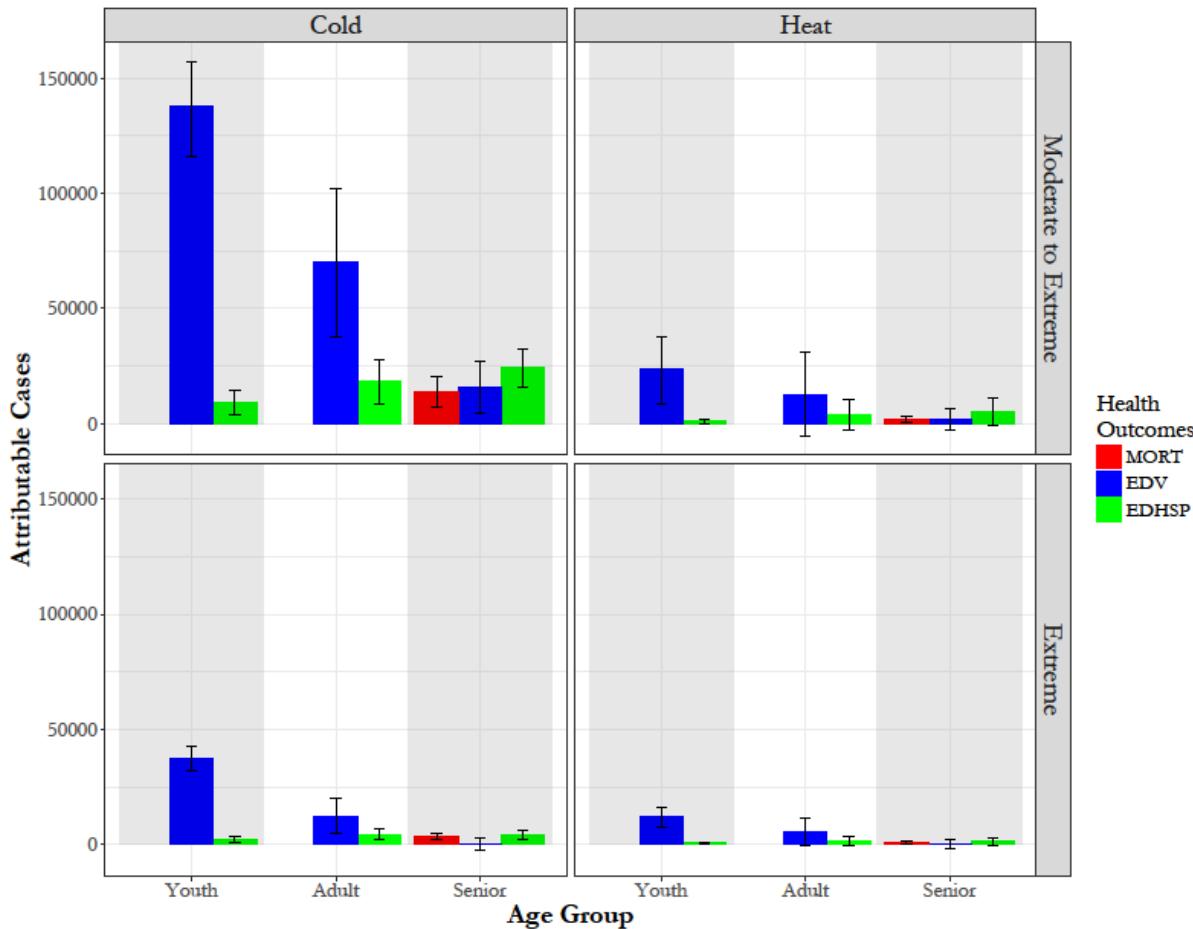
537

538 **Figure 2.** Attributable fraction of three health outcomes by age groups associated with temperature
539 exposure.

540 The uncertainty range is defined by 95% empirical confidence intervals obtained by Monte Carlo
541 simulations ($n=5000$). This figure does not include mortality results regarding 0-19 year olds or 20-
542 64 year olds because there is no increased relative risk of mortality at any exposure level for these
543 age groups.

544

545



546

547 **Figure 3.** Attributable cases of three health outcomes by age groups associated with temperature
548 exposure.

549 The uncertainty range is defined by 95% empirical confidence intervals obtained by Monte Carlo
550 simulations ($n=5000$). This figure does not include mortality results regarding 0-19 year olds or 20-
551 64 year olds because there is no increased relative risk of mortality at any exposure level for these
552 age groups.

553