Effect of the COVID-19 pandemic on heatstroke-related ambulance dispatch in the 47 prefectures of Japan

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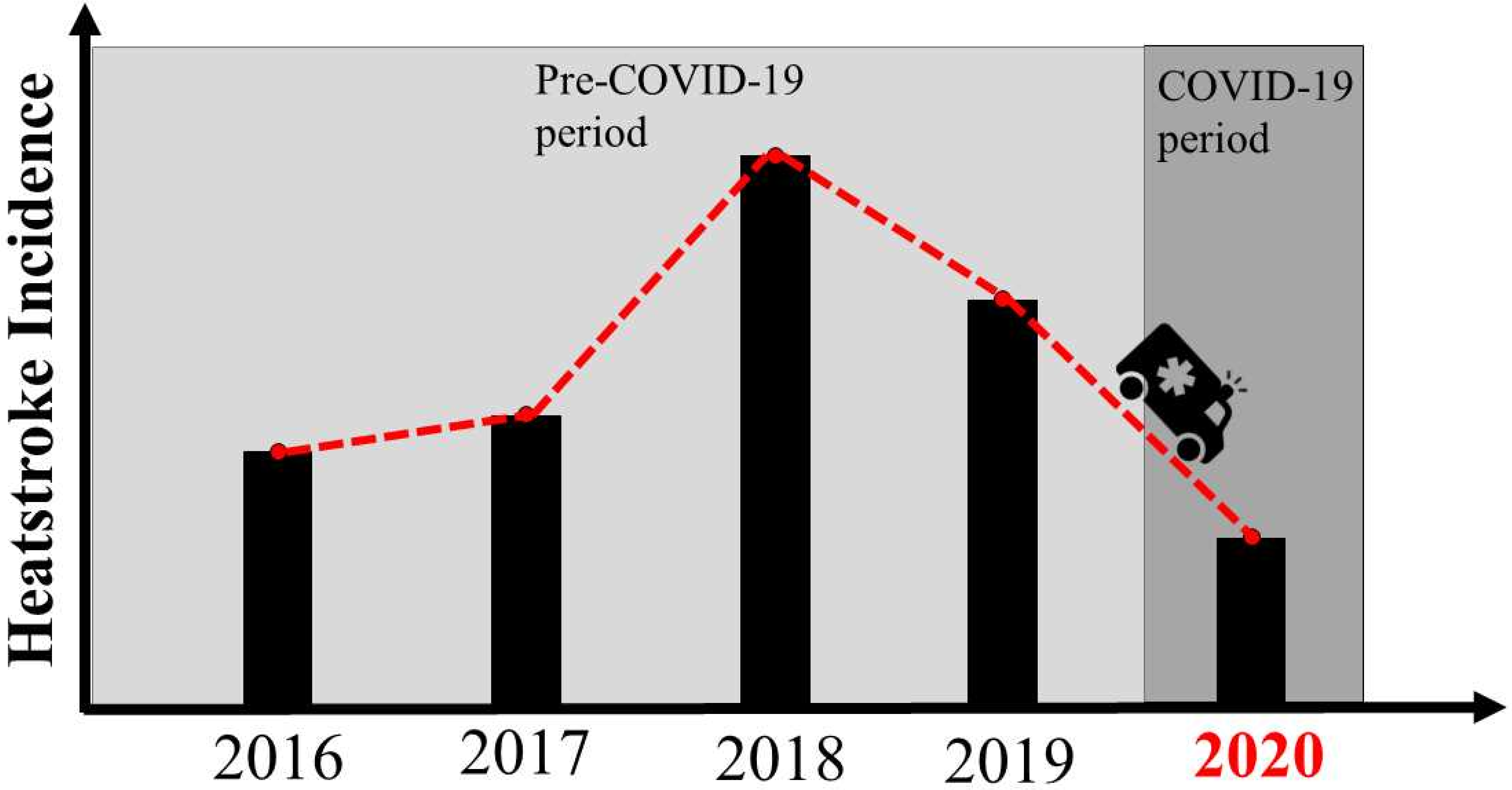

Heatstroke Incidence
Pre-COVID-19 period
COVID-19 period
2016
2017
2018
2019
2020

Abstract

In 2020, Coronavirus disease 2019 (COVID-19) pandemic has brought a huge impact in daily life and has prompted people to take preventive measures. In the summertime, however, the Japanese government has cautioned that some COVID-19 pandemic conditions may affect the risk to heatstroke. This study investigated how the COVID-19 pandemic setting affected heatstroke-related ambulance dispatches (HSAD). Daily HSAD data and relevant weather parameters in June to September period from 2016 to 2020 in 47 prefectures in Japan were obtained from the Fire and Disaster Management Agency (FDMA) database as well as through the respective prefectural governments. A binary variable representing COVID-19 impact was created, whereby years 2016 to 2019 were coded as 0, while 2020 as 1. We employed a two-stage analysis in elucidating the impact of COVID-19 pandemic on HSAD. Firstly, we regressed HSAD with the COVID-19 binary variable after adjusting for relevant covariates to obtain prefecture-specific effect estimates. Prefecture-specific estimates were subsequently pooled via random effects meta-analysis in generating the pooled estimate. Pooled Relative Risk (RR) of HSAD during the COVID-19 pandemic was 0.78 (95% Confidential Interval [CI], 0.75-0.82). We found an overall statistically significant decrease in HSAD risk during the COVID-19 pandemic in Japan. Specifically, the decrease in the risk of HSAD may be linked to the COVID-19 precautionary measures such as stay-home request and availability of alternative consultation services, which may have decreased the direct exposure of the population to extreme heat.

Highlights

- Impact of COVID-19 pandemic setting on heatstroke in Japan
- Risk of HSAD under COVID-19 lower than pre-COVID-19
- Precautionary measures may be linked to the decreased risk

1. Introduction

Globally, a devastating and prolonged pandemic of coronavirus disease 2019 (COVID-19) has brought a huge impact in daily life, leaving many cases of incidence and mortality (Lai et al., 2020). In Japan, the number of COVID-19 newly confirmed cases peaked in the first week of August 2020 and has been a decreasing trend across the country (NIID, 2020). As of October 11, 2020, the total number of confirmed COVID-19 cases and deaths are at 88.2 thousand and 1.6 thousand, respectively (MHLW, 2020c). In response to COVID-19, the Japanese government has made several policy adaptation and requests, such as telework, temporary closure of schools, cancellation of large-scale events (Shaw et al., 2020). The Ministry of Health, Labour and Welfare (MHLW) enacted a recommendation on specific preventive measures for individuals, such as social distance, wearing masks and ventilating indoor space as part of the pandemic response (MHLW, 2020a).

While facing COVID-19 pandemic, heat-related illnesses has been a serious public health concern under a changing climate (Sanderson et al., 2017). Annual temperature in the country has increased by 1.19°C in the last 100 years (MOEJ, 2018). As temperatures increase, several heat-sensitive health outcomes are at risk of increasing, such is the case for heat-stroke ambulance dispatch (HSAD), which has been increasing since 2010 with record-breaking number of cases at 95,137 in 2018 (MIC, 2019; MOEJ, 2018). Additionally, the number of deaths due to heatstroke has also been increasing reaching 1,581 deaths in 2018 (MHLW, 2019). Several previous studies have reported that older people are more vulnerable to heat exposure (Ito et al., 2018; Kuzuya, 2013; Yokota and Miyake, 2016). Based on recent nationally-representative data, people aged more than 65 years old account for 52% of HSAD cases in 2019 and 81.5% of death due to heatstroke in 2018 (MHLW, 2019; MIC, 2019). As a country which has entered the super-aged society, heatstroke is recognized as a serious public health concern and has led to an increase in heat awareness in recent years (Martinez et al., 2011).

In response to the current situation, MHLW has made public warnings particularly for the possibility in the increase of heatstroke cases during summertime under the new lifestyle in the COVID-19 period. Prior to summer, an MHLW-led technical working group has cautioned that several preventive measures under the COVID-19 setting, such as open room ventilation, in the absence of air conditioning, as well as wearing snug-fit masks when outdoors, may possibly contribute to the predisposition of heat-related illnesses, such as heatstroke (MHLW, 2020d).

Previous studies have documented the association of HSAD and meteorological parameters, such as maximum and average temperature, during the summer season in

Japan (Fuse et al., 2014; Murakami et al., 2012; Ng et al., 2014). However, to the best of our knowledge, no study has been done to examine whether the current COVID-19 period conditions have affected the risk of HSAD.

2. Methods

2.1 Data source

Daily HSAD data in June and September from 2016 to 2020 of the 47 prefectures in Japan were obtained from the Fire and Disaster Management Agency (FDMA) database (FDMA, 2020b). All HSAD data were obtained as aggregated daily counts from the FMDA, which are reported by the prefectural governments. Heat stroke-related diagnoses are coded using the International Classification of Diseases (ICD) 10. Specifically, the following diagnoses are reported and aggregated as heat stroke: “heatstroke and sun stroke” (T67.0), “heat syncope” (T67.1), “heat cramp” (T67.2), “heat exhaustion, anhidrotic” (T67.3), “heat fatigue, unspecified” (T67.5), “heat fatigue, transient” (T67.6), “heat edema” (T67.7), and “other effects of heat and light” (T67.8) (FDMA, 2020c; JAAM, 2015). Whereas, relevant meteorological parameters such as (average/minimum/maximum) temperature (in degrees Celsius; °C) and relative humidity (in %) in the study period were obtained from the Atmospheric Environment Regional Observation System (AEROS) (AEROS, 2020). We utilized a binary variable to collectively represent the impact of COVID-19 period/conditions, whereby 2016 to 2019 were coded with 0 and 2020 was 1.

2.2 Data management and analysis

Health outcome and exposure data were compiled and managed in Microsoft Excel. We employed a two-stage analysis to assess the impact of COVID-19 conditions on HSAD. In the first-stage analysis, we examined the prefecture-specific associations by utilizing a generalized linear model with a quasi-Poisson distribution accounting for overdispersion. Prefecture-specific HSAD was regressed with the COVID-19 indicator variable after adjusting for the relevant covariates. In this study, maximum temperature and relative humidity were treated as *a priori* confounders (Murakami et al., 2012; Ng et al., 2014), together with the day of the week (DOW), holiday, month and date (for the day of the year); as shown in Equation 1.

$$Y_t = Quasipoisson_t \qquad \text{[Equation 1]}$$

$$Y_t = \alpha + \beta_1\, COVID19 + \beta_2\, MaxTemp_{thr} + \beta_3\, Humidity + \beta_4\, DOW$$

$$+ \beta_5\, Holiday + \beta_6\, Month + \beta_7\, Date + \varepsilon$$

Whereby, Y_t is the daily HSAD; α is the intercept; $COVID19$ is a binary variable; $MaxTemp_{thr}$ is the maximum temperature with threshold; $Humidity$ is relative humidity; DOW is a categorical variable of day of the week; $Holiday$ is a binary variable of national holiday in Japan; $Month$ is a binary variable representing the months of June and July; $Date$ is the temporal variable representing continuous time; ε is the error term; all beta coefficients of the relevant independent variables are represented as ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_{5,}\ \beta_{6,}\ and\ \ \beta_7$). In the second-stage analysis, we performed a random effects meta-analysis to pool the prefecture-specific effects estimates. Temperature was assumed with a threshold due to the discernable pattern of increase after a change point, as shown in Figure S1. We examined the possible change point temperature whereby we observe a sharp increase in the number of HSAD cases. Prefecture-specific absolute temperatures were transformed to relative temperatures using an empirical cumulative distribution function which is inherent to the "base" package of R statistical programming (R Core Team, 2020). Prefecture-specific relative temperatures were utilized for a change point detection via a segmented regression implemented through the "segmented" package (Muggeo, 2003). These change point temperatures were then treated as the prefecture-specific thresholds of the relative temperature (Table S1). We then plotted the distribution of the prefecture-specific thresholds (Figure S2). After observing an apparent skewed distribution of the thresholds, we took the median value of this distribution, which was at the 80th temperature percentile. We implemented the prefecture-specific threshold specification for the absolute temperature using prefecture-specific 80th temperature percentile as an upper threshold point, which was parameterized through the *onebasis* function in the “dlnm” package (Gasparrini, 2011). In brief, the association of HSAD and absolute maximum temperature below 80th temperature percentile is assumed to be null, whereas beyond the threshold is assumed to follow linear functional shapes.

We also considered the additional control for PM2.5 in the model, however, due to the unavailability of the 2019 data, we did not include it in the final model. The non-inclusion of the PM2.5 into the final model is also supported by the sensitivity analysis in Table S2. In brief, since current publicly available PM2.5 data is only available from 2016 to 2018 and 2020, we shortened the period to 2016-2018 for the non-pandemic setting, instead of the 2016-2019. There is no significant difference among the prefecture-specific estimates and the pooled estimate, even after adjusting for PM2.5 (in Table S2). We assumed that this non-significant difference after PM2.5 adjustment would also be the same in context of the 2016-2019 period. A more detailed description can be found in the accompanying text of Table S2. In this study, p-value of 0.05 was considered as statistically significant. All analyses were performed using R statistical programming (R Core Team, 2020).

3. Results

Summary statistics for HSAD and meteorological parameters of the 47 prefectures are provided in the Table 1. While overall mean daily HSAD cases of the 47 prefectures in pre-pandemic and pandemic periods are nearly similar (mean=11.2 and mean=11.3, respectively), pre-pandemic (2016-2019) variations in daily HSAD were slightly higher than during the pandemic (standard deviation = 23.7 and standard deviation =22.8, respectively). Highest maximum temperature was observed in 2018 with 29.8°C, while the lowest one was in 2017 with 29.2°C. On the other hand, relative humidity was lowest in 2017 with 73.8%, with the highest record of the study period in 2019 at 76.7%.

A more detailed summary statistic for all study prefectures are listed in Table S3 of the Supplementary Materials. Majority of the prefecture-level estimates, in Figure 1, indicated potential protective effect for HSAD, with lowest relative risk (RR) recorded in Chiba (RR=0.57, 95% CI: 0.44 – 0.74). Kumamoto, on the other hand, recorded a statistically significant highest RR of 1.26 (95% CI: 1.01 – 1.57). Pooled effects estimate from the random effects meta-analysis indicated an overall protective effect with an RR of 0.78 (95% CI: 0.75 – 0.82), with significant moderate heterogeneity (I^2=48.74%).

4. Discussion

We found an overall statistically significant decrease in HSAD risk during the COVID-19 pandemic in Japan. Under the COVID-19 pandemic, non-binding self-restriction requests were issued by the Japanese government because the legislation in Japan does not allow its government to apply an enforcement of a forced lockdown (Shaw et al., 2020). However, some studies conducted in Japan actually have observed some behavioral changes, such as hand hygiene, social distancing, and even going-out self-restriction under certain contexts (Machida et al., 2020; Parady et al., 2020). Along with preventive strategies for heatstroke and COVID-19, it is possible that behavioral changes followed by a raised awareness of staying healthy may have been a protective influence on HSAD, either apparent reduction of HSAD or possible reduction of heatstroke itself, during the COVID-19 pandemic setting. The potential factors behind the overall reduction may be linked to the precautionary measures in response to COVID-19, namely: stay-home request and availability of alternative consultation services.

4.1. Stay-home request

The frequency of HSAD in outdoor settings, which mostly occur in roads (15.6%) and general outdoor public areas (12.5%), may have simply decreased by staying indoors longer (MIC, 2019). Whereas for HSAD occurring in indoor settings, some studies reported inconsistent results on self-perceptions of risks for heat impacts and changes in their preventive practices (Bassil and Cole, 2010). A few studies found preventive measures, such as staying in an air-conditioned space, were practiced among vulnerable people who recognized their risk to heat (Kosatsky et al., 2009). It is plausible that the stay-home request with increased public warnings for heatstroke may have led to a reduced risk in HSAD both in outdoor and indoor settings.

4.2. Alternative consultation services

Based on previous studies conducted in Japan and the United States, the number of patients transported by ambulance or visited emergency departments have decreased due to increasing concerns about the risk of contracting COVID-19 (Boserup et al., 2020; Katayama et al., 2020; Lange et al., 2020). In Japan, call centers and consultation centers for COVID-19 have been established as alternative consultation service to triage suspected cases properly (MHLW, 2020b).

4.3. Potential increase in HSAD risk: Case of Kumamoto

While several prefectures indicated a decrease in the risk of HSAD during the COVID-19 pandemic, it is interesting to note that Kumamoto prefecture exhibited a statistically significant increase (RR=1.26; 95% CI: 1.01 – 1.57). The increase in the risk may possibly be related to the record-breaking rainfall which occurred in the Kyushu region due to seasonal rain front, causing thousands of houses damaged completely or partially and prolonged power outage notably in some areas of Kumamoto prefecture (FDMA, 2020a; JMA, 2020; Kyushu Electric Power Co., 2020). Hundreds to thousands of households in the areas could not use air-conditioners, and even to operate shelters in this year, preventive measures to prevent both COVID-19 and heatstroke were required (Kumamoto Prefectural Government, 2020; Kyushu Electric Power Co., 2020), which may have further increased the HSAD risk. While this is an isolated case, the potential for a natural hazard to amplify temperature-related health risks should be explored in future studies which present similar scenarios.

This study has several limitations. First, the data from some prefectures in Japan was not available, the addition of these data, whenever possible, is warranted. Second, we used HSAD data only in a period of June and July, which have not included August and September where additional HSAD may be observed. Third, given the ecological nature of the study, several personal-level characteristics were not considered. The apparent statistically significant low-to-moderate heterogeneity (I^2=48.74%) (Higgins et al., 2003) may be related to several unaccounted factors varying between prefectures, which, however, is beyond the scope of this study. Future studies may potentially examine this through further analyses with suitable meta-regressors.

Amidst these limitations, the study has several strengths. To the best of our knowledge, this is the first study to examine the impact of the COVID-19 pandemic setting on HSAD. Likewise, the multi-location setting allows for a more robust estimate with increased precision. We believe that the study results provide insightful observations on the impact of the COVID-19 pandemic setting on HSAD and its implication with the currently best available data. Also, results from this study would provide a platform to further understand the individual-level characteristics which could explain such protective effect.

5. Conclusion

COVID-19 pandemic setting resulted to a decrease in HSAD in Japan. The decrease in HSAD may possibly be attributed to several precautionary measures targeting to COVID-19.

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Table 1. Annual summary statistics of daily HSAD and meteorological parameters during summer (June to September) in 47 prefectures

	Pre-COVID-19					COVID-19
Year	2016	2017	2018	2019	Total (2016-2019)	2020
HSAD (cases/day)	8.31 (±12.9)	8.65 (±14.1)	16.2 (±34.4)	11.7 (±25.5)	11.2 (±23.7)	11.3 (±22.8)
Maximum temp (°C)	29.5 (±3.99)	29.2 (±3.95)	29.8 (±4.69)	29.3 (±3.95)	29.4 (±4.16)	29.6 (±4.02)
Humidity (%)	75.7 (±10.4)	73.8 (±10.8)	75.1 (±10.7)	76.7 (±9.82)	75.3 (±10.5)	77.4 (±10.3)

* mean (± standard deviation); degrees Celsius (°C); percentage (%); HSAD ≡ heat stroke ambulance dispatch

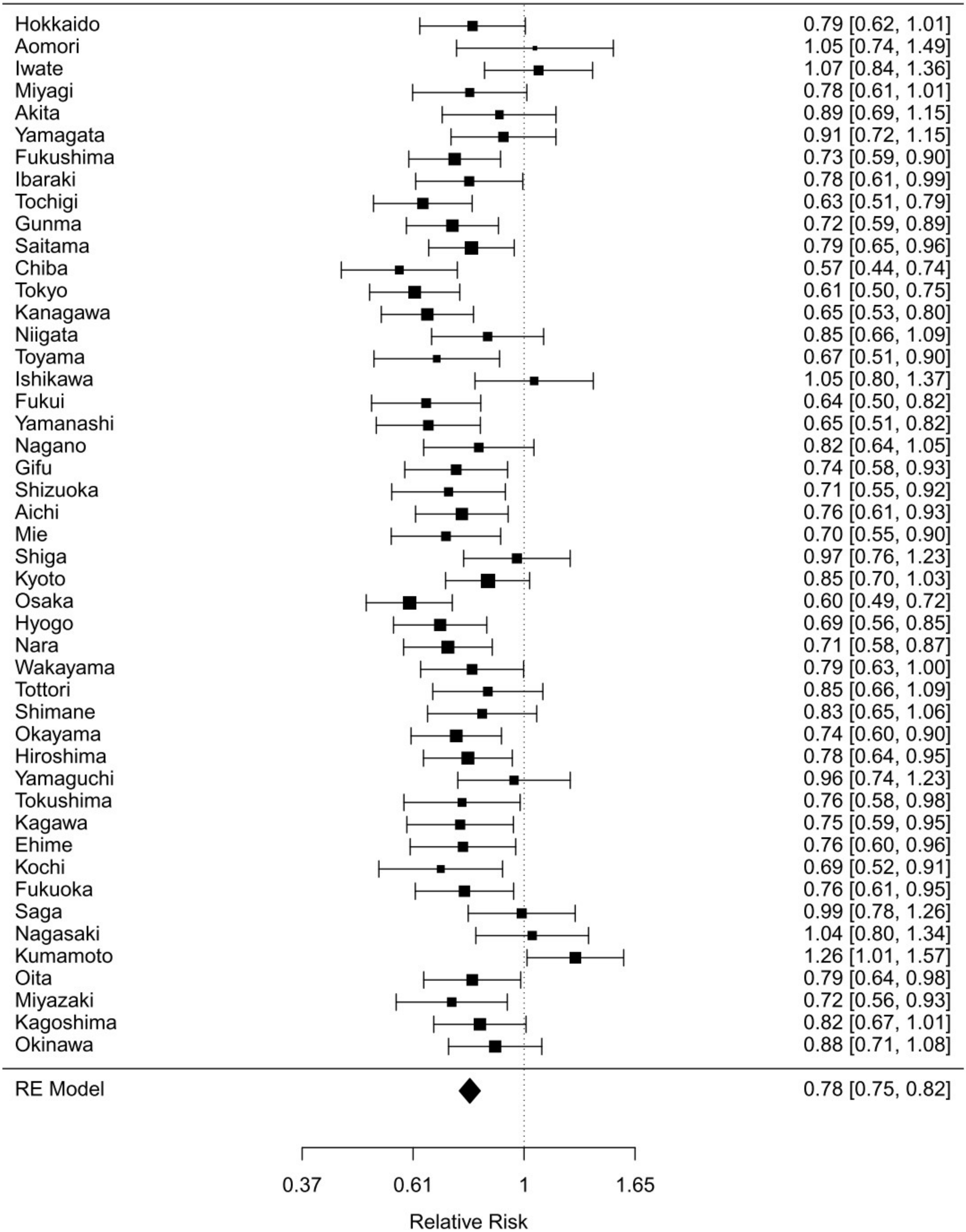

Figure 1. Forest plot of prefecture-specific relative risk estimates

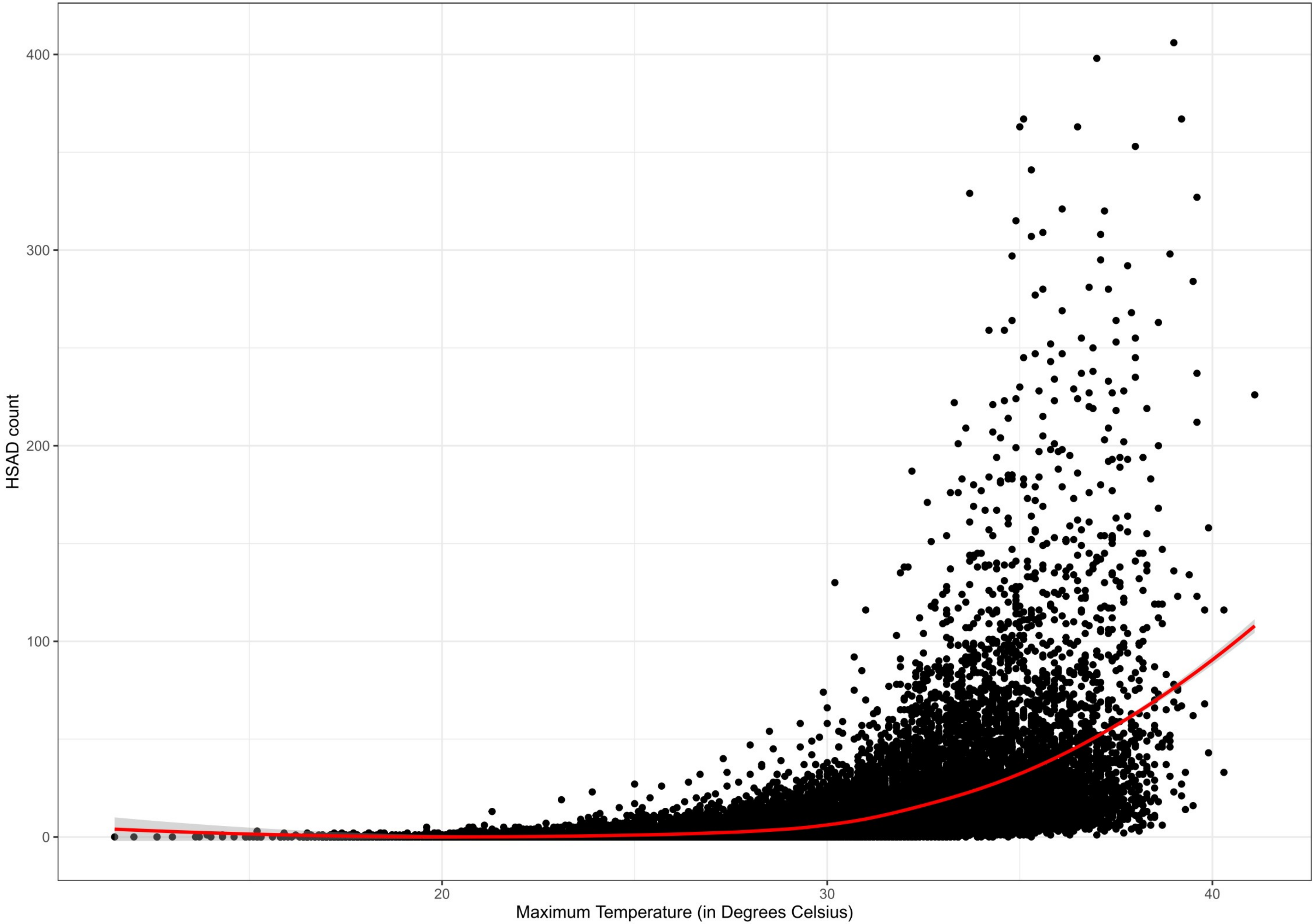

Figure S1. Simple linear regression (with loess fit; in red) of daily HSAD and maximum temperature

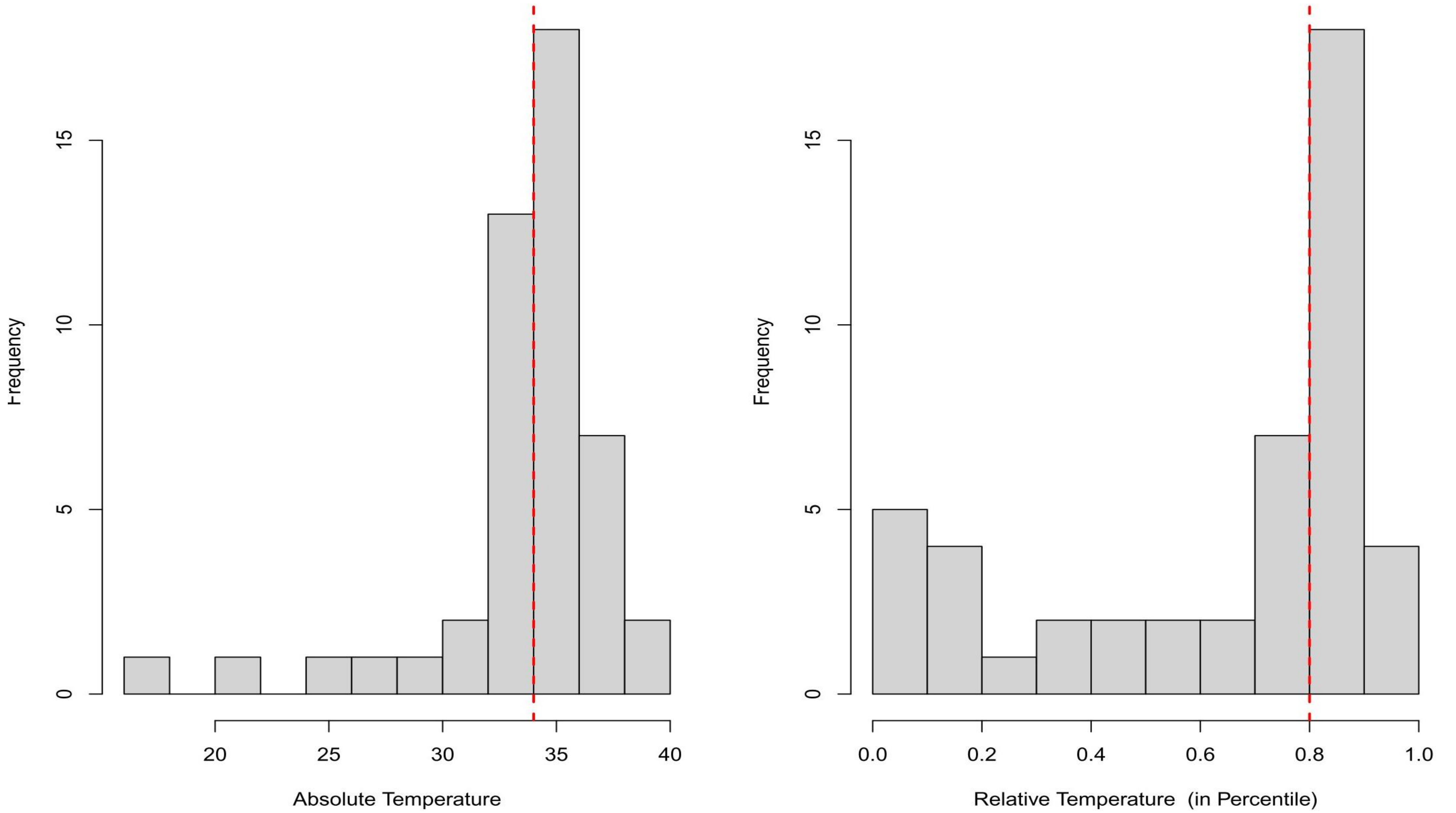

Figure S2. Absolute (left) and relative (right) temperature distribution of prefecture specific change point temperatures with respective median values (in vertical red dotted lines)

Table S1. Absolute and relative temperature (in percentile) estimated using segmented regression modeling

Prefecture	Absolute Temperature	Relative Temperature (percentile)
Hokkaido	25.49937515	0.863717671
Aomori	29.30000699	0.970491278
Iwate	17.20005141	0.877051469
Miyagi	33.10004441	0.890091218
Akita	32.5000052	0.843153283
Yamagata	36.48220178	0.78032788
Fukushima	20.79981204	0.863938731
Ibaraki	31.88936982	0.934426442
Tochigi	36.67876592	0.856906075
Gunma	36.60000896	0.888531694
Saitama	27.00020216	0.89205246
Chiba	34.70016828	0.121312276
Tokyo	35.09999639	0.799999513
Kanagawa	35.3994623	0.796722321
Niigata	32.89999986	0.521976092
Toyama	33.59001142	0.840908734
Ishikawa	33.49998045	0.767213413
Fukui	34.40432624	0.835301634
Yamanashi	37.40007273	0.815768973
Nagano	34.20606379	0.893305249
Gifu	39.00108607	0.859016258
Shizuoka	33.5994669	0.742621858
Aichi	36.7999329	0.875407941
Mie	33.40000694	0.957606189
Shiga	36.41828812	0.850097074
Kyoto	38.19986604	0.214788734
Osaka	34.86958007	0.0475398
Hyogo	32.99997708	0.136066277
Nara	34.50004213	0.049174448
Wakayama	31.98401028	0.597683718
Tottori	34.76247425	0.067178614
Shimane	34.22331681	0.079175636
Okayama	36.70000243	0.940984778
Hiroshima	35.29951745	0.436067575

Yamaguchi	35.30100106	0.198353206
Tokushima	34.00002118	0.696712235
Kagawa	35.35892346	0.426253702
Ehime	34.45761273	0.813726026
Kochi	33.93166729	0.667211239
Fukuoka	34.6132924	0.838131612
Saga	34.0999966	0.365516082
Nagasaki	33.14702573	0.805200545
Kumamoto	33.79999228	0.708195388
Oita	34.69999996	0.162295099
Miyazaki	32.60000141	0.795081413
Kagoshima	35.29997643	0.07374183
Okinawa	32.09999905	0.326230412

Table S2. Sensitivity analyses regarding the adjustment and non-adjustment of PM2.5

Model	Specifications	[1]Pooled Estimates	p-value
I	Period Coverage: 2016-2020 Prefectures: All 47 prefectures PM2.5: Not adjusted	0.78 (0.75 – 0.82)	1.00
II	Period Coverage: 2016-2018 and 2020 (excluding 2019) Prefectures: All 47 prefectures PM2.5: Not adjusted	0.70 (0.64 – 0.76)	0.55
III	Period Coverage: 2016-2018 and 2020 (excluding 2019) Prefectures: All 47 prefectures PM2.5: Adjusted	0.79 (0.74 – 0.85)	0.79

[1] The pooled estimates are estimated via random effects meta-analysis through a restrictive maximum likelihood (REML) parameterization.

We initially started with Model I with full period coverage without adjusting for PM2.5. Since at the moment, the harmonized and publicly available PM2.5 data for all prefectures is not yet available for 2019, we proceeded with the utilizing the pre-pandemic period (2016 to 2018) together with the advanced reported (non-harmonized) 2020 data; as shown in Models II and III. We observe that the adjustment of PM2.5 (Model III) was not significantly different from the non-adjustment in Model II. Utilizing these results, we assumed that the non-adjustment of PM2.5 in the full model with the 47 prefectures for 2016 to 2020 would not be significantly different even with adjustment evident in the calculated p-value.

Table S1. Summary statistics by prefecture, comparing pre COVID-19 (2016-2019) and COVID-19 (2020)

Prefecture	Pre-COVID-19 period (2016-2019)						COVID-19 period (2020)					
	HSAD		Maximum Temperature (℃))		Relative Humidity (%)		HSAD		Maximum Temperature (℃)		Relative Humidity (%)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Hokkaido	9.545081967	20.82699876	24.25819672	4.196250212	72.8852459	9.360844415	8.918033	12.76915	25.12295	3.935929	75.46721	7.971213
Aomori	3.206967213	6.096098377	25.58545082	3.92984858	78.07581967	8.443579468	3.508197	6.619837	26.21393	3.823618	79.55738	8.410982
Iwate	4.37704918	7.823597086	26.4557377	4.382376488	79.31557377	9.080000547	4.893443	6.771119	26.93689	3.93833	81.31148	9.264776
Miyagi	7.733606557	14.46438442	26.44651639	4.142996881	79.52459016	10.89502881	8.795082	14.65636	26.79918	4.282339	83.07377	9.690387
Akita	4.006147541	6.550229483	26.89651639	4.189559743	76.86680328	9.612442977	4.139344	6.018313	27.3623	3.628613	78.58197	9.532754
Yamagata	4.31147541	7.218880068	28.17889344	4.368106503	74.58811475	9.371218451	4.983607	6.917439	28.78443	4.236247	75.93443	10.07799
Fukushima	9.008196721	14.64234578	28.42745902	4.7467685	75.99590164	10.9488255	9.090164	12.85585	28.7623	4.691408	78.85246	10.49807
Ibaraki	12.37909836	19.18936579	28.04467213	4.042979096	80.09221311	8.329316673	12.95082	17.04435	28.17623	4.094161	82.15574	7.463432
Tochigi	7.653688525	12.69015313	28.76844262	4.219849939	78.85860656	9.99663638	7.565574	11.35744	28.89344	4.211902	82.36066	8.465843
Gunma	10.08606557	17.12799894	29.45881148	4.516831882	73.13114754	12.56258309	10.06557	13.38047	29.80164	4.533821	77.27869	11.79176
Saitama	30.79918033	47.78206686	29.97213115	4.645432497	74.08196721	11.96218557	33.01639	45.29809	30.08033	4.734446	80.0082	10.00371
Chiba	22.7807377	34.79595963	28.85245902	3.680376133	76.80327869	9.363426025	24.66393	34.08512	29.01885	3.770072	77.4918	7.999221
Tokyo	39.43237705	65.345799	29.07766393	4.101946885	80.0942623	10.56957626	47.85246	70.40106	29.37705	4.214434	82.52459	9.17976
Kanagawa	24.36065574	37.12420256	28.79754098	3.902107325	78.96311475	9.568228576	26.9918	39.30396	29.18607	3.945713	80.91803	8.229749
Niigata	10.24385246	14.82547211	27.94446721	4.010024672	76.90163934	8.68940192	9.696721	13.09463	28.38115	3.556145	79.14754	9.30269
Toyama	3.635245902	5.58103892	28.93831967	4.14977138	77.67418033	9.864918728	3.729508	5.489339	29.53525	4.065109	80.83607	9.722905
Ishikawa	4.903688525	7.15169648	28.98483607	3.899867788	71.53278689	9.139965201	5.344262	7.438753	29.35246	3.516577	73.28689	9.476792
Fukui	3.256147541	4.71769389	29.7647541	4.008833616	74.89139344	9.118796601	2.983607	3.863334	30.0959	3.79792	77.7377	9.481433
Yamanashi	3.608606557	5.889859007	30.82868852	4.129798152	68.31762295	10.59558705	3.827869	5.267541	30.90328	4.115239	76.58197	9.066185
Nagano	7.375	11.49451927	28.67991803	4.374643006	75.36885246	8.876705847	7.204918	9.035228	29.0377	4.152055	77.13934	9.387274
Gifu	10.56557377	17.70450479	30.95286885	3.951844625	69.20491803	11.91116228	9.491803	10.93652	31.19754	3.807571	71.39344	12.36601
Shizuoka	13.4897541	18.46089984	29.47786885	3.331900748	75.65778689	8.575052207	16.46721	26.21185	29.96148	3.326911	80.18033	8.329988
Aichi	33.99795082	52.7537964	30.80553279	3.886953659	69.70696721	11.63714723	33.61475	42.46018	31.11148	3.810559	74.7623	11.74597
Mie	9.446721311	15.34454499	29.33668033	3.639429695	69.65983607	10.64428902	10.09016	12.27037	29.51639	3.337846	71.07377	10.79345
Shiga	5.93647541	8.834205356	29.49139344	3.801956659	75.31147541	8.352925656	5.327869	7.207024	29.72459	3.634188	77.96721	8.541522
Kyoto	14.15778689	20.91936462	31.23893443	4.043551473	67.92213115	10.19069118	12.36885	15.20505	31.32213	4.034265	69.58197	11.42915
Osaka	38.71106557	54.2277928	31.03094262	3.745185209	69.70696721	9.738584779	39.90984	51.60947	31.1377	3.696108	71.01639	10.53054
Hyogo	26.05327869	35.05075858	29.82991803	3.366535151	71.95696721	10.04303842	24.90984	29.73631	29.84344	3.387214	73.54098	10.8202
Nara	7.805327869	11.13041102	30.6647541	3.910895057	74.30942623	9.668666622	6.909836	8.193935	31.07131	3.932162	74.31148	9.942049
Wakayama	5.493852459	6.631698745	30.30983607	3.345060653	73.1352459	9.145085839	5.434426	6.78597	30.37623	3.415958	74.36885	8.816027
Tottori	3.450819672	5.094753043	30.11086066	4.208252487	76.10655738	9.012705954	3.401639	3.531815	30.2459	4.100537	76.94262	9.503631

Shimane	3.540983607	4.942208172	29.13627049	4.003927233	79.10860656	8.421791897	3.360656	3.865648	29.14672	4.060212	79.47541	9.452109
Okayama	12.62909836	16.73932691	30.66598361	3.809044496	73.96106557	9.745030877	10.7377	11.82993	30.92705	3.942836	75.32787	10.49789
Hiroshima	14.19262295	18.39716373	30.22090164	3.696645575	66.37295082	10.33267211	12.38525	13.85488	30.12787	3.622594	66.38525	10.29117
Yamaguchi	5.989754098	8.068616003	30.74979508	3.941033537	77.70081967	9.63186017	5.008197	6.997633	30.34508	3.95577	79.29508	9.41222
Tokushima	3.774590164	4.981527461	29.92520492	3.477932775	76.76229508	10.38938273	4.090164	4.882088	30.19262	3.564614	77.12295	10.1057
Kagawa	5.135245902	6.973560183	30.59631148	3.768167045	72.37295082	10.21776475	5.393443	5.781929	30.91721	3.852501	73.18033	10.55174
Ehime	7.395491803	9.311258126	30.38278689	3.567384599	73.2397541	10.12396964	7.180328	7.639627	30.53197	3.405083	74.12295	8.991803
Kochi	4.282786885	5.811016835	30.21536885	3.064486496	78.67622951	9.7907097	3.877049	4.520985	30.15656	3.252335	80.54098	9.331496
Fukuoka	21.88319672	27.12940857	30.55245902	3.651614098	75.55737705	8.954183339	20.51639	24.33419	30.25574	3.516503	75.45902	8.90366
Saga	4.965163934	6.244242981	31.02192623	3.830161128	74.44467213	10.68366368	4.245902	5.371045	30.6123	3.486185	76.9918	10.67591
Nagasaki	7.18442623	8.888702845	29.83258197	3.333660063	80.43237705	9.744557628	6.467213	8.356899	29.22541	2.845514	83.66393	8.68228
Kumamoto	11.6454918	13.77523222	31.16659836	3.762051287	75.41803279	10.85187947	10.7459	11.98729	30.9582	3.535063	77.61475	10.22187
Oita	6.399590164	7.576181188	29.86331967	3.791542902	77.59221311	10.50919715	6.032787	6.701344	29.91639	3.494301	78.64754	9.384286
Miyazaki	6.375	7.746016397	29.77479508	3.135869181	82.63319672	8.21319395	6.040984	7.474914	30.15492	3.471992	82.06557	7.256502
Kagoshima	11.2192623	11.45543449	31.0522541	3.077886125	78.28893443	8.023868429	10.89344	12.93519	30.58934	3.343399	80.17213	7.57518
Okinawa	7.776639344	6.262343653	31.32971311	1.912113745	79.99180328	6.969273604	6.590164	5.29268	31.37951	1.703663	83.53279	5.027502

* SD=standard deviation; degrees Celsius (°C); percentage (%)