Seasonal temperature variability and emergency hospital admissions for respiratory diseases: a population-based cohort study

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ABSTRACT

Background: Climate change not only increases global mean temperature, but also changes short- (e.g. diurnal) and long-term (e.g. intraseasonal) temperature variability. Numerous studies have shown that mean temperature and short-term temperature variability are both associated with increased respiratory morbidity or mortality. However, data on the impact of long-term temperature variability is sparse.

Objective: We aimed to assess the association of intraseasonal temperature variability with respiratory disease hospitalizations among elders.

Methods: We ascertained the first occurrence of emergency hospital admissions for respiratory diseases in a prospective Chinese elderly cohort of 66820 older people (≥ 65 years) with 10 to 13 years of follow up. We used an ordinary kriging method based on 22 weather monitoring stations in Hong Kong to spatially interpolate daily ambient temperature for each participant's residential address. Seasonal temperature variability was defined as the standard deviation (SD) of daily mean summer (June-August) or winter (December-February) temperatures. We applied Cox proportional hazards regression with time-varying exposure of seasonal temperature variability to respiratory admissions.

Results: During the follow-up time, we ascertained 12689 cases of incident respiratory diseases, of which 6672 were pneumonia and 3075 were chronic obstructive pulmonary disease (COPD). The hazard ratios per 1°C increase in wintertime temperature variability were 1.20 (95% confidence interval: 1.08, 1.32), 1.15 (1.01, 1.31), and 1.41 (1.15, 1.71) for total respiratory

diseases, pneumonia, and COPD, respectively. The associations were not statistically significant for summertime temperature variability.

Conclusion: Wintertime temperature variability was associated with higher risk of incident respiratory diseases.

What is the key question?

Is seasonal temperature variability associated with increased risk of respiratory disease hospitalizations among elders?

What is the bottom line?

Wintertime temperature variability was associated with higher risks of incidence of total respiratory diseases, pneumonia, and chronic obstructive pulmonary disease, and such associations were stronger in females and participants in a lower social-economic position.

Why read on?

This large prospective cohort study is the first to show the impact of seasonal temperature variability on respiratory diseases admissions, and it highlights the potential role of changing seasonal temperature variability introduced by climate change on respiratory system.

INTRODUCTION

Respiratory diseases, including pneumonia and chronic obstructive pulmonary disease (COPD), contribute to substantial health burden worldwide. Pneumonia affects approximately 450 million people a year, and is a leading cause of hospitalization and death worldwide.[1] A total of 3.2 million people died of COPD in 2015, which is the fourth leading cause of death in the world.[2]

It is now well recognized that climate change has increased global temperature over the past few decades, primarily due to the increased emissions of anthropogenic greenhouse gases (GHGs).[3] Climate change is also projected to cause changes in the frequency, severity, and duration of extreme weather events, including changing temperature variability in short-term (e.g. diurnal temperature range) and long-term (e.g. intraseasonal) ways.[4-7] It is expected that climate change will impact respiratory diseases significantly through influencing viral activity and transmission (e.g. respiratory syncytial virus), altering vectors and the host immune response, and changing in allergen disposition.[8 9]

Mean and variability are two main characteristics of temperature. Numerous time-series and case-crossover studies have reported that short-term exposure to both cold and hot temperatures were associated with increased risks of respiratory mortality[10] and hospital admissions.[11] Most of those studies focused on the adverse health effects of short-term mean temperature. A few studies also assessed the health effects of short-term temperature variability (e.g. diurnal temperature range and temperature change between neighboring days or diurnal temperature range). For example, Lim et al. (2012) reported that diurnal temperature range were significantly associated with respiratory hospitalizations using four metropolitan areas in Korea with total population of 18.3 million.[12] To the best of knowledge, no study has been conducted to investigate the impacts of seasonal (long-term) temperature variability on incident respiratory disease hospital admissions.

The present study aimed to estimate the association between seasonal temperature variability, the standard deviation (SD) of daily mean summer (June-August) or winter (December-February) temperatures, and the incidence of respiratory disease hospital admissions in a prospective Chinese elderly cohort in Hong Kong. We also assessed whether the associations were modified by age, sex, marital and socioeconomic status, and housing type to identify vulnerable subpopulations.

METHODS

Study population

The Chinese elderly cohort in Hong Kong is a prospective cohort, into which all residents of Hong Kong aged 65 years or older (≥ 65 years) were eligible to enroll. From 1998 to 2001, 66820 elders, about 9% of older people in Hong Kong, enrolled in the 18 Elderly Health Centres of the Department of Health, one in each of the 18 districts in Hong Kong, and were followed up till December 2010. Each participant had physical examinations and face-to-face interviews by registered nurses or doctors using a standardized structured questionnaire during each year of follow up.[13] The collected information included demographic characteristics (e.g. age and sex), socioeconomic status (e.g. personal monthly expenditure), lifestyle (e.g. smoking status and physical activity) and body mass index (BMI). Details of this cohort profile were described elsewhere.[13] Ethics approval was obtained from the Ethics Committee of the Faculty of Medicine, The University of Hong Kong and of the Department of Health of Hong Kong.

Health outcomes

We used a common unique identifier (the Hong Kong identity card number) to link the cohort with the Hospital Authority Corporate Data Warehouse, which covers all publicly funded hospitals that provide 24-hour accident and emergency services and covers 90% of hospital beds for Hong Kong residents.[14] Hospital admissions were identified using primary discharge diagnoses for emergency hospital admissions for respiratory diseases (International Classification of Diseases, 9th revision: 460:519), pneumonia (480:486, 487.0), and COPD (490:492, 494:496). Incident cases for respiratory diseases were ascertained as the first occurrence of emergency hospital admissions after enrollment.

Ambient temperature

We extracted daily mean ambient temperature data from the 22 weather monitoring stations in Hong Kong within a land area of 1104 km^2 from 1998-2010 (**Figure 1**). Among various algorithms (e.g. kriging, inverse distance weighting, and trend surface analysis) to spatial interpolate daily mean ambient temperature, the kriging method yields a more realistic spatial behavior of the climatological variable of interest.[15 16] Ordinary kriging is the most commonly used kriging method, which estimates daily temperature at locations without monitors based on the weighted average of adjacent observed sites within a given area. Ordinary kriging has been described as the “anchor algorithm of geostatistics” because of its remarkable robustness under a range of conditions.[17] We used ordinary kriging to interpolate the daily ambient temperature based on the 22 weather monitoring stations for each participant according to his/her residential address. The performance of the ambient temperature prediction model was validated by leave-one-out cross-validation. The R^2 of leave-one-out cross-validation was found to be very high (R^2=0.93). We then calculated the standard deviation (SD) of daily mean summer (June–August) temperature (summertime temperature variability) and the SD of daily mean winter (December–February) temperature (wintertime temperature variability) for each participant’s address. High or low temperature variability was dichotomously defined as higher or lower than the median of seasonal temperature variability.

$PM_{2.5}$ Exposure

We estimated fine particulate matter ($PM_{2.5}$) exposure based on Surface Extinction Coefficients (SEC) from Aerosol Optical Depth (AOD) retrieved from remote sensing data of the two National Aeronautics and Space Administration (NASA) Earth Observing System satellites.[18] AOD data were originally retrieved at a 10×10 km resolution, and were refined into 1×1 km resolution by modifying the Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm.[19] The relationship between SEC and $PM_{2.5}$ for each year from 1998 to 2010 was calibrated using grid cells with both SEC and $PM_{2.5}$ measurements. This yearly calibration was then used to estimate $PM_{2.5}$ at the residential location of each participant. The estimated $PM_{2.5}$ concentrations have been used in earlier studies in this cohort to reveal the association of $PM_{2.5}$ with mortality or hospital admissions. [20-22]

Individual and ecological covariates

We controlled for individual-level potential confounders, including age, sex, marital status, BMI, physical activity, housing type, education attainment, smoking status, medication taken, and personal monthly expenditure. As Tertiary Planning Units (TPUs) are the most commonly used units in the population census report in Hong Kong, we calculated the Social Deprivation Index (SDI) to control for TPU-level social deprivation. Details for the calculation of SDI were described elsewhere.[23 24] We also controlled for smoking rate (>15 years of age) at district-level.

Statistical Analysis

We used Cox proportional hazards models to estimate the association between seasonal temperature variability and incident respiratory diseases. Survival time was calculated from enrollment date to first hospital admission to respiratory diseases or death or 31 December 2010 (censoring), whichever came first. In order to separate the independent effects of summertime or wintertime temperature variability, we included yearly mean temperature and summertime and wintertime temperature variability simultaneously in the model and treated them as time-varying exposures. To do this, we used the counting process approach to the Cox proportional hazards model.[25] We controlled for individual-, TPU-, and district-level risk factors as mentioned above and included a linear term for year of follow-up to adjust for time trends. To allow for possible non-proportionality of hazard, age in year was treated as the stratification variable. We also examined age (≤70 y and >70 y), sex (female and male), marital status (married and unmarried), education attainment (below primary, primary, and secondary or above), personal monthly expenditure (low, medium, and high), and housing type (public and aided, private, and others) as the potential modifiers of the effects of seasonal temperature variability by including an interaction term between seasonal temperature variability and one effect modifier at a time in the model, and *p*-value of the interaction term was used to indicate statistical significance.

We performed a number of sensitivity analyses to test the robustness of our results. First, we used inverse distance weighting to spatially interpolate daily temperature for each participant, and then refitted the Cox proportional hazards regression model. Second, to control for competing diseases, we excluded participants who died or who had incidence of respiratory diseases during the first year after enrolment or excluded those who self-reported COPD/asthma at the baseline. Third, considering $PM_{2.5}$ concentration may vary from year to year, we further controlled for time-varying $PM_{2.5}$ in addition to all potential confounders mentioned above. We did not control for $PM_{2.5}$ in the main analysis as the role of air pollution on the association between ambient temperature and morbidity or mortality is complex and has not be fully elucidated.[26] Fourth, participants may move their homes during the 10 to 13 years of follow-up, so we excluded participants who changed their home addresses. We also tested the assumption of linearity for seasonal temperature variability by using natural cubic spline functions with three degrees of freedom.

The results were expressed as hazard ratio (HR) per 1°C increase in seasonal temperature variability. All analyses were conducted in *R* statistical environment version 3.3.0, with packages “geoR” to interpolate individual’s daily ambient temperature using ordinary kriging methods, and “survival” for survival analysis to estimate the hazard ratio.

RESULTS

A total of 66820 older people was enrolled in the initial study cohort. After excluding participants without sufficient address information for geocoding or with missing covariates, a final sample of 61446 (92.0%) was included in the final analyses. The spatial distribution of these 61446 older people is shown in **Figure 1**.

Table 1 shows the baseline descriptive characteristics of the 61446 participants included in this study. The mean age at entry of this cohort was 72 years old and female participants accounted for 65.9%. A total of 14168 (23.1%) participants' BMI were less than 21.6, and 16100 (26.2%) participants' BMI were greater than 26.3. The majority of participants did physical activity 7 times/week. About one-fifth (19.3%) were former smokers, and 9.6% were current smokers. About half the participants (46.0%) had education attainment below primary. Nearly half the participants (53.1%) took regular medication. Participants who were exposed to a higher wintertime temperature variability were more likely to be older, female, smokers, and have lower personal monthly expenditure but less likely to have a secondary or higher education and live in private house when compared with those exposed to a lower wintertime temperature variability (**Table 1**). There were no apparent long-term trends for yearly mean and seasonal mean temperatures from 1998 to 2010 based on temperatures monitored by the 22 weather stations (**Supplementary Figure S1**).

During the study period, summertime and wintertime temperature variability both approximated a normal distribution (**Figure 2**) with mean SDs of 1.4ºC and 3.2 ºC for summertime and wintertime, respectively. After 10-13 years of follow-up (from 1998 to 2010), there were 12689 emergency hospital admissions for respiratory diseases, among them pneumonia and COPD accounted for 52.6% (6672) and 24.2% (3075), respectively (**Table 2**).

Seasonal temperature variability and incident respiratory diseases

The associations of summertime and wintertime temperature variabilities with total incident respiratory diseases, pneumonia, and COPD were presented in **Table 2**. In the basic models stratified by age in years and adjusted for sex and year of follow-up, summertime temperature variability was not associated with increased risks of total incident respiratory diseases, pneumonia or COPD. The associations between wintertime temperature variability and incident respiratory diseases were all statistically significant. The HRs were modestly attenuated for summertime temperature variability in the fully adjusted models with additional adjustment for yearly mean temperature, marital status, housing type, BMI, education attainment, personal monthly expenditure, physical activity, medication taken, smoking status, SDI, and smoking rate at district level. For example, the fully adjusted HR for total respiratory diseases was 1.02 (0.80, 1.29) compared to 1.12 (0.91, 1.39) in the basic model. Results for wintertime temperature variability were also modestly attenuated in the full models but remained statistically significant. The HR was 1.20 (1.08, 1.32) for total incident respiratory diseases, 1.15 (1.01, 1.31) for pneumonia, and 1.41 (1.15, 1.71) for COPD per 1^{o}C change in wintertime temperature variability in the fully adjusted models.

In this Hong Kong elderly cohort, about 11.1% elders changed home addresses during the follow-up period. Excluding those participants from the analysis did not change the Cox regression results substantially (**Supplementary Table S1**). Sensitivity analyses excluding participants according to other criteria or further controlling for time-varying $PM_{2.5}$ exposure gave similar results (**Table 3**). We also used inverse distance weighting to spatially interpolate daily temperature for each participant and refitted the Cox proportional hazards regression, and we found results were similar to those using the ordinary kriging method (**Supplementary Table S2**). By comparing the linear and natural cubic spline models, we did not find any evidence of departure from linearity for the association between seasonal temperature variability and respiratory diseases hospitalizations.

Effect modification for seasonal temperatures variability

We examined associations of seasonal temperature variability with incident respiratory diseases in the fully adjusted models stratified by age (≤70 y and >70 y), sex (female and male), marital status (married and unmarried), education attainment (below primary, primary, and secondary or above), personal monthly expenditure (low, medium, and high), and housing type (public and aided, private, and others). No significant difference was observed by stratified characteristics, except for sex and personal monthly expenditure for the wintertime temperature variability (**Table 4**). Female and those with lower personal monthly expenditures had greater hazard ratios when exposed to wintertime temperature variability. Female also exhibited increased risk of respiratory hospitalizations after exposure to summertime temperature variability (**Supplementary Table S3**).

DISCUSSION

We found an association between wintertime temperature variability and total incident respiratory diseases, pneumonia, and COPD among a prospective Chinese elderly cohort that accounted for about 9% of all elders in Hong Kong. Such associations were stronger in females and participants in a lower social-economic position. We did not find any association between summertime temperature variability and incident respiratory diseases.

In the literature, temperature variability within a day or a few neighboring days has been consistently associated with respiratory mortality or hospitalizations.[12 27-30] For example, diurnal temperature change was generally associated with emergency hospital admissions for total respiratory, pneumonia, and COPD in four largest cities in Korea using a temperature-matched case-crossover study design.[12] Zhan et al. (2017) used the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) data from 106 communities of the United States during 1987 to 2000 to investigate the effect of temperature change between neighboring days (TCNs) on mortality, and found that prominent effects of TCNs on mortality for total respiratory, pneumonia, and COPD diseases.[28]

Temperature variability over a longer time duration (e.g. intraseasonal), however, has rarely been studied for its potential health effects. We identified three epidemiological studies that had previously examined the health impacts of seasonal temperature variability, measured as the SD of intraseasonal temperature, and all of these studies focused on mortality.[31-33] To our knowledge, this is the first study to link seasonal temperature variability with incident respiratory hospitalizations, thus our findings may enrich our understanding towards the health impacts of seasonal temperature variability.

In our study, we found a positive association between wintertime temperature variability and incident respiratory diseases. This is consistent with previous studies using mortality as the health outcome. For example, Shi et al. (2016) reported that for each 1°C increase in SD of winter temperature associated with 4.1% (95% CI, 3.0-5.2%) increases in annual deaths using Medicare data with 2.7 million residents aged 65 years and older for the years 2000-2008 in the New England region of the USA.[32]

Summertime temperature variability was not associated with incident respiratory diseases in our analyses, which is inconsistent with previous studies.[31 33] This difference may be due to differences in city climates. Multi-city studies have suggested that warm regions or areas with moderate winter climates have more significant cold effects than hot effects.[34 35] This phenomenon can be explained by long-term adaptation, as people in warm areas are generally more sensitive to cold weather.[36] Hong Kong has a subtropical climate, of which the summer is hot and humid. Epidemiological studies have suggested that heat effects in Hong Kong are not that evident,[14 37 38] possibly due to extensive use of air conditioning.

The biological mechanisms linking seasonal temperature variability with incident respiratory diseases have not been elucidated, although plausible explanations have been postulated. Temperature variability has been shown to affect the immune system's capability to resist infectious agents and cause more inflammatory nasal responses in patients with persistent allergic rhinitis, which may trigger respiratory events.[39 40] Also, exposure to seasonal temperature variability has been reported to impede one's ability to adapt to local climate, which may increase the likelihood of adverse health outcomes like respiratory diseases. [41 42] For example, locations with larger seasonal temperature variability produced stronger associations between daily temperature and mortality.[35 43]

We found greater effects of wintertime temperature variability among females, which is consistent with previous short-term temperature variability studies.[44-46] The reason for that is probably due to biological difference. We found elders with lower personal monthly expenditure were more sensitive to increased wintertime temperature variability. Low personal monthly expenditure is regarded as an indicator of low socioeconomic position. The increased vulnerability of people with low socioeconomic status may be related to poor baseline health status, limited access to health care and poor living condition.[46 47]

This study has some limitations. First, we obtained first occurrence of hospital admissions for respiratory diseases after enrollment. Respiratory disease hospitalizations prior to enrollment were not available so we could not identify participants who previously had respiratory diseases. However, sensitivity analysis excluding the participants with self-reported COPD/asthma at baseline gave similar estimates, which confirm the robustness of our findings. Second, as the subject recruitment was on a volunteering basis.[13] The participants in this study cohort could be more health conscious than the rest of the elderly population in Hong Kong. Third, the observed association between seasonal temperature variability might relate to the residents' perception of temperature modified by humidity and wind chill, for which not any fine resolution spatial data are available yet. Finally, individual household adaptation behaviors, such as heater or air conditioner usage, may affect the residents' personal exposure to seasonal temperature variability, measured only by outdoor weather stations. Although we did include house type in the regression model, it is still possible that the observed associations might be affected by temperature exposure misclassification. Despite these limitations, this is one of the few studies to examine the impacts of seasonal temperature variability on hospitalizations. Our findings might help us to better understand the impacts of climate change.

In conclusion, this study provides evidence that wintertime temperature variability increases the risks of incident total respiratory, pneumonia, and chronic obstructive pulmonary diseases in older people. These findings should help better understand the health impacts of climate change.

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Contributors FL and LWT contributed to the conception and design and interpreted the results; RSYL and CMW collected the cohort data; SZS and QH conducted statistical analyses; SZS, FL, JH, YW, LWT drafted the manuscript for important intellectual content. All authors critically reviewed and accepted the final version of the manuscript.

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Table 1. Descriptive characteristics of the prospective Chinese elderly cohort at baseline (1998-2001) by seasonal temperature variability.

Characteristic (%)	Total	Summertime temperature variability* (mean±SD: 1.4±0.2)		Wintertime temperature variability† (mean±SD: 3.2±0.5)	
		Low (1.2±0.1)	High (1.6±0.1)	Low (3.0±0.2)	High (3.4±0.1)
Participants, n	61446	30723	30723	30722	30724
Individual-level covariates					
Age at entry, yr					
≤ 70	29038 (47.3)	14450 (47.0)	14588 (47.5)	14848 (48.3)	14190 (46.2)
> 70	32408 (52.7)	16273 (53.0)	16135 (52.5)	15874 (51.7)	16534 (53.8)
Sex					
Male	20933 (34.1)	10384 (33.8)	10549 (34.3)	10930 (35.6)	10003 (32.6)
Female	40513 (65.9)	20339 (66.2)	20174 (65.7)	19792 (64.4)	20721 (67.4)
BMI quartiles					
1^{st} [<21.6]	14168 (23.1)	7100 (23.1)	7068 (23.0)	7143 (23.3)	7025 (22.9)
2^{nd}- 3^{rd} [21.6-26.3]	31178 (50.7)	15574 (50.7)	15604 (50.8)	15616 (50.8)	15562 (50.7)
4^{th} [>26.3]	16100 (26.2)	8049 (26.2)	8051 (26.2)	7963 (25.9)	8137 (26.5)
Smoking status					
Never	43668 (71.1)	21946 (71.4)	21722 (70.7)	22058 (71.8)	21610 (70.3)
Former	11871 (19.3)	5830 (19.0)	6041 (19.7)	5791 (18.8)	6080 (19.8)
Current	5907 (9.6)	2947 (9.6)	2960 (9.6)	2873 (9.4)	3034 (9.9)
Exercise in days/week					
Never [0]	9406 (15.3)	4667 (15.2)	4739 (15.4)	4784 (15.6)	4622 (15.0)
Medium [1-6]	7788 (12.7)	3996 (13.0)	3792 (12.3)	4172 (13.6)	3616 (11.8)
High [7]	44252 (72.0)	22060 (71.8)	22192 (72.2)	21766 (70.8)	22486 (73.2)
Education attainment					
Below primary	28241 (46.0)	14201 (46.2)	14040 (45.7)	13268 (43.2)	14973 (48.7)
Primary	22656 (36.9)	11434 (37.2)	11222 (36.5)	11162 (36.3)	11494 (37.4)
Secondary or above	10549 (17.2)	5088 (16.6)	5461 (17.8)	6292 (20.5)	4257 (13.9)
Housing type					
Private	32458 (52.8)	16359 (53.2)	16099 (52.4)	18239 (59.4)	14219 (46.3)
Public and aided	25096 (40.8)	12503 (40.7)	12593 (41.0)	10664 (34.7)	14432 (47.0)
Other	3892 (6.3)	1861 (6.1)	2031 (6.6)	1819 (5.9)	2073 (6.7)
Expenses/month in USD$					
Low [<128]	10122 (16.5)	5021 (16.3)	5101 (16.6)	5169 (16.8)	4953 (16.1)
Medium [128-384]	42151 (68.6)	21092 (68.7)	21059 (68.5)	20576 (67.0)	21575 (70.2)
High [≥385]	9173 (14.9)	4610 (15.0)	4563 (14.9)	4977 (16.2)	4196 (13.7)
Medication taken					
Yes	32627 (53.1)	16397 (53.4)	16230 (52.8)	16430 (53.5)	16197 (52.7)
No	28819 (46.9)	14326 (46.6)	14493 (47.2)	14292 (46.5)	14527 (47.3)
TPU-level covariates					
SDI (mean ± SD)	13.8 (2.0)	13.9 (2.1)	13.8 (2.0)	14 (2.3)	13.7 (1.8)
District-level covariate					
Smoking rate (mean ± SD)	11.6 (0.4)	11.6 (0.3)	11.5 (0.4)	11.6 (0.3)	11.5 (0.4)

Abbreviation: BMI = body mass index; TPU = tertiary planning units; SDI = social deprivation index.

*High and low summertime temperature variability was defined by the median (1.4ºC) of the standard deviation of daily mean summer temperature;

†High and low wintertime temperature variability was defined by the median (3.2 ºC) of the standard deviation of daily mean winter temperature.

Table 2. Hazard ratio (HR) and 95% CI per 1°C increase of seasonal temperature variability on incident respiratory diseases in the prospective Chinese elderly cohort in Hong Kong.

Incident Diseases	Cases	Summertime temperature variability		Wintertime temperature variability	
		Basic model[*]	Full model[†]	Basic model[*]	Full model[†]
Total respiratory diseases	12689	1.12 (0.91, 1.39)	1.02 (0.80, 1.29)	1.50 (1.39, 1.62)	1.20 (1.08, 1.32)
Pneumonia	6672	1.06 (0.78, 1.43)	1.04 (0.75, 1.44)	1.31 (1.18, 1.46)	1.15 (1.01, 1.31)
COPD	3075	1.14 (0.75, 1.74)	1.05 (0.65, 1.69)	1.96 (1.67, 2.30)	1.41 (1.15, 1.71)

Abbreviations: COPD=chronic obstructive pulmonary disease.

*Stratified by age in years, adjusting for sex and year of follow-up, and summertime temperature variability and wintertime temperature variability were mutual adjusted.

†Additionally adjusted for yearly mean temperature, marital status, housing type, BMI, education attainment, personal monthly expenditure, physical activity, medication taken, smoking status, social deprivation index (SDI), and smoking rate at the district level.

Table 3. Hazard ratio (HR) and 95% CI per 1°C increase of seasonal temperature variability on incident respiratory diseases in the sensitivity analyses.

Incident Diseases	Cases	Summertime temperature variability		Wintertime temperature variability	
		Basic model*	Full model†	Basic model*	Full model†
Excluding those with incident respiratory diseases or died in the first year					
Total respiratory diseases	12110	1.11 (0.89, 1.38)	1.01 (0.79, 1.30)	1.47 (1.36, 1.60)	1.18 (1.07, 1.31)
Pneumonia	6591	1.07 (0.79, 1.45)	1.06 (0.76, 1.48)	1.31 (1.18, 1.46)	1.16 (1.01, 1.32)
COPD	2877	1.14 (0.73, 1.76)	1.05 (0.64, 1.71)	1.92 (1.63, 2.26)	1.36 (1.11, 1.66)
Excluding those with self-reported COPD/asthma at baseline					
Total respiratory diseases	10794	1.02 (0.81, 1.29)	0.96 (0.74, 1.25)	1.44 (1.32, 1.57)	1.17 (1.05, 1.30)
Pneumonia	5890	1.10 (0.80, 1.52)	1.12 (0.79, 1.59)	1.28 (1.14, 1.43)	1.13 (0.98, 1.31)
COPD	1896	1.07 (0.62, 1.85)	1.03 (0.56, 1.90)	1.78 (1.45, 2.17)	1.30 (1.01, 1.67)
Further adjusted for time-varying $PM_{2.5}$					
Total respiratory diseases	12689	1.12 (0.91, 1.39)	1.08 (0.84, 1.40)	1.50 (1.39, 1.62)	1.18 (1.06, 1.31)
Pneumonia	6672	1.06 (0.78, 1.43)	1.07 (0.75, 1.52)	1.31 (1.18, 1.46)	1.17 (1.02, 1.34)
COPD	3075	1.14 (0.75, 1.74)	1.15 (0.69, 1.92)	1.96 (1.67, 2.30)	1.41 (1.15, 1.74)

Abbreviations: COPD=chronic obstructive pulmonary disease.

*Stratified by age in years, adjusting for sex and year of follow-up, and summertime temperature variability and wintertime temperature variability were mutual adjusted.

†Additionally adjusted for yearly mean temperature, marital status, housing type, BMI, education attainment, personal monthly expenditure, physical activity, medication taken, smoking status, social deprivation index (SDI), and smoking rate at the district level.

Table 4. Hazard ratio (HR) and 95% CI per 1°C increase in wintertime temperature variability stratified by population characteristics in the prospective Chinese elderly cohort in Hong Kong, 1998 – 2010.

Stratified Characteristics	Total respiratory (n=12689)			Pneumonia (n=6672)			COPD (n=3075)		
	Cases	HR (95% CI)	$P_{Interaction}$	Cases	HR (95% CI)	$P_{Interaction}$	Cases	HR (95% CI)	$P_{Interaction}$
Age at entry, yr									
≤70	3596	1.26 (1.10, 1.45)		1599	1.27 (1.04, 1.55)		855	1.46 (1.10, 1.94)	
>70	9093	1.17 (1.05, 1.30)	0.28	5073	1.12 (0.97, 1.28)	0.19	2220	1.38 (1.12, 1.71)	0.69
Sex									
Male	5368	1.13 (1.02, 1.26)		2901	1.06 (0.92, 1.22)		1792	1.34 (1.09, 1.66)	
Female	7321	1.24 (1.12, 1.38)	0.01	3771	1.22 (1.06, 1.40)	0.002	1283	1.49 (1.20, 1.85)	0.18
Marital status									
Unmarried	6802	1.20 (1.09, 1.34)		3607	1.17 (1.02, 1.35)		1536	1.46 (1.18, 1.80)	
Married	5887	1.19 (1.07, 1.32)	0.68	3065	1.13 (0.98, 1.30)	0.40	1539	1.35 (1.09, 1.68)	0.34
Education attainment									
Below Primary	6350	1.22 (1.10, 1.35)		3300	1.19 (1.04, 1.37)		1398	1.44 (1.16, 1.78)	
Primary	4557	1.17 (1.05, 1.31)	0.28	2388	1.10 (0.95, 1.28)	0.13	1268	1.37 (1.10, 1.71)	0.55
Secondary or above	1782	1.14 (1.00, 1.31)	0.22	984	1.11 (0.93, 1.32)	0.30	409	1.38 (1.05, 1.82)	0.73
Housing type									
Public and aided	5544	1.19 (1.07, 1.33)		2862	1.22 (1.05, 1.41)		1403	1.43 (1.14, 1.79)	
Private	5714	1.22 (1.10, 1.35)	0.53	3002	1.11 (0.97, 1.28)	0.06	1340	1.43 (1.16, 1.77)	0.98
Other	1431	1.15 (1.00, 1.32)	0.56	808	1.15 (0.96, 1.37)	0.44	332	1.27 (0.96, 1.69)	0.37
Expenses/money in USD$									
Low [<128]	1857	1.32 (1.16, 1.50)		1001	1.25 (1.05, 1.48)		427	1.34 (1.02, 1.75)	
Medium [128-384]	8700	1.18 (1.07, 1.31)	0.03	4508	1.14 (1.00, 1.31)	0.17	2181	1.45 (1.19, 1.78)	0.43
High [≥385]	2132	1.17 (1.03, 1.33)	0.06	1163	1.12 (0.95, 1.32)	0.18	467	1.22 (0.93, 1.59)	0.51

Legend of figures

Figure 1. Locations of participants in the prospective Chinese elderly cohort (n=61446) at baseline (1998 to 2001) and weather monitoring stations (n=22) in Hong Kong.

Figure 2. Distribution of the standard deviation of daily mean summer and winter temperatures.