Original research

Short-term association among meteorological variation, outdoor air pollution and acute bronchiolitis in children in a subtropical setting

Shuk Yu Leung,¹ Steven Yuk Fai Lau,² Ka Li Kwok,¹ Kirran N. Mohammad,² Paul Kay Sheung Chan,³ Ka Chun Chong [©] ^{2,4,5}

ABSTRACT Objectives To examine the association among

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¹Department of Paediatrics, Kwong Wah Hospital, Hong Kong, China ²School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong, China ³Department of Microbiology, The Chinese University of Hong Kong, Hong Kong, China ⁴Clinical Trials and Biostatistics Laboratory, Shenzhen Research Institute, The Chinese University of Hong Kong, Shenzhen, China ⁵Centre for Health Systems and Policy Research, The Chinese University of Hong Kong, Hong Kong, China

Correspondence to

Dr Ka Chun Chong, School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong, China; marc@cuhk.edu.hk

Received 7 June 2020 Revised 16 October 2020 Accepted 26 October 2020 Published Online First 20 January 2021 acute bronchiolitis-related hospitalisation in children, meteorological variation and outdoor air pollution. **Methods** We obtained the daily counts of acute bronchiolitis-related admission of children≤2 years old from all public hospitals, meteorological data and outdoor air pollutants' concentrations between 1 January 2008 and 31 December 2017 in Hong Kong. We used quasi-Poisson generalised additive models together with distributed lag non-linear models to estimate the associations of interest adjusted for confounders. Results A total of 29688 admissions were included in the analysis. Increased adjusted relative risk (ARR) of acute bronchiolitis-related hospitalisation was associated with high temperature (ambient temperature and apparent temperature) and was marginally associated with high vapour pressure, a proxy for absolute humidity. High concentration of NO₂ was associated with elevated risk of acute bronchiolitis admission; the risk of bronchiolitis hospitalisation increased statistically significantly with cumulative NO₂ exposure over the range 66.2–119.6 μ g/m³. For PM₁₀, the significant effect observed at high concentrations appears to be immediate but not long lasting. For SO₂, ARR increased as the concentration approached the 75th percentile and then decreased though the association was insignificant. **Conclusions** Acute bronchiolitis-related hospitalisation among children was associated with temperature and exposure to NO₂ and PM₁₀ at different lag times, suggesting a need to adopt sustainable clean air policies, especially to target pollutants produced by motor vehicles, to protect young children's health.

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INTRODUCTION

Acute bronchiolitis is typically caused by viral infection. Respiratory syncytial virus (RSV) is the most common pathogen in childhood respiratory tract infection, especially among those ≤ 2 years old.¹⁻³ Clinical signs and symptoms of acute bronchiolitis include cough, tachypnoea, hyperinflation of lungs, chest retraction, inspiratory crackles and expiratory wheeze.^{2 3}

Acute bronchiolitis causes significant morbidity and mortality among infants and young children worldwide.¹ It is the most common cause of lower respiratory tract infection (LTRI)-related hospitalisation.^{1–3} In the USA, acute bronchiolitis is the leading cause of hospitalisation among infants

Key messages

What is the key question?

Are meteorological variation and outdoor air pollution associated with acute bronchiolitisrelated hospitalisation in children?

What is the bottom line?

 Acute bronchiolitis-related hospitalisation among children was associated with temperature and exposure to NO₂ and PM₁₀ at different lag times.

Why read on?

 This is one of the very few studies that explored the association of interest in a subtropical setting.

 \leq 1 year old.⁴ Nearly all children would be infected at least once by the time they reached the age of 2 years, and an estimated 2%–3% of all children would be hospitalised with acute bronchiolitis during their first year of life.^{2 3 5 6} In temperate regions, the annual epidemics usually last from November all the way till April with a peak observed in January or February.^{5 6} Similar patterns could be seen in European countries where the average RSV season commences in the beginning of December, peaks in early February and ends in early April.⁷

In Hong Kong, acute bronchiolitis is one of the major causes of hospital admissions among infants under the age of one. Up to 5% of total paediatric discharge from all hospitals under the Hong Kong Hospital Authority are attributed to this condition.⁸ In a single hospital study, the estimated incidence of bronchiolitis hospitalisation was 21 per 1000 among children ≤ 2 years old with 86% of them having been infected with RSV.⁹ Different from the USA and Europe, Hong Kong is located within the subtropical region where RSV season remains ill-defined but usually overlaps with the rainy season (ie, from March to September).^{3 8}

Global surveillance suggested that the seasonal periodicity of RSV infection is related to climatic factors.¹⁰ Meteorological conditions including ambient temperature, rainfall and humidity were reported to be associated with RSV activity,^{6 10-12} while altitude, wind speed, dew point and ultraviolet B radiance were reported to be associated



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with bronchiolitis.^{11 12} On the other hand, air pollutants such as primary traffic pollutants, ozone (O_3), fine suspended particulates ($PM_{2.5}$) and environmental nitrogen dioxide (NO_2), as well as living close to major roadways have been reported to be associated with exacerbation of respiratory infections in young children.^{13 14} Hong Kong is a densely populated cosmopolitan city in southern China with hot and humid summers, and mild and dry winters. According to the 2016 Population By-census Hong

southern China with hot and numic summers, and mild and dry winters. According to the 2016 Population By-census, Hong Kong had a population of 7.34 million.¹⁵ Motor vehicles are the main source of air pollutants in Hong Kong. According to the air quality guideline of the WHO, 8 hours daily mean of O₃ should not exceed 100 μ g/m³, while annual mean level of respirable suspended particulates (PM₁₀) and NO₂ should not exceed 20 μ g/m³ and 40 μ g/m³, respectively.¹⁶ Unfortunately, in Hong Kong, the highest 8 hours mean concentration recorded for O₃ was 305 μ g/m³ and the highest annual mean concentrations recorded for PM₁₀ and NO₂ were 46 μ g/m³ and 97 μ g/m³, respectively, in 2017, all of which exceeded the WHO's guideline limits.¹⁷

Previous studies suggested that acute bronchiolitis-related hospitalisation in children is associated with meteorological variation but its association with outdoor air pollution has not been well explored.^{6 9-14 18 19}Furthermore, only limited studies have been conducted in subtropical regions, most of which yielded inconsistent results.^{8 9 18 19} Therefore, in this study, we aim to evaluate the possible short-term association among acute bronchiolitis-related hospitalisation in children, meteorological variation and outdoor air pollution in Hong Kong.

METHODS Study design

This is a retrospective time-series study to assess the short-term impacts of meteorological variation and outdoor air pollution on acute bronchiolitis-related hospitalisation among young children. We obtained the daily counts of acute bronchiolitis-related admission of children ≤ 2 years old from a total of 12 public hospitals with acute paediatric inpatient services, daily meteorological data and daily outdoor air pollutants' concentrations between 1 January 2008 and 31 December 2017.

Hospital admission data

In Hong Kong, paediatric care services are provided by both the public and private sectors. Approximately, 71% of all hospitalisations in 2016 occurred in public hospitals.²⁰ The retrospective data of admissions of children ≤ 2 years old to all public hospitals for acute bronchiolitis (International Classification of Diseases 9th version (ICD-9): 466.1 in principal and secondary diagnosis) from 1 January 2008 to 31 December 2017 were extracted for statistical modelling. Data on influenza-associated hospital admission (ICD-9: 487.0, 487.1, 487.8) were also collected.

Meteorological data

Daily meteorological records measured at a single central monitoring station run by the Hong Kong Observatory were obtained for the study period, including mean ambient temperature (°C), mean relative humidity (RH%) and total rainfall (mm), from the open-access data available on their website (https://www.hko. gov.hk/cis/climat_e.htm). Actual vapour pressure (hPa), a proxy for absolute humidity well adopted in many environmental studies^{21 22} was then derived using Teten's formula²³:

$$e = \frac{RH}{100} \times 6.105 \times exp\left(\frac{17.27 \times TEMP}{237.7 + TEMP}\right)$$

where e, RH and TEMP denote actual vapour pressure, relative humidity and ambient temperature, respectively. Apparent temperature (°C) was derived using the following formula²⁴:

Apparent temperature $= 1.04 \times TEMP + 0.2$

 $\times e - 0.65 \times WIND - 2.7$

where TEMP and e are as defined above and WIND denotes wind speed (m/s).

Ambient air pollutants data

Daily average levels of air pollutants measured at 13 general air monitoring stations (Central/Western, Eastern, Kwai Chung, Kwun Tong, Sham Shui Po, Shatin, Tai Po, Tap Mun, Tseng Kwan O, Tsuen Wan, Tuen Mun, Tung Chung and Yuen Long), including nitrogen dioxide (NO₂), sulphur dioxide (SO₂), ozone (O₃) and particulate matters (PM_{10}), were retrieved from the official website of the Environmental Protection Department of Hong Kong (https://cd.epic.epd.gov.hk/EPICDI/air/station/? lang=en). Data from Tap Mun station were excluded because it is situated in a remote area with very low population density, thus, might not represent the exposure of the general population. Data from the remaining 12 general air monitoring stations were averaged for downstream analysis.

Statistical analyses

Descriptive statistics were used to describe the demographic characteristics of the patients. A quasi-Poisson generalised additive model was used in conjunction with the distributed lag non-linear models (DLNMs) to assess the potentially lagged non-linear short-term associations between acute bronchiolitis-related hospitalisation of young children, meteorological variation and outdoor air pollution. In the DLNM, cross-basis is a bidimensional functional space created by combining two preselected sets of basis functions, which specify the relationships in the dimensions of an independent variable and lags, respectively. Algebraically, the cross-basis function of an independent variable X at time t with a maximum lag of L can be expressed in the following form:

$$cb(X, t, L) = \sum_{j=1}^{\nu_x} \sum_{k=1}^{\nu_1} \boldsymbol{r}_{ij.}^T \boldsymbol{c}_{.k} \eta_{jk}$$

where \mathbf{r}_{ij} is an $(L + 1) \times 1$ vector representing the jth basis variable of X across the (L+1) lags, \mathbf{c}_k is an $(L + 1) \times 1$ vector obtained by transforming the lag vector $\mathbf{l} = [0, 1, \dots, L]$ using the *k*th basis function in the lag dimension, v_x and v_i are the dimensions of the basis functions of \mathbf{x}_t and respectively, and η_{jk} is the unknown regression coefficient.²⁵

The form of the primary model is as follows:

 $log [E (Y_{t})] = + cb (TEMP, t, L) + cb (RH, t, L) + cb (factor (RAINFALL), t, L) + cb (NO_{2}, t, L) + cb (log (PM_{10}), t, L) + cb (O_{3}, t, L) + cb (log (SO_{2}), t) + cb (log (SO_{2}), t, L) + cb (log (SO_{2}), t) + cb (log (SO_{2}),$

cb (factor (HOLIDAY), t, L) + ns (DOS_t, df = 7 per year) +

factor
$$(DOW_t) + s(\sqrt{FLU_t}, k = 7)$$

where $E(Y_t)$ is the daily expected count of acute bronchiolitis admissions on day *t*; TEMP, RH, RAINFALL denote ambient temperature, relative humidity, and total rainfall, respectively; DOS_t and DOW_t denote day of study and day of week on day *t* respectively; α is the overall intercept; *factor*(.) is a set of indicator functions for any categorical independent variable, and s(.) denotes a smoothing spline function with maximum basis dimension k. In this study, natural cubic spline functions (ns) with 2 and 3 knots placed at equally spaced intervals were chosen as the basis function of the meteorological parameters (except for rainfall) and pollutants, respectively, which is equivalent to 3 and 4 degrees of freedom (df) respectively; whereas an ns function with 2 knots placed at logarithmically equal intervals, which is equivalent to 4 df, was selected as the basis function of lag. DOS was modelled using an ns function with 7 df per year. The incubation period for acute bronchiolitis is usually 5-7 days and disease period is usually 1-2 weeks⁵; hence, the maximum lags for independent variables were assumed to be 21 days. Total rainfall was categorised into three groups, namely 0mm, 0 to 38.8mm (the 95th percentile) and >38.8mm, so as to better examine the effect of extreme rainfall and reduce the influence of outliers.²⁶ SO₂ and PM_{10} were log transformed to reduce skewness and the influence of outliers. An indicator variable HOLIDAY which denotes whether a specific day was a holiday, DOS, DOW and the square root of the number of influenza-associated hospital admission on the same day (FLU) were included in the model for confounder control. To further assess the adjusted effect of absolute humidity and apparent temperature on the daily counts of acute bronchiolitis admissions, two secondary models with vapour pressure in place of ambient temperature and relative humidity, and apparent temperature in place of ambient temperature were fitted due to high correlations between these meteorological variables (online supplemental appendix section A).

All results were reported in terms of overall cumulative adjusted relative risks (ARR), which accumulated the ARRs over the lag period of 21 days, along with the corresponding 95% CI, and ARR plots by lag at selected percentiles, at which the adjusted risks at a specific lag and percentile were compared with that at the reference value on the concurrent day. The reference values for rainfall and all pollutants were 0 mm and their corresponding 5th percentile, respectively, whereas the medians were chosen as the reference values for ambient temperature, apparent temperature, relative humidity and vapour pressure.

Model diagnostics and sensitivity analysis

Adjusted R^2 and residual plots were used to assess the goodness of fit of the final models. Partial autocorrelation function (PACF) plots were used to assess partial autocorrelation of residuals, with absolute values of pacfs <0.1 at the first 30 lag days regarded as adequate fit.²⁷ Sensitivity analyses were conducted to assess the robustness of the final results to the initial model choices. To be specific, changes in the overall cumulative ARRs induced by the alternation of the *df*s of the basis functions for meteorological parameters (2 and 4 except for rainfall), pollutants (3 and 5), and lag dimensions (3 and 5), as well as that of *ns* function for DOS (6 and 8 per year) were examined. The cut-off values for categorising total rainfall were also altered (online supplemental appendix section B).

All statistical analyses were performed using R V.3.6.0. (R Development Core Team, 2018: https://www.rproject.org/) and the raw outputs were listed in online supplemental appendix section E.

RESULTS

A total of 31523 admissions from 2008 to 2017 were retrieved from the database, out of which 1835 were elective admission, and thus, were excluded in the analysis. Among the remaining 29 688 admissions, 66% were infants ≤ 12 months, 4% were preterm babies (<37 weeks), 68% were male and 99% were Asian. The median (IQR) length of stay was 3 days (2–4 days). 21.5% of cases were admitted more than once with acute bronchiolitis. During the study period, a total number of 10 deaths were recorded, corresponding to a mortality rate of 0.04% (table 1). The major causes of these deaths were respiratory failure and multiple organ failure. Each hospital applies different practices based on different priorities. Some hospitals might not examine nasopharyngeal aspirates (NPA) for pathogens since the results would not affect their medical management. From the available NPA results, RSV was the most common pathogen causing acute bronchiolitis in infants.

During the study period, the median (IQR) number of daily acute bronchiolitis admission was 8 (5–10) (table 2). The median (IQR) mean daily ambient temperature and mean relative humidity were 24.8°C (19.2°C–28.2°C) and 79% (74%–86%), respectively. According to the results, acute bronchiolitis was shown to exhibit seasonal pattern, with a major peak in spring (February–April) which could attain >400 cases per month, and a minor peak in late summer (September–October) having around 250 cases per month (figure 1).

Figure 2A–D show the overall cumulative ARRs and percentilespecific (5th, 25th, 75th and 95th percentiles) ARRs of acute bronchiolitis-related hospitalisation among children≤2 years old. The patterns of the overall cumulative ARR for ambient temperature and apparent temperature were similar, which showed an overall increasing trend (figure 2A,B). For ambient temperature, when the median (24.8°C) was taken as reference, the overall cumulative ARRs at the 5th, 25th, 75th and 95th percentiles were 0.990 (95% CI 0.721 to 1.361), 1.048 (95% CI 0.846 to 1.298), 1.034 (95% CI 0.904 to 1.182), and 1.108 (95% CI 0.871 to 1.409), respectively; whereas for apparent temperature, when the median (23.6°C) was taken as reference, resulted ARRs at the four percentiles were 1.005 (95% CI 0.761 to 1.326), 1.044 (95% CI 0.873 to 1.247), 1.112 (95% CI 0.962 to 1.286), and 1.323 (95% CI 1.011 to 1.731), respectively. It was found that, at the 75th and 95th percentiles of both ambient temperature and apparent temperature, the ARRs were statistically significant since lag 16-17 days.

For relative humidity (figure 2C), the overall cumulative ARR was comparatively higher when relative humidity was low compared with when it was high. When the median relative humidity (79.0%) was taken as reference, the overall cumulative ARRs at the 5th, 25th, 75th and 95th percentiles were 1.012 (95% CI 0.828 to 1.236), 0.987 (95% CI 0.901 to 1.080), 1.034 (95% CI 0.936 to 1.143) and 1.087 (95% CI 0.836 to 1.414), respectively. A delayed effect of high relative humidity (95th percentile) on the admission was evident: the estimated ARR was <1 from the concurrent day up to lag 4 days and was >1 afterwards.

The adjusted association between vapour pressure and the risk of acute bronchiolitis-related hospitalisation looked like a combination of the association of ambient temperature and that of relative humidity (figure 2D). Although the association appeared to be flattened U-shape, the risks were relatively higher at the higher end. Using median (24.7 hPa) as the reference value, the overall cumulative ARRs at the 5th, 25th, 75th and 95th percentiles were 1.056 (95% CI 0.851 to 1.311), 1.019 (95% CI 0.884 to 1.173), 1.070 (95% CI 0.903 to 1.267) and 1.125 (95% CI 0.864 to 1.466), respectively. While at the 5th percentile, the risk was relatively lower from the concurrent day to lag 3 days and was relatively higher up to lag 17 days. At moderately high (75th percentile) and very high (95th

ariable	N (%)
dmission	29688
Emergency	
dmission age, months	
Mean (SD)	10.6 (6.6)
0–6 moths	10247 (34.5%)
7–12 moths	9224 (31.1%)
13–18 moths	6116 (20.6%)
19–24 moths	4101 (13.8%)
estation age	
Preterm (<37 weeks)	1145 (3.9%)
Full term (≥37 weeks)	28543 (96.1%)
ender	
Male	20147 (67.9%)
Female	9541 (32.1%)
ace	
Asian	26 418 (89.0%)
Non-Asian	452 (1.5%)
Unknown	2818 (9.5%)
rincipal diagnosis	
Acute bronchiolitis	27 009 (91.0%)
Pneumonia	837 (2.8%)
Acute respiratory disease	392 (1.3%)
Gastroenteritis	314 (1.1%)
Croup	281 (0.9%)
Influenza	199 (0.7%)
Febrile convulsions	130 (0.4%)
Others for example, infection disease	526 (1.8%)
ength of hospitalisation (days)	520 (110 /0)
Mean (SD)	3.7 (12.6)
1	4815 (16.2%)
2	8312 (28.0%)
3	6180 (20.8%)
4	3760 (12.7%)
5	2301 (7.8%)
6	1532 (5.2%)
7	942 (3.2%)
>7	1846 (6.2%)
>/ nplanned readmission*	6383 (21.5%)
	6383 (21.5%) 10/23 305 (0.04%)
eath episode	10/25 505 (0.04%)
Pospiratory supertial visus	0605/22.011 /44.00/)
Respiratory syncytial virus	9695/22 011 (44.0%)
Parainfluenzae	636/9607 (6.6%)
Metapneumovirus	424/6098 (7.0%)
Adenovirus	403/21 276 (1.9%)
Influenza A	71/6937 (1.0%)
Influenza B	18/6901 (0.3%) unscheduled emergency

percentile) vapour pressures, the association was more complicated. The estimated ARR was >1 from lag 1 to 5 or 6 days as well as lag 15 days onwards, and was statistically significant since lag 18 days.

Total rainfall did not show a statistically significant relationship with the risk of hospitalisation adjusted for other variables in the model (figure 3). Nevertheless, there was apparently a harvesting effect at extreme rainfall (>38.8 mm), at which the risk was relatively higher during the first few lag days. We have tested the robustness of different cut-off values for categorising total rainfall and our results were not sensitive to the variation (online supplemental appendix section B).

The overall cumulative effects and percentile-specific (25th, 50th, 75th and 95th percentiles) effects of the air pollutants on acute bronchiolitis-related hospitalisation among children ≤ 2 years old are shown in figure 4A–D. High concentrations of NO₂ were associated with elevated risks of acute bronchiolitis admission. In particular, the overall cumulative risk of bronchiolitis hospitalisation increased significantly when NO₂ was between 66.2 and 119.6 µg/m³. The overall cumulative ARRs at the 25th, 50th, 75th and 95th percentiles were 1.013 (95% CI 0.849 to 1.208), 1.038 (95% CI 0.831 to 1.297), 1.237 (95% CI 0.961 to 1.592) and 1.643 (95% CI 1.155 to 2.338), respectively. At high concentration of NO₂, the estimated risk was statistically significantly higher after a lag of 2 weeks.

At very high concentrations of PM_{10} , the estimated overall cumulative adjusted risks tended to be higher than that at their corresponding 5th percentile despite statistical insignificance. For PM_{10} , the overall cumulative ARRs at the 25th, 50th, 75th and 95th percentiles were 1.084 (95% CI 0.916 to 1.282), 0.962 (95% CI 0.730 to 1.267), 0.793 (95% CI 0.572 to 1.099) and 0.756 (95% CI 0.522 to 1.094), respectively, and its effect appears to be immediate but not long lasting: the risk on the concurrent day was significantly higher at all percentile levels than if the exposure level had been the fifth percentile. The ARRs on the concurrent day at the four percentiles were 1.046 (95% CI 1.009 to 1.083), 1.056 (95% CI 1.005 to 1.110), 1.063 (95% CI 1.001 to 1.128) and 1.072 (95% CI 1.000 to 1.150), respectively.

For O_3 , the overall cumulative ARRs at the 25th, 50th, 75th and 95th percentiles were 0.838 (95% CI 0.703 to 1.001), 0.934 (95% CI 0.751 to 1.162), 0.965 (95% CI 0.758 to 1.230) and 0.962 (95% CI 0.711 to 1.301), respectively, except for the 25th percentile the risk tended to be higher during lag 1–7 days and was lower afterwards.

For SO₂, the estimated ARR was above 1 when $\log(SO_2)$ was between 1.65 and 3.35, which was equivalent to the interval 5.21–28.5 µg/m³ in the original scale. The overall cumulative ARRs at the 25th, 50th, 75th and 95th percentiles were 1.083 (95% CI 0.916 to 1.279), 1.179 (95% CI 0.952 to 1.460), 1.234 (95% CI 0.955 to 1.596) and 1.065 (95% CI 0.740 to 1.534), respectively. The patterns of ARR by lag at the four selected percentiles were similar. The estimated ARR was greater than 1 across lag 1–15 days.

Concerning model diagnostics, the adjusted R^2 of the primary model was 47.4%, and that of the two secondary models with apparent temperature and vapour pressure were 48.0% and 47.2%, respectively. The absolute values of PACFs of the residuals for the first 30 lags were all <0.1. In the sensitivity analyses, reducing the annual number of df for calendar time from 7 to 6 had the largest effect on the results (online supplemental appendix section C and D).
 Table 2
 Summary statistics of daily acute bronchiolitis hospital admissions, meteorological conditions and air pollutant concentrations in Hong

 Kong during 2008 to 2017

	Minimum	5th percentile	25th percentile	Median	75th percentile	95th percentile	Maximum
Daily numbers of admissions due to acute bronchiolitis	0.0	3.0	5.0	8.0	10.0	15.0	27.0
Temperature (°C)	4.9	14.1	19.2	24.8	28.2	30.1	32.4
Apparent temperature (°C)	-7.3	8.9	16	23.6	29.2	32.4	35.1
Relative humidity (%)	29.0	59.0	74.0	79.0	86.0	94.0	99.0
Total rainfall (mm)	0.0	0.0	0.0	0.0	1.9	38.8	307.1
Vapour pressure (hPa)	4.4	10.6	17.3	24.7	31.3	33.5	35.5
NO ₂ (µg/m ²)	12.6	29.0	39.6	49.4	62.5	86.5	163.6
Ο ₃ (μg/m²)	4.7	12.6	20.8	35.0	55.0	85.2	149.1
SO ₂ (μg/m²)	3.1	5.2	7.3	10.2	14.9	26.3	73.3
PM ₁₀ (μg/m ²)	7.6	15.0	23.9	37.6	57.4	87.7	572.9

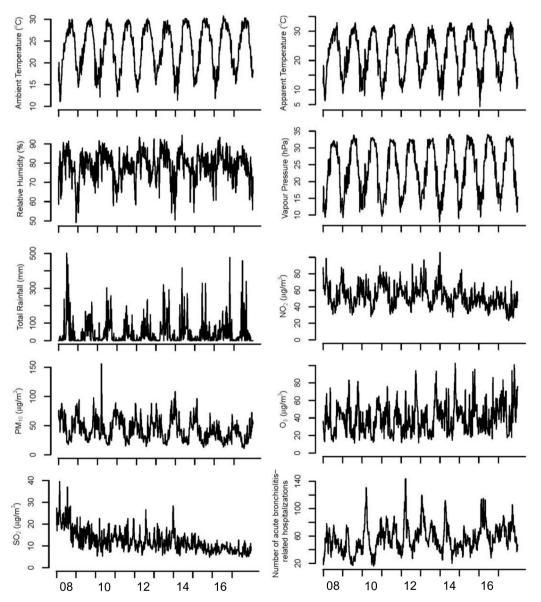


Figure 1 Seasonal variation in the weekly numbers of acute bronchiolitis-related admissions, meteorological parameters (monthly average ambient temperature, apparent temperature, relative humidity, vapour pressure and total rainfall), and air pollution level (monthly average nitrogen dioxide (NO_3) , ozone (O_3) , sulphur dioxide (SO_3) , and PM_{10}) in Hong Kong during 2008 to 2017.

Respiratory epidemiology

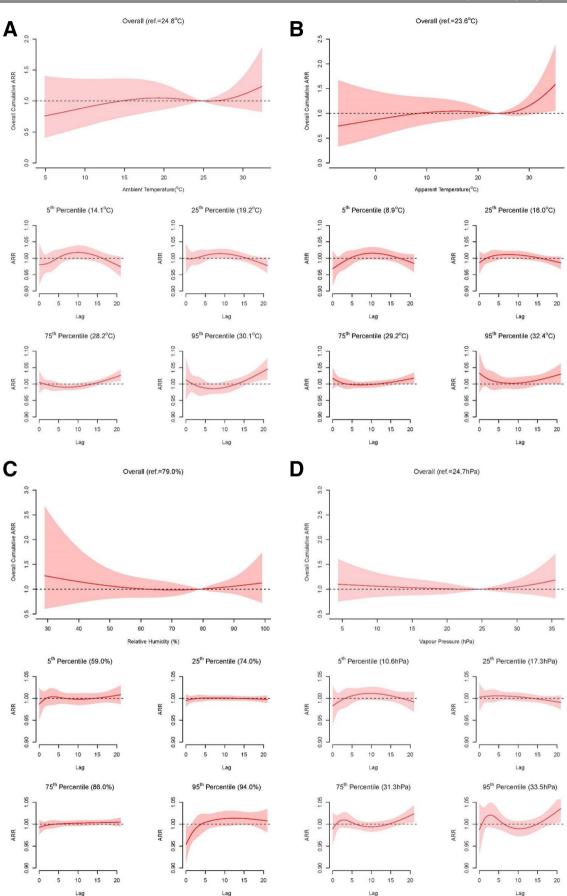


Figure 2 Overall cumulative adjusted relative risk along lags and adjusted relative risk by lag at selected percentiles against different meteorological variables. The reference values for (A) ambient temperature, (B) apparent temperature, (C) relative humidity and (D) vapour pressure for comparison were their corresponding median.

Overall (ref.= 0mm)

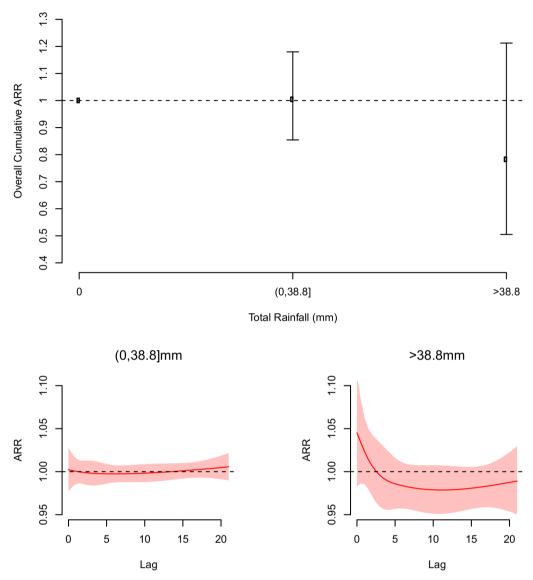


Figure 3 Adjusted cumulative relative risk along lags and adjusted relative risk by lag at selected percentiles against total rainfall. The reference value for a comparison was set to zero.

DISCUSSION

To our knowledge, few studies have investigated the short-term effects of meteorological variables and outdoor air pollution on acute bronchiolitis admissions in subtropical settings. In this study, a total of 29688 emergency paediatric acute bronchiolitis admissions from all Hong Kong public hospitals over a 10-year period were analysed and studied whether they were associated with meteorological variables and outdoor air pollutants. Our results showed that increased acute bronchiolitis-related hospitalisation was associated with high temperature (ie, ambient temperature and apparent temperature), and was marginally associated with absolute humidity. Although the result is generally in line with the study from Mäkinen *et al*²⁸, which showed an increasing trend in the risk of LTRIs when temperature and absolute humidity increased, we acknowledge that an effect of high temperature on bronchiolitis has not been well established in the literature. An investigation conducted in Malta suggested that majority of bronchiolitis-related hospital admissions occurred in winter in subtropical region,²⁹ while another

study conducted in China indicated that ambient temperature was negatively correlated with bronchiolitis-related hospitalisations among children.³⁰ Yet, by now, there has not been much consensus within the field on 'risky' temperature range for acute bronchiolitis. This was similar with another study on pneumonia in children aged <5 years old where the temperature effect was inconsistent.³¹ Apart from that, a large proportion of admissions for LRTI (many of which were attributed to RSV) was shown to be independently associated with absolute humidity in children in northern Spain.³² Nevertheless, only limited literatures have documented the association between absolute humidity and acute bronchiolitis-related or RSV-related admissions, especially when compared with other respiratory infections such as influenza.^{21 22}

Among the air pollutants, high level of NO₂ was associated with increased risk of acute bronchiolitis admission and the overall effect became statistically significant over the range $66.2-119.6\,\mu\text{g/m}^3$ when compared with value at the 5th percentile. NO₂ is a common outdoor air pollutant primarily produced

Respiratory epidemiology

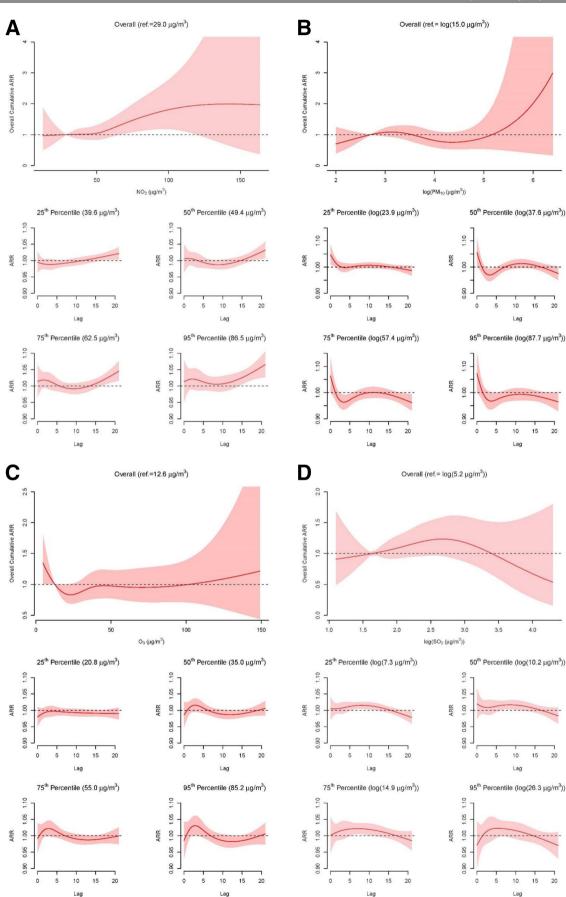


Figure 4 Overall cumulative adjusted relative risk along lags and adjusted relative risk by lag at selected percentiles against different pollutants, including (A) NO₂, (B) PM₁₀, (C) O₃, and (D) SO₂. The reference values for comparison were their corresponding 5th percentile.

by motor vehicles and power plants as a byproduct of hightemperature combustion. At ambient pressure and temperature, NO₂ exists in its gaseous state and is relatively insoluble in water. These properties allow deeper penetration of NO₂ into the respiratory tree (ie, the lower respiratory tracts) where it would react with water from mucosal lining of the bronchioles and form corrosive chemicals including nitric and nitrous acids.³³ The nitrous vapour could cause microlesions in the respiratory tract and increase susceptibility to infections, including those caused by RSV.³³ According to a recent large birth cohort study conducted in Indonesia among children aged 0-3 years, an IQR increase in NO, exposure would increase the risk for acute respiratory tract infection by an estimated 18%.³⁴ With reference to the WHO guideline for air quality, the annual mean level of NO_2 should not exceed 40 $\mu g/m^{3.16}$ During our study period, the median (IQR) daily mean NO₂ level was 49.4 μ g/m³ (39.6 to $62.5 \,\mu\text{g/m}^3$), and in 1770 days (48.5%) it exceeded the WHO's annual safe level.¹⁷ Considering the aforementioned, it is thus very important for Hong Kong to adopt sustainable clean air policies as soon as possible to protect young children's health. Regarding the sustained effect of NO₂ observed in our study, we tend to interpret the findings from toxicological perspectives. Seaton and Dennekamp³⁵ proposed the epidemiological association between illness and NO, might be confounded by particles number. Given the toxic effects of ultrafine particles has been evident at low concentrations in animals, we speculate the delayed effect of NO, might actually be the cumulative effect of successive exposure to ultrafine particles.³⁵ Follow-up studies should be conducted to test and verify this speculation.

A number of studies have been showing that exposure to PM would increase the risk of respiratory infections and other illnesses.^{13 36 37} In an investigation conducted in the USA, Karr et al^{13} found both chronic and subchronic exposures to PM₂₅ were associated with elevated risk of bronchiolitis hospitalisation in infants (ie, around a 9% increase in risk for every 10 μ g/ m^3 increase in PM₂₅). PM₁₀ was found to be related to bronchiolitis consultation and hospitalisation in both Malaysia and France.^{36 37} We found a significant positive effect of PM₁₀ on acute bronchiolitis admissions only within a short time window, suggesting that most of the effects of PM_{10} were acute. This might explain why we did not find cumulative effects of PM₁₀ over 21 days. One possible reason might be the relatively low PM_{10} concentration in Hong Kong (ie, 43.2 μ g/m³) as compared with the WHO guideline level of 50 μ g/m³ for 24 hours mean. At low concentration, the adverse effect of PM₁₀ on pulmonary health might not be clinically severe enough to cause hospitalisation, which might also explain why we could not find a cumulative effect of PM_{10} on bronchiolitis hospitalisations. Given that $PM_{2.5}$ has the ability to go even deeper into the lungs than PM₁₀ does, and furthermore to enter the blood system, the damaging effect of PM₂₅ on respiratory health might be stronger than that of PM_{10} at low concentrations. It is thus speculated that replacing PM_{10} with $PM_{2.5}$ might be a better way to explore the overall cumulative risk of exposure to particular matters on acute bronchiolitis hospitalisation. Further research is needed to verify this hypothesis.

Similarly, no positive association was observed between O_3 and acute bronchiolitis admission. In a recent study, a 20-ppb increase in O_3 was associated with a significant increase in emergency department visits for respiratory conditions (by 1.7%–5.1%).³⁸ Children exposed to high ozone levels had significantly decreased lung function, which may have reduced their defence against viral infections (eg, RSV) and increased their susceptibility to bronchiolitis.³⁹ Nevertheless, it was argued that O_3

could reduce the risk of respiratory infection that might be attributed to the virucidal activity of O_3 and its relationship with host defence.⁴⁰

The present study has several potential limitations. First, acute bronchiolitis is a clinical diagnosis, and therefore subject to variation among public hospitals due to differences in the availability of virus testing, differences in the diagnostic criteria used by doctors to diagnose bronchiolitis, and differences in coding practices. It is thus possible that acute bronchiolitis might be coded in the medical record system as other respiratory conditions. Meanwhile, criteria adopted in determining the need for hospitalisation changes over time. That being so, we might have underestimated the frequency of acute bronchiolitis hospitalisation in our study. Nevertheless, since over 90% of admissions in our dataset were principally diagnosed with acute bronchiolitis, our results shall remain robust (table 1). Second, this study used surveillance data in public hospitals which does not include data from private hospitals. However, the public healthcare services accounted for over 90% inpatient services in Hong Kong. Third, exposure measurement error is a common concern in environmental epidemiology, especially when studying the short-term impacts of environmental variables, given that meteorological condition and air pollutant levels change across time and space. For example, a child might be exposed to more air pollutants if she/he has smoking parents and lives in a household with 24 hours air conditioning that located close to busy roads. The error in exposure measurement might lead to inaccurate estimation of relative risks which, unfortunately, can hardly be avoided. Fourth, the increased incidence rate observed in this study might be affected by residual confounding. Unmeasured factors, such as parental smoking status, household crowding, indoor metrological condition (eg, temperature, relative humidity and air movement) and indoor air pollution (eg, NO2, PM10, PM25, O₂, formaldehyde, volatile organic compounds, radon and airborne bacteria level) could be potential confounders and/or effect modifiers that might distort the results of the study. Fifth, given that different pathogens prefer different environment for survival and transmission,²¹ the findings of our study may not be consistent with results from pathogen-specific (eg, RSV, influenza, etc) analyses of acute bronchiolitis. We acknowledge the lack of information about pathogen causing the admissions is one of the main limitations in this study. Also, as RSV infection is a major determinant for acute bronchiolitis hospitalisation in children, we took the incubation period into account in addition to the symptomatic period and assumed a maximum lag of 21 days for the delayed effects in our study. Our results may thus be less compatible with other similar investigations that generally studied the short-term effects of pollutants using a shorter maximum lag (eg, 3-7 days). Last but not least, interaction effects between the meteorological factors and pollutants were not considered in this study. Our preliminary analysis has shown that although the interaction effects were not strong in general, when meteorological factors were at medium level and pollutants were at medium or high level, their joint effects on the outcome were usually statistically significant (detailed results not given), hence worth further investigation in future studies.

In conclusion, our findings showed that high temperature (ambient temperature and apparent temperature) and exposure to NO_2 and PM_{10} were associated with acute bronchiolitisrelated hospitalisation among children at different lag times. The significant relationship with pollutants suggests the need to adopt sustainable clean air policies in Hong Kong, especially to target pollutants produced by motor vehicles, to protect young children's health. Since acute bronchiolitis continues to be a public health burden on the already-stressed healthcare system, policy-makers are urged to develop more cost-effective approaches to manage acute bronchiolitis in children. We believe that our findings could rationalise an evidence-based allocation of resources and formulation of environmental policies to minimise the burden of disease associated with acute bronchiolitis in young children.

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Contributors SYL and KCC conceived the study. SYL, KCC and SYFL performed the analysis. KLK and SYL contributed to the acquired data of the study. SYL, PKSC, KCC and KM contributed to the results interpretation. SYL, KCC, SYFL, PKSC and KM drafted the paper. All authors have read and approved the final paper.

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ORCID iD

Ka Chun Chong http://orcid.org/0000-0001-5610-1298

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Respiratory epidemiology

Appendix

Short-term Association among Meteorological Variation, Outdoor Air Pollution and Acute Bronchiolitis in Children in a Subtropical Setting

Shuk Yu Leung^{1,2}, Steven Yuk Fai Lau², Kwok Ka Li¹, Kirran N. Mohammad², Paul Kay Sheung Chan^{3,4}, Ka Chun Chong^{2,5}

¹ Department of Paediatrics, Kwong Wah Hospital, Hong Kong, China

² School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong, China
 ³ Department of Microbiology, Faculty of Medicine, The Chinese University of Hong Kong, Hong Kong

Special Administrative Region, China

⁴ Stanley Ho Centre for Emerging Infectious Diseases, Faculty of Medicine, The Chinese University of Hong Kong, Hong Kong Special Administrative Region, China

⁵ Clinical Trials and Biostatistics Laboratory, Shenzhen Research Institute, The Chinese University of Hong Kong, China

Correspondence to Dr. Ka Chun Chong, School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong, China; <u>marc@cuhk.edu.hk</u>; (852) 2252 8716

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D. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of pollutants at different parameter settings

E. R outputs of the modelling analysis

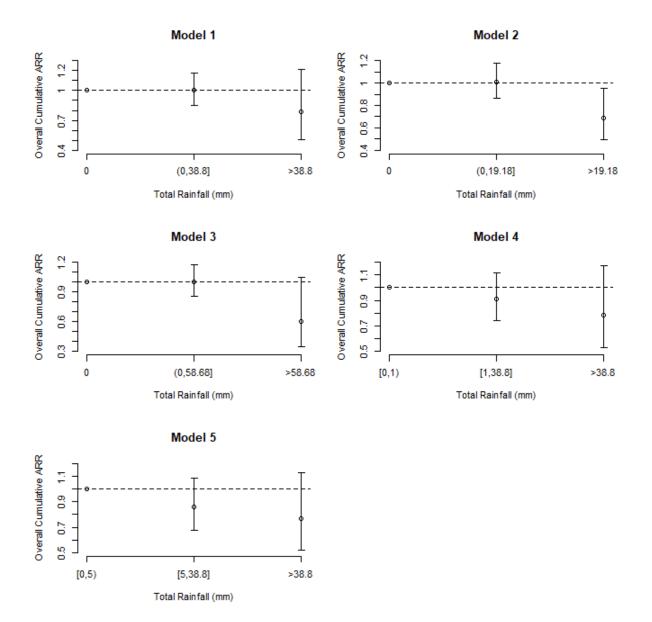
	Ambient	Apparent	Relative	Vapour	Rainfall	NO ₂	log(SO ₂)	O 3	log(PM ₁₀)
	Temperature	Temperature	Humidity	Pressure		NO2	log(302)	03	10g(1 1v110)
Ambient									
Temperature		0.973	0.227	0.942	0.121	-0.337	0.023	-0.093	-0.468
Apparent									
Temperature			0.281	0.939	0.105	-0.250	0.097	-0.199	-0.476
Relative									
Humidity				0.506	0.352	-0.329	-0.384	-0.439	-0.515
Vapour									
Pressure					0.239	-0.439	-0.095	-0.277	-0.619
Rainfall						-0.133	-0.150	-0.191	-0.309
NO ₂							0.576	0.191	0.697
log(SO ₂)								-0.068	0.417
O 3									0.566
log(PM ₁₀)									

A. Pearson correlation coefficient between the meteorological factors and pollutants during the study period (2008 - 2017)

Thorax

B. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of rainfall using different sets of cutoffs

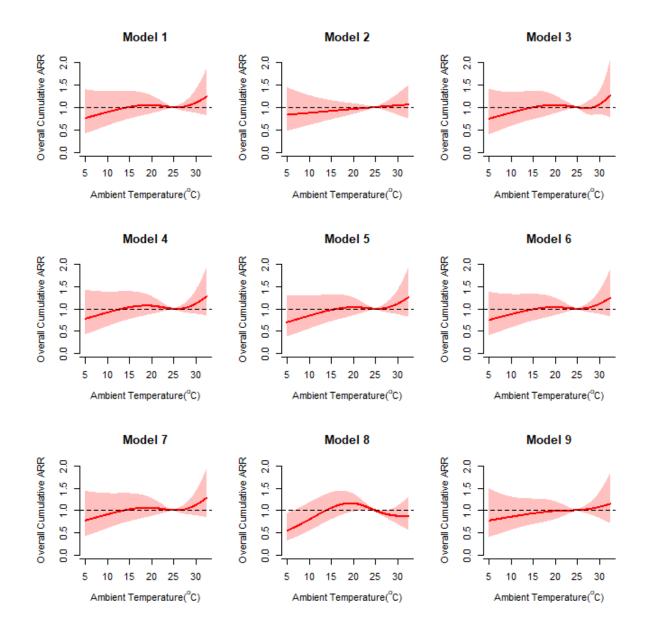
- Model 1: (i) Rainfall = 0; (ii) $0 < \text{Rainfall} \le 95^{\text{th}}$ percentile; and (iii) Rainfall > 95^{th} percentile
- Model 2: (i) Rainfall = 0; (ii) $0 < \text{Rainfall} \le 90^{\text{th}}$ percentile; and (iii) Rainfall > 90^{th} percentile
- Model 3: (i) Rainfall = 0; (ii) $0 < \text{Rainfall} \le 97.5^{\text{th}}$ percentile; and (iii) Rainfall > 97.5th percentile
- Model 4: (i) $0 \le \text{Rainfall} \le 1$; (ii) $1 < \text{Rainfall} \le 97.5^{\text{th}}$ percentile; and (iii) Rainfall > 97.5th percentile
- Model 5: (i) $0 \le \text{Rainfall} \le 5$; (ii) $5 < \text{Rainfall} \le 97.5^{\text{th}}$ percentile; and (iii) Rainfall > 97.5th percentile



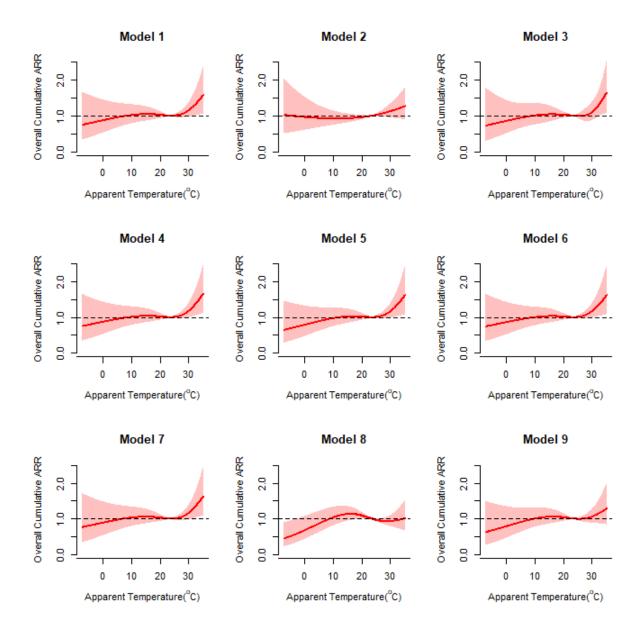
C. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of meteorological parameters: (a) ambient temperature, (b) apparent temperature, (c) relative humidity, (d) vapour pressure, and (e) total rainfall at different parameter settings

- Model 1: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- Model 2: df for the meteorological parameters = 2; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- Model 3: df for the meteorological parameters = 5; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- Model 4: df for the meteorological parameters = 3; df for the pollutants = 3; df for lag = 4, df for day of study per year = 7
- Model 5: df for the meteorological parameters = 3; df for the pollutants = 5; df for lag = 4, df for day of study per year = 7
- Model 6: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 3, df for day of study per year = 7
- Model 7: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 5, df for day of study per year = 7
- Model 8: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 6
- Model 9: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 8

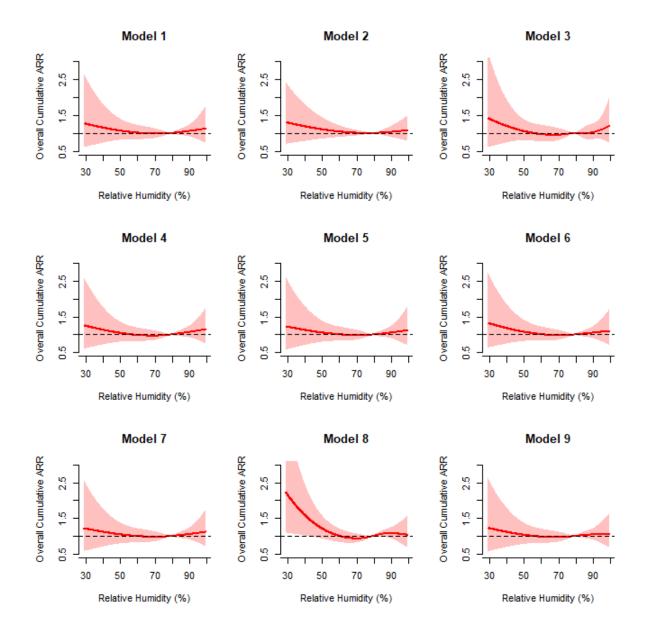
(a) Ambient Temperature (ref. = 24.8°C)



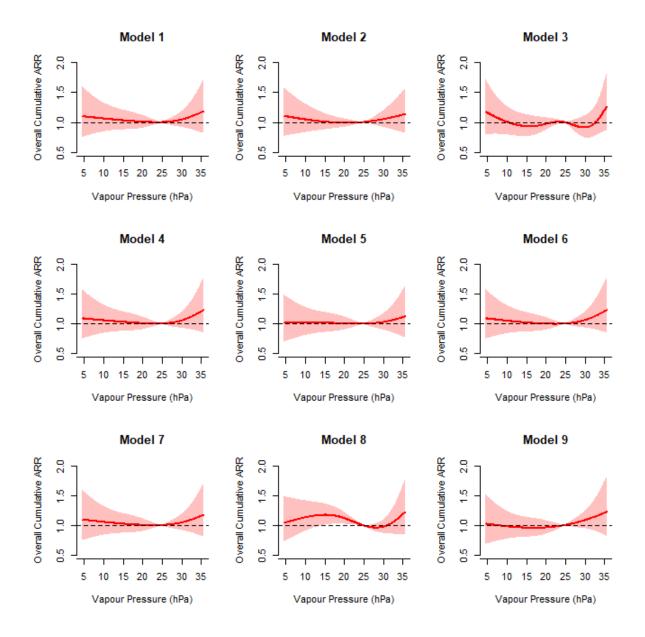
(b) Apparent Temperature (ref. = 23.6°C)



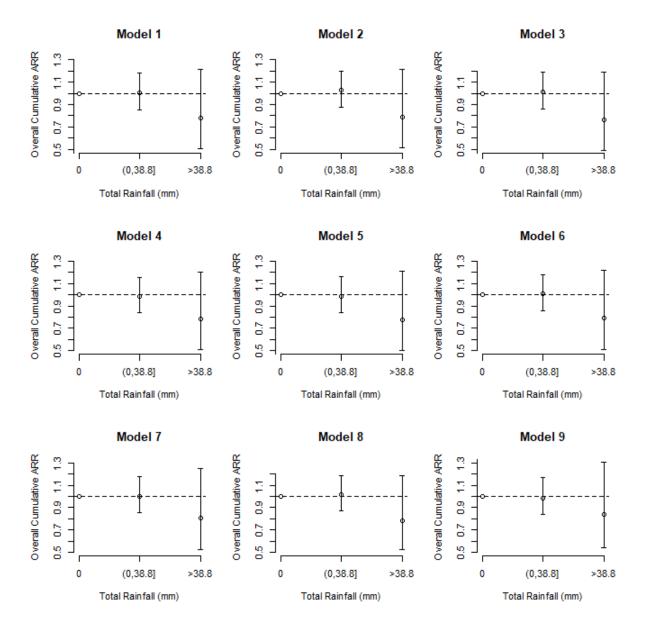
(c) Relative Humidity (ref. = 79.0%)



(d) Vapour Pressure (ref. = 24.7 hPa)



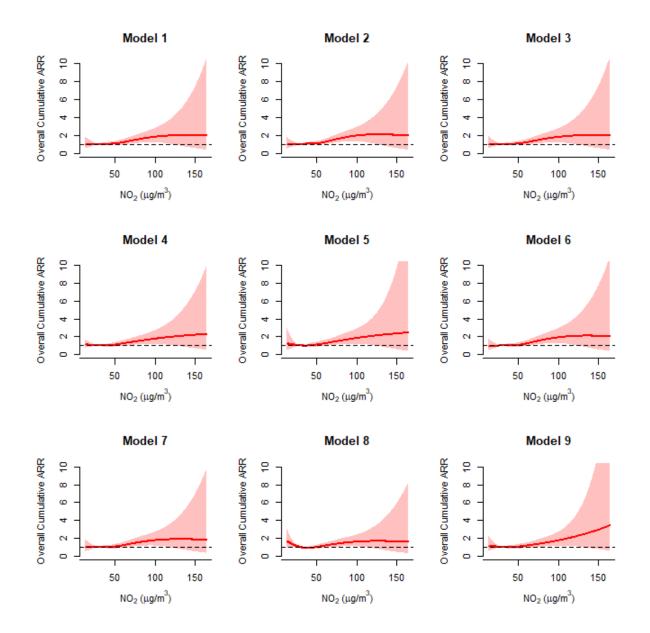
(e) Rainfall (ref. = 0)



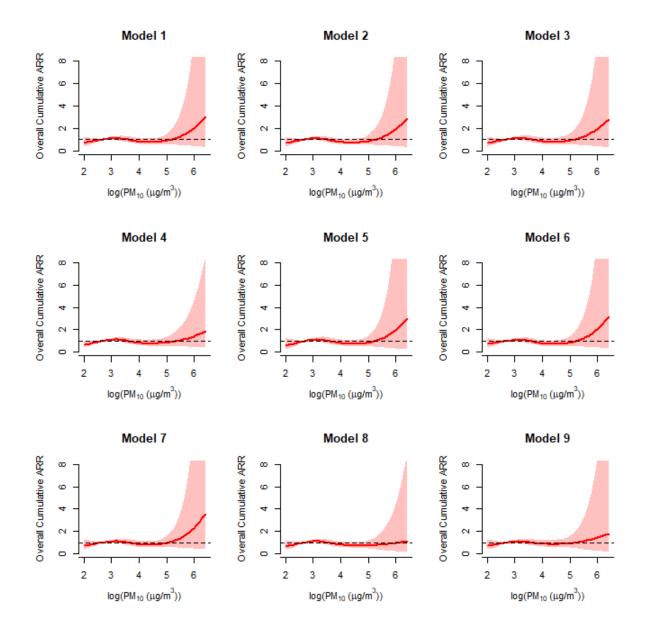
D. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of pollutants: (a) NO₂, (b) PM₁₀, (c) O₃, and (d) SO₂ at different parameter settings

- Model 1: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- Model 2: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- Model 3: df for the meteorological parameters = 5; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- Model 4: df for the meteorological parameters = 3; df for the pollutants = 3; df for lag = 4, df for day of study per year = 7
- Model 5: df for the meteorological parameters = 3; df for the pollutants = 5; df for lag = 4, df for day of study per year = 7
- Model 6: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 3, df for day of study per year = 7
- Model 7: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 5, df for day of study per year = 7
- Model 8: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 6
- Model 9: df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 8

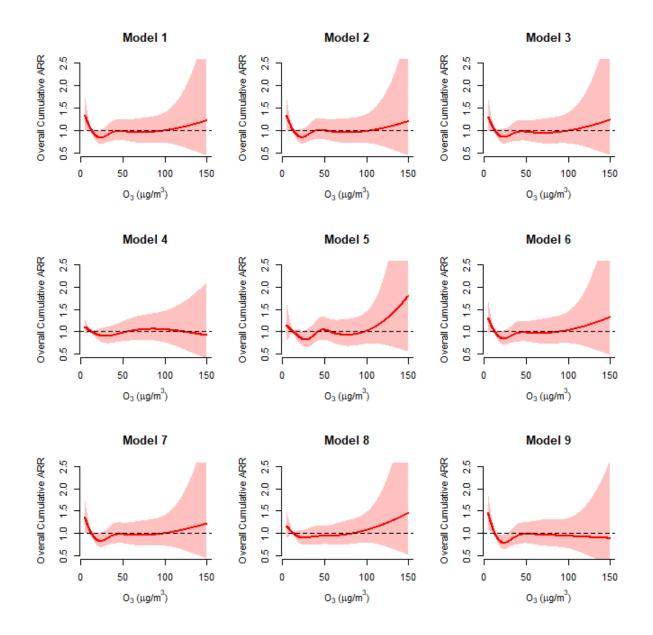
(a) NO₂ (ref. = 29.0 μ g/m³)



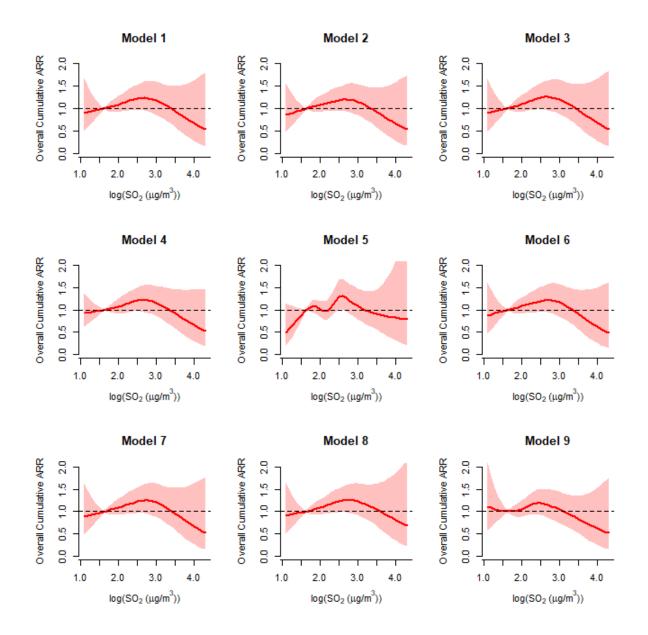
(b) $\log(PM_{10})$ (ref. = $\log(15.0 \ \mu g/m^3)$)



(c) O_3 (ref. = 12.6 μ g/m³)



(d) $log(SO_2)$ (ref. = $log(5.2 \ \mu g/m^3)$)



E. R outputs of the modelling analysis

1. Primary model: $\log[E(Y_t)] = \alpha + cb(temperature_t) + cb(relative humdity_t) + cb(factor(rainfall_t)) + cb(NO_{2_t}) + cb(log(SO_{2_t})) + cb(O_{3_t}) + cb(log(PM_{10_t})) + cb(factor(Holiday_t)) + ns(DOS_t, df = 7 per year) + factor(DOW_t) + s(\sqrt{influenza_{tr}} k = 7)$

Parametric coefficients:

Parametric coefficients:					
		Std. Error			
(Intercept)	1.4512548	0.7160001		0.042750	*
temp.cbv1.l1	0.0439784	0.0418318		0.293187	
temp.cbv1.l2	-0.0878345	0.0390152		0.024430	*
temp.cbv1.13	0.0446216	0.0618343		0.470570	
temp.cbv1.14	-0.0034920	0.0423107		0.934228	
temp.cbv2.ll	0.1231761	0.1142025		0.280852	
temp.cbv2.12	-0.1643616	0.1065041		0.122864	
temp.cbv2.13	0.1794677	0.1601544		0.262540	
temp.cbv2.14	-0.0698977	0.1133739		0.537590	
temp.cbv3.ll	0.0137331	0.0511297		0.788258	
temp.cbv3.12	-0.1119861	0.0500760		0.025394	*
temp.cbv3.13	0.0684730	0.0706839		0.332752	
temp.cbv3.14	0.0674186	0.0498300		0.176153	
humid.cbv1.l1	-0.0266661	0.0328741		0.417331	
humid.cbv1.l2	0.0259349	0.0323173		0.422314	
humid.cbv1.13	0.0136069	0.0448957		0.761849	
humid.cbv1.14	-0.0470236	0.0330892		0.155373	
humid.cbv2.l1	-0.0812557	0.1074348		0.449505	
humid.cbv2.l2	0.1865052	0.1062710		0.079349	•
humid.cbv2.13	-0.0743799	0.1565142		0.634655	
humid.cbv2.14	-0.1123834	0.1107212		0.310171	
humid.cbv3.l1	-0.0198497	0.0412145		0.630106	
humid.cbv3.l2	0.0941500	0.0406179		0.020511	*
humid.cbv3.13	-0.0571965	0.0556244		0.303899	
humid.cbv3.14	0.0217260	0.0391004		0.578488	
rainfall.cbv1.l1	-0.0022131	0.0110607		0.841422	
rainfall.cbv1.l2	-0.0047411	0.0115397		0.681211	
rainfall.cbv1.l3	0.0032760	0.0145790		0.822220	
rainfall.cbv1.l4	0.0045150	0.0105962		0.670061	
rainfall.cbv2.ll	-0.0104598	0.0280257		0.709005	
rainfall.cbv2.l2	-0.0495716	0.0304926		0.104106	
rainfall.cbv2.13 rainfall.cbv2.14	0.0254501 -0.0359519	0.0361916 0.0268185		0.481977 0.180151	
o3.cbv1.l1	0.0345359	0.0298613		0.247540	
o3.cbv1.11 o3.cbv1.12	-0.0307839	0.0298613		0.24/540	
o3.cbv1.12	-0.0591781	0.0298285		0.149856	
o3.cbv1.14	0.0178601	0.0293947		0.149856	
o3.cbv2.l1	0.0179539	0.0389989		0.645280	
o3.cbv2.12	0.0066618	0.0398056		0.867098	
o3.cbv2.13	-0.0294685	0.0524620		0.574350	
o3.cbv2.14	-0.0338190	0.0377101		0.369880	
o3.cbv3.l1	0.0729922	0.0746161		0.328026	
o3.cbv3.12	-0.0630899	0.0762029		0.407773	
o3.cbv3.13	-0.1670266	0.0999883		0.094919	
o3.cbv3.14	0.0555581	0.0730619		0.447053	•
o3.cbv4.l1	0.1574924	0.0703358		0.025210	*
o3.cbv4.12	-0.1800452	0.0740213		0.025210	
o3.cbv4.13	-0.0433764	0.0938465		0.643963	
o3.cbv4.14	0.1376333	0.0706558		0.051503	
so2.cbv1.11	0.0134665	0.0521547		0.796266	•
so2.cbv1.12	0.0984224	0.0509775		0.053602	
	0.0001221		1.001	2.000002	•

so2.cbv1.l3	0.0114321	0.0712974	0.160 0.872620
so2.cbv1.l4	-0.0912327	0.0503946	-1.810 0.070326 .
so2.cbv2.l1	0.0464193	0.0474932	
so2.cbv2.l2	0.0811822	0.0475452	1.707 0.087824 .
so2.cbv2.13	-0.0280440	0.0639681	
so2.cbv2.l4	-0.0241849	0.0459626	
so2.cbv3.ll	0.0549618	0.1204914	0.456 0.648313
so2.cbv3.12	0.2331202	0.1208678	1.929 0.053847 .
so2.cbv3.13	-0.1215267	0.1657625	-0.733 0.463524
so2.cbv3.14	-0.1651787	0.1167885	-1.414 0.157352
so2.cbv4.l1	0.0026564	0.0769013	0.035 0.972447
so2.cbv4.l2 so2.cbv4.l3	0.0560959	0.0811260	
so2.cbv4.13 so2.cbv4.14	-0.0973958 -0.0658722	0.1074898 0.0757302	-0.906 0.364949 -0.870 0.384455
no2.cbv1.l1	-0.0616957	0.0527942	
no2.cbv1.12	0.0017939	0.0542495	0.033 0.973623
no2.cbv1.13	-0.0009991	0.0715642	
no2.cbv1.14	0.1019180	0.0538348	1.893 0.058420 .
no2.cbv2.ll	0.0188803	0.0511363	0.369 0.711990
no2.cbv2.12	-0.0198304	0.0538109	
no2.cbv2.13	0.0673643	0.0691143	0.975 0.329787
no2.cbv2.14	0.0877127	0.0512704	1.711 0.087210 .
no2.cbv3.l1	-0.1785233	0.1212393	
no2.cbv3.l2	0.1512279	0.1246071	1.214 0.224969
no2.cbv3.13	0.0090424	0.1643940	0.055 0.956138
no2.cbv3.l4	0.2665555	0.1212167	2.199 0.027944 *
no2.cbv4.ll	-0.0688453	0.1023508	-0.673 0.501221
no2.cbv4.l2	0.1026636	0.1061544	0.967 0.333554
no2.cbv4.l3	0.0079176	0.1451105	0.055 0.956490
no2.cbv4.l4	0.1460566	0.1029970	1.418 0.156262
pm10.cbv1.l1	-0.0236306	0.0549739	
pm10.cbv1.12	-0.0261759	0.0527177	-0.497 0.619553
pm10.cbv1.13	0.1661722	0.0743066	2.236 0.025395 *
pm10.cbv1.14	-0.1381865	0.0528898	-2.613 0.009021 **
pm10.cbv2.l1	-0.0436518	0.0515316	-0.847 0.397004
pm10.cbv2.12	-0.0538285	0.0513311	
pm10.cbv2.13	0.0703806	0.0739057	0.952 0.341010
pm10.cbv2.14	-0.1381750	0.0517831	-2.668 0.007658 **
pm10.cbv3.l1	0.0970854	0.1293034	0.751 0.452804
pm10.cbv3.l2	-0.2039492	0.1259097	-1.620 0.105365
pm10.cbv3.l3 pm10.cbv3.l4	0.3679024 -0.2342362	0.1741204 0.1248315	2.113 0.034679 * -1.876 0.060682 .
pm10.cbv4.l1	0.0010267	0.1237157	0.008 0.993379
pm10.cbv4.12	-0.0726563	0.1305394	-0.557 0.577847
pm10.cbv4.13	0.2272455	0.1722491	1.319 0.187162
pm10.cbv4.14	0.0032430	0.1298638	0.025 0.980079
holiday.cbv1.l1	0.0195226	0.0139753	1.397 0.162523
holiday.cbv1.12	-0.0377211	0.0125888	-2.996 0.002751 **
holiday.cbv1.13	-0.0213359	0.0183454	-1.163 0.244904
holiday.cbv1.14	-0.0291242	0.0132594	-2.196 0.028123 *
factor(dow)2	-0.0587772	0.0221779	-2.650 0.008080 **
factor(dow)3	-0.0737656	0.0235202	-3.136 0.001726 **
factor(dow)4	-0.0442848	0.0237874	-1.862 0.062731 .
factor(dow)5	-0.0751847	0.0237134	-3.171 0.001535 **
factor(dow)6	-0.0899525	0.0235340	-3.822 0.000135 ***
factor(dow)7	-0.0397347	0.0228790	-1.737 0.082524 .
ns(dos, df = $10 \times \text{trend_df}$)1	0.8616721	0.3091919	2.787 0.005351 **
ns(dos, df = $10 \times \text{trend_df}$)2	-0.0458647	0.4184533	-0.110 0.912729
ns(dos, df = $10 \times \text{trend_df}$) 3	0.9980103	0.3923718	2.544 0.011017 *
ns(dos, df = $10 * trend_df$) 4	0.3362908	0.4123966	0.815 0.414868
ns (dos, $df = 10 * trend_df) 5$	0.4138532	0.3848843	1.075 0.282331
ns (dos, $df = 10 * trend_df) 6$	-0.2839202	0.4000807	-0.710 0.477965
ns (dos, df = $10 \times \text{trend}_d$ f) 7	-0.0838325	0.3579476	-0.234 0.814841
ns (dos, df = $10 * \text{trend}_df$) 8	1.2097265	0.3573797	3.385 0.000720 ***
ns (dos, df = $10 \times \text{trend}_df$) 9	-0.8398919	0.4148958	-2.024 0.043012 *
ns (dos, df = 10 * trend_df)10 ns (dos, df = 10 * trond_df)11		0.4126791	-0.416 0.677585
<pre>ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12</pre>		0.4416006	-0.364 0.715533
		0.3867686 0.3747890	1.612 0.107152 -1.503 0.132918
<pre>ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14</pre>		0.3554162	3.886 0.000104 ***
ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15		0.3546676	1.976 0.048262 *
		2.00100/0	

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ns(dos, df = 10 * trend df)16 0.0950378	0.3999787	0.238 0.812200	
ns(dos, df = 10 * trend df) 17 - 0.7546348		-1.812 0.070136	
ns(dos, df = 10 * trend df)18 0.3153634	0.4294361	0.734 0.462775	
ns(dos, df = 10 * trend df)19 0.3169441	0.3761137	0.843 0.399465	
ns(dos, df = 10 * trend_df)20 0.9033308	0.3660175	2.468 0.013635	*
ns(dos, df = 10 * trend_df)21 -0.1041196	0.3738877	-0.278 0.780662	
ns(dos, df = 10 * trend_df)22 1.1412016	0.3575339	3.192 0.001426	* *
ns(dos, df = 10 * trend_df)23 0.1288197	0.3916974	0.329 0.742270	
ns(dos, df = 10 * trend_df)24 0.7538852	0.3893076	1.936 0.052891	•
$ns(dos, df = 10 * trend_df)25 0.9750480$	0.4100772	2.378 0.017474	*
ns(dos, df = 10 * trend_df)26 0.1975424	0.3802096	0.520 0.603402	
ns(dos, df = $10 * trend_df$) 27 -0.4322074		-1.146 0.251890	
$ns(dos, df = 10 * trend_df)28 0.6356608$	0.3621247	1.755 0.079286	
$ns(dos, df = 10 * trend_df)29 1.0673142$	0.3595173	2.969 0.003011	* *
$ns(dos, df = 10 * trend_df) 30 0.1287451$	0.4219465	0.305 0.760292	
ns(dos, df = 10 * trend_df)31 0.1093384	0.3945192	0.277 0.781687	
$ns(dos, df = 10 * trend_df) 32 0.5879758$	0.4081295	1.441 0.149771	
$ns(dos, df = 10 * trend_df) 33 0.5000772$	0.3804599	1.314 0.188798	
ns(dos, df = 10 * trend_df)34 0.6856981	0.3469802	1.976 0.048213	
$ns(dos, df = 10 * trend_df)35 1.1784024$	0.3723688	3.165 0.001566	* *
ns (dos, df = $10 \times \text{trend}_df$) 36 0.0960919	0.3497702	0.275 0.783541	
ns (dos, df = $10 \times \text{trend}_df$) 37 0.2188771	0.4076512	0.537 0.591356	de ale
ns (dos, df = $10 * trend_df$) 38 1.1243102	0.3909058	2.876 0.004050	* *
ns (dos, df = $10 * trend_df$) 39 0.5472236	0.4055893	1.349 0.177359	
ns (dos, df = 10 * trend_df) 40 0.3836715	0.3869929	0.991 0.321551	
<pre>ns(dos, df = 10 * trend_df)41 -0.0475495 ns(dos, df = 10 * trend_df)42 -0.5383873</pre>		-0.123 0.902332	
ns(dos, df = 10 * trend df)42 = 0.5383675 ns(dos, df = 10 * trend df)43 1.5538601	0.3875989 0.3523201	-1.389 0.164913 4.410 1.06e-05	* * *
ns(dos, df = 10 * trend df)44 = 0.4011037	0.4129479	0.971 0.331458	
ns(dos, df = 10 * trend df)45 0.1423757	0.4001527	0.356 0.722010	
ns(dos, df = 10 * trend df)46 0.1128887	0.4155741	0.272 0.785911	
ns(dos, df = 10 * trend df)47 0.4619514	0.3811831	1.212 0.225638	
ns(dos, df = 10 * trend df) 48 0.1630531	0.3813022	0.428 0.668953	
ns (dos, $df = 10 * trend df) 49 - 0.2127009$		-0.545 0.586127	
ns(dos, df = 10 * trend df)50 0.6608814	0.3591247	1.840 0.065816	
ns(dos, df = 10 * trend df)51 0.2155257	0.4203650	0.513 0.608186	
ns(dos, df = 10 * trend df)52 0.1086832	0.4229558	0.257 0.797224	
ns(dos, df = 10 * trend df)53 0.6313049	0.3956350	1.596 0.110653	
ns(dos, df = 10 * trend df)54 0.3613383	0.4008369	0.901 0.367407	
ns(dos, df = 10 * trend df)55 0.5361872	0.3478824	1.541 0.123338	
ns(dos, df = 10 * trend_df)56 0.9130877	0.3846419	2.374 0.017657	*
ns(dos, df = 10 * trend_df)57 0.6538293	0.3522626	1.856 0.063527	•
ns(dos, df = 10 * trend_df)58 0.8777681	0.4292818	2.045 0.040956	*
ns(dos, df = 10 * trend_df)59 0.2278709	0.4058652	0.561 0.574531	
ns(dos, df = 10 * trend_df)60 0.1307263	0.4172703	0.313 0.754080	
ns(dos, df = $10 * trend_df$) 61 0.6635502	0.3857125	1.720 0.085463	
$ns(dos, df = 10 * trend_df) 62 0.6422523$	0.3559697	1.804 0.071282	•
$ns(dos, df = 10 * trend_df) 63 0.4363803$	0.3762755	1.160 0.246236	
$ns(dos, df = 10 * trend_df)64 1.1266372$	0.3555550	3.169 0.001545	* *
ns (dos, df = $10 * trend_df$) 65 0.0357018	0.4227793	0.084 0.932707	
ns (dos, df = $10 * trend_df$) 66 0.5818062	0.4249520	1.369 0.171054	++
ns (dos, df = $10 * trend_df$) 67 1.0917789	0.4220827	2.587 0.009732	
ns (dos, df = $10 * trend_df$) 68 0.5217567	0.3044827	1.714 0.086695	•
ns (dos, df = $10 * trend_df$) 69 0.5761929	0.7550888	0.763 0.445468	
ns(dos, df = 10 * trend_df)70 -0.0060447	0.1//0000	-0.034 0.9/2004	
Signif. codes: 0 `***' 0.001 `**' 0.01	`*' 0.05 `.'	0.1 `′ 1	
Approximate significance of smooth terms edf Ref.df F p-valu			
s(sqrt(influ)) 1.259 1.482 9.878 0.0003			
Signif. codes: 0 `***' 0.001 `**' 0.01	`*' 0.05 `.'	0.1 `′ 1	
R-sq.(adj) = 0.474 Deviance explained GCV = 1.0821 Scale est. = 0.98661 n =			

2. Secondary model 1: $\log[E(Y_t)] = \alpha + cb(Apparent Temperature_t) + cb(Relative Humdity_t) + cb(factor(Rainfall_t)) + cb(NO_{2_t}) + cb(log(SO_{2_t})) + cb(O_{3_t}) + cb(log(PM_{10_t})) + cb(factor(Holiday_t)) + ns(DOS_t, df = 7 per year) + factor(DOW_t) + s(\sqrt{Influenza}_{t,k} = 7)$ Family: quasipoisson Link function: log Formula:

```
ad ~ AT.cb + humid.cb + rainfall.cb + o3.cb + so2.cb + no2.cb +
pm10.cb + holiday.cb + factor(dow) + ns(dos, df = 10 * trend_df) +
s(sqrt(influ), k = 7)
```

Parametric coefficients:

Parametric coefficients:					
	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.6660412	0.7586414	2.196	0.028155	*
AT.cbv1.l1	0.0552618	0.0477023	1.158	0.246754	
AT.cbv1.12	-0.1034158	0.0444522	-2.326	0.020054	*
AT.cbv1.13	0.0631939			0.356829	
AT.cbv1.14	-0.0334739			0.479496	
AT.cbv2.11	0.2376932	0.1459218		0.103427	
AT.cbv2.12	-0.2115769	0.1356748		0.118987	
AT.cbv2.13	0.1915229	0.2004322		0.339369	
AT.cbv2.14	-0.1378967			0.340076	
AT.cbv3.l1	0.0423648	0.1445228		0.370479	
		0.0472982			т
AT.cbv3.12	-0.0966215	0.0457569		0.034793	
AT.cbv3.13	0.1121366	0.0661026		0.089903	
AT.cbv3.14	-0.0018263	0.0468047		0.968877	
humid.cbv1.l1	-0.0218804	0.0356452		0.539365	
humid.cbv1.l2	0.0224829	0.0347639		0.517850	
humid.cbv1.13	-0.0009628	0.0477471		0.983914	
humid.cbv1.14	-0.0370310	0.0348635		0.288234	
humid.cbv2.ll	-0.0646684	0.1164570	-0.555	0.578728	
humid.cbv2.12	0.1329434	0.1113794	1.194	0.232716	
humid.cbv2.13	-0.0641735	0.1653667	-0.388	0.697990	
humid.cbv2.14	-0.0963373	0.1162263	-0.829	0.407234	
humid.cbv3.l1	-0.0068002	0.0432011	-0.157	0.874933	
humid.cbv3.12	0.0665029	0.0423867	1.569	0.116753	
humid.cbv3.13	-0.0534840			0.353040	
humid.cbv3.14	0.0285791	0.0404871		0.480312	
rainfall.cbv1.l1	-0.0031316	0.0115235		0.785827	
rainfall.cbv1.l2	-0.0049700	0.0121226		0.681846	
rainfall.cbv1.13	0.0040544	0.0150196		0.787220	
rainfall.cbv1.14	0.0053266	0.0109031		0.625197	
rainfall.cbv2.ll	-0.0105060	0.0292174		0.719184	
rainfall.cbv2.l2	-0.0421359	0.0321307		0.189816	
rainfall.cbv2.l3	0.0412199	0.0378669		0.276433	
rainfall.cbv2.14					
	-0.0502319	0.0282973		0.075965	•
o3.cbv1.l1	0.0348665	0.0295563		0.238217	
o3.cbv1.12	-0.0416967	0.0294356		0.156711	
o3.cbv1.13	-0.0463252	0.0409948		0.258546	
o3.cbv1.14	0.0248903	0.0290758		0.392031	
o3.cbv2.l1	0.0227358	0.0387075		0.556992	
o3.cbv2.12	0.0025551	0.0397889		0.948801	
o3.cbv2.13	-0.0224234	0.0527896		0.671032	
o3.cbv2.14	-0.0292102	0.0378654	-0.771	0.440512	
o3.cbv3.l1	0.0649870	0.0744233	0.873	0.382613	
o3.cbv3.12	-0.0755945	0.0759536	-0.995	0.319676	
o3.cbv3.13	-0.1363626	0.1003953	-1.358	0.174474	
o3.cbv3.14	0.0494855	0.0731764	0.676	0.498929	
o3.cbv4.l1	0.1564937	0.0718709	2.177	0.029519	*
o3.cbv4.12	-0.1974352	0.0761727	-2.592	0.009585	* *
o3.cbv4.13	-0.0179600	0.0957428		0.851213	
o3.cbv4.14	0.1257924	0.0725845		0.083180	
so2.cbv1.l1	0.0167104	0.0541531		0.757662	-
so2.cbv1.12	0.0831071	0.0531672		0.118118	
so2.cbv1.13	0.0001811	0.0739389		0.998046	
so2.cbv1.14	-0.0649959	0.0516835		0.208634	
so2.cbv2.l1	0.0512144	0.0489616		0.295632	
so2.cbv2.12	0.0512144	0.0492383		0.169864	
so2.cbv2.13				0.564428	
	-0.0380584	0.0660353			
so2.cbv2.14	-0.0034456	0.0473060	-0.0/3	0.941941	

so2.cbv3.ll	0.0512808	0.1243337	0.412 0.680040	
so2.cbv3.l2	0.1955869	0.1250029	1.565 0.117758	
so2.cbv3.13	-0.1419627	0.1713154	-0.829 0.407355	
so2.cbv3.14	-0.1093854	0.1195790	-0.915 0.360387	
so2.cbv4.l1	-0.0021016	0.0774203	-0.027 0.978345	
so2.cbv4.l2	0.0148940		0.183 0.854773	
so2.cbv4.13	-0.1435432	0.1088079	-1.319 0.187182	
so2.cbv4.14	-0.0180096	0.0761196	-0.237 0.812985	
no2.cbv1.l1	-0.0651355	0.0527155	-1.236 0.216693	
no2.cbv1.12	0.0240398	0.0527676	0.456 0.648722	
no2.cbv1.13	-0.0233851		-0.324 0.746104	
no2.cbv1.14 no2.cbv2.11	0.0724792 0.0133337	0.0537295 0.0507296	1.349 0.177440 0.263 0.792692	
no2.cbv2.12	0.0124311	0.0529264		
no2.cbv2.13	0.0291712		0.424 0.671676	
no2.cbv2.14	0.0585159	0.0513353	1.140 0.254420	
no2.cbv3.l1	-0.1983282	0.1208347		
no2.cbv3.12	0.2152031	0.1223656	1.759 0.078722 .	
no2.cbv3.13	-0.0379806	0.1657823	-0.229 0.818806	
no2.cbv3.14	0.2064575	0.1214117	1.700 0.089135 .	
no2.cbv4.l1	-0.0736111	0.1029959	-0.715 0.474845	
no2.cbv4.l2	0.1499224	0.1062928	1.410 0.158496	
no2.cbv4.l3	0.0300032	0.1462432	0.205 0.837460	
no2.cbv4.14	0.1414452	0.1034423	1.367 0.171598	
pm10.cbv1.l1	-0.0413979	0.0564995	-0.733 0.463785	
pm10.cbv1.12	-0.0148565	0.0534441	-0.278 0.781043	
pm10.cbv1.l3	0.1699841	0.0763136	2.227 0.025984 *	
pm10.cbv1.14	-0.1356220	0.0539619		
pm10.cbv2.ll	-0.0655134	0.0532196		
pm10.cbv2.12	-0.0535008	0.0528486	-1.012 0.311449	
pm10.cbv2.13	0.0908371		1.203 0.228942	
pm10.cbv2.14	-0.1419105	0.0531216	-2.671 0.007590 **	
pm10.cbv3.l1	0.0621278	0.1325245 0.1281867	0.469 0.639242 -1.537 0.124382	
pm10.cbv3.l2	-0.1970264 0.3798868	0.1281887	2.128 0.033372 *	
pm10.cbv3.13 pm10.cbv3.14	-0.2472232	0.1270476	-1.946 0.051750 .	
pm10.cbv4.l1	0.0051321	0.1264202	0.041 0.967621	
pm10.cbv4.12	-0.0879770	0.1327344	-0.663 0.507501	
pm10.cbv4.13	0.2528895	0.1743678	1.450 0.147063	
pm10.cbv4.14	-0.0317103	0.1314118	-0.241 0.809334	
holiday.cbv1.l1	0.0229240	0.0140656	1.630 0.103241	
holiday.cbv1.12	-0.0384166	0.0127883		
holiday.cbv1.13	-0.0271741	0.0184173	-1.475 0.140180	
holiday.cbv1.l4	-0.0262329	0.0133766	-1.961 0.049950 *	
factor(dow)2	-0.0649037	0.0225217	-2.882 0.003979 **	
factor(dow)3	-0.0786969	0.0238626	-3.298 0.000984 ***	
factor(dow)4	-0.0522564	0.0241511	-2.164 0.030556 *	
factor(dow)5	-0.0788882	0.0240608		
factor(dow)6	-0.0962840	0.0238861	-4.031 5.68e-05 ***	
factor (dow) 7	-0.0411008	0.0231921	-1.772 0.076455 .	
ns(dos, df = $10 \times \text{trend}_d$ f)1	0.9348702	0.3096874	3.019 0.002557 **	
<pre>ns(dos, df = 10 * trend_df)2 ns(dos, df = 10 * trend_df)3</pre>	-0.0803316 1.0230267	0.4164357 0.3934626	-0.193 0.847047 2.600 0.009362 **	
ns(dos, df = 10 * trend_df)4	0.2611783	0.4190711	0.623 0.533175	
ns (dos, df = $10 \times \text{trend} \text{ df}$) 4	0.4308111	0.3930425	1.096 0.273117	
ns (dos, df = $10 \times \text{trend} \text{ df}$) 6	-0.3433589	0.4087290	-0.840 0.400932	
ns (dos, df = $10 \times \text{trend} \text{ df}$) 7	-0.0118598	0.3584741	-0.033 0.973610	
ns (dos, df = 10 * trend df) 8	1.1995473	0.3593351	3.338 0.000852 ***	
ns (dos, $df = 10 * trend df) 9$	-0.9221487	0.4106954	-2.245 0.024812 *	
ns (dos, $df = 10 * trend df$) 10		0.4136076	-0.451 0.651848	
ns (dos, $df = 10 * trend df$) 11		0.4413071	-0.644 0.519641	
ns(dos, df = $10 \times \text{trend_df}$)12	0.6536305	0.3931383	1.663 0.096487 .	
ns(dos, df = $10 \times \text{trend_df}$)13	-0.5691370	0.3824402	-1.488 0.136800	
ns(dos, df = $10 \times \text{trend_df}$)14	1.3880733	0.3552156	3.908 9.50e-05 ***	
ns(dos, df = $10 \times \text{trend}_df$)15	0.7389734	0.3566781	2.072 0.038359 *	
ns(dos, df = $10 * trend_df$)16	0.0195143	0.3967728	0.049 0.960777	
ns(dos, df = $10 * trend_df$)17		0.4170666	-1.901 0.057432 .	
ns (dos, df = $10 \times \text{trend}_d$ f) 18	0.2183160	0.4275896	0.511 0.609683	
ns (dos, df = 10 * trend_df) 19		0.3729369	0.897 0.370026	
ns(dos, df = $10 * trend_df$)20		0.3714831	2.491 0.012783 *	
ns(dos, df = $10 * \text{trend df}$)21	-0 1336046	0.3742418	-0.357 0.720934	

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ns(dos, d	$df = 10^{-3}$	<pre>trend_df)22</pre>	1.1972173	0.3591861	3.333 0.000868	* * *
ns(dos, d	$df = 10^{-3}$	<pre>trend df)23</pre>	0.0118967	0.3885849	0.031 0.975578	
ns(dos, d	$df = 10^{-3}$	* trend df)24	0.7251224	0.3867721	1.875 0.060907	
ns(dos, d	$df = 10^{-3}$	trend df)25	0.8458428	0.4134686	2.046 0.040862	*
ns(dos, d	$df = 10^{-3}$	trend df)26	0.2569205	0.3719087	0.691 0.489729	
ns(dos, d	$df = 10^{-3}$	trend df)27	-0.4461225	0.3833977	-1.164 0.244669	
		trend df)28	0.6629031	0.3611692	1.835 0.066530	
		trend df)29		0.3682964	2.821 0.004810	
		trend df) 30		0.4257700	0.349 0.727173	
		trend df)31	0.0513062	0.3928524	0.131 0.896100	
		trend df) 32	0.4906748	0.4061067	1.208 0.227040	
		trend df)33	0.5155347	0.3745580	1.376 0.168796	
		<pre>trend_df)34</pre>		0.3520285	1.991 0.046530	*
		<pre>trend_df)35</pre>		0.3748126	3.139 0.001712	
		<pre>trend df)36</pre>		0.3514770	0.350 0.726291	
		trend df) 37		0.4026633	0.337 0.736446	
		<pre>trend_df)38</pre>		0.3907503	2.820 0.004830	* *
		trend df) 39		0.4022368	1.161 0.245703	
		trend df)40		0.3783013	1.028 0.304148	
		trend df)41		0.3917498	-0.066 0.947734	
		trend df) 42		0.3885952	-1.438 0.150490	
		trend df)43			4.459 8.52e-06	* * *
		trend df)44		0.4151729	0.742 0.458061	
		trend df)45		0.4048381	0.101 0.919603	
		trend df)46		0.4174507	-0.031 0.975148	
		<pre>trend_df)47</pre>		0.3781409	1.166 0.243530	
		<pre>trend_df)48</pre>		0.3867899	0.424 0.671837	
		<pre>trend_df)49</pre>		0.3913279	-0.576 0.564575	
		trend df) 50		0.3620310	1.901 0.057358	
		trend df)51		0.4167186	0.318 0.750804	•
		trend df) 52		0.4269387	-0.039 0.968648	
		trend df) 53		0.3981041	1.305 0.191935	
		trend df) 54		0.3929122	0.834 0.404474	
		trend df) 55		0.3528137	1.528 0.126723	
		trend df)56		0.3848434	2.259 0.023946	*
		trend df) 57			1.976 0.048187	
		trend df) 58		0.4301806	1.706 0.088078	
		trend df) 59		0.4069458	0.377 0.706125	•
		trend df) 60		0.4202259	0.010 0.991994	
		trend df)61		0.3811990	1.725 0.084586	
		<pre>trend_df)62</pre>		0.3593769	1.762 0.078142	
		trend df) 63		0.3790214	0.985 0.324672	•
		trend df)64		0.3587700	3.151 0.001641	* *
		trend df) 65		0.4220216	-0.183 0.854613	
		<pre>trend_df)66</pre>		0.4265496	1.244 0.213616	
		trend_df)67		0.4293260	2.060 0.039513	
		trend df) 68			1.792 0.073166	
		<pre>trend_df)69</pre>			0.788 0.430797	•
		<pre>trend_df)70</pre>			-0.388 0.697708	
	AT - 10	crena_ar), o	0.0000000	0.1/04200	0.300 0.037700	
Signif. c	odes: () `***' 0.001	***/ 0.01	** 0.05	0.1 1 1	
0191111.0		0.001	0.01	0.00		
Approxima	ate signi	lficance of s	mooth terms	:		
**		edf Ref.df	F p-value			
s(sqrt(in	nflu)) 1.	.47 1.833 6.	815 0.00122	* *		
 Signif. c	odes () `***' 0.001	·**/ 0.01	`*' 0.05 ` '	0.1 1 1	
519H11. C			0.01		~··	
R-sq.(adj	j) = 0.	.48 Devianc	e explained	= 48.6%		
GCV = 1.0)847 Sca	ale est. = 0 .	98601 n =	3507		

3. Secondary model 2: $\log[E(Y_t)] = \alpha + cb(Vapour Pressure_t) + cb(factor(Rainfall_t)) + cb(NO_{2_t}) + cb(log(SO_{2_t})) + cb(O_{3_t}) + cb(log(PM_{10_t})) + cb(factor(Holiday_t)) + ns(DOS_t, df = 7 per year) + factor(DOW_t) + s(\sqrt{Influenza_t}, k = 7)$ Family: quasipoisson Link function: log

Formula:

```
ad ~ VP.cb + rainfall.cb + o3.cb + so2.cb + no2.cb + pm10.cb +
holiday.cb + factor(dow) + ns(dos, df = 10 * trend_df) +
s(sqrt(influ), k = 7)
```

Parametric coefficients:

Parametric coefficients:					
		Std. Error			
(Intercept)	1.3553095	0.5661917		0.016731	*
VP.cbv1.ll	-0.0051677	0.0275582		0.851264	
VP.cbv1.12	-0.0370730	0.0268103		0.166819	
VP.cbv1.13	0.0166116	0.0390717		0.670749	
VP.cbv1.14	-0.0001894	0.0271655	-0.007	0.994437	
VP.cbv2.ll	0.0736201	0.0682986	1.078	0.281147	
VP.cbv2.12	-0.1653748	0.0687627	-2.405	0.016224	*
VP.cbv2.13	0.0694318	0.0948159		0.464047	
VP.cbv2.14	-0.0303909	0.0677348		0.653694	
VP.cbv3.ll	0.0501825	0.0367864	1.364	0.172606	
VP.cbv3.12	-0.0702289	0.0341507	-2.056	0.039815	*
VP.cbv3.13	-0.0011149	0.0510029	-0.022	0.982561	
VP.cbv3.14	0.0573688	0.0354223		0.105417	
rainfall.cbv1.l1	-0.0089060	0.0095426		0.350734	
rainfall.cbv1.l2	0.0117857	0.0097057		0.224713	
rainfall.cbv1.l3	0.0042138	0.0131819		0.749243	
rainfall.cbv1.l4	0.0049149	0.0094476		0.602940	
rainfall.cbv2.ll	-0.0185781	0.0234733		0.428733	
rainfall.cbv2.l2	-0.0031497	0.0254193		0.901395	
rainfall.cbv2.l3	0.0097602	0.0311368		0.753949	
rainfall.cbv2.14	-0.0329604	0.0236611		0.163703	
o3.cbv1.l1	0.0350348	0.0279724		0.210480	
o3.cbv1.l2	-0.0471171	0.0278681		0.090980	•
o3.cbv1.13	-0.0414443	0.0393413		0.292206	
o3.cbv1.14	0.0141358	0.0277313		0.610266	
o3.cbv2.l1	0.0324395	0.0363703		0.372497	
o3.cbv2.12	-0.0195819	0.0370433		0.597102	
o3.cbv2.13	-0.0096331	0.0501870		0.847797	
o3.cbv2.14 o3.cbv3.11	-0.0289869	0.0358466 0.0717748		0.418780	
o3.cbv3.12	0.0665267	0.0732998		0.354053 0.225386	
o3.cbv3.13	-0.1384151	0.0969419		0.153435	
o3.cbv3.14	0.0581507	0.0704800		0.409390	
o3.cbv4.l1	0.1555801	0.0703260		0.027013	*
o3.cbv4.12	-0.1850006	0.0742172		0.012724	
o3.cbv4.13	-0.0411989	0.0938417		0.660670	
o3.cbv4.14	0.1450825	0.0711142		0.041413	*
so2.cbv1.l1	0.0192957	0.0464112		0.677615	
so2.cbv1.12	0.0453044	0.0455387		0.319876	
so2.cbv1.13	0.0652402	0.0636952		0.305786	
so2.cbv1.14	-0.0983907	0.0451572		0.029410	*
so2.cbv2.l1	0.0575265	0.0423461		0.174398	
so2.cbv2.l2	0.0219654	0.0425749		0.605940	
so2.cbv2.13	0.0162539	0.0574158	0.283	0.777124	
so2.cbv2.14	-0.0230780	0.0414628	-0.557	0.577840	
so2.cbv3.ll	0.0597653	0.1104291	0.541	0.588398	
so2.cbv3.12	0.1164419	0.1119523	1.040	0.298365	
so2.cbv3.13	-0.0011307	0.1518771	-0.007	0.994060	
so2.cbv3.14	-0.1620714	0.1076844	-1.505	0.132400	
so2.cbv4.ll	-0.0106711	0.0716659	-0.149	0.881640	
so2.cbv4.l2	-0.0269358	0.0756726		0.721898	
so2.cbv4.13	-0.0254380	0.1003181		0.799840	
so2.cbv4.14	-0.0690957	0.0707578		0.328881	
no2.cbv1.ll	-0.0544867	0.0501652		0.277490	
no2.cbv1.l2	0.0321086	0.0505383		0.525255	
no2.cbv1.l3	-0.0337680	0.0679432		0.619218	
no2.cbv1.14	0.1157413	0.0508129		0.022799	*
no2.cbv2.ll	0.0281539	0.0492771	0.571	0.567807	

no2.cbv2.12	0.0265271	0.0510940	0.519 0.603667
no2.cbv2.13	0.0314189	0.0663276	0.474 0.635749
no2.cbv2.14			2.096 0.036128 *
	0.1039874	0.0496052	
no2.cbv3.l1	-0.1666180	0.1183115	-1.408 0.159132
no2.cbv3.12	0.2087022	0.1203854	1.734 0.083075 .
no2.cbv3.13	-0.0291471	0.1604221	-0.182 0.855837
no2.cbv3.l4	0.2799515	0.1178405	2.376 0.017571 *
no2.cbv4.ll	-0.0545403	0.1007962	-0.541 0.588477
no2.cbv4.l2	0.1379325	0.1043397	1.322 0.186270
no2.cbv4.l3	-0.0173810	0.1432889	-0.121 0.903460
no2.cbv4.14	0.1642793	0.1012649	1.622 0.104836
pm10.cbv1.l1	-0.0407622	0.0533743	-0.764 0.445095
pm10.cbv1.12	-0.0517256	0.0510717	-1.013 0.311224
pm10.cbv1.13	0.2054219	0.0720623	2.851 0.004389 **
pm10.cbv1.14	-0.1512313	0.0515482	-2.934 0.003371 **
pm10.cbv2.l1	-0.0694038	0.0512745	-1.354 0.175961
pm10.cbv2.l2	-0.0543270	0.0506952	-1.072 0.283956
pm10.cbv2.13	0.0810566	0.0727806	1.114 0.265480
pm10.cbv2.14	-0.1532471	0.0514432	-2.979 0.002912 **
pm10.cbv3.l1	0.0800839	0.1273213	0.629 0.529397
pm10.cbv3.12	-0.2573946	0.1233464	-2.087 0.036983 *
pm10.cbv3.l3	0.4379224	0.1715185	2.553 0.010716 *
pm10.cbv3.14	-0.2506877	0.1233479	-2.032 0.042193 *
pm10.cbv4.l1	0.0507315	0.1222589	0.415 0.678203
pm10.cbv4.12	-0.1276988	0.1284987	-0.994 0.320402
*		0.1718410	1.421 0.155304
pm10.cbv4.13	0.2442471		
pm10.cbv4.14	-0.0219763	0.1290729	-0.170 0.864814
holiday.cbv1.l1	0.0216149	0.0139777	1.546 0.122103
holiday.cbv1.12	-0.0389137	0.0126002	-3.088 0.002029 **
holiday.cbv1.l3	-0.0243269	0.0182945	-1.330 0.183692
holiday.cbv1.l4	-0.0253565	0.0132018	-1.921 0.054853 .
factor(dow)2	-0.0593118	0.0221940	-2.672 0.007566 **
factor(dow)3	-0.0739103	0.0235176	-3.143 0.001688 **
factor(dow)4	-0.0438628	0.0237731	-1.845 0.065114 .
factor(dow)5	-0.0746431	0.0237100	-3.148 0.001657 **
factor(dow)6	-0.0892264	0.0235227	-3.793 0.000151 ***
factor(dow)7	-0.0417234	0.0228870	-1.823 0.068387 .
ns(dos, df = $10 \times \text{trend df}$)1	1.0053188	0.3018644	3.330 0.000876 ***
ns (dos, $df = 10 * trend df) 2$	-0.0733716	0.4172199	-0.176 0.860415
ns (dos, $df = 10 * trend df$) 3	1.0199234	0.3882061	2.627 0.008645 **
ns (dos, df = 10 * trend df) 4	0.3463243	0.4060638	0.853 0.393784
ns (dos, df = 10 * trend df) 5	0.4701391	0.3666328	1.282 0.199818
ns (dos, df = $10 \times \text{trend} \text{ df}$) 6	-0.2401648	0.3955762	1.202 0.199010
iis(aos, ar = ro - crena ar)o	-0.2401040	0.3333702	-0 607 0 543807
ma(daa) dE = 10 + to and dE 7	0 0000474	0 2522107	-0.607 0.543807
ns (dos, $df = 10 * trend_df$) 7	-0.0260474	0.3533197	-0.074 0.941236
ns(dos, df = $10 \times \text{trend_df}$) 8	1.2971209	0.3541993	-0.074 0.941236 3.662 0.000254 ***
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9</pre>	1.2971209 -0.8712522	0.3541993 0.3967492	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 *
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10</pre>	1.2971209 -0.8712522 -0.1775152	0.3541993 0.3967492 0.4185246	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9</pre>	1.2971209 -0.8712522 -0.1775152	0.3541993 0.3967492	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 *
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10</pre>	1.2971209 -0.8712522 -0.1775152	0.3541993 0.3967492 0.4185246	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11</pre>	1.2971209 -0.8712522 -0.1775152 -0.1639397 0.6751854	0.3541993 0.3967492 0.4185246 0.4219056	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13</pre>	1.2971209 -0.8712522 -0.1775152 -0.1639397 0.6751854 -0.5013254	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14</pre>	1.2971209 -0.8712522 -0.1775152 -0.1639397 0.6751854 -0.5013254 1.3977460	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 ***
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15</pre>	1.2971209 -0.8712522 -0.1775152 -0.1639397 0.6751854 -0.5013254 1.3977460 0.8347699	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 *
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<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354 \end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 .
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<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)20</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.36734312 0.36337431	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 *
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)22 ns(dos, df = 10 * trend_df)21</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\end{array}$	0.3541993 0.3967492 0.4185246 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 ***
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<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751 \end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806 0.3922070	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 *
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24 ns(dos, df = 10 * trend_df)24</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751 \end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806 0.3922070	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 *
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24 ns(dos, df = 10 * trend_df)24</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.40538940\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012 \end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3524784 0.3942280 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806 0.3922070 0.3956940	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 * 2.391 0.016845 *
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)25 ns(dos, df = 10 * trend_df)25 ns(dos, df = 10 * trend_df)26</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.40538940\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012 \end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633280 0.3535204 0.3766806 0.3922070 0.3956940 0.3644274	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 * 2.391 0.016845 * 0.690 0.490161
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)22 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)27</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012\\ -0.3910095\\ 0.6571490\end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3555204 0.3766806 0.3922070 0.3956940 0.3644274 0.3693294 0.3495717	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 * 2.391 0.016845 * 0.690 0.490161 -1.059 0.289810 1.880 0.060210 .
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)25 ns(dos, df = 10 * trend_df)25 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)28 ns(dos, df = 10 * trend_df)28 ns(dos, df = 10 * trend_df)28 ns(dos, df = 10 * trend_df)28</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012\\ -0.3910095\\ 0.6571490\\ 1.2016442\end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3524784 0.3942280 0.4188475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806 0.3922070 0.3956940 0.3644274 0.3693294 0.3495717 0.3569473	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 1.812 0.07015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 * 2.391 0.016845 * 0.690 0.490161 -1.059 0.289810 1.880 0.060210 . 3.366 0.000770 ***
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)20 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)22 ns(dos, df = 10 * trend_df)22 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24 ns(dos, df = 10 * trend_df)25 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)29 ns(dos, df = 10 * trend_df)23</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.1639397\\ 0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012\\ -0.3910095\\ 0.6571490\\ 1.2016442\\ 0.0220232\end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806 0.3922070 0.3956940 0.3644274 0.3693294 0.3693271 0.3659473 0.4114475	-0.074 0.941236 3.662 0.000254 *** -2.196 0.028160 * -0.424 0.671486 -0.389 0.697618 1.812 0.070015 . -1.387 0.165508 4.007 6.27e-05 *** 2.368 0.017925 * 0.131 0.896029 -1.750 0.080206 . 0.635 0.525386 1.103 0.269970 2.557 0.010602 * -0.314 0.753430 3.466 0.000535 *** 0.235 0.814518 2.030 0.042382 * 2.391 0.016845 * 0.690 0.490161 -1.059 0.289810 1.880 0.060210 . 3.366 0.000770 *** 0.054 0.957316
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)26 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)28 ns(dos, df = 10 * trend_df)30 ns(dos, df = 10 * trend_df)31</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012\\ -0.3910095\\ 0.6571490\\ 1.2016442\\ 0.0220232\\ 0.1566382 \end{array}$	0.3541993 0.3967492 0.4185246 0.325418 0.3614264 0.3428010 0.3524784 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633280 0.3535204 0.3768806 0.3922070 0.3956940 0.3644274 0.3693294 0.3693294 0.3495717 0.3569473 0.4114475 0.3897626	$\begin{array}{c} -0.074 & 0.941236 \\ 3.662 & 0.000254 *** \\ -2.196 & 0.028160 * \\ -0.424 & 0.671486 \\ -0.389 & 0.697618 \\ 1.812 & 0.070015 \\ -1.387 & 0.165508 \\ 4.007 & 6.27e-05 *** \\ 2.368 & 0.017925 * \\ 0.131 & 0.896029 \\ -1.750 & 0.080206 \\ . \\ 0.635 & 0.525386 \\ 1.103 & 0.269970 \\ 2.557 & 0.010602 * \\ -0.314 & 0.753430 \\ 3.466 & 0.00535 *** \\ 0.235 & 0.814518 \\ 2.030 & 0.042382 * \\ 2.391 & 0.016845 * \\ 0.690 & 0.490161 \\ -1.059 & 0.289810 \\ 1.880 & 0.060210 \\ . \\ 3.366 & 0.00770 *** \\ 0.054 & 0.957316 \\ 0.402 & 0.687796 \\ \end{array}$
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)15 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)19 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)22 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)24 ns(dos, df = 10 * trend_df)26 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)28 ns(dos, df = 10 * trend_df)29 ns(dos, df = 10 * trend_df)29 ns(dos, df = 10 * trend_df)31 ns(dos, df = 10 * trend_df)31</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.175152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012\\ -0.3910095\\ 0.6571490\\ 1.2016442\\ 0.220232\\ 0.1566382\\ 0.5486411 \end{array}$	0.3541993 0.3967492 0.4185246 0.4219056 0.3725418 0.3614264 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633743 0.3633280 0.3535204 0.3766806 0.3922070 0.3956940 0.3644274 0.3693294 0.3693294 0.369473 0.4114475 0.3897626 0.3934679	$\begin{array}{c} -0.074 \ 0.941236\\ 3.662 \ 0.000254 \ ***\\ -2.196 \ 0.028160 \ *\\ -0.424 \ 0.671486\\ -0.389 \ 0.697618\\ 1.812 \ 0.070015 \ .\\ -1.387 \ 0.165508\\ 4.007 \ 6.27e-05 \ ***\\ 2.368 \ 0.017925 \ *\\ 0.131 \ 0.896029\\ -1.750 \ 0.080206 \ .\\ 0.635 \ 0.525386\\ 1.103 \ 0.269970\\ 2.557 \ 0.010602 \ *\\ -0.314 \ 0.753430\\ 3.466 \ 0.000535 \ ***\\ 0.235 \ 0.814518\\ 2.030 \ 0.042382 \ *\\ 2.391 \ 0.016845 \ *\\ 0.690 \ 0.490161\\ -1.059 \ 0.289810\\ 1.880 \ 0.060210 \ .\\ 3.366 \ 0.000770 \ ***\\ 0.054 \ 0.957316\\ 0.402 \ 0.687796\\ 1.394 \ 0.163294 \end{array}$
<pre>ns(dos, df = 10 * trend_df)8 ns(dos, df = 10 * trend_df)9 ns(dos, df = 10 * trend_df)10 ns(dos, df = 10 * trend_df)11 ns(dos, df = 10 * trend_df)12 ns(dos, df = 10 * trend_df)13 ns(dos, df = 10 * trend_df)14 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)16 ns(dos, df = 10 * trend_df)17 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)18 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)21 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)23 ns(dos, df = 10 * trend_df)26 ns(dos, df = 10 * trend_df)27 ns(dos, df = 10 * trend_df)28 ns(dos, df = 10 * trend_df)30 ns(dos, df = 10 * trend_df)31</pre>	$\begin{array}{c} 1.2971209\\ -0.8712522\\ -0.1775152\\ -0.6751854\\ -0.5013254\\ 1.3977460\\ 0.8347699\\ 0.0515214\\ -0.7347354\\ 0.2638040\\ 0.4053899\\ 0.9291309\\ -0.1141378\\ 1.2252529\\ 0.0883765\\ 0.7963751\\ 0.9461921\\ 0.2515012\\ -0.3910095\\ 0.6571490\\ 1.2016442\\ 0.0220232\\ 0.1566382 \end{array}$	0.3541993 0.3967492 0.4185246 0.325418 0.3614264 0.3428010 0.3524784 0.3488010 0.3524784 0.3942280 0.4198475 0.4153546 0.3674312 0.3633280 0.3535204 0.3768806 0.3922070 0.3956940 0.3644274 0.3693294 0.3693294 0.3495717 0.3569473 0.4114475 0.3897626	$\begin{array}{c} -0.074 & 0.941236 \\ 3.662 & 0.000254 *** \\ -2.196 & 0.028160 * \\ -0.424 & 0.671486 \\ -0.389 & 0.697618 \\ 1.812 & 0.070015 \\ -1.387 & 0.165508 \\ 4.007 & 6.27e-05 *** \\ 2.368 & 0.017925 * \\ 0.131 & 0.896029 \\ -1.750 & 0.080206 \\ . \\ 0.635 & 0.525386 \\ 1.103 & 0.269970 \\ 2.557 & 0.010602 * \\ -0.314 & 0.753430 \\ 3.466 & 0.00535 *** \\ 0.235 & 0.814518 \\ 2.030 & 0.042382 * \\ 2.391 & 0.016845 * \\ 0.690 & 0.490161 \\ -1.059 & 0.289810 \\ 1.880 & 0.060210 \\ . \\ 3.366 & 0.00770 *** \\ 0.054 & 0.957316 \\ 0.402 & 0.687796 \\ \end{array}$

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ns(dos, df = 10 * trend df)35 1.1660641 0.361	3343 3.227 0.001262 **
ns(dos, df = 10 * trend df)36 0.2220552 0.344	5922 0.644 0.519359
ns(dos, df = 10 * trend df)37 0.1518120 0.403	
ns(dos, df = 10 * trend df)38 1.1555986 0.384	
ns(dos, df = 10 * trend df) 39 0.4897097 0.406	
ns (dos, df = 10 * trend df) 40 0.4762154 0.364	
ns (dos, df = 10 * trend_df) 41 -0.0188192 0.387	
ns (dos, df = $10 * trend_df$) 42 -0.5647915 0.372	
$ns(dos, df = 10 * trend_df)43 1.7093045 0.349$	
ns(dos, df = 10 * trend_df)44 0.3305572 0.398	
$ns(dos, df = 10 * trend_df)45 0.1669668 0.407$	
ns(dos, df = 10 * trend_df)46 0.0622764 0.405	5984 0.154 0.878010
ns(dos, df = 10 * trend_df)47 0.5551462 0.366	050 1.517 0.129415
ns(dos, df = 10 * trend df)48 0.1556012 0.375	5963 0.414 0.678696
ns(dos, df = 10 * trend df)49 -0.1621871 0.382	3264 -0.424 0.671842
ns(dos, df = 10 * trend df)50 0.7622711 0.351	7725 2.167 0.030307 *
ns(dos, df = 10 * trend df)51 0.1223278 0.418	0.293 0.769830
ns(dos, df = 10 * trend df)52 0.1600776 0.407	3557 0.392 0.694723
ns(dos, df = 10 * trend df)53 0.5942923 0.395	
ns(dos, df = 10 * trend df)54 0.3892705 0.376	
ns(dos, df = 10 * trend df)55 0.6049207 0.344	
ns (dos, df = 10 * trend df) 56 0.8654396 0.373	
ns(dos, df = 10 * trend df)57 0.8190290 0.348	
ns(dos, df = 10 * trend df)58 0.7551938 0.411	
ns (dos, df = $10 \times \text{trend}_{df}$) 59 0.2679309 0.412	
ns (dos, df = $10 * trend_df$) 60 0.0836855 0.407	
ns(dos, df = 10 * trend_df)61 0.6969491 0.373	
ns(dos, df = 10 * trend_df)62 0.7025813 0.353	
ns (dos, df = $10 * trend_df$) 63 0.4321847 0.371	
ns(dos, df = 10 * trend_df)64 1.2265577 0.353	
ns(dos, df = 10 * trend_df)65 -0.0542336 0.412	
ns(dos, df = 10 * trend_df)66 0.6087704 0.414	
ns(dos, df = 10 * trend_df)67 1.0404031 0.424	
ns(dos, df = 10 * trend_df)68 0.6124457 0.261	
ns(dos, df = 10 * trend_df)69 0.5883909 0.749	1997 0.785 0.432481
ns(dos, df = 10 * trend_df)70 0.0603472 0.169	5749 0.356 0.722114
Signif. codes: 0 `***' 0.001 `**' 0.01 `*' 0.0	5 `.' 0.1 ` ' 1
Approximate significance of smooth terms:	
edf Ref.df F p-value	
s(sqrt(influ)) 1.03 1.059 14.78 9.19e-05 ***	
Signif. codes: 0 `***' 0.001 `**' 0.01 `*' 0.0	5 `.' 0.1 ` ' 1
R-sq.(adj) = 0.472 Deviance explained = 47.6	5
GCV = 1.081 Scale est. = 0.98971 n = 3632	