

On the lagged non-linear association between air pollution and
COVID-19 cases in Belgium

Supplementary material

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1 Figures and Tables

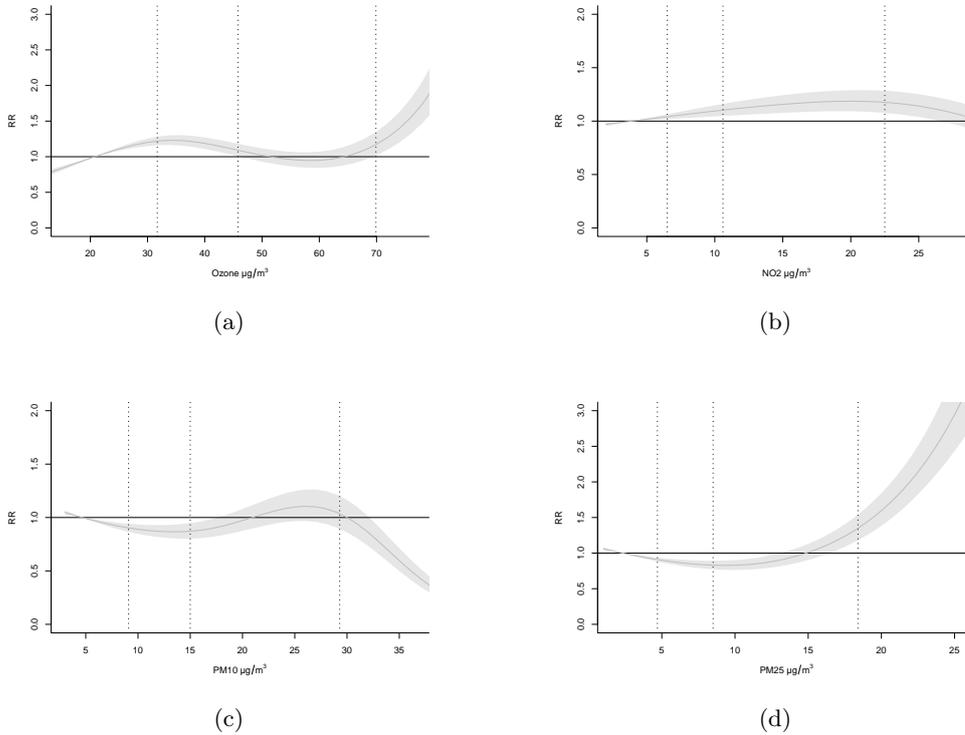


Fig. 1: Cumulative effects of exposure to (a) O_3 ; (b) NO_2 ; (c) PM_{10} ; (d) $PM_{2.5}$. Dotted lines denote percentiles of pollutant concentrations: 20%, 50% and 95%.

Table 1: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for models with a spatial but without a temporal random effect.

Pollutant	20% quantile	50% quantile	95% quantile
O_3	0.85(0.80, 0.90)	0.57(0.54, 0.61)	0.28(0.26, 0.30)
NO_2	1.91(1.86, 1.95)	4.60(4.37, 1.85)	10.72(9.96, 11.52)
PM_{10}	0.30(0.29, 0.32)	0.16(0.14, 0.17)	3.03(2.70, 3.39)
$PM_{2.5}$	0.61(0.59, 0.63)	0.44(0.41, 0.48)	4.87(4.46, 5.31)
BC	1.49(1.46, 1.51)	2.82(2.70, 2.95)	13.61(12.36, 14.98)

Table 2: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for models with a temporal but without a spatial random effect.

Pollutant	20% quantile	50% quantile	95% quantile
O_3	1.44(1.38, 1.50)	1.50(1.43, 1.59)	2.14(1.99, 2.29)
NO_2	0.90(0.89, 0.91)	0.79(0.77, 0.80)	0.76(0.73, 0.78)
PM_{10}	0.79(0.77, 0.81)	0.66(0.63, 0.69)	0.62(0.59, 0.65)
$PM_{2.5}$	0.77(0.76, 0.79)	0.57(0.55, 0.59)	0.57(0.54, 0.60)
BC	0.91(0.90, 0.91)	0.78(0.76, 0.79)	0.72(0.69, 0.75)

Table 3: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for models without any spatial or temporal random effect.

Pollutant	20% quantile	50% quantile	95% quantile
O_3	1.13(1.06, 1.19)	0.78(0.73, 0.83)	0.50(0.47, 0.53)
NO_2	1.00(0.98, 1.01)	1.00(0.97, 1.04)	1.32(1.26, 1.39)
PM_{10}	0.31(0.30, 0.32)	0.15(0.15, 0.16)	2.09(1.95, 2.24)
$PM_{2.5}$	0.47(0.46, 0.49)	0.25(0.24, 0.27)	2.35(2.19, 2.52)
BC	1.00(0.99, 1.01)	1.01(0.98, 1.04)	1.51(1.43, 1.59)

2 Additional analyses

2.1 Case time series design

Since the negative binomial family cannot be used directly within this case time series design in R, we fitted a conditional quasipoisson model, with mean

$$\log(p_{ij}) = \alpha_i + s_1(x_t \dots x_{t-8}) + s_2(z_t, z_{t-1}, z_{t-2}) + \text{factor}(j)$$

where α_i represents the municipality-specific intercept, x represents the BC exposure and z the vaccination rate. This model has the advantage of relying only on intra-municipality contrasts, without the need of a spatial random effect. We chose to include the week number as a factor and not as a smooth trend due to the numerous peaks and declines anticipated in the COVID-19 incidence pattern. The resulting estimated cumulative RR are 1.25 (1.22, 1.28) for $0.27 \mu g/m^3$, 1.81 (1.71, 1.92) for $0.44 \mu g/m^3$ and 6.34 (5.45, 7.38) for $1.20 \mu g/m^3$. Figure 2 shows the lag-response curve for the median and 99% BC pollution quantile as well as the cumulative RR.

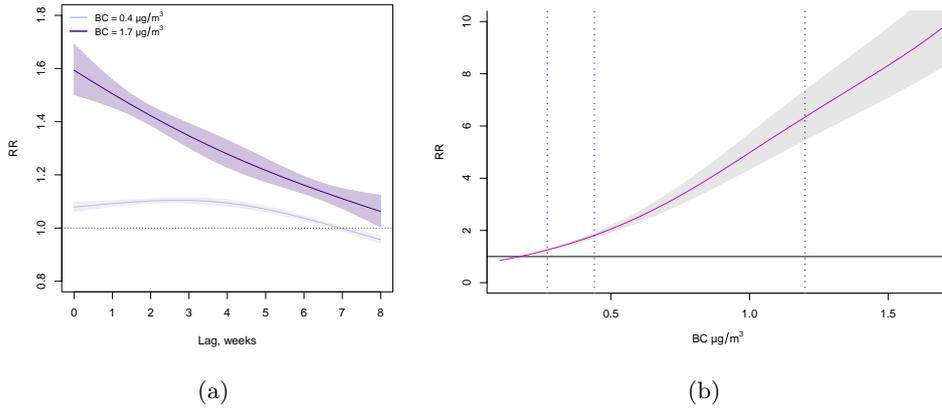


Fig. 2: Lag-response of COVID-19 to Black Carbon (BC) pollution; (a) lag-response association between the risk of COVID-19 and two levels of BC pollution and (b) Cumulative effects of the exposure to BC on the relative risk (RR) of COVID-19, using the case time series approach.

Figure 3 shows that estimated cumulative RR for all other pollutants using the case time series design. Some differences can be found with Figure 1, particularly for NO_2 , but further analysis indicated that these discrepancies stem from the distinction between the Poisson and negative binomial model, rather than the distinction between the Bayesian spatio-temporal and case time series approach. A comparison of the DIC values for the spatial-temporal INLA modelling approach between the negative binomial and Poisson model showed significantly lower values for the negative binomial model compared to the Poisson model (i.e. about 300000 compared to about 500000) for all single-pollutant models, supporting its selection as the more appropriate choice.

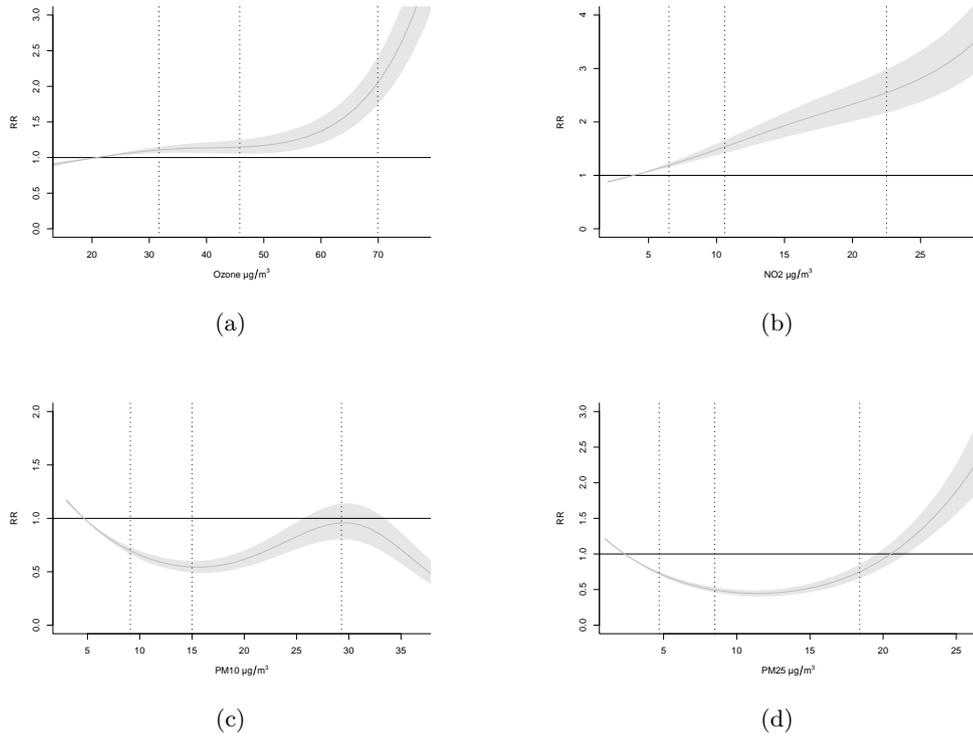


Fig. 3: Cumulative effects of exposure to (a) O_3 ; (b) NO_2 ; (c) PM_{10} ; (d) $PM_{2.5}$ based on the case time series approach.

2.2 Adding additional covariates

We also performed a sensitivity analysis, adding two additional covariates to the model containing only BC , namely population density and the deprivation index. The resulting estimated cumulative RR are 1.23 (1.21, 1.26) for $0.27 \mu g/m^3$, 1.73 (1.64, 1.82) for $0.44 \mu g/m^3$ and 5.08 (4.47, 5.78) for $1.20 \mu g/m^3$. Figure 4 again shows a lag-response curve as well as cumulative RR.

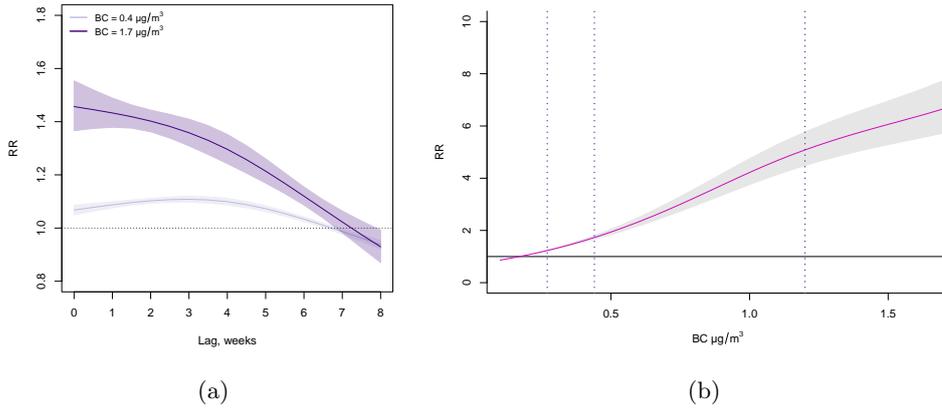


Fig. 4: Lag-response of COVID-19 to Black Carbon (BC) pollution; (a) lag-response association between the risk of COVID-19 and two levels of BC pollution and (b) Cumulative effects of the exposure to BC on the relative risk (RR) of COVID-19, using the model with two additional covariates.

For the other single-pollutant models, the estimated cumulative RR from the models with two additional covariates, can be found in Table 4. Comparing this table to Table 2 of the paper, it can be seen that the results are very similar.

Table 4: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for an analysis including population density and deprivation as additional confounders.

Pollutant	20% quantile	50% quantile	95% quantile
O_3	1.22(1.16, 1.28)	1.09(1.01, 1.19)	1.17(1.02, 1.35)
NO_2	1.04(1.02, 1.06)	1.10(1.04, 1.15)	1.16(1.06, 1.27)
PM_{10}	0.90(0.87, 0.94)	0.87(0.80, 0.95)	1.04(0.90, 1.21)
$PM_{2.5}$	0.90(0.87, 0.93)	0.82(0.76, 0.89)	1.34(1.17, 1.53)
BC	1.23(1.21, 1.26)	1.73(1.64, 1.82)	5.08(4.46, 5.79)

2.3 Linear exposure relationship (DLM)

We also fitted models with a linear relationship in the variable dimension. We did allow for a non-linear relationship in the lag dimension to deal with temporal correlations. The results for all pollutants can be found in Table 5.

Table 5: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for an analysis assuming a linear relationship in the variable dimension.

Pollutant	20% quantile	50% quantile	95% quantile
O_3	1.19(1.16, 1.23)	1.50(1.41, 1.61)	2.23(1.95, 2.55)
NO_2	0.99(0.98, 1.00)	0.98(0.96, 1.01)	0.95(0.88, 1.03)
PM_{10}	0.95(0.92, 0.98)	0.89(0.84, 0.95)	0.76(0.66, 0.88)
$PM_{2.5}$	1.08(1.05, 1.10)	1.20(1.14, 1.26)	1.59(1.39, 1.80)
BC	1.10(1.09, 1.11)	1.29(1.26, 1.32)	2.65(2.41, 2.91)

2.4 Linear lag relationship

We also fitted models with a linear lag relationship. We did allow for a non-linear relationship in the variable dimension. The results for all pollutants can be found in Table 6.

Table 6: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for an analysis assuming a linear relationship in the lag dimension.

Pollutant	20% quantile	50% quantile	95% quantile
O_3	1.22(1.16, 1.28)	1.09(1.01, 1.18)	1.17(1.01, 1.35)
NO_2	1.04(1.02, 1.07)	1.11(1.05, 1.16)	1.18(1.08, 1.29)
PM_{10}	0.89(0.85, 0.93)	0.85(0.78, 0.92)	1.03(0.89, 1.19)
$PM_{2.5}$	0.90(0.87, 0.93)	0.82(0.76, 0.88)	1.39(1.22, 1.60)
BC	1.21(1.18, 1.23)	1.64(1.56, 1.73)	4.52(3.99, 5.13)

The cumulative RR are very similar but we can also look into the lag-specific RR for BC . Table 7 show that there are some non-overlapping confidence intervals for the lag-specific RR of BC . Figure 5 shows the lag-specific RR for (a) the DLNM and (b) a linear relationship in the lag dimension.

Table 7: The estimated lag-specific RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for an analysis assuming a linear relationship in the lag dimension.

Lag	Non-linear		Linear	
	$0.4\mu\text{g}/\text{m}^3$	$1.7\mu\text{g}/\text{m}^3$	$0.4\mu\text{g}/\text{m}^3$	$1.7\mu\text{g}/\text{m}^3$
0	1.06(1.05, 1.08)	1.44(1.35, 1.53)	1.11(1.10, 1.13)	1.53(1.46, 1.60)
1	1.08(1.07, 1.09)	1.41(1.36, 1.47)	1.10(1.09, 1.11)	1.40(1.45, 1.50)
2	1.10(1.09, 1.11)	1.38(1.34, 1.42)	1.08(1.07, 1.09)	1.37(1.33, 1.40)
3	1.10(1.09, 1.11)	1.34(1.29, 1.39)	1.06(1.06, 1.07)	1.29(1.27, 1.32)
4	1.09(1.08, 1.11)	1.28(1.23, 1.33)	1.06(1.05, 1.06)	1.22(1.20, 1.24)
5	1.07(1.06, 1.08)	1.20(1.15, 1.24)	1.03(1.03, 1.04)	1.15(1.13, 1.18)
6	1.03(1.02, 1.04)	1.11(1.07, 1.14)	1.02(1.01, 1.02)	1.09(1.06, 1.12)
7	0.98(0.97, 0.99)	1.01(0.97, 1.05)	1.00(0.99, 1.01)	1.03(0.99, 1.07)
8	0.93(0.92, 0.95)	0.92(0.86, 0.98)	0.99(0.98, 1.00)	0.98(0.93, 1.02)

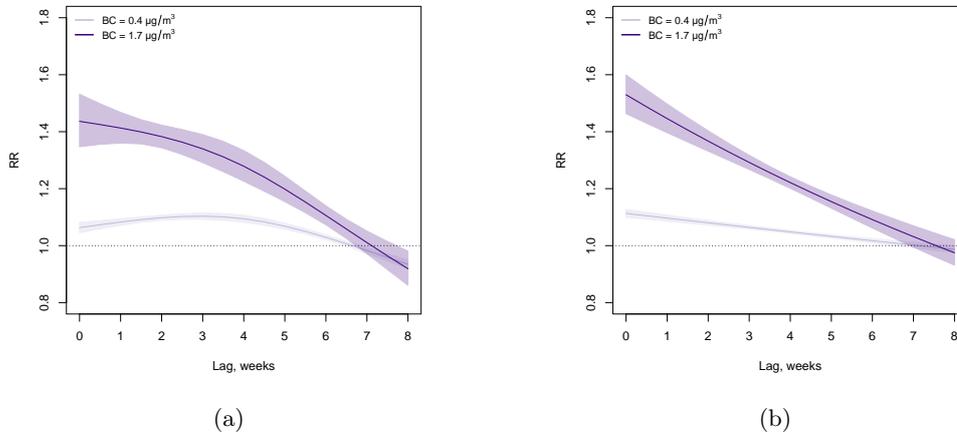


Fig. 5: Lag-response between the risk of COVID-19 to BC pollution (for median and 99% level BC pollution) for: (a) DLNM; (b) Linear relationship in the lag dimension.

2.5 Bi-pollutant models

The results of several bi-pollutant models can be found in Table 8. All of the models contain the vaccination rate a covariate as well.

Table 8: The estimated cumulative RR for different levels of the different pollutants with 95% CI, compared to the 5% pollution quantile, for bi-pollutant models.

Model	Pollutant	20% quantile	50% quantile	95% quantile
O_3 - BC	O_3	1.76(1.66, 1.86)	2.39(2.16, 2.64)	3.42(2.87, 4.07)
	BC	1.25(1.22, 1.28)	1.82(1.72, 1.93)	7.32(6.33, 8.47)
O_3 - NO_2	O_3	1.24(1.17, 1.33)	1.22(1.08, 1.36)	1.48(1.23, 1.80)
	NO_2	1.06(1.03, 1.09)	1.15(1.09, 1.22)	1.28(1.14, 1.43)
PM_{10} - BC	PM_{10}	0.71(0.67, 0.74)	0.50(0.46, 0.55)	0.33(0.28, 0.40)
	BC	1.26(1.23, 1.29)	1.83(1.73, 1.94)	5.99(5.20, 6.89)
$PM_{2.5}$ - BC	$PM_{2.5}$	0.81(0.78, 0.84)	0.63(0.58, 0.69)	0.71(0.60, 0.83)
	BC	1.24(1.21, 1.26)	1.74(1.65, 1.84)	4.17(3.62, 4.81)
O_3 - PM_{10}	O_3	1.27(1.21, 1.34)	1.11(1.02, 1.21)	1.15(0.98, 1.34)
	PM_{10}	0.89(0.85, 0.93)	0.87(0.79, 0.95)	1.24(1.06, 1.46)