보건학석사 학위논문

대기오염과 건강의 인과성 추론

Causal inference in assessing the impact of air pollution on mortality

2018년 8월

서울대학교 보건대학원

보건학과 보건통계학전공

최 하 연

대기오염과 건강의 인과성 추론

Causal inference in assessing

the impact of air pollution on mortality

지도교수 김 호

이 논문을 보건학석사 학위논문으로 제출함

2018년 5월

서울대학교 보건대학원

보건학과 보건통계학전공

최 하 연

최하연의 석사학위논문을 인준함

2018년 6월

위 원 장 이 승 묵 (인)

부 위원장 황 승 식 (인)

위 원 김 호 (인)

Abstract

Causal inference in assessing the impact of air pollution on mortality

Hayon Michelle Choi

Department of Biostatistics and Epidemiology

The Graduate School of Public Health

Seoul National University

Background: Numerous studies have investigated the association between particles less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$) and mortality. However, these have been associational studies that did not use formal causal modeling approaches. We considered the impact of high daily exposure level of $PM_{2.5}$ on mortality in the metropolitan area of Seoul (Republic of Korea), during the year 2003-2012. Particularly, focusing on the historical health impacts of daily air pollution levels under pre-fixed thresholds on health using different causal approaches.

Methods: We applied propensity score matching methods (nearest neighbor

matching and Caliper matching) and inverse probability weighting method to estimate the relative risk (RR) during the study period. We matched each exposed day, namely each day with an exposure higher than pre-fixed threshold exposure, with a day with similar background characteristics but an exposure lower than pre-fixed threshold exposure, using the propensity score. The pre-fixed threshold exposure level was based on the daily high $PM_{2.5}$ (past, and present) in Korea Enforcement Decree of the Framework Act on Environmental Policy (50, 35 $\mu g/m^3$), and the WHO daily high $PM_{2.5}$ exposure level (25 $\mu g/m^3$). Then, we estimated the impact by comparing the risk between the matched days. The risks were compared within different methods and by the changes in pre-fixed threshold in the same method.

Results: For days exceeding the limit of 50 $\mu g/m^3$ for $PM_{2.5}$ average had 0.982 times more risk of mortality than the days not exceeding 50 $\mu g/m^3$, and days exceeding 35 $\mu g/m^3$ $PM_{2.5}$ average had 1.015 times more risk of mortality than the days below 35 $\mu g/m^3$ $PM_{2.5}$, for 1:1 nearest neighbor matching. The relative risk above pre-fixed threshold 35 $\mu g/m^3$ was higher than the days above 50 $\mu g/m^3$, in the nearest matching method.

Conclusions: We conclude that having strengthened the policy (changing daily ”bad” indication for $PM_{2.5}$ from above 35 to above 50 $\mu g/m^3$), could have

avoided higher mortality risks in Seoul during the study period.

Keywords: particles less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$), mortality, causal association, propensity score, Seoul, Republic of Korea

Student Number: 2016-25798

Contents

List of Figures

List of Tables

Appendix

Chapter 1. Introduction

1.1 Motivation

A large number of time series studies have reported associations of daily air pollution and daily deaths [1-3]. Especially, particulate matter is related to the increase in mortality and morbidity [4-6]. Most of the observational epidemiology studies have been associational studies, which do not assess causality. In most cases, the regression method is used to estimate the short-term impact of air pollution. The relationship between daily exposure and daily mortality is estimated through a Poisson regression model and is expressed as the exposure-response curve. Then the risk is calculated by combining the observed death and air pollution on the curve. Since most studies are based on observational epidemiology investigations, these results have indicated associations following causal interpretations [7]. The causal interpretation has been supported by various studies, its consistent findings, and its biological plausibility [8, 9]. For a further insight of causal association between air pollution and health, a prior literature review was conducted.

1.1.1 Prior literature review

Using the PubMed, Science Direct, Scopus, and Web of Science search engines from May 20th to June 1st, 2018 published research articles written in English was searched. The following keywords were used in this literature search: causality, causal inference, air pollution, and epidemiology. Three major criteria were used to select published studies for inclusion in this prior literature review. First, the articles were required to assess the causal association between air pollution and health

outcomes. Second, the association should be demonstrated by using observational data. Lastly, only peer-reviewed studies were considered; books, reports, and abstracts were excluded. 12 studies were included in the prior literature review of this study. The specific flow diagram is shown in Figure 1.

We focused on the methodological aspects of these studies by the year it was published. The selected articles were published during the year 2004 to 2018.

In 2004, a study conducted a matching approach using the case-crossover design to examine the association between deaths and particulate matter with an aerodynamic diameter less than or equal to 10 micron (PM_{10}) [10].

In 2012, Padula AM [11] used the targeted maximum likelihood estimation (T-MLE) to estimate the causal association between exposure to traffic-related air pollution during pregnancy and term low birth weight. T_MLE provides population-level estimate and a parameter of interest with straightforward interpretation. Also, allows estimating the parameter akin to a causal attributable risk on the population intervention model. A different method was proposed in 2012 by Zigler CM [12]. In this study, principal stratification was used to examine the causal effects of an air quality regulation on health.

In 2013, Díaz I [13] have assessed the causal effect of pollution level policies by

using an inverse probability of treatment weighted (IPTW), augmented IPTW and targeted minimum loss-based estimators (TMLE). Comparing the expectation of the outcome under the policy of interest with its current results, it provides a measure of

the gain obtained by implementing the policy. This approach which is the stochastic intervention framework derives a causal interpretation.

The following year, Bor J [14] used the regression discontinuity designs for causal inference without randomized trials.

Weisskopf MG [15] explained the causal association between perinatal air pollution exposure and risk of autism spectrum disorder (ASD) through the directed acyclic graphs (DAGs) in 2015. DAGs representing different possible sets of basic assumptions about the causal relationship among key variables were investigated. Furthermore, another study [16] applied the propensity score method for causal modelling.

In 2016, Wang Y [17] applied a variant of the difference-in-differences approach, which serves to an approximate random assignment of exposure across the population. This approach controls geographical differences correlated with the pollution variables. Schwartz J [18] used an instrumental variable approach, developing an instrument for variations in local pollution concentrations that is unlikely to be correlated with deaths.

In 2017, Baccini M [19] applied a matching method based on propensity score to estimate the total number of attributable deaths. Wu Xiao [20] considered the confounding adjustment by propensity score sub-classification, inverse probability treatment weighting (IPTW) and matching. Lee YJ [21] showed the causation between traffic-related air pollution particle exposures and asthma exacerbations

through the 9 different Hill's criteria, in 2018.

According to the studies cited above, various methods were used to estimate the causal association between air pollution and health outcomes. Among them, the propensity score matching method and the inverse probability treatment weighting method was used in more than 2 studies above (3 and 2 studies each among 12 studies). Therefore, in this study, we applied the propensity score matching method and the inverse probability treatment weighting method to assess the causal relationship between particles less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$) and mortality in Seoul, Republic of Korea.

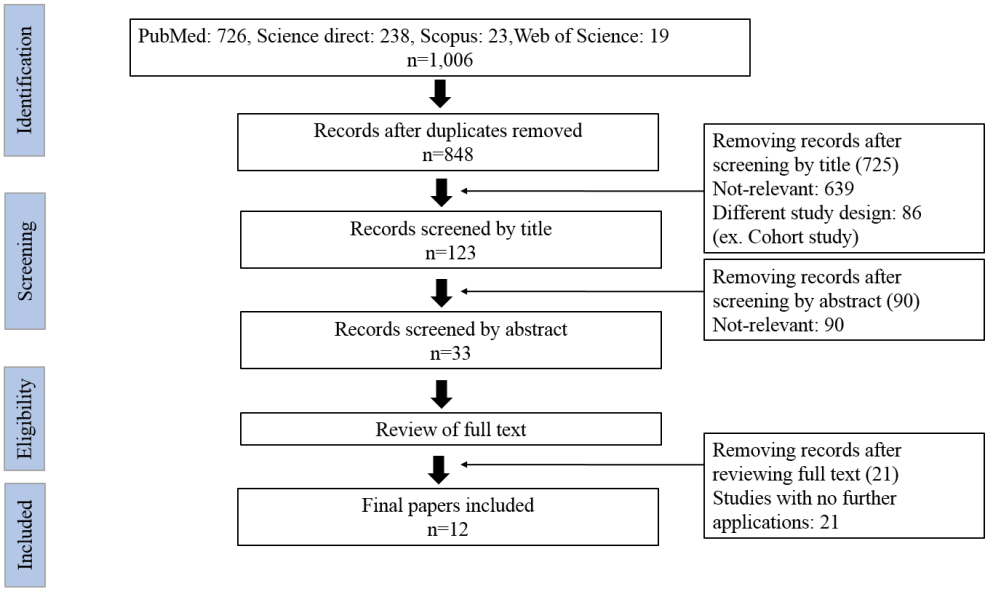

Figure 1. Flow diagram for prior literature review

1.2 Background

Particulate matters (PM) have resulted in 7 million premature deaths according to the World Health Organization [22]. PM was classified as Group One carcinogens, which are identified as causing cancer to humans, in 2013 [23]. PM is emitted mainly from a factory, coal-fired power plants, and transportation vehicles, such as trucks, and is composed of various complex components [24, 25]. Particles that have a diameter of 10 μm or less are accumulated in the body, causing diseases. Particles with a diameter ranging from 2.5 to 10 μm are PM_{10} (fine dust), and particles with a diameter smaller than 2.5 μm are $PM_{2.5}$ (ultrafine dust). $PM_{2.5}$ is easily penetrated into a human body, causing more harmful health outcomes than PM_{10}.

The high concentrations of $PM_{2.5}$ negatively affect the health of the people living in urban areas [26, 27]. As the $PM_{2.5}$ concentrations have increased recently in the Korea, there is serious concern about the health damage of the general population. Korea's average $PM_{2.5}$ concentration was 32.0 $\mu g/m^3$ in 2015, which was the worst among 35 OECD countries and more than twice the average of the OECD countries' $PM_{2.5}$ exposure (14.5 $\mu g/m^3$) [28]. According to Korea Ministry of Environment [29-31], the national average concentration of PM_{10} decreased every year (60 $\mu g/m^3$ in 2015, 56 $\mu g/m^3$ in 2016 and 54 $\mu g/m^3$ in 2017), however, the national average concentration of $PM_{2.5}$ did not (28 $\mu g/m^3$ in 2015, 30 $\mu g/m^3$ in 2016 and 31 $\mu g/m^3$ in 2017).

In Korea, a $PM_{2.5}$ was recorded as "bad" when the daily $PM_{2.5}$ concentration

exceeded 50 μg/m^3. Recently in 27th March 2018, the Korea Ministry of Environment strengthened the daily threshold to 35 μg/m^3 to be recorded as “bad” (Enforcement Decree of the Framework Act on Environmental Policy) [32]. The government officials are curious about the effect that the enforcement of the reduction policy will produce to the public, which is of great help to obtain some implications concerning whether the performed reduction is well done. For this purpose, this study presents the historical health impacts of daily air pollution levels under pre-fixed thresholds on health in Seoul, Republic of Korea.

1.3 Objectives

In this study, we used the propensity score matching method and the inverse probability treatment weighting method to estimate the effect of air pollution on health. We assessed the causal impact as the relative risk (RR) of particulate matter ≤ 2.5 μm in aerodynamic diameter ($PM_{2.5}$) on mortality in Seoul (Republic of Korea), during years 2003 through 2012. Specifically, we compared the risk in days with exposure levels higher than 50 $\mu g/m^3$, with the risk that we would have observed if all those day exposure levels had been lower than 50 $\mu g/m^3$. The pre-fixed thresholds were based on the daily high $PM_{2.5}$ (past, and present) in Enforcement Decree of the Framework Act on Environmental Policy, and the WHO daily high $PM_{2.5}$ exposure level (25 $\mu g/m^3$). Evaluating the impact under a pre-fixed threshold could present a hypothetical intervention setting [8], and allowing a causal association to regulatory standards in Seoul, Republic of Korea.

Chapter 2. Materials and Methods

2.1 Data

2.1.1 Mortality data

We analyzed data from Seoul, the largest city in Korea. Mortality data were obtained from the Korea National Statistics Office for the years 2003-2012. It provided information on the date of death and the underlying cause of death. The all-cause non-accidental mortality (*International Classification of Diseases, Ninth Revision,* codes 0-799) was used as the outcome.

2.1.2 Weather and air quality data

Hourly meteorological data for the study period, including temperature (°C), relative humidity (%), and barometric pressure (hPa) were collected from the Korean Meteorological Administration (KMA). We calculated the daily average for each meteorological data.

Air quality measurements were conducted in 27 monitoring stations in Seoul. Based on the 15-minute interval measurements for 5 air pollutants ($PM_{2.5}$, O_3, NO_2, CO, and SO_2) in each monitoring station, the Korean National Institute of Environmental Research (KNIER) conducts the hourly average for different air pollutant concentrations in each monitoring site. We calculated the daily mean for 5 air pollutants in Seoul during the entire study period as follows. First, we calculated the hourly mean for each pollutant based on all 27 stations, and then the 24-hour

daily average was computed. Outliers were removed for $PM_{2.5}$ (values higher than 200μg/m^3) regarding it as measurement error.

2.1.3 Notation

$PM_{2.5}$ exposure in day i was indicated as X_i, i = 1,.., N, and the treatment indicator W_i, 1 when $X_i \geq$ 50 μg/m^3, and 0 when $X_i <$ 50 μg/m^3 (total 2 exposure threshold levels for the treatment indicator was used (50, 35, and 25 μg/m^3)). We defined days with W_i=1 as "exposed days" and W_i=0 as "unexposed days".

2.2 Methodological background

2.2.1 Propensity score

The propensity score is the conditional probability that a unit being assigned to a particular exposure when the specific covariate values are given [33]. If Z_i is a vector of covariates for day i, the propensity score is defined as the day-level probability of observing $PM_{2.5} \geq 50$ μg/m^3, conditional on Z_i (1).

$$propensity\ \ score_i = P(W_i = 1 \mid Z_i) \quad (1)$$

Rosenbaum and Rubin stated that propensity score could reduce confounding bias [34]. The choice of the covariates Z_i considering the principal ignorability in estimating the propensity score is an essential issue [35]. Specifically, the potential confounding variables in air pollution and mortality relationship, such as meteorological conditions are chosen as the covariates. The covariates selected in this study was best variable sets explaining the $PM_{2.5}$ (the model with the smallest AIC). The sensitivity analysis is presented in Table A1 in the Appendix.

2.2.1.1 Matching

The propensity score matching is a matching procedure using the distance measure between units, which is the propensity score. Propensity score matching assigns the study subjects to the exposed and unexposed group, considering the level of covariates affecting the results. Particularly, the "nearest neighbor matching", matches each exposed day i to the unexposed day i with closest propensity score [36]. Also, there is the Caliper matching, where the exposed day i is matched to

the unexposed day i when it is in a certain propensity score range (Caliper width) [37]. The commonly used width is 0.2 times the standard deviation of the calculated propensity score [38]. Both the matching methods could be matched in a ratio of 1:1, 1:2, 1:3, and further on.

2.2.1.1 Inverse probability weighting

Inverse probability weighting is used to compensate the imbalance in exposed and unexposed groups through the propensity score [39]. It is an alternative to regression-based adjustment of the outcomes. This approach gives $\frac{1}{propensity\ score_i}$ weight to the exposed group and $\frac{1}{(1-propensity\ score_i)}$ weight to the unexposed group.

2.3 Statistical analysis

2.3.1 Propensity score estimation

A logistic propensity model is shown in (6).

$$\log \frac{\mathrm{P}(W_i=1|x_1,x_2,\ldots,x_p)}{\mathrm{P}(W_i=0|x_1,x_2,\ldots,x_p)} = \beta_{0,i} + \sum_{t=1}^{p} \beta_{t,i} x_{t,i} \qquad (6)$$

$PM_{2.5}$ exposure level in day i is indicated as W_i ($W_i = 1$ if exposure was ≥ 25, 35, 50 μg/m^3 (each), $W_i = 0$ if exposure was < 25, 35, 50 μg/m^3 (each)), $x_{t,i}$ is covariate t in day i (total number of covariates are p). The probability for day i to be assigned in the exposed group $W_i = 1$ was calculated in (7).

$$\widehat{\mathrm{P}}(W_i = 1|x_1, x_2, \ldots, x_p) = \frac{\exp\left(\hat{\beta}_{0,i} + \sum_{t=1}^{p} \hat{\beta}_{t,i} x_{t,i}\right)}{1 + \exp\left(\hat{\beta}_{0,i} + \sum_{t=1}^{p} \hat{\beta}_{t,i} x_{t,i}\right)} = propensity\ \ score_i \qquad (7)$$

A linear regression with natural splines of temperature (4 df), yesterday's temperature (4 df), humidity (5 df), seasonal trends (5*(number of years) df), max O_3 (2 df), mean NO_2 (2 df), and mean SO_2 (2 df) and a linear term for CO were modeled in this analysis.

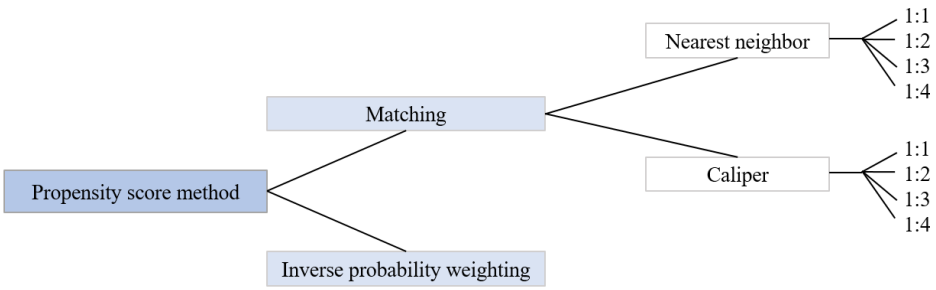

Figure 2. The propensity score methods used in this study

2.3.2 Relative risk estimation

In this study, propensity score matching method and inverse probability weighting method was used (Figure 2). Specifically, in the matching method, the nearest neighbor matching and the Caliper matching was computed with 1:1, 1:2, 1:3, and 1:4 ratios each (exposed: unexposed group). The Caliper width was 0.039 (0.2 times the standard deviation of the calculated propensity score).

$$Y_i = \hat{\tau}_0 + \hat{\gamma} W_i \qquad (8)$$

The matched data was fitted in a regression model with distribution quasi-poisson (8). $\hat{\gamma}$ is the coefficient of the W_i, Y_i is the number of deaths in day i. The relative risk was calculated by taking exponential $\hat{\gamma}$. When there were more exposed days than unexposed days, the unexposed days were matched with replacement.

All statistical analysis was performed using the R, R version 3.4.2.

Chapter 3. Results

3.1 Descriptive statistics

Table 1 presents the descriptive statistics of Seoul in 2003 to 2012. The number of daily deaths in Seoul ranged from 55 to 138, and temperature -14℃ to 30.43℃. $PM_{2.5}$ interquartile range (IQR) is 17.7 to 36.89 μg/m^3. The exposure thresholds were based on the IQR of $PM_{2.5}$. Descriptive table for other pollutants used in the propensity score: max O_3, mean NO_2, mean SO_2, and mean CO is shown. Max O_3 in a range 2.04ppb to 143.19ppb, 10.9ppb to 92.16ppb for mean NO_2 and 1.95ppb to 19.55ppb for mean SO_2. Max CO showed minimum 0.23 to maximum 10.34 ppb during 2003 to 2012.

Table 1. Descriptive statistics of Seoul, Korea, 2003-2012

Percentile	No. of daily deaths	Temperature (℃)	$PM_{2.5}$ (μg/m^3)	O_3 (ppb)	NO_2 (ppb)	SO_2 (ppb)	CO (ppb)
Minimum	55	-14	4.16	2.04	10.9	1.95	0.23
25	85	4.21	17.7	20.34	26.89	3.73	0.48
50	93	14.32	25.66	31.47	35.12	4.76	0.64
75	100	21.92	36.89	45.77	44.97	6.41	0.92
100	138	30.43	99.79	143.19	92.16	19.55	10.34

3.2 Covariates balancing check

The balancing property check for the nearest neighbor matching based on the standardized difference between the exposed and unexposed group and the p-value is shown (H_0: The mean difference for the exposed group and the unexposed group is equal to zero) in Table 2. The unexposed days ($PM_{2.5} \leq 50$ ($\mu g/m^3$)) were 2,636 days and the exposed days ($PM_{2.5} > 50$ ($\mu g/m^3$)) were 268 days, before matching. The absolute standardized difference ranged from 9.35 to 117.65%, and the p-value was mostly small for each variable, indicating difference in value between exposed group and unexposed group, before matching. When 1:1 the nearest neighbor matching was done, the standardized difference ranged from 0.75 to 46.32%, and the p-value increased (expect for the SO_2 and NO_2). Standardized difference range also increased as the number of matched unexposed groups became larger (3.46-53.27% in 1:2, 0.11-58.22% in 1:3, 0.93-65.63% in 1:4). Furthermore, the p-value in 1:4 matching was mostly small among covariates. The balancing property check in nearest neighbor matching for unexposed days ($PM_{2.5} \leq 25$, 35 ($\mu g/m^3$)) and the exposed days ($PM_{2.5} > 25$, 35 ($\mu g/m^3$)) is represented in Table A2 ($PM_{2.5} \leq 35$ ($\mu g/m^3$)) and Table A3 ($PM_{2.5} \leq 25$ ($\mu g/m^3$)) each.

Table 2. Comparison of covariate balance before and after nearest neighbor matching across different ratio, based upon standardized difference (%) of the propensity score between groups. (Unexposed: $PM_{2.5} \leq 50$ ($\mu g/m^3$), Exposed: $PM_{2.5} > 50$ ($\mu g/m^3$))

Covariates	Exposed (N=286)	Unexposed (N=2,636)	Before matching		Nearest neighbor matching							
					1:1		1:2		1:3		1:4	
	Mean (sd)	Mean (sd)	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value
Temperature (℃)	11 (8.98)	13 (10.27)	-21.37	< 0.0001	1.37	0.899	-7.08	0.438	-2.99	0.721	-7394	0.318
Yesterdays' temperature (℃)	10.3 (8.98)	13.1 (10.25)	-29.01	< 0.0001	0.75	0.945	-10.54	0.248	-7.32	0.382	-11.81	0.139
Humidity (%)	63.6 (12.14)	61.5 (15.17)	15.56	0.007	6.21	0.563	6.05	0.507	5.53	0.51	0.93	0.91
SO_2 (ppb)	8.36 (3.44)	5.1 (1.95)	116.74	< 0.0001	46.32	< 0.0001	52.13	< 0.0001	57.83	< 0.0001	64.65	< 0.0001
NO_2 (ppb)	50.2 (14.04)	35.1 (11.47)	117.65	< 0.0001	44.10	< 0.0001	53.27	< 0.0001	58.22	< 0.0001	65.63	< 0.0001
O_3 (ppb)	36.9 (24.73)	34.8 (19.67)	9.35	0.181	3.40	0.747	-3.46	0.703	0.11	0.989	-1.02	0.899
CO (ppb)	1.17 (0.5)	0.72 (0.39)	101.12	< 0.0001	15.83	0.174	28.24	0.002	30.59	< 0.0001	39.66	< 0.0001

The balancing property check (the standardized difference and the p-value for each covariate) for the Caliper matching is shown in Table 3. After 1:1 Caliper matching, the standardized difference ranged from 9.24 to 28.32%, and the difference between exposed and unexposed groups were significant (large p-values). When 1:2 Caliper matching was done, the standardized difference range was 5.98-28.63%. 4.86-28.05% in 1:3 matching and 4.43-27.78% standardized difference in 1:4 matching. The standardized difference was similar among different ratios. Furthermore, the p-values remained large among covariates and different matching ratios. The balancing property check for the Caliper matching for unexposed days ($PM_{2.5} \leq 25$, 35 ($\mu g/m^3$)) and the exposed days ($PM_{2.5} > 25$, 35 ($\mu g/m^3$)) is represented in Table A4 ($PM_{2.5} \leq 35$ ($\mu g/m^3$)) and Table A5 ($PM_{2.5} \leq 25$ ($\mu g/m^3$)) each.

Table 3. Comparison of covariate balance before and after Caliper matching across different ratio, based upon standardized difference (%) of the propensity score between groups. (Unexposed: $PM_{2.5} \leq 50$ ($\mu g/m^3$), Exposed: $PM_{2.5} > 50$ ($\mu g/m^3$))

Covariates	Caliper matching							
	1:1		1:2		1:3		1:4	
	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value
Temperature (℃)	-28.32	<0.0001	-28.09	<0.0001	-28.05	<0.0001	-27.78	<0.0001
Yesterdays' temperature (℃)	-24.92	<0.0001	-28.63	<0.0001	-25.20	<0.0001	-25.05	<0.0001
Humidity (%)	-25.05	<0.0001	-22.90	<0.0001	-22.60	<0.0001	-23.59	<0.0001
SO_2 (ppb)	-9.46	0.003	-8.97	0.018	-11.61	0.006	-7.73	0.105
NO_2 (ppb)	-21.84	<0.0001	-20.15	<0.0001	-20.91	<0.0001	-19.03	<0.0001
O_3 (ppb)	9.24	0.004	5.98	0.102	4.86	0.232	4.43	0.321
CO (ppb)	9.93	0.002	9.59	0.008	9.95	0.014	10.79	0.015

3.3 Relative risk for each method

The relative risk for different exposure thresholds by each method is represented in Table 4. The relative risk ranged from 0.982 (95% CI: 0.962, 1.01) to 1.016 (95% CI: 0.985, 1.024) for 1:1 nearest neighbor matching. While the relative risk for the Caliper matching was 1.016 (95% CI: 0.985, 1.024) in 1:1, and 1.032 (95% CI: 1.022, 1.045) in 1:4 matching, showing a higher risk than the nearest neighbor matching. The inverse weighting relative risk was 1.025 (95% CI: 1.016, 1.034), indicating the high risk.

Days exceeding 35 $\mu g/m^3$ $PM_{2.5}$ average had 1.015 times more risk of mortality than the days below 35 $\mu g/m^3$ $PM_{2.5}$, for 1:1 nearest neighbor matching. Similar results were shown among the nearest neighbor matching (matching ratio (RR; CI), 1:2 (1.016; 1.003, 1.028), 1:3 (1.018; 1.008, 1.031), 1:4 (1.019; 1.009, 1.032)). The relative risks using the Caliper matching relative risk ranging from 1.012 (95% CI: 1.003, 1.018) to 1.019 (95% CI: 1.015, 1.027). Inverse weighting relative risk was 1.02 (95% CI: 1.012, 1.028).

1:1 nearest neighbor matching resulted in 1.016 times more risk of mortality in days with $PM_{2.5}$ over 25 $\mu g/m^3$ than the days below 25 $\mu g/m^3$. The relative risks using the Caliper matching decreased comparing the nearest neighbor matching. Ranging from 0.991 (95% CI: 0.98, 0.997) to 0.996 (95% CI: 0.984, 1.000). The inverse weighting relative risk was 1 (95% CI: 0.992, 1.009).

The relative risk plot for different exposure thresholds by each method is shown in Figure 3. Nearest neighbor matching gives similar results and patterns as the threshold was lower. The Caliper matching also shows similar patterns when 1:2, 1:3, and 1:4 matching. Also, the inverse probability weighting methods' relative risk consistently decreased as the threshold was low. When focusing on the well matching method (the nearest matching method), the relative risk in days over 35 $\mu g/m^3$ was higher than days over 50 $\mu g/m^3$.

Table 4. Relative risk for different $PM_{2.5}$ thresholds by methods

$PM_{2.5}$ threshold ($\mu g/m^3$)	Relative risk (CI)[1]									
	Association	Nearest neighbor matching				Caliper matching				Inverse Weighting
		1:1	1:2	1:3	1:4	1:1	1:2	1:3	1:4	
50	1.003 (0.988, 1.017)	0.982 (0.962, 1.01)	0.99 (0.967, 1.012)	0.997 (0.978, 1.017)	1.016 (0.985, 1.024)	1.016 (0.985, 1.024)	1.031 (1.02, 1.04)	1.031 (1.019, 1.042)	1.032 (1.022, 1.045)	1.025 (1.016, 1.034)
35	1.012 (1.002, 1.023)	1.015 (0.999, 1.03)	1.016 (1.003, 1.028)	1.018 (1.008, 1.031)	1.019 (1.009, 1.032)	1.019 (1.015, 1.027)	1.016 (1.012, 1.024)	1.014 (1.008, 1.02)	1.012 (1.003, 1.018)	1.02 (1.012, 1.028)
25	1.006 (0.997, 1.015)	1.016 (1.004, 1.029)	1.015 (1.006, 1.027)	1.017 (1.009, 1.028)	1.016 (1.008, 1.027)	0.995 (0.983, 0.999)	0.995 (0.984, 1.002)	0.991 (0.98, 0.997)	0.996 (0.984, 1.000)	1 (0.992, 1.009)

1.CI: confidence interval, 95%

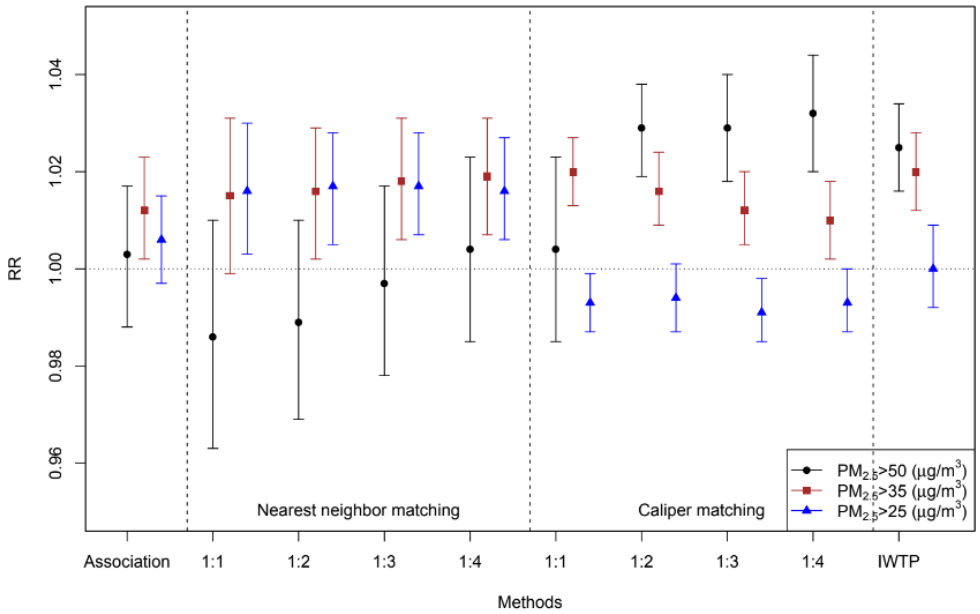

Figure 3. The relative risk plot in different thresholds by methods

Chapter 4. Discussion

We have used various propensity score methods for causal modeling (the nearest neighbor matching, the Caliper matching, and the inverse probability weighting). The relative risk differed by methods, however, showing similar patterns as the $PM_{2.5}$ thresholds were lower. The relative risk was higher in days over 35 $\mu g/m^3$ $PM_{2.5}$ than days over 50 $\mu g/m^3$ $PM_{2.5}$, and lower risks were shown in days over 25 $\mu g/m^3$ $PM_{2.5}$ than days over 35 $\mu g/m^3$ $PM_{2.5}$.

In assessing the short-term effects of air pollution on health, the matching method is commonly used. For instance, case-crossover is a matching study design adjusting the confounding effect of seasonality [40]. In this study, we used the nearest neighbor matching and the Caliper matching, which matches each exposed day to unexposed day by choosing the closest propensity score or choosing a day in a certain propensity score range. Propensity score approach avoids confounding bias in the observational epidemiology study. This study is based on the propensity score matching, which is substantially different from estimating the impacts from a regression model. Since the exposure-response function is under linearity assumptions it could result in under or overestimated impacts [41]. However, by using the propensity score matching method this bias is avoided.

This study approach relies on the un-confoundedness assumption [34]. This assumption could not be proven through the study data, instead was confirmed by

previous literature [42]. Assuming that there are no unmeasured variables that are correlated with both exposure and mortality, this analysis provides a causal estimate. There are only a few confounders, mostly weather and other pollutants, which are included in the propensity score for this study.

Despite the robustness of results, this study has certain limitations, which will be crucial in addressing future studies. When using the propensity score, covariates should have a certain value because the error will occur due to missing values. Since considering all covariates is problematic, there is a limit in presenting a perfect causal relationship. Propensity score method is a statistical method, which cannot alter the fundamental research design.

The key result is that the risk was higher when particle concentration exceeded exposure of 35 $\mu g/m^3$ than exposure of 50 $\mu g/m^3$. Hence, the risk was higher from above the strengthened exposure level (35 $\mu g/m^3$) of Enforcement Decree of the Framework Act on Environmental Policy, than the original exposure level (50 $\mu g/m^3$). This evidence suggests that the policy change in notifying "bad" $PM_{2.5}$ would provide additional health benefits and could prevent additional deaths. Therefore, regulating fine air born particles above 35 $\mu g/m^3$ could result in higher protection for adverse health outcomes in Seoul, Republic of Korea.

The positive association between $PM_{2.5}$ and mortality shown in different causal approaches in this study are supported by numerous toxicological studies. $PM_{2.5}$

exposure has shown association with lung inflammation, increased reactive oxygen species in the lung and heart, and increase blood pressure [43-45]. For instance, participants walking in an urban route showed lower blood pressure while using particle filter mask than without a mask [46]. Also, when exposed to diesel exhaust, volunteers had higher blood pressure and more arterial stiffness [41]. These consistent study results strengthen the causal association between $PM_{2.5}$ and changes in mortality rates.

$PM_{2.5}$ is known for its adverse impacts on visibility and is the cause of visible light scattering [47]. Also, the correlation was shown between visibility and $PM_{2.5}$ in Shenyang, China ($r = 0.51$), where the annual $PM_{2.5}$ average is 50.7 $\mu g/m^3$ (Seoul $PM_{2.5}$ average 43.0 $\mu g/m^3$) [48, 49]. A study investigating the impact of fine particulate matters on visibility impairment in Seoul, Korea, has found the best 20% visibility when $PM_{2.5}$ average is 26.1 $\mu g/m^3$, the worst 20% visibility when $PM_{2.5}$ average is 51.9 $\mu g/m^3$, and the average visibility in 40.6 $\mu g/m^3$ $PM_{2.5}$ [50]. These study results support the low risk shown for days over 50 $\mu g/m^3$ $PM_{2.5}$ in this study. When $PM_{2.5}$ is over 50 $\mu g/m^3$, the high visibility impairment could have been an indicator for people to avoid outdoor activities. However, for days over 35 $\mu g/m^3$ $PM_{2.5}$, which has relatively low visibility impairment than days over $PM_{2.5}$ 50 μg

/m^3, the citizens in Seoul might have had difficulty perceiving the actual concentration of $PM_{2.5}$. Therefore, resulting in higher mortality risks for days over 35 $\mu g/m^3$ $PM_{2.5}$, than for days over 50 $\mu g/m^3$ $PM_{2.5}$.

The specific guideline for particulate matter threshold has not been identified, since the individual variability in exposure levels and in the response to the exposure. Therefore, a certain standard guideline could not lead to absolute protection against adverse health effects of particulate matter for every individual. Instead of setting a standard level, one should aim for the lowest particulate matter concentration possible in the local area. The Environmental Protection Agency (EPA) and the European Commission has revised its own particulate matter standards, by the quantitative risk assessment [51]. This approach compares the alternative control scenarios and estimates the residual risk associated with the guideline value. Similarly, monitoring the reduction in particulate matters, and adopting a set of standards is also encouraged in Korea.

Chapter 5. Conclusions

In this study we focused on the causal impact of a hypothetical intervention setting of $PM_{2.5}$ under a pre-fixed threshold would have had on mortality risk in Seoul during the time frame 2003-2012. Different propensity score method settings we used allowed to estimate the causal impact of this hypothetical intervention. It assessed the impacts in terms of relative risk, comparing different pre-fixed thresholds and methods.

By comparing the relative risk for pre-fixed thresholds of $PM_{2.5}$ exposure (35, 50 $\mu g/m^3$) based on the Enforcement Decree of the Framework Act on Environmental Policy, implications of the strengthened policy were made. Since the risk is higher in days above 35 than days above 50 $\mu g/m^3$, the enforcement of the policy (changing daily indication "bad" $PM_{2.5}$ from above 35 to above 50 $\mu g/m^3$), could help citizens in Seoul to avoid higher risk in the future.

References

1. Naddafi, K., et al., *Health impact assessment of air pollution in megacity of Tehran, Iran.* Iranian Journal of Environmental Health Science & Engineering, 2012. **9**(1): p. 28.
2. Lim, Y.H., et al., *Air pollution and symptoms of depression in elderly adults.* Environ Health Perspect, 2012. **120**(7): p. 1023-8.
3. Kunzli, N., et al., *Public-health impact of outdoor and traffic-related air pollution: a European assessment.* Lancet, 2000. **356**(9232): p. 795-801.
4. Kim, O.J., S.Y. Kim, and H. Kim, *Association between Long-Term Exposure to Particulate Matter Air Pollution and Mortality in a South Korean National Cohort: Comparison across Different Exposure Assessment Approaches.* Int J Environ Res Public Health, 2017. **14**(10).
5. Laden, F., et al., *Reduction in fine particulate air pollution and mortality: Extended follow-up of the Harvard Six Cities study.* Am J Respir Crit Care Med, 2006. **173**(6): p. 667-72.
6. Neas, L.M., J. Schwartz, and D. Dockery, *A case-crossover analysis of air pollution and mortality in Philadelphia.* Environ Health Perspect, 1999. **107**(8): p. 629-31.
7. Hill, A.B., *The Environment and Disease: Association or Causation?* Proceedings of the Royal Society of Medicine, 1965. **58**(5): p. 295-300.
8. Zigler, C.M. and F. Dominici, *Point: clarifying policy evidence with potential-outcomes thinking--beyond exposure-response estimation in air pollution epidemiology.* Am J Epidemiol, 2014. **180**(12): p. 1133-40.
9. Anderson, J.O., J.G. Thundiyil, and A. Stolbach, *Clearing the air: a review of the effects of particulate matter air pollution on human health.* J Med Toxicol, 2012. **8**(2): p. 166-75.
10. Schwartz, J., *Is the association of airborne particles with daily deaths confounded by gaseous air pollutants? An approach to control by matching.* Environmental Health Perspectives, 2004. **112**(5): p. 557-561.
11. Padula, A.M., et al., *Exposure to traffic-related air pollution during pregnancy and term low birth weight: estimation of causal associations in a semiparametric model.* Am J Epidemiol, 2012. **176**(9): p. 815-24.
12. Zigler, C.M., F. Dominici, and Y. Wang, *Estimating causal effects of air quality regulations using principal stratification for spatially correlated multivariate intermediate outcomes.* Biostatistics, 2012. **13**(2): p. 289-302.
13. Diaz, I. and M.J. van der Laan, *Assessing the causal effect of policies: an example using stochastic interventions.* Int J Biostat, 2013. **9**(2): p. 161-74.
14. Bor, J., et al., *Regression discontinuity designs in epidemiology: causal inference without randomized trials.* Epidemiology, 2014. **25**(5): p. 729-37.
15. Weisskopf, M.G., M.A. Kioumourtzoglou, and A.L. Roberts, *Air Pollution and Autism Spectrum Disorders: Causal or Confounded?* Curr Environ Health Rep, 2015. **2**(4): p. 430-9.
16. Schwartz, J., et al., *Estimating Causal Associations of Fine Particles With Daily Deaths in Boston.* Am J Epidemiol, 2015. **182**(7): p. 644-50.
17. Wang, Y., et al., *Estimating Causal Effects of Long-Term PM2.5 Exposure on Mortality in New Jersey.* Environ Health Perspect, 2016. **124**(8): p. 1182-8.
18. Schwartz, J., M.A. Bind, and P. Koutrakis, *Estimating Causal Effects of Local Air Pollution on Daily Deaths: Effect of Low Levels.* Environ Health Perspect, 2017.

125(1): p. 23-29.
19. Baccini, M., et al., *Assessing the short term impact of air pollution on mortality: a matching approach.* Environ Health, 2017. **16**(1): p. 7.
20. Wu, X., et al., *Causal inference in the context of an error prone exposure: air pollution and mortality*. 2017.
21. Lee, Y.J. and N. Rabinovitch, *Relationship between traffic-related air pollution particle exposure and asthma exacerbations: Association or causation?* Ann Allergy Asthma Immunol, 2018. **120**(5): p. 458-460.
22. Organization, W.H., *7Million Premature Deaths Annually Linked to Air Pollution.* 2014.
23. Cancer., I.A.f.R.o., *Outdoor Air Pollution a Leading Environmental Cause of Cancer Deaths*. 2013.
24. Laden, F., et al., *Association of fine particulate matter from different sources with daily mortality in six U.S. cities.* Environ Health Perspect, 2000. **108**(10): p. 941-7.
25. Zíková, N., et al., *On the source contribution to Beijing PM2.5 concentrations.* Atmospheric Environment, 2016. **134**: p. 84-95.
26. Nguyen, T., et al., *Particulate Matter (PM10 and PM2.5) in Subway Systems: Health-Based Economic Assessment.* Sustainability, 2017. **9**(11): p. 2135.
27. Wong, L.P., et al., *Control Measures and Health Effects of Air Pollution: A Survey among Public Transportation Commuters in Malaysia.* Sustainability, 2017. **9**(9): p. 1616.
28. Development, O.f.E.C.-o.a., *Exposure to PM2.5 in Countries and Regions.2017*. 2017.
29. Environment, K.M.o., *Monthly Report of Air Quality. 2015*. 2015.
30. Environment, K.M.o., *Monthly Report of Air Quality. 2016.* 2016.
31. Environment, K.M.o., *Monthly Report of Air Quality. 2017*. 2017.
32. Environment, K.M.o., *Fine dust ($PM_{2.5}$) environment standard strengthened to US, Japan level*. 2017.
33. Pattanayak, C.W., D.B. Rubin, and E.R. Zell, *[Propensity score methods for creating covariate balance in observational studies].* Rev Esp Cardiol, 2011. **64**(10): p. 897-903.
34. Rosenbaum, P.R. and D.B. Rubin, *The central role of the propensity score in observational studies for causal effects.* Biometrika, 1983. **70**(1): p. 41-55.
35. Jo, B. and E.A. Stuart, *On the Use of Propensity Scores in Principal Causal Effect Estimation.* Statistics in medicine, 2009. **28**(23): p. 2857-2875.
36. Abadie, A. and G.W. Imbens, *Bias-Corrected Matching Estimators for Average Treatment Effects.* Journal of Business & Economic Statistics, 2011. **29**(1): p. 1-11.
37. Austin, P.C., *Primer on statistical interpretation or methods report card on propensity-score matching in the cardiology literature from 2004 to 2006: a systematic review.* Circ Cardiovasc Qual Outcomes, 2008. **1**(1): p. 62-7.
38. Austin, P.C., *Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies.* Pharm Stat, 2011. **10**(2): p. 150-61.
39. Halpern, E.F., *Behind the Numbers: Inverse Probability Weighting.* Radiology, 2014. **271**(3): p. 625-628.
40. Levy, D., et al., *A case-crossover analysis of particulate matter air pollution and out-of-hospital primary cardiac arrest.* Epidemiology, 2001. **12**(2): p. 193-9.
41. Lundbäck, M., et al., *Experimental exposure to diesel exhaust increases arterial*

stiffness in man. Particle and Fibre Toxicology, 2009. **6**(1): p. 7.
42. Schwartz, J., et al., *Estimating Causal Associations of Fine Particles With Daily Deaths in Boston.* American Journal of Epidemiology, 2015. **182**(7): p. 644-650.
43. Nurkiewicz, T.R., et al., *Systemic microvascular dysfunction and inflammation after pulmonary particulate matter exposure.* Environ Health Perspect, 2006. **114**(3): p. 412-9.
44. Tamagawa, E., et al., *Particulate matter exposure induces persistent lung inflammation and endothelial dysfunction.* Am J Physiol Lung Cell Mol Physiol, 2008. **295**(1): p. L79-85.
45. Sigaud, S., et al., *Air pollution particles diminish bacterial clearance in the primed lungs of mice.* Toxicol Appl Pharmacol, 2007. **223**(1): p. 1-9.
46. Langrish, J.P., et al., *Beneficial cardiovascular effects of reducing exposure to particulate air pollution with a simple facemask.* Particle and Fibre Toxicology, 2009. **6**: p. 8-8.
47. Sloane, C.S., et al., *Size-segregated fine particle measurements by chemical species and their impact on visibility impairment in Denver.* Atmospheric Environment Part A, General Topics, 1991. **25**(5-6): p. 1013-1024.
48. Zhao, H., et al., *Characteristics of visibility and particulate matter (PM) in an urban area of Northeast China.* Atmospheric Pollution Research, 2013. **4**(4): p. 427-434.
49. Kim, H.S., et al., *Characteristics of the major chemical constituents of PM2.5 and smog events in Seoul, Korea in 2003 and 2004.* Atmospheric Environment, 2007. **41**(32): p. 6762-6770.
50. Kim, Y.J., et al., *Fine particulate matter characteristics and its impact on visibility impairment at two urban sites in Korea: Seoul and Incheon.* Atmospheric Environment, 2006. **40**: p. 593-605.
51. Kuklinska, K., L. Wolska, and J. Namiesnik, *Air quality policy in the U.S. and the EU – a review.* Atmospheric Pollution Research, 2015. **6**(1): p. 129-137.

Appendix

Table A1. Sensitivity analysis for covariates selection by AIC

Variables	AIC
Temperature (□)	1781.8
ns(temperature (□), df=2)	1761.7
ns(temperature (□), df=3)	1761.7
ns(temperature (□), df=4)	1751.2
ns(temperature (□), df=5)	1752.7
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4)	1724.1
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), humidity	1702.9
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=2)	1691.4
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=3)	1674.1
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=4)	1674.3
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5)	1673.9
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=1*year)	1629.1
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=2*year)	1577.2
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=3*year)	1519.5
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=4*year)	1499.8
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year)	1476.8
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), max O_3	1411.2
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), mean NO_2	1258
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), mean SO_2	1134.5
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), max CO	1316.7
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), mean NO_2, mean SO_2	1099.6
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), mean NO_2, mean SO_2, max CO	1075.7
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), mean NO_2, mean SO_2, max CO, max O_3	1071
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), ns(mean SO_2, df=2),	do not

ns(mean NO_2, df=2), ns(max O_3, df=2), ns(max CO, df=2)	converge
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), ns(mean SO_2, df=2), ns(mean NO_2, df=2), ns(max O_3, df=2), max CO	1066.1
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), ns(mean SO_2, df=3), ns(mean NO_2, df=3), ns(max O_3, df=3), max CO	1071.1
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), ns(mean SO_2, df=3), ns(mean NO_2, df=3), ns(max O_3, df=3), max CO, sunshine	1067.9
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), ns(mean SO_2, df=3), ns(mean NO_2, df=3), ns(max O_3, df=3), max CO, day of week	1073.6
ns(temperature (□), df=4), ns(yesterdays' temperature (□),df=4), ns(humidity, df=5) + ns(seasonality, df=5*year), ns(mean SO_2, df=3), ns(mean NO_2, df=3), ns(max O_3, df=3), max CO, mean pressure	1068

Table A2. Comparison of covariate balance before and after nearest neighbor matching across different ratio, based upon standardized difference (%) of the propensity score between groups. (Unexposed: $PM_{2.5} \leq 35$ ($\mu g/m^3$), Exposed: $PM_{2.5} > 35$ ($\mu g/m^3$))

Covariates	Exposed (N=767)	Unexposed (N=2,137)	Before matching		Nearest neighbor matching							
					1:1		1:2		1:3		1:4	
	Mean (sd)	Mean (sd)	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value
Temperature (℃)	12 (9.03)	13.1 (10.54)	-11.05	0.0065	-7.89	0.244	-10.17	0.081	-8.94	0.098	-10.36	0.046
Yesterdays' temperature (℃)	11.4 (9.11)	13.3 (10.49)	-19.63	< 0.0001	-11.26	0.096	-13.85	0.017	-13.1	0.015	-15.10	0.003
Humidity (%)	63 (12.67)	61.2 (15.63)	12.97	0.0012	-4.17	0.537	-4.06	0.487	-1.96	0.717	-1.00	0.864
SO_2 (ppb)	7.07 (2.87)	4.8 (1.75)	95.28	< 0.0001	48.79	< 0.0001	55.10	< 0.0001	59.46	< 0.0001	63.21	< 0.0001
NO_2 (ppb)	46 (12.42)	33 (10.63)	112.21	< 0.0001	49.83	< 0.0001	55.19	< 0.0001	59.58	< 0.0001	65.52	< 0.0001
O_3 (ppb)	37.1 (23.94)	34.3 (18.62)	13.2	0.0031	-1.99	0.763	-0.61	0.915	2.59	0.629	0.96	0.853
CO (ppb)	1.02 (0.55)	0.66 (0.37)	87.97	< 0.0001	28.36	< 0.0001	38.94	< 0.0001	43.24	< 0.0001	47.94	< 0.0001

Table A3. Comparison of covariate balance before and after nearest neighbor matching across different ratio, based upon standardized difference (%) of the propensity score between groups. (Unexposed: $PM_{2.5} \leq 25$ ($\mu g/m^3$), Exposed: $PM_{2.5} > 25$ ($\mu g/m^3$))

Covariates	Exposed (N=1,420)	Unexposed (N=1,484)	Before matching		Nearest neighbor matching							
					1:1		1:2		1:3		1:4	
	Mean (sd)	Mean (sd)	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value
Temperature (℃)	12.2 (9.47)	13.43 (10.76)	-12.17	0.001	-13.78	0.017	-13.79	0.006	-12.02	0.010	-12.73	0.004
Yesterdays' temperature (℃)	11.69 (9.64)	13.92 (10.54)	-22.01	< 0.0001	-16.91	0.003	-18.55	0.0002	-17.54	0.0001	-19.19	< 0.0001
Humidity (%)	62.12 (13.39)	61.27 (16.25)	5.69	0.1245	-4.80	0.407	-5.21	0.299	-4.68	0.319	-7.55	0.092
SO_2 (ppb)	6.45 (2.61)	4.4 (1.44)	97.07	< 0.0001	58.75	< 0.0001	68.63	< 0.0001	72.83	< 0.0001	77.72	< 0.0001
NO_2 (ppb)	43.18 (11.91)	30.04 (9.29)	123.03	< 0.0001	67.76	< 0.0001	79.21	< 0.0001	86.04	< 0.0001	91.96	< 0.0001
O_3 (ppb)	36.93 (23.28)	33.22 (16.52)	18.35	< 0.0001	1.19	0.827	5.56	0.239	9.05	0.041	12.06	0.0047
CO (ppb)	0.94 (0.49)	0.58 (0.24)	92.31	< 0.0001	55.59	< 0.0001	63.61	< 0.0001	67.12	< 0.0001	70.68	< 0.0001

Table A4. Comparison of covariate balance before and after Caliper matching across different ratio, based upon standardized difference (%) of the propensity score between groups. (Unexposed: $PM_{2.5} \leq 35$ ($\mu g/m^3$), Exposed: $PM_{2.5} > 35$ ($\mu g/m^3$))

Covariates	Caliper matching							
	1:1		1:2		1:3		1:4	
	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value
Temperature (℃)	-21.99	< 0.0001	-16.09	< 0.0001	-10.88	0.001	-10.39	0.003
Yesterdays' temperature (℃)	-19.62	< 0.0001	-13.83	< 0.0001	-8.64	0.009	-8.34	0.015
Humidity (%)	-19.68	0.2201	-12.09	0.0001	-9.44	0.005	-8.77	0.012
SO_2 (ppb)	-1.04	0.714	-2.90	0.359	0.50	0.882	2.21	0.536
NO_2 (ppb)	-6.28	0.026	-4.28	0.176	-0.87	0.798	2.98	0.399
O_3 (ppb)	4.21	0.137	-0.29	0.925	-0.07	0.981	-2.75	0.412
CO (ppb)	-2.58	0.362	-4.45	0.122	-8.87	0.001	-8.91	0.0006

Table A5. Comparison of covariate balance before and after Caliper matching across different ratio, based upon standardized difference (%) of the propensity score between groups. (Unexposed: $PM_{2.5} \leq 25$ ($\mu g/m^3$), Exposed: $PM_{2.5} > 25$ ($\mu g/m^3$))

Covariates	Caliper matching							
	1:1		1:2		1:3		1:4	
	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value	std dif (%)	p-value
Temperature (℃)	-5.59	0.032	-3.10	0.255	1.56	0.573	2.42	0.383
Yesterdays' temperature (℃)	-3.55	0.175	-0.27	0.922	4.39	0.112	5.79	0.035
Humidity (%)	0.05	0.983	2.49	0.361	4.94	0.074	6.31	0.023
SO_2 (ppb)	-0.88	0.736	-0.51	0.855	-0.73	0.797	-2.25	0.431
NO_2 (ppb)	1.11	0.669	-2.97	0.284	3.50	0.219	-4.67	0.104
O_3 (ppb)	-6.36	0.015	-8.16	0.0028	-5.88	0.035	-6.77	0.016
CO (ppb)	-0.75	0.775	0.77	0.783	-1.69	0.558	-2.34	0.421

국문 초록

대기오염과 건강의 인과성 추론

최하연

보건학과 보건통계학전공

서울대학교 보건대학원

배경: 기존 많은 역학 연구들을 통해 초 미세먼지 ($PM_{2.5}$)와 사망의 연관성이 입증되었다. 하지만 이들은 대부분 연관성에 관한 연구로 인과 관계 접근법을 사용하지 않았다. 본 연구에서는, 2003년부터 2012년까지 대한민국의 수도인 서울에서 초 미세먼지 ($PM_{2.5}$)와 사망의 관계를 보았다.

구체적으로, 다양한 인과 관계 접근법을 사용하여 초 미세먼지 ($PM_{2.5}$) 특정 농도 이상에서 사망에 미치는 영향을 추론하고자 하였다.

방법: 성향 점수 매칭 방법 (인근 이웃 매칭과 캘리퍼 매칭)과 성향점수 역수 가중치 방법을 사용하여 상대 위험도 (Relative risk) 를 추정하였다. 각각 노출된 날 (특정 기준 $PM_{2.5}$ 농도보다 높은 날)을 비슷한 특성을 지닌 노출되지 않은 날 (특정 기준 $PM_{2.5}$ 농도보다 낮은 날)과 성향점수로 매칭을 하였다. 기준 $PM_{2.5}$ 농도는 환경정책기본법시행령의 과거와 현재

"나쁨" 예보 농도 (50, 35 $\mu g/m^3$)와 WHO 농도 (25 $\mu g/m^3$)를 토대로 정하였다. 성향 점수 매칭 방법을 통해 매칭된 날들의 위험도 영향을 평가하였다. 위험도는 각기 다른 인과 관계 접근법과 같은 접근 내에서는 다른 $PM_{2.5}$ 농도 기준에 따라 비교하였다.

결과: 일일 $PM_{2.5}$ 농도가 50 $\mu g/m^3$ 이상인 날이 그렇지 않은 날에 비해 0.982배의 사망 위험도가 높았으며, 일일 $PM_{2.5}$ 농도가 35 $\mu g/m^3$ 이상인 날이 그렇지 않은 날에 비해 1.015배의 사망 위험이 있었다 (1:1 인근 이웃 접근법 매칭). 인근 이웃 접근법 매칭법 상대 위험도는 기준 농도가 35 $\mu g/m^3$ 이상인 날이 50 $\mu g/m^3$ 이상인 날보다 높았다.

결론: 정책의 규제를 강화 (일일 $PM_{2.5}$ "나쁨" 예보 기준 50 $\mu g/m^3$ - 이상인 날에서 35 $\mu g/m^3$로 강화)함으로써, 서울 시민들이 더 높은 사망 위험도에 노출될 수 있는 확률을 줄여주었다.

주요어: 초 미세먼지 ($PM_{2.5}$), 사망, 인과성 추론, 성향 점수, 서울, 한국

학번: 2016-25798