Impact of Air Pollution on Subjective Well-Being and Health Behaviors: Evidence from a Cross-sectional Study in South Korea

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Abstract

Exposure to air pollution is a potential threat to health and well-being. Controlling for time-invariant regional characteristics, we study the impacts of exposure to fine par-ticulate matter(PM) on people's health behaviors and subjective well-being. Ambient air pollution is found to be associated with lower life satisfaction, a higher likelihood of feeling stressed from health issues, and less value on health perception. More days with air pollution encourage people to exercise less and smoke often. The overall travel time spent on the road increases, taking longer to get to work when days with bad air quality increase. We disclose that the impact of air pollution could be unequal depending on whether one could reduce physical activity to mitigate the detrimental effect of pollution. Workers, especially in low-class elementary occupations, experience lower life satisfaction, and higher health stress.

Keywords: Environment, Air Pollution, Health Concern, Satisfaction in Life

JEL codes: I12, I14, Q51, Q53

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1 Introduction

Particulate matter (PM) or fine particle matter has recently been attracting attention as the major source of air pollution. These microscopic particles not visible by the naked eye are known to reside in the air for an uncertain amount of time. The World Health Organization (WHO) cites high PM levels as the leading cause of various health problems worldwide, recognizing them as the single biggest environmental threat to human health (Cohen et al. 2005). Long-term exposure to high PM levels can cause fatal health issues such as lung cancer and cardiopulmonary diseases, estimated to cause 7 million premature deaths every year (Cohen et al., 2005; Raaschou-Nielsen et al., 2013). Recent studies (An and Yu, 2018; Sass et al., 2017; Zhang et al., 2018) suggest that exposure to ambient air pollution relates to a reduction in physical activities, poor cognitive performance, and adverse health behavior.

Research on air pollution is becoming a new frontier for health and environmental economics (Anderson, 2019; Deryugina et al., 2019). This is mainly because air pollution, the leading cause of contemporary health problems, is now recognized as a new channel for explaining the complex nature of an individual's economic behavior. This paper contributes to this ongoing literature by performing an empirical analysis of the effect of PM level on an individual's health-related behaviors in South Korea. By utilizing a large-scale survey that covers various aspects of an individual's choice and behavior, the paper specifies the link between high PM levels and people's behavior patterns. The paper also provides new insight into the research on PM levels by analyzing the heterogeneous effect of PM levels by their labor characteristics and occupations.

The rest of the paper is organized as follows: Section 2 reviews the recent literature on the health effects of air pollution, and Section 3 explains the construction of our dataset. Section 4 introduces the empirical strategy to analyze the effect of PM levels on certain human behaviors. Section 5 summarizes the empirical results of the analysis. Section 6 concludes, presenting advice on the possible improvements for the Yongwoon survey.

2 Literature Review

The impacts of ambient air pollution on the health status and behaviors among children and adults are actively studied in the field of Economics. Most studies utilize the annual average measures of air pollution to observe for regional or individual-level effects. Studies are mainly conducted in the United States, while recent studies cover cases in the United Kingdom and China. Researches suggest that air pollution level reduces physical activity, evoke psychological distress, and promote adverse health behaviors.

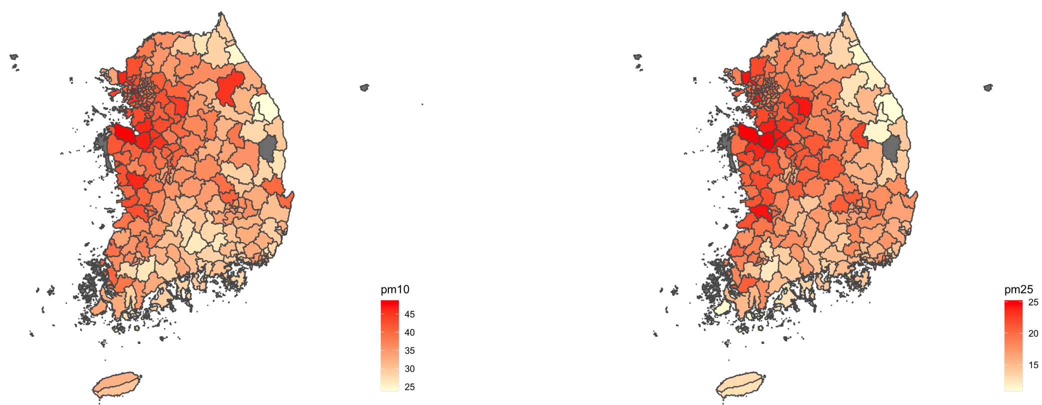
Hankey (2012), using the US environmental protection agency monitoring data, discloses in his cross-sectional study that annual-average air pollution exposure increases physical inactivity and reduction of exercises beneficial to health such as daily steps and hours spent outdoors. Alahmari (2015) from a cohort study in the UK describes how high concentrations in particulate matters and ozone levels were critical to health maintenance and exercising, with the effects being more severe in patients with respiratory symptoms.

An and Yu (2018) find evidence for the impact of air pollution on adverse health behaviors from a longitudinal study in China. Ambient PM2.5 concentration was negatively associated with vigorous physical activity, sedentary lifestyle, and total minutes of walking. The effect on psychological distress is also discussed by Sass et al (2017), finding that particulate matter 2.5 is significantly related to increased psychological distress. Following the emerging studies in the field, our study also utilizes the regional variation of particulate matter levels. Exploiting the detailed dataset on air quality, we observe the effects of both PM10 and PM2.5.

3 Data

In order to perform the empirical analysis, two pieces of data are used: the Yongwoon survey dataset containing individuals' subjective well-being and related health behaviors, and the real-time data from AirKorea containing a nationwide measure of particulate matters per region. To construct the final dataset, air pollution levels are merged with the Yongwoon survey results by district (Sigungu) level. Further details on each data used are as follows.

3.1 Measures for Regional Variation of PM Level



(a) PM10 Level: low → high

(b) PM2.5 Level: low → high

Figure 1: Average PM Level for each District

As the article seeks to identify the effect of fine particulate matter (PM) on individuals' behaviors, we utilize the real-time air pollution data from AirKorea on the exposure level of PM for 229 districts (Sigungu) of South Korea. Established in 2005, AirKorea provides real-time levels of SO_2, CO, NO_2, O_3, PM10, and PM2.5 per district. As we are concerned with analyzing the effect of particulate matter, we use the PM10 and PM2.5 data.

To quantify the level of air pollution using the district PM level, we utilize two specifications aggregating the PM data. First, we create a variable that denotes the number of days each district was exposed to ambient air conditions. We implemented the WHO air quality guidelines, counting the number of days the daily mean of PM10 levels was higher than $46ug/m^3$ (for PM2.5 levels, days when the daily mean was higher than $16ug/m^3$). Second, we create the annual average PM levels for each district in 2021, an index frequently used in previous literature. Figure 1 illustrates the nationwide distribution of annual average PM levels per district. The study later exploits the effect of such dispersion.

3.2 Individuals' Subjective Well-being and other Related Health Behaviors

The dataset for our study mainly exploits the survey questionnaires from the Yongwoon survey on individuals' subjective well-being and other health-related behaviors. Yongwoon survey is a biannual cross-sectional survey in South Korea taken by 10,000 people who were chosen in proportion to their gender, age, and regions. The survey is intended to investigate the political, social, and economic perceptions or activities of South Korean society members. For our main analysis, we use the level of subjective well-being of individuals which was measured by a 5-point Likert scale where 5 indicates "very satisfied" and 1 indicates "very unsatisfied."

For other related health behaviors, variables are extracted from questionnaires "attention on health care," "annual medical expense," "whether the individual smokes," and "whether the individual exercises often." We also use occupation-related questionnaires including "labor participation", "job occupation", and "working habits" of the respondents. Individual-level characteristics are controlled using the information of "gender," "age," "monthly income," "education level," "whether one is single", "whether one lives alone (one-person household)," and "whether there is a patient with chronic illness in the household" from the survey. Table 1 presents the summary statistics for our dataset.

Table 1: Summary Statistics

	Survey Respondents (2022)		
Variables	Obs.	Mean	SD
Female	10,000	0.49	0.50
Age	10,000	44.15	12.85
Life satisfaction	10,000	0.31	0.46
Life dissatisfaction	10,000	0.05	0.22
Value one's health	10,000	0.70	0.46
Stressed from one's health	10,000	0.35	0.48
Monthly average income	10,000	614.33	1182.24
One person household	10,000	0.13	0.34
Single status	10,000	0.35	0.48
High education ($\geq$graduated university)	10,000	0.58	0.49
Low education ($\leq$graduated highschool)	10,000	0.20	0.40

Variables	Obs.	Mean	SD
Full time worker	10,000	0.61	0.49
Average travel time	10,000	66.18	47.83
Elementary workers	10,000	0.06	0.23
Service workers	10,000	0.06	0.25
Low medical expense (≤1,000,000won)	10,000	0.55	0.50
High medical expense (≥5,000,000won)	10,000	0.07	0.25
Chronic patient in household	10,000	0.48	0.50
Exercise (≥once a week)	10,000	0.42	0.49
Smoke (≥once a week)	10,000	0.30	0.46
Risk averse	10,000	0.60	0.49
Risk loving	10,000	0.09	0.29
Interested in Environmental issues	10,000	0.30	0.46
Annual average PM10 level	10,000	38.02	4.94
Annual average PM2.5 level	10,000	19.01	2.79
Days with high PM10 level (2021)	10,000	85.22	25.20
Days with high PM2.5 level (2021)	10,000	174.41	34.19

4 Empirical Strategies

To estimate the impact of exposure to air pollution while controlling for time-invariant heterogeneous regional characteristics, we use a fixed-effects regression approach. An advantage of such an approach is the elimination of stable factors influencing both the individuals' well-being and the regional characteristics related to air pollution levels. Thus, we focus on the intracity variation of the survey respondents per district (Sigungu). Since the Yongwoon panel data consists of one timeframe, we do not take account of time fixed effects. The empirical model has the following form.

$$Y_{is} = \beta_0 + \beta_1 \cdot airpollution_s + \beta_2 X_{is} + \alpha_s + \varepsilon_{is} \tag{1}$$

Y_{is} denotes the health behaviors and subjective well-being of the individual i living in the district(Sigungu) s. For our main regressor $airpollution_s$, we observe the effects of PM10 and PM2.5 each. In measuring the exposure level to fine particulate matter (PM10 and PM2.5), we implement two indices: the number of days exposed to ambient air pollution levels, and the annual average PM levels per district in 2021. The vector X includes the individual's gender, age, monthly income, education level, risk preference, whether one is single, whether one lives alone (one-person household), and whether one is active in environmental activities.

We also control for fixed effects for 229 districts (Sigungu) in South Korea. Standard errors are clustered by district (Sigungu) level.

5 Results

5.1 Effects on Subjective Well-being

Table 2 reports the results on the individual's subjective well-being. The independent variable of interest is days with high PM levels and annual average PM levels. It captures the impact of exposure to air pollution in 2021 on one's reported well-being. The results indicate that individuals exposed to heavy air pollution report lower life satisfaction, exhibit higher levels of stress from health. and reduce the value of health perception. In specific, one day increase in heavy air pollution decreases the likelihood of being satisfied with one's life by 6.7 percentage points, while increasing the chance of reporting heavy dissatisfaction with life by 5.9 percentage points. Also, an additional day of high PM level increases the likelihood of feeling stress from health by 6.0 percentage points, while the likelihood of valuing one's health decreases by 8.9 percentage points. The results are consistent when using the annual average PM levels instead of the number of air pollution days. In sum, exposure to bad air quality reduces the subjective well-being of the residents.

Table 2: Effects on Subjective Well-Being

	PM10				PM2.5			
	(1) Life Satisfaction	(2) Life Dissatisfaction	(3) Value health	(4) Stressed from health	(5) Life Satisfaction	(6) Life Dissatisfaction	(7) Value health	(8) Stressed from health
Panel A: Number of Days with high PM level (2021)								
Days with high PM level	-0.067***	-0.059***	-0.089***	0.060***	-0.004***	0.004***	-0.006***	0.004***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Mean of dep. var	0.313	0.249	0.704	0.078	0.313	0.249	0.704	0.079
R-squared	0.060	0.072	0.063	0.038	0.060	0.072	0.063	0.038
Panel B: Annual Average PM level (2021)								
Annual average PM level	-0.143***	0.125***	-0.188***	0.127***	-0.141***	0.124***	-0.187**	0.126***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)	(0.004)
Mean of dep. var	0.313	0.249	0.704	0.078	0.313	0.249	0.704	0.079
R-squared	0.060	0.072	0.063	0.038	0.060	0.072	0.063	0.038
Observations	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Standard errors are clustered and are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Level of regional fixed effect and cluster levels are determined by 229 districts(Sigungu).

Table 3: Effects on Health Behaviors

	PM10						PM2.5					
	(1) Low medical expense	(2) High medical expense	(3) Commute time	(4) Exercise often	(5) Smoke often	(6) Drink often	(7) Low medical expense	(8) High medical expense	(9) Commute time	(10) Exercise often	(11) Smoke often	(12) Drink often
Panel A: Number of Days with high PM level (2021)												
Days with high PM level	0.099***	-0.099***	17.737***	-0.071***	0.148***	0.051***	0.006***	-0.006***	1.109***	-0.004***	0.009***	0.003***
	(0.003)	(0.003)	(0.466)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.029)	(0.000)	(0.000)	(0.000)
Mean of dep. var	0.547	0.453	66.18	0.423	0.212	0.297	0.547	0.453	66.18	0.423	0.212	0.297
R-squared	0.077	0.077	0.159	0.047	0.145	0.095	0.077	0.077	0.159	0.047	0.145	0.095
Panel B: Annual Average PM level (2021)												
Annual average PM level	0.210***	-0.210***	37.556***	-0.151***	0.314***	0.109***	0.208***	-0.208***	37.205***	-0.149***	0.311***	0.108***
	(0.006)	(0.006)	(0.987)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.978)	(0.007)	(0.005)	(0.005)
Mean of dep. var	0.547	0.453	66.18	0.423	0.212	0.297	0.547	0.453	66.18	0.423	0.212	0.297
R-squared	0.077	0.077	0.159	0.047	0.145	0.095	0.077	0.077	0.159	0.047	0.145	0.095
Observations	8,691	8,691	6,860	10,000	10,000	10,000	8,691	8,691	6,860	10,000	10,000	10,000

Standard errors are clustered and are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Level of regional fixed effect and cluster levels are determined by 229 districts(Sigungu).

5.2 Effects on Health Behaviors

In Table 3, we estimate the effects on health-related behaviors. Results indicate that more days with bad air quality promote adverse health behaviors. People report less exercise, more smoking, and frequent drinking when frequently exposed to air pollution. The likelihood of higher medical expenditure decreased from an increase in the number of days with bad PM levels. Probability of spending less than 1,000,000 won per year increased, and the likelihood of spending more than 5,000,000 won per year decreased. Noticeably, as the number of days with bad air quality increased, both the overall travel time and the travel time using public transit increased. In detail, when people experienced one additional day of bad PM2.5 level, their overall travel time increased by 1.1 minutes while the overall public transit time rose by 2.6 minutes. A twice more increase in public transit time could be from the influence of the Special Act on the Reduction and Management of fine Dust (Act No. 15718). Enacted on February 15, 2019, the Fine Dust Act encourages people to use public transport when PM levels are high. Alternative no-driving systems and free public transportation fees could have incentivized the bus and metro usage.

5.3 Heterogeneous effects by labor participation and job occupation

In this section, we observe two sources of heterogeneity, labor participation, and job occupation. This is to analyze whether the effect of air pollution impacts one's lifestyle differently according to labor participation. To validate such a proposition, we first observe whether the effect of air pollution impacts differently between workers and non-workers, followed by whether the pollution impacts elementary workers (workers in vulnerable environments) differently from their counterparts.

Table 4 shows the results by labor participation. Most results are consistent with the pooled results regardless of labor participation. However, the overall traffic time shows a large difference in labor participation.

Table 4: Heterogeneous Effects by Labor Participation and Job Occupation

	PM10						PM2.5					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Life Satisfaction	Life Dissatisfaction	Care for Health	Stress from Health	Travel time	Public Transit time	Life Satisfaction	Life Dissatisfaction	Care for Health	Stress from Health	Travel time	Public Transit time
Panel A: Workers in Elementary Occupation												
Days with high PM level	-0.519***	0.043	0.491***	0.497***	-2.844	0.096	-0.032***	0.003	0.031***	0.031***	-0.178	0.087
	(0.029)	(0.033)	(0.039)	(0.018)	(3.650)	(1.220)	(0.002)	(0.002)	(0.002)	(0.001)	(0.228)	(1.107)
Mean dep. var	0.194	0.376	0.699	0.108	56.50	67.41	0.194	0.376	0.699	0.108	56.50	67.41
R-squared	0.377	0.313	0.348	0.286	0.317	0.828	0.377	0.313	0.348	0.286	0.317	0.828
Observations	572	572	572	572	543	106	572	572	572	572	543	106
Panel B: Workers (Except Elementary Occupations)												
Days with high PM level	-0.064***	0.065***	-0.095***	0.044***	18.551***	40.086***	-0.004***	0.004***	-0.006***	0.003***	1.159***	2.505***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.470)	(1.883)	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.118)
Mean dep. var	0.320	0.241	0.704	0.0767	67.01	71.06	0.320	0.241	0.704	0.0767	67.01	71.06
R-squared	0.059	0.072	0.063	0.040	0.167	0.219	0.059	0.072	0.063	0.040	0.167	0.219
Observations	6,469	6,469	6,469	6,469	5,933	895	6,469	6,469	6,469	6,469	5,933	895
Panel C: Non-workers												
Days with high PM level	-0.051***	0.069***	-0.241***	0.057***	-7.414***	-0.309	-0.003***	0.004***	-0.015***	-0.004***	1.977***	-0.108
	(0.005)	(0.006)	(0.007)	(0.005)	(1.436)	(1.517)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.383)	(0.530)
Mean dep. var	0.313	0.275	0.703	0.101	81.97	77.46	0.313	0.275	0.703	0.101	81.97	77.46
R-squared	0.108	0.142	0.133	0.101	0.365	0.805	0.108	0.142	0.133	0.101	0.365	0.805
Observations	2,959	2,959	2,959	2,959	384	93	2,959	2,959	2,959	2,959	384	93

Standard errors are clustered and are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Level of regional fixed effect and cluster levels are determined by 229 districts(Sigungu).

Comparing Panel B and Panel C, an additional day of bad PM level increases the travel time for workers while non-workers face a decrease in their overall traffic time. The heterogeneity is more visible for travel time for those using public transportation only. Workers spend 2.5 - 40.09 minutes more on the road when additionally exposed to particulate matters, contrasting to the unaffected non-workers. A potential explanation is the availability of an option to stay safe indoors when air pollution levels are high. While non-workers may avoid travel when air pollution levels are high, those working in industries and jobs which require outdoor activity cannot choose to miss work due to air quality.

Additionally, we extend our focus on labor inequality by sub-grouping workers into elementary occupation and its counterparts. We focus on the point that elementary jobs usually entail a low salary, vulnerable working environments, and undesirable work. Results in table 4 suggest that elementary workers exhibit a larger fall in life satisfaction and higher levels of stress from health compared to their counterparts. The results imply that the negative effects of air pollution on health and well-being are unequal, where impacts are more severe for the lower class workers.

6 Conclusion and Discussion

6.1 Concluding Remarks

The results from our study align with the recent literature disclosing the effects of air pollution exposure on health status and behaviors. Air pollution level is negatively associated with life satisfaction and positively associated with adverse health behaviors and physical inactivity. High levels of PM level significantly reduce life satisfaction, increase the likelihood of feeling stressed from health issues, and reduce the value of health perception. Also, more days with air pollution encourage people to exercise often and smoke less.

Expanding our analysis, we disclose that the impact of air pollution could be unequal depending on whether one could reduce physical activity to mitigate the detrimental effect of pollution. Workers, especially in low-class elementary occupations, faced longer commuting times and harsher impact on life satisfaction and stress concerns from health status. Such unequal heterogeneity effects are alarming as environmental shocks are continuing to expand. Hence the paper calls out for a more active policy interventions to identify and reduce this inequality.

6.2 Suggestions for Improving the Yongwoon Survey

Finally, we conclude the article by offering several suggestions to improve the Yongwoon survey. Firstly, the survey should consider more the demographics and occupational features of the respondents. Since the surveys are collected via computers, most of the respondents are office workers or those with high access to computing devices. As large proportion of contemporary economic researches focus on identifying the effects on various occupational groups, it seems beneficial for the survey to implement a more diversified sampling process for the survey.

Secondly, we propose that the survey should strengthen its compatibility with public administrative datasets. While high compatibility of the data with outside resources is crucial for a more diverse and thorough analysis, the current Yongwoon data has room for improvement in its applicability. For instance, the survey does not use the universal region codes provided by the Ministry of interior and safety. Instead, it utilizes its own region codes without any correspondence table to convert the codes to a compatible form. It took a considerable amount of effort for us to merge different datasets using regions as the matching variable. The usage of a universal region code is recommended.

Adding, we found several typing errors and outdated data from the survey. Region "미추홀구" is misspelled as "미주홀구", and regions such as "여주시" is labeled as "여주군" which is an outdated name. As there are cases where the researcher needs to match different data by region names, it is ideal for the region names of the survey to be written correctly for practicality.

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