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Essays on Environmental Economics: Air Pollution and Avoidance Behavior

대기오염에 대한 정보가 회피행동 및 병원이용에 미치는 영향

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Abstract

Essays on Environmental Economics: Air Pollution and Avoidance Behavior

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Many countries have been providing information on air pollution to protect people from the risk of it. In general, policies on air pollution mean restrictions on emission sources. However, providing information can also protect public health because provided information induces people to adjust their behavior. Recently, the role of information may be greater than ever. With the development of technology, more information on air quality is provided than in the past and people can instantly acquire such information via the Internet. However, contrary to its growing importance, studies on whether information on air pollution changes people's behavior are insufficient; thus in-depth research is needed on the subject.

Chapter 1 provides new empirical evidence concerning the relationship between air pollution information and avoidance behavior. Several studies have shown that

information on air pollution causes avoidance behavior. However, these studies utilized forecast data as information; none have investigated the effect of real-time information on avoidance behavior. This chapter investigates whether real-time information on particulate matter affects people's behavior in Korea by using data on baseball game attendances. Results of this study show that people adjust their behavior in response to real-time information. The number of baseball game attendances decreases by approximately 7% when the real-time alert is issued. The effects of real-time alerts are different annually and to have increased significantly since 2014. This drastic change may be attributed to the increased accessibility and sensitivity of people. Furthermore, the effects of real-time information are statistically the same as that of forecasts..

Chapter 2 examines whether information on air pollution causes avoidance behavior in the labor sector. Although only few researchers have considered the avoidance behavior in the labor sector, it is important to examine this subject in that working hours have a large portion in one's life. Accordingly, this chapter estimates the effects of information such as forecast and real-time alerts, on working hours of outdoor workers. Results suggest that outdoor workers reduce their working hours when forecast and real-time alerts are given. The workers respond to information by adjusting work start or end time, while they cannot immediately react to real-time alerts while working. The effects of information are chiefly derived from the agriculture, forestry, and fishing industries. Furthermore, only workers who can modify their work start and end time or employers react to the information on PM10.

Chapter 3 estimated the impact of particulate matter (PM) and PM information

on the number of hospital visits due to respiratory diseases in Korea. The results showed that, if the forecast for PM appeared bad or very bad, then the number of hospital visits increased. This finding is in contrast to the results of some previous studies that reported that information on air pollution reduces hospital use by avoidance behavior. However, the results of this study confirmed that information can affect hospital use by channels other than avoidance behavior, such as sensitivity, and can thus increase hospital use.

Keywords: air pollution, particulate matter, health, information, real-time information, avoidance behavior, averting behavior, working hours, hospital use

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Introduction of the dissertation

"Clean air is considered to be a basic requirement of human health and well-being" (WHO, 2005). However, poor air quality is constantly threatening people's health. The World Health Organization announced in 2016 that more than 7 million people prematurely died due to air pollution every year, and more than 90% of children worldwide are breathing polluted air (WHO, 2018a; WHO, 2018b) Moreover, a World Bank report in 2016 estimated that the cost of air pollution is over USD 5 trillion annually (World Bank, 2016).

Particulate matter (PM)[1] is a harmful air pollutant, and many countries in Asia and Africa have been suffering from PM pollution. Although these countries have been implementing various policies to protect their people from the threat of PM pollution, the threat is still quite serious. Therefore, additional policies are expected to be in action, and many studies related to PM should be carried out to ensure success of these policies.

The harmfulness of PM has long been studied. After the LA and London smog events in the 1940s–1950s, research on the health effects of air pollution, including PM, started. By the 1970s, researchers agreed on the consensus that high concentrations of air pollution cause cardiopulmonary diseases (Holland et al.,

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[1] PM, especially PM10 and PM2.5, has very small particles with a specific diameter of less than 10 and 2.5 μm and floats in the air. Coarse particles (10–2.5 μm) mostly originate from natural events, such as dust storms, evaporation of sea water, and weathering. Fine particles (under 2.5 μm) are produced by human activities, such as using fossil fuels.

1979). In the 1980s–1990s, studies on various topics were conducted, including effects of the influence of relatively low concentrations, influence over exposure period, and estimation of the form of exposure–response function (Pope III, 2000; Pope III and Dockery, 2006). Recently, researchers have studied whether PM negatively affects non-health aspects, such as human capital formation, labor supply, and labor productivity (Zweig et al., 2009; Sander, 2012; Lavy et al., 2014; Hanna and Olivia, 2015; Chang et al. 2016; Isen et al., 2017).

Most researchers to date have used ambient air pollution data in their studies. However, people, especially susceptible groups, may attempt to avoid the risk when they perceive air pollution. In this case, the actual exposure level may differ from the level of ambient air pollution. Therefore, studies, that identify the effects of air pollution, need to consider avoidance behavior. Recently, considering avoidance behavior has been important than ever. With the development of technology, many countries are providing more information on air quality to their people than in the past, and people can instantly acquire such information via the Internet. Therefore, people are likely to recognize and avoid the risk by using this information. In addition, people's interest in health has grown; thus, awareness of air pollution may be different from the past and thus results in avoidance behavior. However, contrary to its growing importance, studies related to avoidance behavior are insufficient. Therefore, I conducted studies on avoidance behavior.

This dissertation reports the analysis on whether people in Korea adjust their behavior on the basis of information on PM. Korea is an Asian country that suffers from high PM concentration. In the case of Seoul, the capital of Korea, PM (PM10 and PM2.5) concentration is unfavorable for over 120 days per year from 2014 to

2016 according to WHO criteria (Kweather 2017). In addition, the OECD estimated that 20,424 people died prematurely in 2013 given air pollution in Korea and that the number will triple in 2060 if the current air pollution trends continue (OECD 2017). Therefore, the Korean government has been implementing various policies, particularly information provision policy, to protect the people from PM. In Korea, PM concentration of the location of interest can be easily checked in real time via government-operated sites (www.airkorea.or.kr) or popular portals (www.daum.net, www.naver.com). In addition, the PM forecasts have been in operation since 2014; thus, people can recognize expected PM levels for the next day. Therefore, they are likely to adjust their behaviors in response to the information. However, research on whether information on PM causes avoidance behavior or its effect on the health of people is insufficient in Korea.

Recently, people have more access to real-time information than in the past; thus the first chapter of the dissertation examines whether people coordinate leisure outdoor activities in response to real-time information on PM. The second chapter estimates the effect of the information on outdoor workers' working hours. It is important to examine this subject in that working hours have a large portion in one's life. The third chapter identifies the impact of the information on the number of hospital visits. This work is meaningful in that the effect of real-time information, which has not been investigated in previous studies, is estimated. The effect of avoidance behavior in labor, which is examined in Chapter 2, has also not been studied in the previous research. Furthermore, this is the first study to show that information can affect hospital use by channels other than avoidance behavior, such as sensitivity, and can thus increase hospital use.

Chapter 1

Air Pollution, Real-time Information, and Avoidance Behavior: Evidence from Korea

This study provides new empirical evidence concerning the relationship between air pollution information and avoidance behavior. Several studies have shown that information on air pollution causes avoidance behavior. However, these studies utilized forecast data as information; none have investigated the effect of real-time information on avoidance behavior. The current study investigates whether real-time information on particulate matter affects people's behavior in Korea by using data on baseball game attendances. Results of this study show that people adjust their behavior in response to real-time information. The number of baseball game attendances decreases by approximately 7% when the real-time alert is issued. The effects of real-time alerts are different annually and to have increased significantly since 2014. This drastic change may be attributed to the increased accessibility and sensitivity of people. Furthermore, the effects of real-time information are statistically the same as that of forecasts.

1.1 Introduction

The hazard of air pollution is popular in many studies. In particular, particulate matter (PM) air pollution is associated with morbidity and mortality from cardiovascular and respiratory diseases (Pope III and Dockery 2006, EPA 2014). Furthermore, the International Agency for Research on Cancer (IARC) under WHO has classified PM as Group 1 carcinogen in 2013 (IARC 2013). Moreover, several studies have reported that PM negatively influences the cognitive ability and human capital formation (Zweig et al. 2009, Lavy et al. 2014).

Accordingly, countries have been implementing various policies to protect people from the threat of air pollution. These policies include providing information on air pollution levels with action guidelines. The information provision policy is based on the expectation that people will adjust their behavior on the basis of the information on air pollution. Certainly, some studies have shown that information provision on air pollution causes avoidance behavior (Neidell 2009, Zivin and Neidell 2009, Janke 2014, Altindag et al. 2017).

The present study provides new empirical evidence on the relationship between information and avoidance behavior. The development of information and communication technology has facilitated the provision of and access to real-time information. At present, in some countries, people easily check real-time air quality of an area of interest through the Internet or smart devices. Therefore, people who aim to avoid the threat of air pollution may adjust their behavior, depending on the information. This study examines whether real-time information has affected people's outdoor activities by using professional baseball game attendance data.

This study was conducted on the basis of the data from Korea, which has two of the traits important for this study; severe air pollution and high accessibility to information. Korea is an Asian country that suffers from high PM concentration. In the case of Seoul, the capital city of Korea, PM (PM10 and PM2.5) concentration is unfavorable for over 120 days per year from 2014 to 2016 according to WHO criteria (Kweather 2017). In addition, the OECD estimated that 20,424 people died prematurely in 2013 given air pollution in Korea and that the number will triple in 2060 if the current air pollution trends continue (OECD 2017). A recent study suggested that air pollution, including PM, is the most disturbing factor for Koreans in 2017, surpassing North Korea's nuclear weapons and earthquakes (Jung et al. 2017). Moreover, Korea is a country with a high penetration rate of the Internet and smartphones. According to Strategy Analytics, Korea's smartphone penetration rate is 77% in 2017, ranking sixth worldwide and second in Asia (Wu 2017). This high rate represents Koreans' high accessibility to information. Therefore, considering these traits, Koreans are likely to respond sensitively to air pollution information. In addition, approximately a half of air pollution in Korea are caused by exogenous factors, such as Asian dust (Hankyoreh 2017) and the pollutants from outside are quasi-randomly distributed over all areas in the country (Jia and Ku 2018); Thus, residential sorting problem, appeared if pollution-sensitive people move to clean places, may be insignificant.

The current study examines the effects of real-time information on PM. In contrary to forecasts, the effect of real-time information on avoidance behavior has not yet been studied. The Korean government provides the current air quality information hourly on their website (www.airkorea.or.kr). Even if one has no access to their website, people can easily obtain information from other websites or applications. Thus, investigating whether the information affects people's behavior will be the main contribution of this study.

In this study, I focus on PM10, which indicates PM with aerodynamic diameters less than or equal to 10 $\mu g/m^3$. According to Kim et al. (2015), Korea's interest in

PM began in 2011 after the event that, by the end of 2010 and early 2011, the PM10 concentration in Seoul skyrocketed to 1,191 $\mu g/m^3$. However, until the release of the information on PM2.5 in 2015, people who attempted to avoid PM air pollution are likely to behave in response to PM10 information. Therefore, the present study aims to determine whether information on PM10 has caused avoidance behaviors by using the baseball game attendance data from 2012 to 2016.

1.2 Previous Research

As effectively summarized in Pope III and Dockery (2006), PM was found to be associated with morbidity and mortality due to respiratory and cardiovascular diseases. In addition, PM is related to human capital formation. Some recent studies have shown that PM negatively affects children's schooling and cognition (Zweig et al. 2009, Lavy et al. 2014); moreover, PM exposure in one's early life has worsened performances, such as test score and labor market outcome (Sander 2012, Isen et al. 2017). Research based on Korea has confirmed the negative effects of PM (Hong et al. 1999, Lee et al. 2000, Lee et al. 2002, Ha et al. 2003).

The air pollution considered in the abovementioned studies is based on the pollution degree measured at fixed-site outdoor monitors. However, a gap exists between the level of air pollution in the atmosphere and people's actual exposure. The difference is determined by people's actions. People who perform numerous outdoor activities may have a smaller difference than people who do not. In addition, this difference occurs when people recognize the danger by acquiring information and attempting to avoid it through avoidance behaviors, such as reducing outdoor activities or wearing masks. If the effects of air pollution on health is estimated without considering avoidance action, then the social cost of pollution can be underestimated (Currie et al. 2014). Therefore, avoidance behavior must be considered to accurately estimate the effects of air pollution on health. Given the recent increase in the provision and accessibility of information, the importance of avoidance behavior seems greater than before.

There are several previous ones related to air pollution and avoidance behavior. Neidell (2009) and Altindag et al. (2017) showed that air quality information, such as smog alerts or Asian dust warnings reduced outdoor activities and alleviated the bad effects of the air pollution on health. While, Janke (2014) reported that the positive effects of the information on health were limited and occurred only on asthma patients, although air pollution warnings reduced the daily visitors to an outdoor facility. Nam and Jeon (2019) found that the number of baseball game spectators decreased when daily average PM was forecasted as bad or very bad. The abovementioned studies exploit outdoor activity data to determine whether avoidance behavior was present. However, various types of data can be used for studies on avoidance behavior. Moretti and Neidell (2011) estimated the welfare costs of avoidance behavior by using daily boat traffic as an instrumental variable. Sheldon and Sankaran (2019) showed that bad air quality caused by Indonesian forest fire increase Singaporean domestic electricity demand. Zhang and Mu (2018) and Liu et al. (2018) showed that high PM concentration increases sales or online searches on anti-PM2.5 masks and air filters.

1.3 Data

Data Sources

Hourly ambient air pollution data was obtained from the National Institute of Environmental Research (NIER) of Korea. The Korean government and local governments operate more than 250 monitoring stations (based on a report in 2017) and collect hourly data on pollutants, such as SO_2, NO_2, CO, O_3, PM10, and PM2.5[2]. The NIER receives the data from the governments and provides them to the public. The collected information on air pollution is announced not only at the station level but also at the county or provincial level. People can easily obtain real-time information from various websites or applications. The real-time PM10 information is provided numerically and categorically. Categorical information is classified into the following four levels, depending on the concentration of PM10: 0–30 are expressed as good, 31–80 as moderate, 81–150 as bad, and over 151 as very bad. Moreover, each category is displayed in different colors, such as blue, green, yellow, and red, to express the level of risk intuitively.

Forecast information on PM10 is a potential confounding factor to disturb estimation of the effects of real-time information since they can be highly correlated. Therefore, forecast data obtained from the government operating website (www.airkorea.or.kr) is controlled in the analysis model. The Korean government has been operating an air quality forecast system since 2014. The system announces the next day forecast of PM and ozone four times a day at 5 a.m., 11 a.m., 5 p.m., and 11 p.m. I selected the data that were announced the day before

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[2] PM2.5 has been available since 2015.

at 5 p.m. because this information is published on the evening main news. The forecast is provided at four levels, namely, good, moderate, bad, and very bad. They are not provided as numerical values.

Weather data were obtained from the climate data open portal (data.kma.go.kr) operated by the Korea Meteorological Administration. The portal provides hourly weather data for more than 90 monitors across the country. Given that several counties had no weather station, the weather observed from the nearest station to the administrative office of a county was defined as the weather of the county.

As a proxy of outdoor activity, I used the baseball game attendance data provided by the Korea Baseball Organization on their website. These data contain information, such as the ballpark, home team, away team, and the number of attendances of a game. Baseball is one of the most popular sports in Korea. Given that a season runs from March to October, we can observe an extensive variation in terms of PM. Moreover, considering that baseball games are typically held at night in summer, the effect of ozone, which is another pollutant causing avoidance behavior, can be eliminated. The long duration of the game (approximately 3 h) is suitable for investigating avoidance behavior. As of 2016, 10 teams participated in the Korean professional baseball league, and every team had approximately 140 matches annually. In 2012, eight teams existed, but two additional teams had been added within the analysis period.[3] Therefore, differences existed in the number of teams that participate in the league yearly. Furthermore, several teams changed the

[3] Eight teams existed in 2012, and two teams joined the league in 2013 and 2015.

home ballpark within the period.[4]

To estimate the effect of real-time information, the deadline for canceling a reservation should be known. Every team had a different deadline to cancel reservations, and such data were collected from online reservation sites. However, actual data on canceled reservations could not be obtained, thereby compelling me to only use the number of attendance of baseball games.

Summary Statistics

In Table 1.1, the average PM10 concentration of the entire sample is approximately 43. When the hourly PM10 with categorically bad or very bad (81 and over) at reservation cancellation deadline of baseball games is defined as real-time alerts, 257 of the total observations are exposed to the alert. The average concentration of PM10 of days with the real-time alerts is 89.71. When bad and very bad forecasts are defined as forecast alerts, 110 out of 3,004 observations are exposed to the forecast alert.

The average number of attendance in a baseball game is approximately 11,500. Although the concentration of PM10 is systematically high under the real-time alerts, the average number of attendances is not systematically low. Thus, the confounding factors such as the weather should be controlled to determine the true effect of PM10 and its information on the attendances.

Figure 1.1 depicts the locations of the ballparks, which are concentrated in the

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[4] One team moved its ballpark in 2014, and two teams moved in 2016.

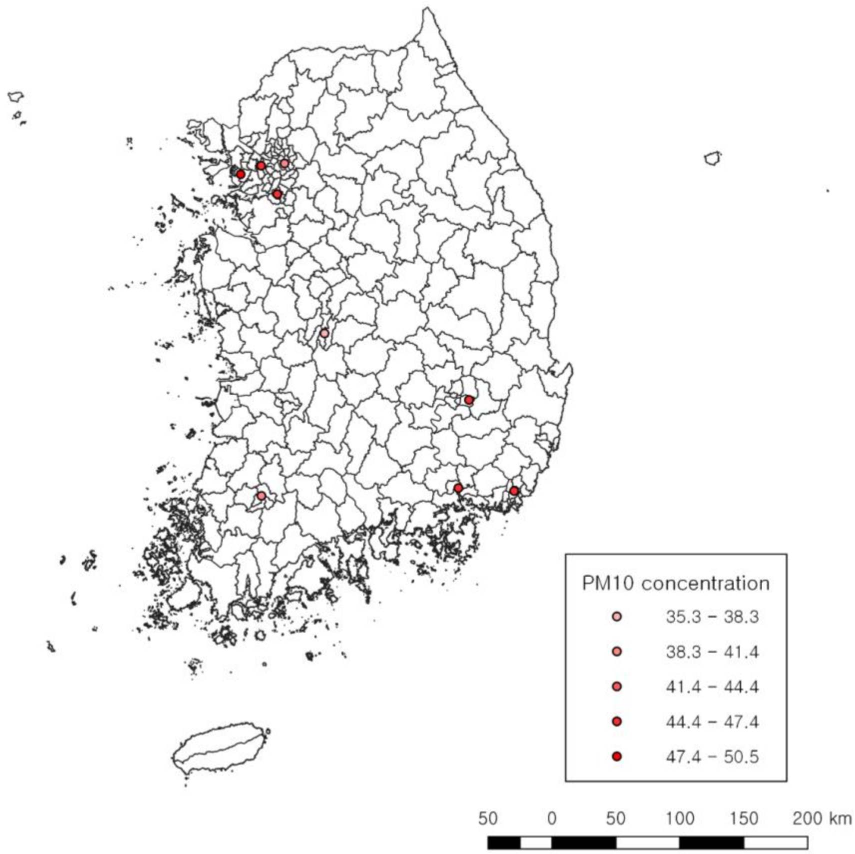
northwestern (capital area) and southeastern parts of the country. The average PM10 concentration of the counties with ballparks is determined from 35 to 50 during the analysis period. A total of 10 teams are in the Korea baseball league, but the two teams share one ballpark. Thus, nine ballparks are displayed on the map.

<Table 1.1> Summary Statistics

		Real-time Alerts	
VARIABLES	Total	NO	YES
Attendance	11579.02 (6325.48)	11589.87 (6365.32)	11463.04 (5893.19)
PM10 (μg/㎥)	43.08 (22.5)	38.72 (15.7)	89.71 (30.17)
Forecast Alert (%)	3.66 (18.79)	1.57 (12.42)	26.07 (43.99)
Real-time Alert (%)	8.56 (27.97)	0 (0)	100 (0)
Temperature (℃)	21.6 (5.21)	21.77 (5.2)	19.75 (4.92)
Precipitation (mm)	2.5 (10.23)	2.68 (10.64)	0.6 (3.07)
Wind Speed (m/s)	2.32 (1)	2.31 (1)	2.39 (0.99)
Humidity (%)	67.23 (15.18)	67.54 (15.05)	63.94 (16.16)
N	3,004	2,747	257

Note: Standard deviations are in parentheses; Sample period is from 2012 to 2016; Forecast began in 2014.

<Figure 1.1> Location of Baseball Ballpark and its Average PM10 Concentration



Note: The location of the ballpark was based on 2016. A total of 10 teams are in the Korea baseball league, but the two teams share one ballpark. Thus, nine ballparks are displayed on the map.

1.4 Methodology

Identification Strategy

The influence of real-time information is estimated by using an hourly PM10 concentration at the cancellation deadline of baseball game reservations. In Korea, people are able to cancel the reservation 2−4h before the start of the game, although the regulations for the reservation cancellation are different by teams.[5] If a person who reserves a baseball game has determined a cancellation of a reservation in response to the real-time PM information, he or she may rely on the information provided before the deadline. Therefore, the information available at the deadline is used as the real-time information that people respond to. However, anticipating people to rely only on information at the deadline to adjust their behavior is uncertain. In addition, to use this variable, determining if people adjust their behavior through reservation cancellation is necessary. Thus, additional analysis is conducted to investigate whether people respond to real-time information of the time close to the deadline and whether people's reaction to the information differs before and after the deadline.

The real-time information is classified into the following categories, depending on the concentration of PM10: 0–30 are expressed as good, 31–80 as moderate, 81–150 as bad, and over 151 as very bad. In addition, each category is displayed in different colors, such as blue, green, yellow, and red, to express the level of risk intuitively. For an accurate estimate of the effect of real-time information, using

[5] The cancellation fee is 10% of ticket prices which vary from 10$ to 80$.

real-time PM10 concentration itself is ideal in the analysis. However, verifying whether the response to the concentration is the effect of the information or not is infeasible, considering that PM10 is related to visibility and bodily response. Therefore, to determine the effect of real-time information, the dummy variable, which indicates that real-time PM10 concentration is bad or very bad, is generated and named it a real-time alert. However, even in this case, the effect of real-time alerts may also be due to visibility and bodily reaction. Thus, I control the average PM10 concentration of the day until the game starts in the model to mitigate the problem.

As previously described, the forecast information on PM10 is a potential confounding factor to disturb estimation of the effects of real-time information. Therefore, forecast alerts dummy, which indicates whether PM10 on a day is forecasted as bad or very bad, is controlled in the analysis models. The value of this variable is 0 before 2014 in which the forecast system is introduced.

Basically, home and away teams are controlled as dummy variables. Certain teams have changed the ballpark within the analysis period. To control the effect of changing the home ballpark, interaction terms of home team and year dummy variables are included in the analysis model. In Figure 1.3, teams can be clustered around the northwest and southeast areas, and some teams even share a ballpark. Therefore, the number of away fans of a team may vary, depending on the location of the ballpark of a home team. In addition, a rivalry between teams can affect the number of attendances of a game. To prevent this issue, the interaction terms of home and away team dummy variables are included in the model. Occasionally, a home team plays at a subfield, rather than at the home ballpark for an event. The number of these games is negligible; therefore, these cases of the game sample are excluded from the analysis.

Econometric Specification

This study aims to estimate the effect of real-time information on outdoor activities. The number of baseball game attendances is used as a proxy variable for outdoor activities. Outdoor sports data have been used in previous studies to verify avoidance behavior (Neidell 2009, Altindag et al. 2017).

I estimate the effect of information using the following equation:

$$Y_{ct} = \alpha + \beta_2 RA_{ct} + f_1(PM_{ct}) + \gamma_1 FA_{ct} + f_2(HT_{ct}, AT_{ct})$$
$$+ f_3(W_{ct}) + \delta_t Time_t + \epsilon_{ct}, \tag{1}$$

where Y_{ct} is the number of attendances of the game held in county c on day t. *RA* is the dummy variable that indicates alerts issued on the real-time PM10 concentration. *PM* is a set of variables containing the average PM10 concentration until the game starts and its square values. *FA* is a dummy variable indicating whether forecast alert on PM10 is issued. *HT* and *AT* are the home and away team dummy variables, correspondingly. These variables are controlled to capture the average time-invariant characteristics of a team. The interaction terms of home and away team dummy variables are also included to control special relations between teams, which consequently affect the number of attendances. *W* is a set of variables, such as temperature, precipitation, wind speed, and relative humidity. These meteorological confounding factors are controlled with flexible forms. *Time* is a set of time dummy variables (i.e., year, month, day of week, holiday, and MERS[6] period). In addition, the interaction terms of home and year dummy variables are included to control the ballpark change effect. On the basis of Equation 1, the baseline results are estimated, and various robustness checks are conducted.

1.5 Results

<u>Baseline Results</u>

Table 1.2 summarizes the results of the baseline model. By comparing each column, we can identify that the real-time alerts are closely correlated with other confounding variables and appropriate controls are needed in that the coefficients of the alerts vary largely by control variable sets. Therefore, the most credible results are exhibited in Column (5) and (6), which control all available confounding factors mentioned in Equation 1. According to the results, real-time alerts issued at the deadline reduce the number of attendances by approximately 900. Given that RA is likely to occur on the day when FA is issued, a correlation is observed between the two variables, which may cause an omitted variable bias. Even if FA is inserted in the model, however, the magnitude and statistical significance of the real-time effect remain almost unchanged. Column (6) represents the result using log attendances as a dependent variable. The results suggest that real-time alerts reduce the number of attendances by approximately

[6] In Korea, the Middle East Respiratory Syndrome (MERS) was prevalent for 68 days from May 20, 2015 to July 28, 2015, and the high infectivity of the disease caused people to reduce external activities. Therefore, this period was specifically controlled.

7%. Although previous studies have shown that forecast alerts change people's behavior, few studies have investigated the effects of real-time information. The baseline results of this study denote that people adjust their behavior in response to real-time information.

Robustness Checks

I perform various robustness checks on the effect of the real-time alerts on the number of baseball game attendances and its results support the baseline results. Column (1) in Table 1.3 represents the effects of real-time alerts on the day when the forecast alert does not occur and Column (2) reports the result of the model which includes the interaction term of RA and FA. Both analyses are conducted to clearly eliminate the influence of correlation between RA and FA, and the results reconfirm large negative effects of real-time alerts.

Column (3) shows the result of replacing continuous PM10 concentration variables to interval dummy variables. In the baseline model, the average PM10 concentration until the game started is controlled as a quadratic function, but this analysis is conducted to consider the possibility of the non-quadratic relationship between the PM10 concentration and number of attendances.

Column (4) demonstrates the result of the model that controls week dummy variables instead of month dummies. If within a month, trends occur in PM10 (or alerts occurrence) and in the number of attendance, then the regression result can show a significant relationship between the two variables, although it is only a

<Table 1.2> Effects of Real-time Alerts on Baseball Game Attendances

VARIABLES	(1) Attendance	(2) Attendance	(3) Attendance	(4) Attendance	(5) Attendance	(6) ln(Attendance)
RA	-1,949***	-1,849***	-1,369***	-923.0***	-902.7***	-0.0678**
	(516.0)	(507.2)	(376.1)	(281.4)	(280.2)	(0.0270)
Weather		○	○	○	○	○
Team FE			○	○	○	○
Time FE				○	○	○
FA					○	○
R-squared	0.009	0.100	0.587	0.759	0.760	0.728
Observations	3,004	3,004	3,004	3,004	3,004	3,004

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; The analysis period is from 2012 to 2016.

temporal effect. Therefore, to eliminate the bias caused by the possible temporal effect, a shorter period than a month is controlled.

Model (5) in Table 1.3 shows the result of the analysis conducted without the games with maximum crowds. The baseline model can be considered a censored model with an upper limit because ballparks set the maximum number of people to be accommodated. Therefore, to eliminate the distortion caused by the upper limit, the analysis is performed without the case of full attendance. This model with corrected distortion may present more accurate results than the baseline model. The result presented in Column (5) represents the smaller effects of real-time alerts than the baseline model, but the effects still remain largely negative and statistically significant.

In 2016, Nexen, one of the Korean professional baseball teams, changed its home stadium to Gocheok Skydome which is the first and the only domed stadium in Korea. The influence of the information could be different from that of other stadiums, given that games held in dome stadium are not affected by PM. Model in Column (6) identifies the effect of real-time information on the number of attendances of domed stadium by including the interaction term of real-time information and Gocheok Skydome dummy in the model.[7] Models (7) in Table 1.3 demonstrate the effects of information on the number of attendances at the indoor sport, basketball.[8] The number of attendances of Gocheok Skydome and basketball

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[7] The effect of Gocheok Skydome on the number of attendances is already captured in the model since the interaction terms of home teams and year dummy variables are controlled in the model.

[8] Data for basketball games from 2014-2015 was used.

<Table 1.3> Robustness Checks for Effects of Real-time Alerts

VARIABLES	(1) w/o FA days	(2) w/ Interaction of RA and FA	(3) PM10 Interval	(4) Week dummy instead of Month	(5) w/o Maximum Crowd	(6) Effect of Domed Stadium	(7) Basketball
RA	-778.3**	-993.0***	-874.9***	-895.9***	-686.0**	-889.2***	-324.3*
	(352.5)	(295.0)	(328.4)	(281.6)	(278.0)	(292.3)	(175.5)
RA * Gocheok Skydome						42.65	
						(612.3)	
Weather	○	○	○	○	○	○	○
Team FE	○	○	○	○	○	○	○
Time FE	○	○	○	○	○	○	○
Forecast alerts		○	○	○	○	○	○
Observations	2,894	3,004	3,004	3,004	2,686	3,004	448
R-squared	0.754	0.758	0.758	0.763	0.734	0.760	0.669

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; In Column (2), the interaction term of RA and FA is included but not shown: Data for basketball games from 2014-2015 was used; In 2016, Nexen, one of the Korean professional baseball teams, changed its home stadium to Gocheok Skydome which is the first and the only domed stadium in Korea.

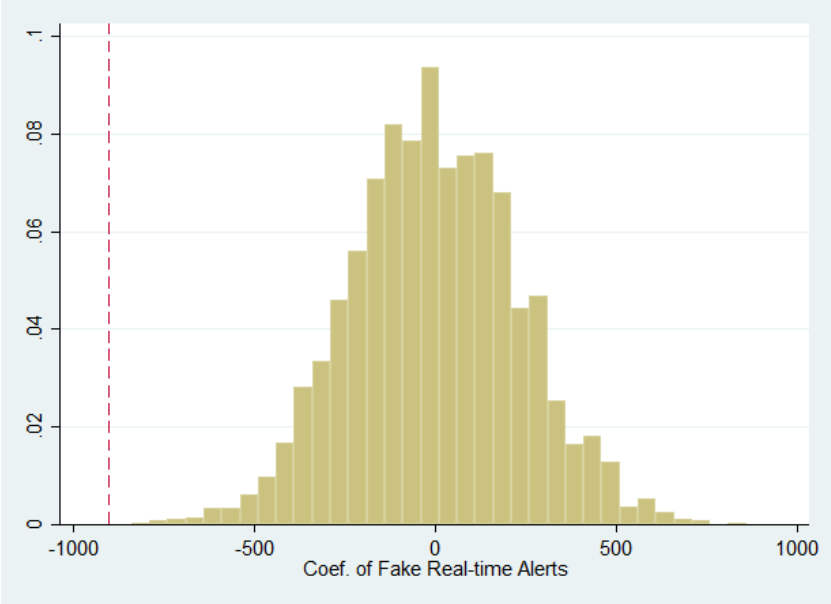
games is negatively affected by the real-time alerts. Results in Model (6) and (7) may reflect that people are unwilling to be exposed to high level of PM10 on the way to the stadium.

Falsification Test

I also conduct a simulation test on the baseline models. The simulation estimates the effects of fake real-time alerts on the basis of Equation 1. After calculating the probability of occurrence of the real-time alerts by year and county, a fake alert variable is created on the basis of the probability. Then, the baseline regression is conducted using the fake alert, rather than the actual variable. This process is repeated 3,000 times and its coefficient value is recorded. Table 1.4 and Figure 1.2 display the statistics and distribution of the estimated coefficients.

In this table and figure, the influence of fake variables is nearly zero on average, and the value of the baseline model's coefficients is located at the edge of the distribution. Thus, this test confirms that the result of the baseline model is non-coincidental.

<Figure 1.2> Distribution of the Regression Coefficients of Fake Real-time Alerts



Note: The red vertical dashed line indicates the coefficient of RA in baseline models

<Table 1.4> Statistics of Regression Coefficients of Fake Real-time Alerts

# of simulation	Mean of Fake Coef. (A)	Std. Dev. of Fake Coef. (B)	Coef. of Real Model (C)	(C-A)/B
3000	0.211	231.91	-902.7	-3.89

<u>Effect of Real-time Alerts near the Deadline</u>

Even if people adjust their behavior in response to real-time information, imagining that they only respond to information of a particular time, such as a deadline, is difficult. The baseline model uses the information available at the deadline as real-time information that people respond to. If people do not adjust their behavior through reservation cancellation, however, real-time information after the deadline can also affect the attendance. In addition, even in the case that people modify the plan through reservation cancellation, all information given before the deadline may affect people's behavior. Therefore, I check the effect of the information of the time near before and after the deadline to verify whether using the real-time alert at the deadline is reasonable or not. The following model is used for the analysis:

$$Y_{ct} = \alpha + \beta_k \sum_{k=-6}^{6} RA\_k_{ct} + f_1(PM_{ct}) + \gamma_1 FA_{ct}$$

$$+f_2(HT_{ct}, AT_{ct}) + f_3(W_{ct}) + \delta_t Time_t + \epsilon_{ct}, \quad (2)$$

where *RA_k* is the dummy variable that indicates whether the real-time PM10 is bad at a time when k is hours away from the deadline. The value of k is −6 to 6. That is, real-time alerts occurring within 6 h before and after the deadline are used for this analysis. Considering that the real-time concentration of PM10 is highly correlated with the concentration of the surrounding times, the *RA_k* with 2 or 3 h intervals are used in the actual model. Table 1.5 and Figure 1.3 present the estimation results using Equation 2.

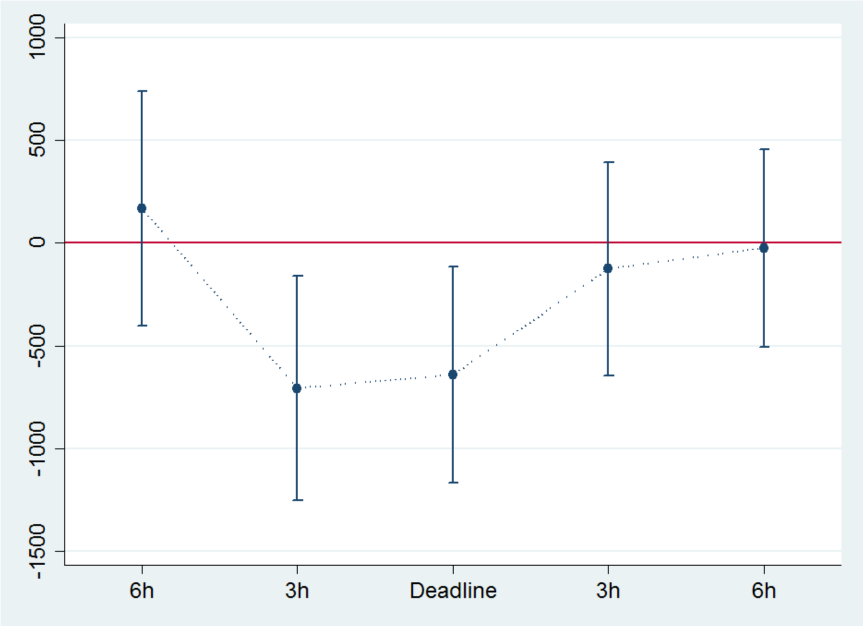
The above-mentioned results show that the effect of real-time information has started to occur at nearly 3 h before the deadline, and the information after the deadline has no effect. In addition, the effect is considerable when the deadline is near. Therefore, people adjust their behavior through the reservation cancellation, and using the information at the deadline is reasonable. However, the sum of the significant coefficients at the 90% level is nearly −1,300 in both models and is larger than the estimated effect in the baseline model. This finding denotes that using the real-time alert at the deadline can effectively reflect people behavior but can underestimate the coefficient.

<Table 1.5> Reaction to Real-time Information near Deadline

VARIABLES	(1) 2hours Intervals	(2) 3hours Intervals
Before 6h	286.4	169.2
	(367.4)	(347.1)
Before 5h		
Before 4h	-527.6	
	(367.9)	
Before 3h		-706.1**
		(332.2)
Before 2h	-638.1*	
	(352.7)	
Before 1h		
Deadline	-747.0**	-641.0**
	(337.8)	(318.7)
After 1h		
After 2h	249.5	
	(361.9)	
After 3h		-126.0
		(314.9)
After 4h	372.3	
	(334.9)	
After 5h		
After 6h	-286.3	-24.52
	(298.9)	(291.4)
Observations	3,004	3,004
R-squared	0.761	0.760

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

<Figure 1.3> Effect of Real-time Alerts near the Deadline - 3 Hours Interval



Note: The vertical bar of a point represents 90 percent confidence intervals.

Regression Discontinuity Design (RDD)

This study addresses the effects of real-time alerts. The real-time alerts indicate that the real-time PM10 pollution levels are categorically bad or very bad and these categories are determined by real-time PM10 concentration; therefore, the RDD is applicable. The model used for the RDD is expressed as follows:

$$Y_{ct} = \alpha + f_1(PM_{ct}) + \gamma_1 FA_{ct} + f_2(HT_{ct}, AT_{ct}) + f_3(W_{ct}) + \delta_t Time_t + \epsilon_{ct}, \quad (3)$$

$$\epsilon_{ct} = \alpha + \tau RA_{ct} + \theta_1 poly(PMD_{ct} - cut) + \theta_2 poly(PMD_{ct} - cut) * RA_{ct},$$

$$where\ cut - h \ \leq PMD < cut + h. \quad (4)$$

Even when analyzing using the RDD, confounding factors, included in the baseline model, must be controlled. However, an excessive number of control variables are included in the model when compared to the limited number of samples in RDD.[9] Therefore, the residual from Equation 3 is used in the RDD. In Equation 4, PMD indicates the continuous PM10 concentration at the cancellation deadline, and the RA is a dummy variable that indicates whether the PM10 is categorically bad or very bad at that time. The PMD is included in various polynomial forms. *cut* represents the cutoff point, which is 81 in this study. Then, 20 and 10 are used for bandwidth h.[10] Table 1.6 lists the RD estimates derived from various bandwidths and functional forms.

<Table 1.6> RD Estimates of the Effect of Real-time Alerts on Baseball Game Attendances

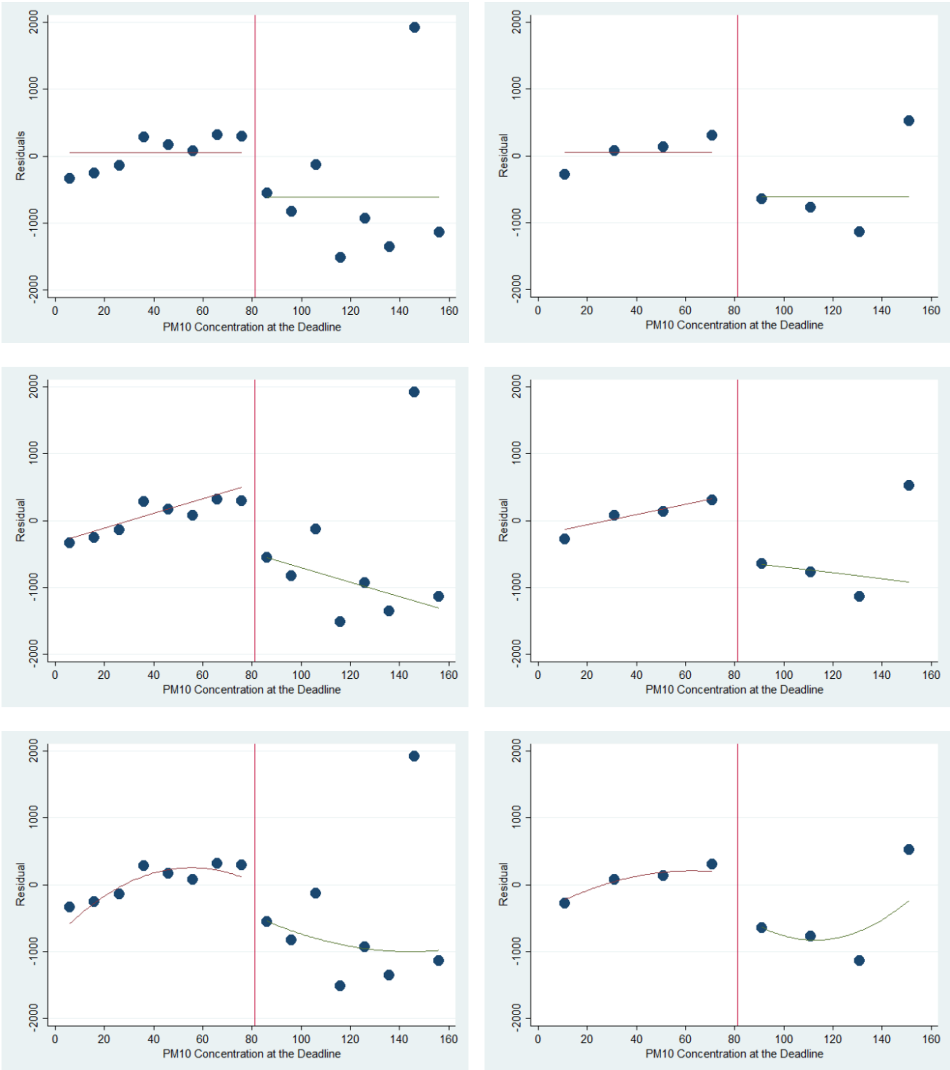
Bandwidth	20	10
Polynomial of order		
Zero	-745.6**	-756.8*
	(317.3)	(419.4)
One	-731.4	-438.5
	(583.7)	(816.0)
Two	-665.4	-1,088
	(865.6)	(1,221)
Observations	455	224

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

9 The number of control variables in the baseline model is more than 140.

10 Hahn, Todd, and van der Klaauw (2001) stated that an optimal bandwidth is proportional to $N^{-0.2}$. Moreover, Lee and Lemieux (2010) claimed that $h \propto N^{-\delta}$ with $0.2 < \delta < 0.4$ is practically preferred for technical reasons. When the bandwidth is set to 20 or 10, δ is 0.31 or 0.41 on average. The figure does not deviate significantly from the value suggested by Lee and Lemieux (2010).

<Figure 1.4> Graphical Presentation of RDD with Various Bandwidths and Polynomial Orders



Note: The vertical line of a plot indicates the threshold of bad on real-time PM10 concentration. A point in figures is an average of the residuals within a bandwidth. The fitted lines in this figure represent the estimates from the entire sample and not exactly the same with the RDD results. Nevertheless, this figure illustrates the effect of real-time alerts intuitively.

The results from Table 6 seem to have a significant effect only if the polynomial is 0. Conversely, the magnitudes of the coefficients show large negative values for all bandwidths and polynomials.

Figure 1.4 graphically expresses these results. The bandwidths of the first and second columns are 10 and 20, respectively. Each row in Figure 1.4 represents a polynomial order from 0 to 2, and the vertical lines in figures represent the cutoff point. A point in figures is an average of the residuals within a bandwidth. The fitted lines in this figure represent the estimates from the entire sample and not exactly the same with the RDD results. Nevertheless, this figure illustrates the effect of real-time alerts intuitively.

<u>Effect of Real-time Alert by Year</u>

I analyze whether the effects of real-time information vary by year. Air pollution sensitivity and information accessibility, which may influence people's avoidance tendency, can change over time. Therefore, the effect of real-time information can be different by year and this possibility is verified by using the model expressed as follows:

$$Y_{ct} = \alpha + \sum_{q=2012}^{2016} \beta_q RA_{ct} * 1(YEAR = q) + f_1(PM_{ct}) + \gamma_1 FA_{ct}$$
$$+ f_2(HT_{ct}, AT_{ct}) + f_3(W_{ct}) + \delta_t Time_t + \epsilon_{ct}. \quad (5)$$

While the baseline model estimates the average effect of real-time alert within the analysis periods, this model finely estimates the yearly effect. For the estimation, the interaction terms of real-time alert and year dummy variables are used and β_q represent the effects of the interaction terms.

Table 1.7 summarizes the results of this regression. Real-time alerts do not have any effect until 2013, but the responses have exploded since 2014. Column (2) in Table 1.7, which is the result of the regression conducted without the case of maximum crowds, shows nearly the same outcomes. Figure 1.5 graphically summarizes the results of the analysis.

The levels of PM10 pollution have no significant changes during this period. Therefore, the cause of the change in the effect of real-time alerts must be found elsewhere. Since NIER started to publish air pollution data by using an open API system in Dec 2013; people have been able to search real-time information on PM through famous portals or applications since then.[11] In addition, because the air quality forecasts were disseminated through news and articles, the introduction of the forecasts system increased the number of PM-related articles at this time.[12] The increment of the number of articles may have influenced people's sensitivity to PM. Furthermore, PM was classified by the IARC in October 2013 as Group 1 carcinogen (IARC 2013). Therefore, it can be inferred that the increase in accessibility and sensitivity resulting from these changes have affected the effects of real-time information. Figure 1.6 depicts the Google search trend for PM10 in

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[11] Before the open API system, it was possible to check real-time information only through the government-operated website (airkorea.or.kr).

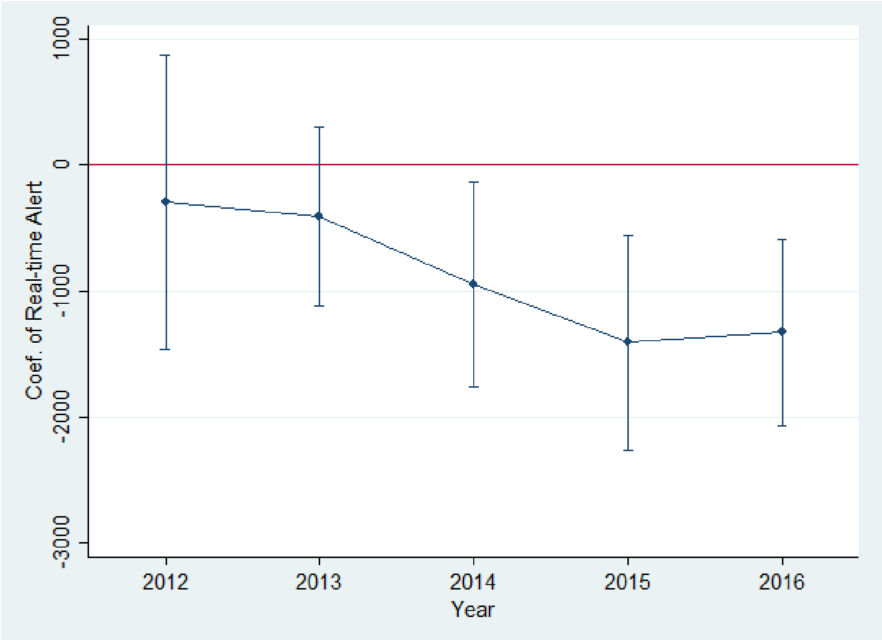
[12] Kim et al. (2015) showed that the number of articles related to PM increased rapidly in late 2013.

<Table 1.7> Effects of Real-time Alerts by Year

VARIABLES	(1) Total	(2) w/o Maximum Crowd
Real-time Alert in 2012	-289.8	483.6
	(712.2)	(728.8)
Real-time Alert in 2013	-405.9	-15.06
	(432.5)	(445.5)
Real-time Alert in 2014	-946.3*	-977.4**
	(498.2)	(481.3)
Real-time Alert in 2015	-1,407***	-1,409***
	(519.8)	(524.3)
Real-time Alert in 2016	-1,330***	-1,149**
	(450.9)	(454.0)
Observations	3,004	2,686
R-squared	0.760	0.737

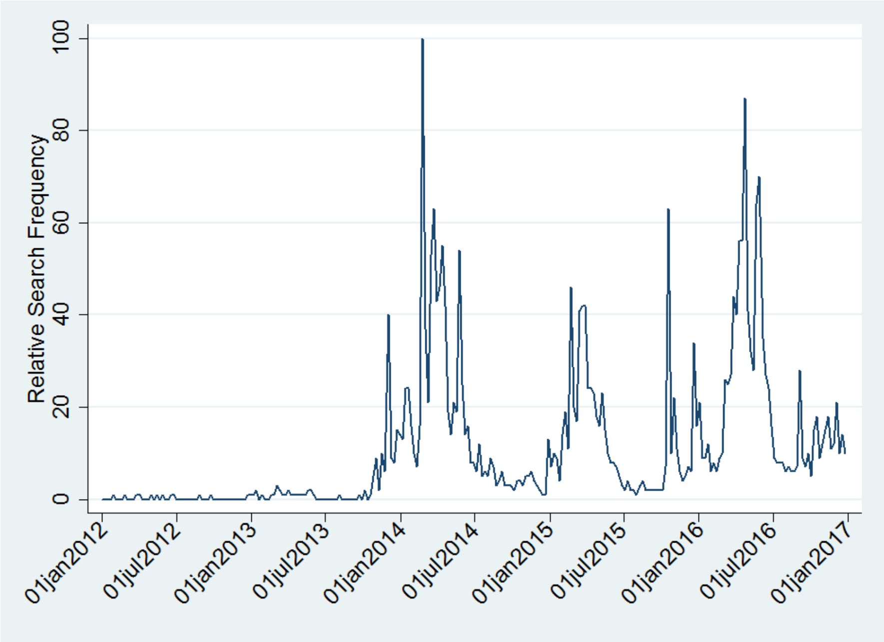
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; Real-time Alert in 2012-2016 indicate the interaction terms of RA and year dummy and baseline variable (constant * RA) is not included in the model.

<Figure 1.5> Change of the Effects of Real-time Alerts by Year



Note: The vertical bar of a point represents 90 percent confidence intervals

<Figure 1.6> Google Search Trend of PM10 by Week



Source: https://trends.google.co.kr/trends/

Korea from 2012 to 2016.[13] The drastic increase of the relative search frequency from late 2013 represents that the accessibility and sensitivity have surged.

Comparison of Real-time Alerts with Forecast Alerts

The analysis models based on the data from 2012 to 2016, use forecast information as a control variable. In this section, the effects of real-time and forecast alerts are compared by using the data after 2014 in which the forecast system was introduced. Given that the effects of real-time alerts have surged since

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[13] Google search trend data are from www.trends.google.com. This graph shows the relative frequency of the search normalized to the 0–100 range.

2014, it is appropriate to use the data after 2014 to compare the two information (RA, FA).

In Column (1) in Table 1.8, the effect of real-time alerts seems larger than the forecasts. In the cast that the interaction effect of both alerts is considered, however, the relative volumes of the effects are reversed. When the interaction effect of two variables is ignored, the effect is reflected in the effects of both variables, and FA seems to be more affected by the exclusion of interaction term. In fact, when FA is present, the probability of the appearance of RA simultaneously is about 60%, while when RA is present, the probability that the FA will appear at the same time is only 30%. The results of Column (3) and (4), which estimate the effect of an alert on the day when the other alert is unannounced, show almost the same results with Column (2). Although the regression coefficient of forecast alerts is larger

<Table 1.8> Comparison of the Effects of Real-time Alerts to the Forecast Alerts

	(1)	(2)	(3)	(4)
VARIABLES	Baseline	w/ Interactions	w/o FA days	w/o RA days
RA	-941.0***	-1,186***	-1,048**	
	(327.7)	(363.1)	(431.6)	
FA	-661.5**	-1,284***		-1,253***
	(333.9)	(392.1)		(445.3)
RA * FA		1,392**		
		(592.5)		
Observations	1,951	1,951	1,841	1,774
R-squared	0.736	0.736	0.727	0.736

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; This analysis is conducted based on the data after 2014 in which forecasts on air quality was introduced.

than that of real-time alerts in Table 1.8, they are significantly not different. Therefore, it can be said that the sizes of the effects are statistically the same.

Additionally, the results of the analysis show that the interaction term between forecast and real-time alert completely offsets the effect of one of the two alerts. Therefore, we can infer that only people, who adjust their behavior on the basis of the forecasts, react to the real-time alerts.

1.6 Conclusion

This study investigates the impact of PM10-related information on avoidance behavior in outdoor activities by using professional baseball game attendance data. Baseline results suggest that the number of attendances decreases by approximately 900 when real-time alerts are issued. Various robustness checks support the baseline results. In addition, the effects of real-time alerts are found to be different annually and to have increased significantly since 2014. The drastic increase of the effect of real-time alerts in 2014 may be attributed to the increased accessibility and sensitivity of people due to the introduction of open API system, the increase in PM-related articles, and the classification of PM as a carcinogenic (Group 1) in late 2013 by IARC. The comparison analysis, using the data after 2014, shows that people are equally dependent on forecasts and real-time information to adjust their behavior and only people, who adjust their behavior on the basis of the forecasts, react to the real-time alerts.

Several drawbacks are identified in this study. Owing to the data limitations, determining whether heterogeneity exists on the effect by groups, such as age, is infeasible. Second, although various types of avoidance behaviors exist, such as anti-PM mask usage; this study only focuses on outdoor activities. Lastly, the current study does not address the welfare analysis on avoidance behavior. Despite these shortcomings, however, this study presents meaningful new empirical evidence on information and avoidance behavior.

Appendix 1

Appendix 1.1 – Comparison to Tobit model

The baseline model can be considered a censored model with an upper limit because ballparks set the maximum number of people to be accommodated and Tobit analysis can be more effective than ols. Thus I compared the result of the baseline model and that of the Tobit model. However, since the number of maximum crowds varies from team to team and year to year, it is difficult to conduct Tobit analysis with the number of spectators as a dependent variable. Thus, the comparison is conducted by using the seat occupancy rate of the game as a dependent variable.

<Appendix Table 1.1> The Results of the Baseline and Tobit Models for Occupancy Rate

	(1)	(2)
VARIABLES	Baseline Model	Tobit
Real-time Information	-0.0345***	-0.0384***
	(0.0125)	(0.0130)
Mean of Occupancy Rate	<0.5898>	<0.5898>
Observations	3,004	3,004
R-squared (Pseudo R-Squared)	0.662	(2.3684)

The results show that there is not much difference between the baseline model and the Tobit model. RA is found to decrease the seat occupancy rate by about 3.5%

and this represents that RA reduces the attendances of about 6% compared to the mean occupancy rate. The volumes of the results are almost the same with the baseline results using the log attendances as the dependent variable.

Appendix 1.2 - Inter-temporal Substitution Check

If inter-temporal substitution for decreased spectators due to RA exists, the number of attendances may not decrease in the whole season. Therefore I checked whether the past day's information affects the number of attendances of today's game. In this analysis, the number of RA occurrences and the number of RA or FA occurrences in the past 1, 3, 5, and 10 matches were additionally included in the model to find out the inter-temporal substitution. The results of the analysis are shown in Appendix Table 1.2

The results show that inter-temporal substitution does not exist through the above results. The number of RAs in the past seems to affect the number of spectators in today's game, and the number of RAs or FAs in the past days is found to rather decrease the attendance.

< Appendix Table 1.2> The Results of the Analysis controlling Past Day's Information

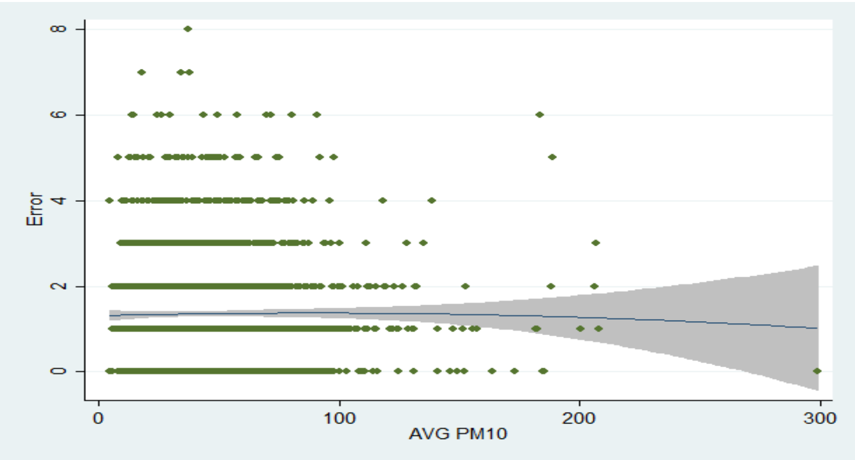
VARIABLES	(1) RA p1	(2) RA p3	(3) RA p5	(4) RA p10	(5) RA or FA p1	(6) RA or FA p3	(7) RA or FA p5	(8) RA or FA p10
FA	-794.5**	-943.3***	-944.4***	-1,067***	-776.3**	-921.5***	-923.2***	-1,001**
	(315.5)	(313.1)	(328.4)	(398.5)	(314.8)	(312.3)	(328.1)	(395.3)
RA	-779.1***	-742.5***	-730.5**	-604.4*	-777.1***	-737.6**	-727.9**	-616.9*
	(277.3)	(287.7)	(298.5)	(337.9)	(277.2)	(287.7)	(298.5)	(337.4)
Previous Info.	-58.13	21.36	83.05	-7.312	-132.7	-45.89	20.97	-137.5**
	(224.6)	(124.2)	(95.35)	(72.37)	(211.0)	(115.1)	(87.69)	(68.44)
Observations	2,958	2,866	2,774	2,544	2,958	2,866	2,774	2,544
R-squared	0.767	0.765	0.764	0.758	0.767	0.765	0.764	0.759

Note: RA or FA treats RA and FA as a single occurrence, even if they occur at the same time. P# represents the information of the past # days. "Previous Info." indicates the variable set by the name of the column.

Appendix 1.3 – Quality of Service

If the quality of the game lowered on a fine dusty day, this may decrease people's attendance. Therefore I verified whether there was a relationship between real-time information and game quality. The number of errors in the game was used as a proxy variable for game quality. The following figure displays the scatter plot between the average concentration of PM until the game start and the number of errors in the game and shows the quadratic fitted line (95% confidence intervals).

<Appendix Figrue 1.1> Relationship between the Average PM and Number of Errors



< Appendix Table 1.3> Effect of RA on the Number of Errors

VARIABLES	# of Errors
RA	0.0301
	(0.108)
Observations	3,004
R-squared	0.063

Both the figure and the result of the regression show that the RA was not related to the number of error.

Appendix 1.4 The Differential Effect by Popularity or Importance of games

The effect of information can be differed by Popularity and Importance of games. Therefore I checked whether the information have different effects by the rank of the home team or the rank difference between the home and away teams, which indicated the popularity or importance of the game. (The ranks on the 15th and 30th day of each month were typed in and the interval between them was linear interpolated.)

The following table shows the results of the models that control the rank of the home team and the rank difference. The results represent that the effect of RA does not vary by the popularity or Importance of games.

< Appendix Table 1.4> Results of the Models that Control Rank Related Variables

VARIABLES	(1) Attdnc	(2) Attdnc	(3) Attdnc
RA	-894.7***	-1,349***	-1,268***
	(284.2)	(451.3)	(445.6)
Rank (Home)	-523.0***	-530.6***	-523.3***
	(45.49)	(46.16)	(45.46)
Rank Difference	-87.36***	-87.48***	-95.15***
	(33.32)	(33.32)	(34.85)
RA * Rank (Home)		97.60	
		(78.17)	
RA * Rank Difference			126.3
			(97.93)
Observations	3,004	3,004	3,004
R-squared	0.771	0.771	0.771

Chapter 2

Air-pollution, Information, and Avoidance Behavior in Labor: Evidence from Korea

This study examines whether information on air pollution causes avoidance behavior in the labor sector. Although only few researchers have considered the avoidance behavior in the labor sector, it is important to examine this subject in that working hours have a large portion in one's life. Accordingly, the present study estimates the effects of information such as forecast and real-time alerts, on working hours of outdoor workers. Results suggest that outdoor workers reduce their working hours when forecast and real-time alerts are given. The workers respond to information by adjusting work start or end time, while they cannot immediately react to real-time alerts while working. The effects of information are chiefly derived from the agriculture, forestry, and fishing industries. Furthermore, only workers who can modify their work start and end time or employers react to the information on PM10.

2.1 Introduction

Ambient particulate matter (PM) has a negative effect on health. It causes respiratory and cardiovascular diseases (Pope III and Dockery, 2006; EPA, 2014) and is classified as a Group 1 carcinogen (IARC, 2013). Moreover, some studies have revealed that human capital formation is negatively affected by PM (Zweig et al. 2009, Levy et al. 2014). Accordingly, countries have been eager to protect their people from the threats of PM by implementing various policies, such as information provision.

The aim of this study is to examine whether information provision on PM leads to avoidance behavior in the labor force by using the time use survey data in Korea. Similar to other countries, the Korean government provides air pollution information to the people. The purpose of the policy is to induce the people to adjust their behaviors in response to the information and thereby protect their health. Several studies have reported that air pollution information caused the avoidance behavior and consequently improve one’s health (Neidell, 2009; Janke, 2014; Altindag et al., 2017; Liu et al., 2018, Zhang et al., 2018). The avoidance behaviors considered in abovementioned previous research are outdoor leisure activities or purchase behavior of protective tools, such as anti-PM masks, whereas air pollution-averting tendency in the labor sector has not been studied. Therefore, the present study focuses on whether people adjust their behavior in response to air pollution information, even in the labor sector in which behavioral response is deemed difficult.

Several researchers have investigated the relationship between air pollution information and avoidance behavior. Neidell (2009) examined the effect of ozone alert on outdoor activities and the health of people in Southern California. The results of the study show that forecast alerts on ozone decreased the number of visitors to outdoor facilities, such as a zoo, and reduced children’s asthma hospitalization. Janke (2014) reported that badly forecasted information has a negative effect on the number of visitors to a zoo in the United Kingdom. However, the author claimed that the effects of the avoidance behavior on health were very limited and the effect occurred only on people with asthma. Antindag et al. (2017) examined the influence of PM pollution and the warning on Asian Dust in Korea. They addressed that PM exposure during pregnancy negatively affected infants' health and the warning on Asian Dust mitigated harmful effects. They also showed that the number of attendances of a soccer game greatly reduced when the warnings were issued. However, the abovementioned studies only considered outdoor leisure activities to verify the existence of avoidance behavior and did not cover the avoidance behavior in the labor sector.

Hanna and Olivia (2015) and Kim et al. (2017) examined the association between air quality and labor supply. Hanna and Olivia (2015) found that exogenous air quality improvement due to the closure of a refinery in Mexico City subsequently increased working hours per week of surrounding neighbors by 3.5%. Kim et al. (2017) explored mid- and long-term effects of air pollution on labor supply by using Indonesia's forest fire as an instrumental variable. They showed that air pollution from the forest fire decreased labor supply in the midterm and certain parts of the effects remained in the long run. However, these studies are different from the current study, which focuses on the effect of information provision and considers only short-term effects.

Seo (2015) studied the short-term effects of PM on working hours. By using Korean Time Use Survey data in 2009, she claimed that the increase in daily average PM10 negatively affected the working hours of women and the effects were not different between risky industries and others. However, Seo (2015) only estimated the effects of PM10 itself, not information on PM10, and used data from 2009, a time when Koreans were not yet interested in PM-related pollution.

Moreover, the method used in the study seems to be not rigorous.

The Korean government has been forecasting air quality information, such as PM and ozone, since 2014. In addition, real-time information on PM10 has been served since 2006, and one can easily check the information from the government website (www.airkorea.or.kr) or famous portals in Korea (e.g., www.naver.com and www.daum.net).[14] Therefore, the current study investigates the influence of the forecasts and real-time information on the working hours by using Korean Labor & Income Panel Study (KLIPS) data in 2014.

This study is meaningful as it deals with the avoidance behavior in the labor sector and the effects of real-time information, which have not been covered by previous studies.

2.2 Data

The 17th KLIPS data and its additional survey on time use and quality of life were used for this study. KLIPS, launched by Korea Labor Institute in 1998 and published annually, is a longitudinal survey data on labor market activities of Korean and its 17th data was surveyed in 2014. The additional survey of the 17th KLIPS contains time usage of an individual on the survey day for every 30 minutes. An individual's working hours, obtained from the survey, were used as the main dependent variable of this study. In addition, demographic and socioeconomic

[14] Access to real-time air quality information through portals has become possible since late 2013.

information from the original KLIPS data were used as control variables in the regression model.

The effect of PM can be discriminatory depending on workplace conditions, and outdoor workers are likely to respond more to the information on PM. However, determining outdoor workers through KLIPS data is impossible. Therefore, the present study used the 4th Korean Working Conditions Survey (KWCS) to identify the workers. The 4th KWCS is a cross-sectional data, published by Korea Occupational Safety and Health Agency in 2014, providing information on more than 50,000 Korean workers' working conditions. The workers, who responded to work either in vehicles or outdoors in the 4th KWCS, were defined as outdoor workers, and outdoor worker ratio by cells, which were classified by industry (21) and job (9), was obtained. This ratio was then matched to the KLIPS data based on the cells.

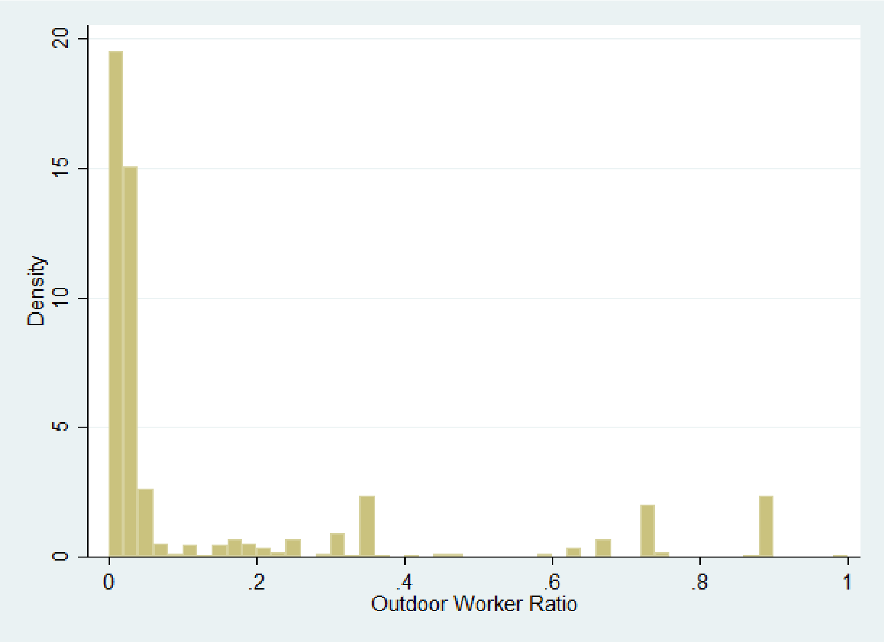
The National Institute of Environmental Research of Korea provides real-time PM information. The Korean government has been operating more than 200 air pollution monitoring stations nationwide and observed pollution concentrations announced online every hour. As KLIPS provides the location of the workplace at province levels, the province-level PM10 concentration, derived by averaging the concentrations of each monitor within a province, was matched to the KLIPS data. The province-level data are the same as what people can identify online. Real-time PM information is provided numerically and categorically: 0–30 is classified as good, 31–80 moderate, 81–150 bad, and over 151 very bad. Moreover, each level has a color to intuitively express the risk, such as blue, green, yellow, and red. Thus, people may react to a category, not figures.

Forecast data can be obtained from the government website, www.airkorea.or.kr. As the PM forecast is presented on a higher level than at the province, the forecast data can be easily matched to KLIPS. The government announces forecasts on PM and ozone of the next day, four times in a day: 5 a.m., 11 a.m., 5 p.m., and 11 p.m. The 5 p.m. forecast was selected in this study because the information is released on the evening news. The forecast is only provided at four levels: good, moderate, bad, and very bad.

Weather variables, which may influence air pollution and working hours, are potential confounding factors in this analysis. Thus, weather data, obtained from the Korea Meteorological Administration, were used in the analysis. As weather data was provided at a monitoring station level, it was converted to province-level data by the same method used for real-time pollution data. Temperature, precipitation, relative humidity, and wind speed were controlled in the form of a quadratic function.

Table 2.1 represents the summary statistics of the data. Figure 2.1 depicts the distribution of outdoor worker ratio of analysis samples.

<Figure 2.1> Histogram on Outdoor Worker Ratio in KLIPS



<Table 2.1> Summary Statistics

Variable	Total		OR < 0.5		OR >= 0.5	
	Mean (Std. Dev.) %		Mean (Std. Dev.) %		Mean (Std. Dev.) %	
Daily PM10 (μg/㎥)	57.24	(16.05)	57.36	(15.95)	56.26	(16.78)
# of Real-time Alerts	3.49	(5.25)	3.52	(5.25)	3.26	(5.3)
Forecast Alerts	0.08	(0.27)	0.08	(0.27)	0.07	(0.25)
Work Hours (m)	535.97	(121.9)	537.10	(117.48)	527.42	(150.94)
Work Start Time	8.27	(1.75)	8.40	(1.7)	7.28	(1.86)
Work End Time	17.78	(2.08)	17.89	(2.01)	16.93	(2.33)
Outdoor Worker Ratio	0.14	(0.26)	0.06	(0.1)	0.79	(0.1)
Age	46.21	(12.2)	44.79	(11.59)	56.92	(11.32)
Gender (male=1)	0.63	(0.48)	0.60	(0.49)	0.86	(0.35)
Education (high=1)	0.44	(0.5)	0.48	(0.5)	0.12	(0.33)
Health	2.43	(0.62)	2.41	(0.61)	2.62	(0.68)
Income (10,000 won)	252.04	(195.64)	259.25	(196.73)	197.84	(178.29)
Temperature (℃)	16.92	(4.97)	17.13	(4.88)	15.34	(5.36)
Precipitation (mm)	1.48	(5.33)	1.52	(5.46)	1.17	(4.2)
Wind Speed (m/s)	2.18	(0.85)	2.19	(0.86)	2.09	(0.82)
Relative Humidity (%)	63.58	(13.41)	63.61	(13.49)	63.35	(12.84)
Month (%)						
3	13.17		12.36		19.28	
4	32.14		31.88		34.11	
5	29.63		29.85		27.97	
6	19.61		20.22		15.04	
7	3.41		3.52		2.54	
8	0.82		0.9		0.21	
9	1.12		1.18		0.64	
10	0.05		0.06		0.00	
11	0.00		0.00		0.00	
12	0.05		0.03		0.21	
Employment Status (%)						
Regular	53.72		58.80		15.47	
Temporal	19.89		19.18		25.21	
Employer/ Self-Employed	26.40		22.02		59.32	
N	4,023		3,551		472	

2.3 Methodology

2.3.1 Identification Strategy

This study examines whether forecast and real-time information on PM influence the working hours of outdoor workers. As mentioned above, forecasts are provided at four levels (good, moderate, bad, and very bad). To verify the effect of forecast information, bad or very bad forecasts are defined as forecast alerts, and a dummy variable is created to indicate whether forecast alerts are issued or not.

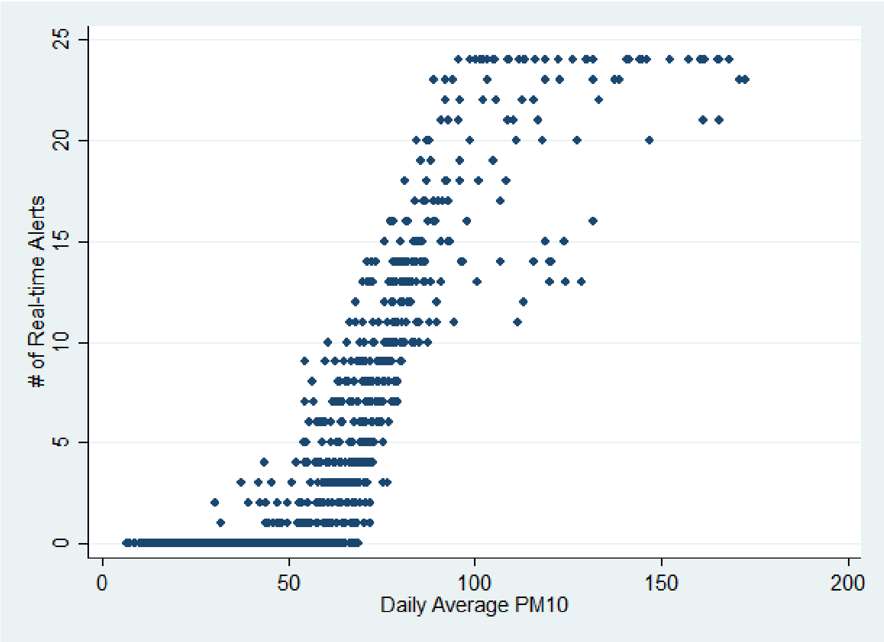
To identify the effect of real-time information, Real-time PM10, categorized as bad or very bad, is defined as real-time alerts, and then generates a variable indicating the number of the occurrence of real-time alerts in a day. This variable is expressed as follows:

$$RA_{pt} = \sum_{h=0}^{23} 1(PM10_{pth} \geq 81). \tag{1}$$

In Equation (1), RA indicates the number of real-time alerts given in province p and on day t and has a value from 0 to 23. h represents an hour on day t. If people react to the number of bad occurrences when the daily average PM10 concentration is controlled, I interpret it as a response to the real-time information.

Figure 2.2 depicts the relationship between daily average PM10 and RA. This study uses the variation, which appears when a line is drawn vertically at a point on the x-axis, to identify the effect of real-time information. However, the variation does not exist in pollution-free days. On the other hand, a variation that occurs in highly polluted days cannot appropriately verify the effect of information. The presence of non-bad hours in a highly polluted day means that the hourly PM concentration is very high when the real-time alerts were given. Thus, people can recognize and avert risks through a body reaction or visibility. Therefore, only individuals, who were surveyed on days with daily average PM10 between 30 and 100μg/㎥, were used for the analysis.[15]

<Figure 2.2> Correlation between Daily Average PM10 and the number of Real-time Alerts



[15] The distribution of hourly PM10 concentration based on the sample restriction is presented in Appendix F1.

2.3.2 Economic Specification

The main regression model is as follows:

$$Y_{ijpt} = \alpha + \beta_1 RA_{pt} * OR_j + \beta_2 FA_{pt} * OR_j + \gamma_1 RA_{pt} + \gamma_2 FA_{pt} + \gamma_3 OR_j$$
$$+ f_1(PM10_{pt}) + f_2(PM10_{pt}) * OR_j + g_1(W_{pt}) + g_2(W_{pt}) * OR_j$$
$$+\gamma_4 SES_i + \gamma_5 time_t + \varepsilon_{ijpt}. \quad (2)$$

Y_{ijpt} is the working hours of an individual *i* who belongs to cell *j*, in province *p*, on day *t*. *RA* is the number of real-time alerts in a day and has a value from 0 to 24 and *FA* is a dummy variable indicating that forecast alerts are given. OR is the outdoor worker ratio of cell j. *PM10* is the daily average PM10 concentration, and *W* is the vector of the weather variables, such as the average, highest, or lowest temperature, precipitation, wind speed, and humidity. PM10 and weather are controlled through a quadratic function. *SES* is a vector of an individual's demographic and socioeconomic characteristics, such as age, sex, educational level, health status, income, industry, and occupation. Age and income are controlled as quadratic functions, whereas education, health, industry, and occupation are included as dummy variables in the analysis. Finally, *time* is a set of month and day of week dummies. The purpose of this model is to identify the impact of information. If *FA* and *RA* influence working hours when the daily average PM concentration is controlled, then this result can be interpreted as the effect of information. In addition, the interaction terms of information variables (*FA*, *RA*) and *OR* were used to estimate the discriminatory reaction depending on working conditions. Thus, β_1 and β_2 are the coefficients of interest. As PM10 and weather can have a discriminatory effect on outdoor workers, the interaction terms of *OR* and variables (*PM10*, *W*) were included in the model.

2.4 Results

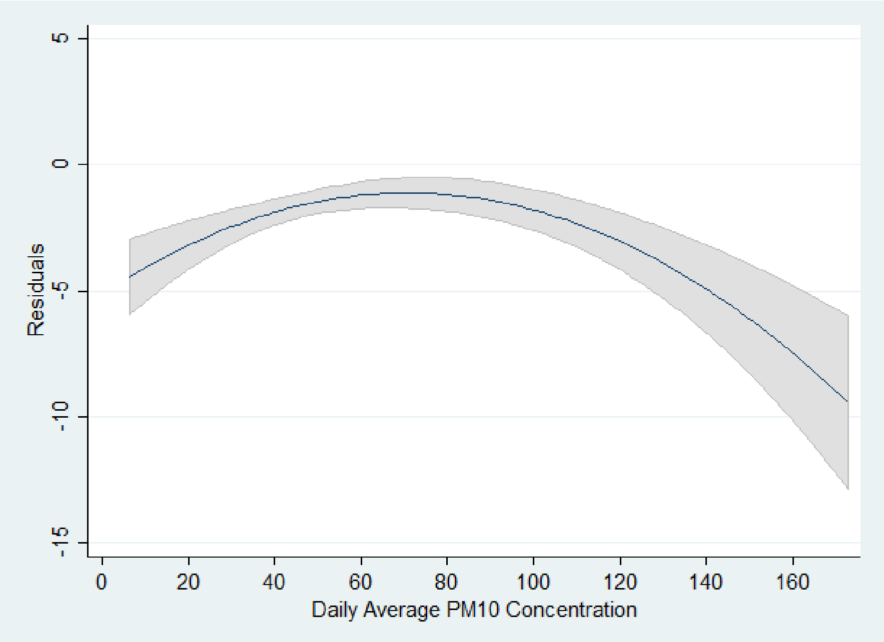
Prior to the main analysis, the relationship between the average daily PM10 concentration and working hours was examined. The purpose of this analysis is not to identify the effect of the information, so the range of the daily average PM10 is not limited. Figure 2.3 displays the relationship between the daily average PM10 concentration and the residual obtained from the following equation:

$$Y_{ijpt} = \alpha + \gamma_1 g(W_{pt}) + \gamma_2 SES_i + \gamma_3 time_t + \varepsilon_{ijpt}. \tag{3}$$

The residual indicates the working hours that removed the influence of the control variables. Figure 2.3 shows a quadratic fitted line of the residuals. The fitted line represents that the trend of working hours declined at PM10 concentrations between 60 and 80. Therefore, this study estimates the contribution of the avoidance behavior, in response to the information, to the declining trend.

At this point, analyses were conducted to identify the effect of the information on working hours. Table 2.2 shows the results of the analysis that do not consider the differential effects of outdoor workers. Panels A and B indicate the results of the models only containing FA and RA, respectively, and Panel C simultaneously considers FA and RA. Each column represents a model with different control variables. When differential effects are not considered, the information on PM (FA, RA) has no significant effects on working hours.

<Figure 2.3> Quadratic Fitted Line with 95% Confidence Interval of Regression Residuals



The results in Table 2.3 estimates the differential effects of the information to outdoor workers by multiplying the information variables (FA and RA) and outdoor worker ratio variable (OR). The results show that FA significantly influences the working hours of outdoor workers. On average, the workers in a cell with 100% outdoor worker ratio are analyzed to work approximately 65 minutes less than the workers in a cell with 0% outdoor worker ratio when forecast alerts occur. Real-time information had no significant effects on working hours in this model.

RA is the number of the occurrence of real-time alerts in a day. However, the alerts can have differential effects depending on provision timing. Thus, RA was split into two variables, indicating the number of real-time alerts before noon (RA_am) and afternoon (RA_pm). The two variables have a value from 0 to 12.

<Table 2.2> Regression Results w/o considering any Differential effects

VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A					
FA	-9.016	-5.176	-3.085	-5.358	-3.502
	(7.143)	(7.532)	(7.255)	(7.038)	(7.897)
R-squared	0.000	0.001	0.077	0.176	0.185
Panel B					
RA	-0.700*	-0.0666	-0.484	-0.427	-0.342
	(0.366)	(0.931)	(0.897)	(0.868)	(0.924)
R-squared	0.001	0.001	0.077	0.176	0.185
Panel C					
FA	-5.079	-5.176	-2.705	-5.040	-3.151
	(7.561)	(7.574)	(7.296)	(7.081)	(7.978)
RA	-0.614	-0.000331	-0.449	-0.359	-0.290
	(0.387)	(0.936)	(0.902)	(0.873)	(0.934)
R-squared	0.001	0.001	0.077	0.176	0.185
Daily Avg PM10		O	O	O	O
Demographic Info.			O	O	O
Occupational Info.				O	O
Weather, Time					O
Observations	4,023	4,023	4,023	4,023	4,023

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

<Table 2.3> Regression Results considering Differential effects of Outdoor Workers

VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A					
FA	4.198	7.554	6.432	5.469	6.257
	(8.125)	(8.571)	(8.252)	(7.989)	(8.821)
FA * OR	-97.86***	-95.55***	-73.80**	-81.37***	-68.43**
	(28.58)	(30.60)	(29.52)	(28.25)	(29.29)
R-squared	0.005	0.006	0.082	0.179	0.192
Panel B					
RA	-0.399	0.0222	-0.348	0.0953	0.117
	(0.420)	(1.050)	(1.012)	(0.978)	(1.042)
RA * OR	-2.151	-1.802	-2.378	-4.791	-4.607
	(1.414)	(3.933)	(3.785)	(3.642)	(3.737)
R-squared	0.003	0.003	0.080	0.177	0.191
Panel C					
FA	7.500	7.614	6.770	5.478	6.339
	(8.598)	(8.616)	(8.295)	(8.033)	(8.901)
FA * OR	-93.77***	-95.26***	-72.46**	-78.00***	-64.92**
	(30.79)	(30.83)	(29.75)	(28.46)	(29.51)
RA	-0.539	-0.0768	-0.434	0.0213	0.0355
	(0.444)	(1.055)	(1.016)	(0.982)	(1.051)
RA * OR	-0.420	-0.284	-1.213	-3.553	-3.591
	(1.522)	(3.959)	(3.813)	(3.666)	(3.763)
R-squared	0.005	0.006	0.082	0.179	0.192
Daily Avg PM10		O	O	O	O
Demographic Info.			O	O	O
Occupational Info.				O	O
Weather, Time					O
Observations	4,023	4,023	4,023	4,023	4,023

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The results indicated that the real-time alerts in the morning significantly reduce working hours of outdoor workers. On average, when RA increased by 1, workers in a cell whose OR is 1 (meaning that 100% outdoor work ratio) are found to spend approximately 8 minutes lesser in working than those in a cell whose OR is 0. Tables 2.3 and 2.4 represent that outdoor workers tended to avoid the risk of PM pollution by adjusting their working hours on the basis of PM10-related information. [16]

Table 2.5 demonstrates how the workers adjusted their working hours. Each column in Table 2.5 indicates the results of the model with different dependent variables: Working hours, hours spent at the workplace, work start time, work end time, and hours doing other actions in the workplace are used for columns 1, 2, 3, 4, and 5, correspondingly. The results are estimated from the models including all control variables. Outdoor workers avoided the risk by adjusting their work end time when forecast alerts were given. RA affected working hours through the modification of work start time.

To identify whether outdoor workers react to real-time alerts during work, hour-level analyses are conducted. The purpose of this analysis is to verify that outdoor workers promptly adjust their working hours in response to real-time alerts when they are in the workplace. FA was excluded in this analysis. Column 1, as a dependent variable, uses working hours in the hour when a real-time alert was

[16] In the above results, the coefficients of information variables are quite large, while the overall reduction of working hours due to the information is not that large. The effects of one occurrence of FA or RA_am on per capita working time are -9.2 (-65.7*0.14) minutes and -1.19 minutes (-8.5*0.14), respectively.

<Table 2.4> Differential effects of Real-time Alerts depending on Provision Timing

VARIABLES	(1)	(2)	(3)
FA	6.220	6.790	6.662
	(8.816)	(8.898)	(8.927)
FA * OR	-65.69**	-71.91**	-66.49**
	(29.30)	(29.38)	(29.51)
RA_am	0.659		0.452
	(0.985)		(1.169)
RA_am * OR	-8.542**		-8.023*
	(3.587)		(4.268)
RA_pm		-0.627	-0.405
		(1.039)	(1.232)
RA_pm * OR		5.362	0.987
		(3.617)	(4.302)
Daily Avg PM10	O	O	O
Demographic Info.	O	O	O
Occupational Info.	O	O	O
Weather, Time	O	O	O
Observations	4,023	4,023	4,023
R-squared	0.193	0.192	0.193

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; RA_am and RA_pm indicate the number of real-time alerts before noon and afternoon, respectively.

given. The working hours during 2 and 3 hours after a real-time alert is given are exploited in Column 2 and 3 exploit the, respectively. As workers may not be able to immediately respond to a real-time alert during work, various hourly intervals are used. Panel A shows the results based on the hours staying in the workplace of individuals used in the main model. Meanwhile, Panel B only uses hours when real-time PM10 concentrations are between 60 and 100. Since the threshold of bad in real-time information is 81, Panel B can be thought as the results of the

<Table 2.5> Analyses on Working Hour Adjustment Path

VARIABLES	(1) Hours Worked	(2) Time in Work Place	(3) Work Start Time	(4) Work End Time	(5) Other Action in WP
FA	6.220	12.83	-5.325	7.503	6.608
	(8.816)	(10.36)	(7.509)	(9.011)	(5.380)
FA * OR	-65.69**	-86.96**	23.22	-63.74**	-21.27
	(29.30)	(34.43)	(24.95)	(29.94)	(17.88)
RA_am	0.659	0.467	-0.650	-0.183	-0.192
	(0.985)	(1.157)	(0.839)	(1.007)	(0.601)
RA_am * OR	-8.542**	-10.84**	6.980**	-3.860	-2.298
	(3.587)	(4.215)	(3.055)	(3.666)	(2.189)
Observations	4,023	4,023	4,023	4,023	4,023
R-squared	0.193	0.173	0.213	0.192	0.086

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1: WP in Column 5 indicates Work Place.

<Table 2.6> Analyses on the Immediate Avoidance Possibilities

VARIABLES	(1) 1 hour	(2) 2 hour	(3) 3 hour
Panel A			
RA(Hourly)	0.0664	0.225	1.173
	(0.331)	(0.588)	(0.845)
RA(Hourly) * OR	-0.564	0.732	0.980
	(1.258)	(2.234)	(3.205)
Observations	42,950	42,907	42,765
R-squared	0.244	0.287	0.363
Panel B (PM10 b/w 60-100)			
RA(Hourly)	0.699	0.592	1.424
	(0.487)	(0.873)	(1.263)
RA(Hourly) * OR	-2.855	-2.660	-2.529
	(1.784)	(3.197)	(4.616)
Observations	17,646	17,629	17,573
R-squared	0.251	0.294	0.366

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

regression discontinuity design with a bandwidth of 20. The results show that the immediate adjustment during work is not achieved even if the real-time alerts are given.

Table 2.7 presents the results of various robustness checks. Column 1 shows the results of the model, which replaced the daily average PM10 controlled in the form of quadratic function, to the dummy variables for ten intervals of PM10. Even if PM10 was controlled as interval dummies, the change of the coefficient of interest is negligible. Column 2 presents that the effects of the information remained nearly the same as baseline results even though the restriction on daily average PM10 is eased.

In Column 3, an additional restriction, which excludes the days when the maximum hourly PM10 concentration is over 100 from the analysis data, is applied to the baseline model. When considering a maximum hourly PM10 concentration for the sample restriction, the effects of visibility and bodily reaction on working hours can be more clearly removed. The results of this model show larger forecast effects than the baseline model. The effect of RA loses significance, but its volume remains the same.

Columns 4 and 5 show the results of the models using different definitions of outdoor workers and cells, respectively. In the baseline model, the workers who worked outdoors or in vehicles are defined as outdoor workers. Here, only people who work outdoors are redefined as outdoor workers and a new outdoor worker ratio is generated based on the new definition. The ratio is then used for the analysis in Column 4. Column 5 presents the results of the model replacing the definition of the cell of the baseline model, which considers industry and job, to the new definition. The new cells consider industry, job, sex, and education levels; and then a new ratio is generated based on the new defined cells. The results in Columns 4 and 5 support the baseline results.

Columns 6 and 7 are the results of the model replacing FA and RA on a survey day to the next day's information, respectively. FA in column 6 represents FA of the next day, and RA_am in Column 7 is RA_am of the next day. The results of these analyses demonstrate that the placebo variables did not influence working hours.

Even if daily PM10 is controlled for in the baseline model, RA may be associated with the average PM10 concentration of the time that real-time alerts were given. Therefore, the RA effect in the baseline model cannot be the effect of the information but the effect of high levels of PM10. Thus, in Column 8, the average PM10 concentration on the time that real-time PM10 alerts were given is additionally controlled to eliminate the possible source of bias. The results report that the effect of RA in the baseline model is not derived from the high level of PM.

The results of the analysis, excluding industries, having the outdoor worker ratio over 20%, from the baseline model, are shown in Table 2.8. The analysis identifies whether the effects of information are concentrated in a particular industry. There are four industries whose outdoor worker ratio is 20% or over. A notable part of this analysis is presented in Column 1. When industry 1 (agriculture, forestry, and fishing) is excluded, most of the effects of FA disappeared. As the agriculture, forestry, and fishing industries are highly affected by the weather, people who belong to these industries may have high accessibility to air quality forecasts.

<Table 2.7> Robustness Checks

VARIABLES	(1) Avg PM10 Interval	(2) Avg PM10 b/w 0-130	(3) Max PM10 under 100	(4) Different OW Def.	(5) Different Cell Def.	(6) Future FA	(7) Future RA	(8) Consider PM10 at bad
FA	4.904	3.736	2.486	6.229	5.970	3.353	6.624	5.797
	(8.799)	(8.215)	(12.88)	(8.637)	(8.815)	(8.388)	(8.865)	(8.831)
FA * OR	-59.28**	-45.65*	-118.5**	-91.30***	-59.55**	-6.568	-68.06**	-67.32**
	(29.51)	(27.57)	(48.27)	(33.95)	(29.04)	(28.78)	(29.32)	(29.36)
RA_am	0.526	0.0324	3.732**	0.550	0.809	0.772	-0.287	-0.187
	(1.014)	(0.823)	(1.760)	(0.963)	(0.981)	(1.010)	(0.716)	(1.186)
RA_am * OR	-8.058**	-7.239**	-9.591	-9.808**	-9.981***	-9.048**	-1.061	-9.809**
	(3.790)	(2.936)	(7.649)	(4.105)	(3.569)	(3.705)	(2.431)	(4.154)
Observations	4,023	5,013	3,270	4,023	4,017	4,023	4,023	4,023
R-squared	0.194	0.184	0.205	0.192	0.193	0.192	0.192	0.194

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; FA in Column 6 represents the FA of the next day, and RA_am in Column 7 is RA_am of the next day.

<Table 2.8> Identification whether the Effects of Information are Concentrated in a Particular Industry

VARIABLES	(1) w/o ind#1	(3) w/o ind#6	(4) w/o ind#8	(6) w/o ind#15
FA	-0.354	4.887	6.719	5.730
	(8.784)	(9.197)	(8.895)	(9.084)
FA * OR	0.880	-81.22**	-110.2***	-56.01*
	(39.26)	(31.72)	(32.90)	(30.97)
RA_am	0.335	0.700	0.840	0.772
	(0.983)	(1.017)	(0.989)	(1.019)
RA_am * OR	-4.426	-8.083**	-9.643**	-10.81***
	(4.754)	(4.019)	(4.035)	(3.711)
Observations	3,787	3,665	3,800	3,863
R-squared	0.183	0.204	0.194	0.191

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Ind#1 = agriculture, forestry, and fishing, ind#6 = construction, ind#8 = transportation, ind#15 = public administration and defense, compulsory social security.

The effects of RA_am also lose its significance and the value of the coefficients is reduced when industry 1 is excluded. Moreover, excluding industry 6 and 8 (construction and transportation) increases the effects of information. Thus, it can be inferred that outdoor workers in industry 6 and 8 cannot adjust their working hours in response to PM information.

The differential effects by groups are estimated in Table 2.9 by using a sub-sample analysis. Each column indicates the analysis based on different sub-samples. Each group was divided with the discretion on work start and end time, employment status, age, and gender. The results in Column 1 and 2 show that only people with the discretions can adjust their behavior in response to PM10 information. Moreover, Columns 3 to 5 show that only employers rearranged their working hours when bad information was provided. The results, that only people, who have the discretion and employers reacted to information on PM10, suggest that the effects of FA and RA on working hours appear in terms of labor supply. In addition, these results support the argument that the adjustment of working hours is a result of averting behavior.

The results in Column 6 to 10 demonstrate that, even though certain coefficients are insignificant, the elderly reacted to the information more than other age groups, and people responded to information regardless of sex, but women were more sensitive.

The results in Table 2.10 show whether the effects of the FA are different depending on the FA status of past days. In Column (1), the first number in parentheses represents yesterday's FA status and the second represents today's FA. For example, FA (11) indicates that yesterday's FA is 1, and today's FA is also 1. In Column (2), the first number in parentheses indicates the FA status of yesterday or the day before yesterday and the second represents today's FA. The results show that, although some coefficients are not significant, FA act to decrease working hours of outdoor workers regardless of the FA status of past days and that there is no inter-temporal substitution.

Table 2.11 examines the rearrangement patterns of time usage caused by avoidance behavior. The name of each column indicates the dependent variable used in the analysis. The results of this analysis show that changes in working hours of outdoor workers caused by FA are chiefly replaced by family affairs or leisure and most of the increased leisure time is spent watching TV. The changes in labor time due to real-time information on PM10 in the morning are replaced by a leisure activity but not watching TV.

<Table 2.9> Differential Effects of the Information by Groups

VARIABLES	(1) w/ Discretion	(2) w/o Discretion	(3) Regular Employee	(4) Temporal Employee	(5) Employer	(6) Age 20-39	(7) Age 40-59	(8) Age Over 60	(9) Woman	(10) Man
FA	9.104	1.418	-0.942	-10.09	47.34**	10.34	-5.047	10.95	-3.535	15.71
	(19.42)	(9.876)	(9.733)	(24.59)	(21.91)	(13.71)	(11.92)	(33.55)	(15.38)	(10.70)
FA * OR	-89.92*	-15.24	-23.58	-47.30	-109.5**	-51.59	19.21	-107.2	-158.6*	-48.48
	(49.84)	(40.03)	(56.72)	(86.10)	(48.01)	(97.18)	(47.72)	(66.31)	(94.80)	(30.66)
RA_am	0.0269	0.851	1.364	-3.699	0.295	2.921*	-1.695	0.688	1.339	0.545
	(2.133)	(1.110)	(1.105)	(2.609)	(2.519)	(1.508)	(1.371)	(3.456)	(1.647)	(1.230)
RA_am * OR	-14.09**	-1.527	5.515	7.820	-16.00***	-1.445	-2.586	-16.07*	-19.42	-8.171**
	(6.252)	(4.926)	(7.355)	(9.792)	(6.033)	(11.42)	(5.056)	(8.284)	(13.55)	(3.698)
Observations	1,202	2,821	2,161	800	1,062	1,300	2,095	628	1,495	2,528
R-squared	0.277	0.180	0.135	0.396	0.295	0.221	0.207	0.349	0.258	0.150

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the term "discretion" in Column 1 and 2 is about work start and end time.

<Table 2.10> Inter-temporal Substitution Check

VARIABLES	(1) Yesterday	(2) Yesterday or Two days ago
OR	9.353	-21.83
	(195.4)	(194.1)
FA (01)	-4.431	-5.494
	(11.98)	(12.00)
FA (10)	-6.607	-7.962
	(8.937)	(7.875)
FA (11)	14.34	12.92
	(12.78)	(12.75)
FA (01) * OR	**-59.19**	**-62.94**
	(38.77)	**(38.73)**
FA (10) * OR	**-16.71**	**-36.64**
	(31.83)	**(24.22)**
FA (11) * OR	**-75.33***	**-77.46***
	(41.76)	**(41.72)**
Observations	4,023	4,023
R-squared	0.193	0.194

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

<Table 2.11> Rearrangement Patterns of Time Usage Caused by Avoidance Behavior

	(1)	(2)	(3)	(4)	(4-1)
VARIABLES	Hours Worked	Self-Management	Family Affairs	Leisure	Watching TV
FA	6.220	-4.778	-11.09**	1.298	-3.648
	(8.816)	(6.250)	(5.472)	(7.725)	(5.016)
FA * OR	-65.69**	-22.17	54.98***	58.89**	48.89***
	(29.30)	(20.77)	(18.18)	(25.67)	(16.67)
RA_am	0.659	0.0807	0.0328	-0.529	0.505
	(0.985)	(0.698)	(0.611)	(0.863)	(0.560)
RA_am * OR	-8.542**	0.533	-0.295	5.347*	-0.187
	(3.587)	(2.543)	(2.226)	(3.143)	(2.041)
Observations	4,023	4,023	4,023	4,023	4,023
R-squared	0.193	0.103	0.379	0.131	0.182

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Self-Management is the sum of the time used for (1) Bedtime and (2) Personal care in 17^{th} KLIPS additional survey; Family Affairs is the sum of the time used for (7) Parenting, (8) Taking care of children and other family members, and (9) Home-keeping activity in 17^{th} KLIPS additional survey; Leisure is the time used (11) Leisure in 17^{th} KLIPS additional survey.

2.5 Conclusion

This study provides new empirical evidence for air pollution information and the avoidance behavior in the labor sector. The results of this study demonstrate that information on PM10, such as forecasts and real-time information, causes avoidance behavior in the labor sector. Outdoor workers reduce their working hours based on forecast information. In the case of real-time information, real-time alerts given in the morning negatively affect working hours, whereas alerts given in the afternoon do not have any effect on it. Various robustness checks support the results.

Outdoor workers tend to adjust their behavior by finishing their work early when the forecast alerts are given. Meanwhile, the real-time alerts in the morning influence working hours through the modification of work start time. However, most of the effects of FA and RA are found in the agriculture, forestry, and fishing industries; and outdoor workers in other industries, such as construction and transportation, tend to have difficulty in altering their working hours. Moreover, sub-sample regression results by groups suggest that only people who have the work start and end time discretion, and employers reacted to information on PM10. These results verify that the effects of FA and RA on working hours appear in terms of labor supply and support the argument that the adjustment of working hours is a result of the avoidance behavior.

The results confirm that the information provision policy will alleviate the negative health effects of air pollution through avoidance behavior. At the same time, this study implies that the cost of the avoidance behavior can be high as people reduce their working hours to avoid the risk. Even if the cost of the averting behavior is high, the information provision policy cannot be stopped, considering that the primary duty of governments is to protect their people. Therefore, eliminating unnecessary costs and increasing net benefits by providing more accurate information are important.

In addition, the current study shows that certain types of outdoor workers cannot avoid pollution. Outdoor workers who cannot modify their work start and end time or who are not employers or self-employed are likely to be exposed to air pollution even though information on PM is provided. Therefore, additional policies are needed to protect their health. For example, a policy, which mandates to provide an anti-PM mask to outdoor workers on a day with high PM pollution, is expected to compensate for the problem.[17]

Several shortcomings exist in this study. This study only focuses on the time adjustments in the labor sector. Other types of avoidance behavior, such as wearing an anti-PM mask, are not considered. Moreover, the cost-benefit analysis on the avoidance behavior cannot be conducted in the current study. Despite these drawbacks, the new empirical evidence found in this study is valuable.

[17] The Korean government enacted the anti-PM mask provision policy in 2017.

Appendix 2

Appendix 2.1 - Distribution of the Number of Samples, OR, FA, and RA by Cells

< Appendix Table 2.1> Distribution of the Number of Samples - KLIPS

	Job#1	Job#2	Job#3	Job#4	Job#5	Job#6	Job#7	Job#8	Job#9	Total
Ind#1	0 (0)	0 (0)	7 (0.17)	1 (0.02)	0 (0)	211 (5.24)	1 (0.02)	1 (0.02)	15 (0.37)	236 (5.87)
Ind#2	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Ind#3	14 (0.35)	113 (2.81)	136 (3.38)	4 (0.1)	21 (0.52)	1 (0.02)	178 (4.42)	294 (7.31)	40 (0.99)	801 (19.91)
Ind#4	1 (0.02)	3 (0.07)	8 (0.2)	1 (0.02)	0 (0)	0 (0)	2 (0.05)	4 (0.1)	1 (0.02)	20 (0.5)
Ind#5	0 (0)	1 (0.02)	2 (0.05)	0 (0)	0 (0)	0 (0)	2 (0.05)	4 (0.1)	2 (0.05)	11 (0.27)
Ind#6	13 (0.32)	17 (0.42)	46 (1.14)	2 (0.05)	6 (0.15)	1 (0.02)	190 (4.72)	26 (0.65)	57 (1.42)	358 (8.9)
Ind#7	2 (0.05)	40 (0.99)	72 (1.79)	2 (0.05)	358 (8.9)	0 (0)	20 (0.5)	11 (0.27)	55 (1.37)	560 (13.92)
Ind#8	0 (0)	5 (0.12)	42 (1.04)	2 (0.05)	5 (0.12)	0 (0)	3 (0.07)	119 (2.96)	47 (1.17)	223 (5.54)
Ind#9	2 (0.05)	3 (0.07)	1 (0.02)	191 (4.75)	22 (0.55)	0 (0)	2 (0.05)	1 (0.02)	58 (1.44)	280 (6.96)
Ind#10	2 (0.05)	64 (1.59)	27 (0.67)	0 (0)	5 (0.12)	0 (0)	5 (0.12)	0 (0)	4 (0.1)	107 (2.66)
Ind#11	5 (0.12)	12 (0.3)	56 (1.39)	1 (0.02)	62 (1.54)	0 (0)	0 (0)	1 (0.02)	2 (0.05)	139 (3.46)
Ind#12	7 (0.17)	31 (0.77)	15 (0.37)	0 (0)	8 (0.2)	0 (0)	6 (0.15)	7 (0.17)	21 (0.52)	95 (2.36)
Ind#13	2 (0.05)	82 (2.04)	21 (0.52)	3 (0.07)	0 (0)	0 (0)	1 (0.02)	1 (0.02)	5 (0.12)	115 (2.86)
Ind#14	1 (0.02)	11 (0.27)	26 (0.65)	12 (0.3)	10 (0.25)	0 (0)	6 (0.15)	5 (0.12)	52 (1.29)	123 (3.06)
Ind#15	0 (0)	18 (0.45)	70 (1.74)	29 (0.72)	0 (0)	2 (0.05)	2 (0.05)	5 (0.12)	34 (0.85)	160 (3.98)
Ind#16	1 (0.02)	182 (4.52)	24 (0.6)	10 (0.25)	0 (0)	1 (0.02)	1 (0.02)	5 (0.12)	13 (0.32)	237 (5.89)
Ind#17	6 (0.15)	170 (4.23)	15 (0.37)	37 (0.92)	0 (0)	0 (0)	1 (0.02)	7 (0.17)	22 (0.55)	258 (6.41)
Ind#18	0 (0)	15 (0.37)	8 (0.2)	21 (0.52)	2 (0.05)	0 (0)	1 (0.02)	0 (0)	3 (0.07)	50 (1.24)
Ind#19	0 (0)	22 (0.55)	19 (0.47)	73 (1.81)	4 (0.1)	0 (0)	70 (1.74)	19 (0.47)	24 (0.6)	231 (5.74)
Ind#20	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	17 (0.42)	17 (0.42)
Ind#21	0 (0)	0 (0)	2 (0.05)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	2 (0.05)
Total	56 (1.39)	789 (19.61)	597 (14.84)	389 (9.67)	503 (12.5)	216 (5.37)	491 (12.2)	510 (12.68)	472 (11.73)	4,023 (100)

Note: The number in the table shows the number of samples, and the figure in the brackets represents the ratio of samples of the cell. Ind#1 = agriculture, forestry, and fishing; Ind#2 = mining and quarrying; Ind#3 = manufacturing; Ind#4 = electricity, gas, steam and water supply; Ind#5 = sewerage, waste management, materials recovery and remediation activities; Ind#6 = construction; Ind#7 = wholesale and retail trade; Ind#8 =

transportation; Ind#9 = accommodation and food service activities; Ind#10 = information and communications; Ind#11 = financial and insurance activities; Ind#12 = real estate activities and renting and leasing; Ind#13 = professional, scientific and technical activities; Ind#14 = business facilities management and business support services; Ind#15 = public administration and defense, compulsory social security; Ind#16 = education; Ind#17 = human health and social work activities; Ind#18 = arts, sports and recreation related services; Ind#19 = membership organizations, repair and other personal services; Ind#20 = activities of households as employers; undifferentiated goods- and services- producing activities of households for own use; Ind#21 = Activities of extraterritorial organizations and bodies; Job#1 = manager; Job#2 = professionals and related workers; Job#3 = clerks; Job#4 = service workers; Job#5 = sales workers; Job#6 = skilled agricultural, forestry and fishery workers; Job#7 = craft and related trades workers; Job#8 = plant, machine operators and assemblers; Job#9 = elementary occupations

< Appendix Table 2.2> Distribution of the Number of Samples - KWCS

	Job#1	Job#2	Job#3	Job#4	Job#5	Job#6	Job#7	Job#8	Job#9	Total
Ind#1	1 [0]	3 [0.01]	9 [0.02]	2 [0]	5 [0.01]	5,286 [10.98]	1 [0]	1 [0]	138 [0.29]	5,446 [11.31]
Ind#2	0 [-]	0 [-]	6 [0.01]	0 [-]	0 [-]	0 [-]	3 [0.01]	5 [0.01]	1 [0]	15 [0.03]
Ind#3	109 [0.23]	637 [1.32]	1,923 [3.99]	106 [0.22]	177 [0.37]	38 [0.08]	1,359 [2.82]	2,489 [5.17]	480 [1]	7,318 [15.2]
Ind#4	4 [0.01]	20 [0.04]	51 [0.11]	3 [0.01]	3 [0.01]	0 [-]	15 [0.03]	25 [0.05]	12 [0.02]	133 [0.28]
Ind#5	2 [0]	2 [0]	22 [0.05]	0 [-]	2 [0]	0 [-]	2 [0]	29 [0.06]	17 [0.04]	76 [0.16]
Ind#6	81 [0.17]	305 [0.63]	525 [1.09]	5 [0.01]	38 [0.08]	4 [0.01]	1,156 [2.4]	290 [0.6]	364 [0.76]	2,768 [5.75]
Ind#7	26 [0.05]	336 [0.7]	919 [1.91]	28 [0.06]	6,624 [13.76]	8 [0.02]	127 [0.26]	168 [0.35]	697 [1.45]	8,933 [18.55]
Ind#8	9 [0.02]	37 [0.08]	258 [0.54]	24 [0.05]	41 [0.09]	1 [0]	36 [0.07]	1,095 [2.27]	240 [0.5]	1,741 [3.62]
Ind#9	25 [0.05]	24 [0.05]	68 [0.14]	3,630 [7.54]	283 [0.59]	0 [-]	116 [0.24]	8 [0.02]	475 [0.99]	4,629 [9.61]
Ind#10	14 [0.03]	325 [0.67]	206 [0.43]	9 [0.02]	29 [0.06]	1 [0]	20 [0.04]	17 [0.04]	34 [0.07]	655 [1.36]
Ind#11	36 [0.07]	70 [0.15]	639 [1.33]	10 [0.02]	808 [1.68]	0 [-]	0 [-]	3 [0.01]	31 [0.06]	1,597 [3.32]
Ind#12	24 [0.05]	595 [1.24]	250 [0.52]	1 [0]	59 [0.12]	0 [-]	13 [0.03]	40 [0.08]	409 [0.85]	1,391 [2.89]
Ind#13	5 [0.01]	586 [1.22]	308 [0.64]	7 [0.01]	8 [0.02]	0 [-]	8 [0.02]	10 [0.02]	20 [0.04]	952 [1.98]
Ind#14	12 [0.02]	61 [0.13]	266 [0.55]	74 [0.15]	89 [0.18]	40 [0.08]	110 [0.23]	55 [0.11]	1,034 [2.15]	1,741 [3.62]
Ind#15	1 [0]	161 [0.33]	701 [1.46]	263 [0.55]	4 [0.01]	16 [0.03]	17 [0.04]	10 [0.02]	556 [1.15]	1,729 [3.59]
Ind#16	24 [0.05]	2,096 [4.35]	313 [0.65]	125 [0.26]	7 [0.01]	2 [0]	8 [0.02]	33 [0.07]	103 [0.21]	2,711 [5.63]
Ind#17	10 [0.02]	1,474 [3.06]	225 [0.47]	414 [0.86]	3 [0.01]	1 [0]	17 [0.04]	26 [0.05]	153 [0.32]	2,323 [4.82]
Ind#18	4 [0.01]	109 [0.23]	69 [0.14]	201 [0.42]	26 [0.05]	15 [0.03]	10 [0.02]	6 [0.01]	44 [0.09]	484 [1.01]
Ind#19	4 [0.01]	104 [0.22]	173 [0.36]	1,486 [3.09]	41 [0.09]	0 [-]	867 [1.8]	449 [0.93]	143 [0.3]	3,267 [6.78]
Ind#20	0 [-]	0 [-]	0 [-]	1 [0]	1 [0]	0 [-]	0 [-]	2 [0]	234 [0.49]	238 [0.49]
Ind#21	0 [-]	0 [-]	4 [0.01]	0 [-]	0 [-]	0 [-]	1 [0]	1 [0]	0 [-]	6 [0.01]

Total	391 [0.81]	6,945 [14.42]	6,935 [14.4]	6,389 [13.27]	8,248 [17.13]	5,412 [11.24]	3,886 [8.07]	4,762 [9.89]	5,185 [10.77]	48,153 [100]

Note: The number in the table shows the number of samples, and the figure in the brackets represents the ratio of samples of the cell. Ind#1 = agriculture, forestry, and fishing; Ind#2 = mining and quarrying; Ind#3 = manufacturing; Ind#4 = electricity, gas, steam and water supply; Ind#5 = sewerage, waste management, materials recovery and remediation activities; Ind#6 = construction; Ind#7 = wholesale and retail trade; Ind#8 = transportation; Ind#9 = accommodation and food service activities; Ind#10 = information and communications; Ind#11 = financial and insurance activities; Ind#12 = real estate activities and renting and leasing; Ind#13 = professional, scientific and technical activities; Ind#14 = business facilities management and business support services; Ind#15 = public administration and defense, compulsory social security; Ind#16 = education; Ind#17 = human health and social work activities; Ind#18 = arts, sports and recreation related services; Ind#19 = membership organizations, repair and other personal services; Ind#20 = activities of households as employers; undifferentiated goods- and services- producing activities of households for own use; Ind#21 = Activities of extraterritorial organizations and bodies; Job#1 = manager; Job#2 = professionals and related workers; Job#3 = clerks; Job#4 = service workers; Job#5 = sales workers; Job#6 = skilled agricultural, forestry and fishery workers; Job#7 = craft and related trades workers; Job#8 = plant, machine operators and assemblers; Job#9 = elementary occupations

< Appendix Table 2.3> Outdoor Worker Ratio by Cells (%)

	Job#1	Job#2	Job#3	Job#4	Job#5	Job#6	Job#7	Job#8	Job#9	Total
Ind#1	-	-	0.00	0.00	-	89.80	0.00	100.00	75.86	85.53
Ind#2	-	-	-	-	-	-	-	-	-	-
Ind#3	0.00	1.24	0.15	3.54	3.76	86.84	2.65	2.71	4.49	2.23
Ind#4	0.00	0.00	0.00	0.00	-	-	0.00	0.00	16.67	0.83
Ind#5	-	0.00	0.00	-	-	-	0.00	36.67	41.18	20.82
Ind#6	21.43	18.04	2.22	0.00	7.69	100.00	34.41	62.75	67.72	35.93
Ind#7	3.70	0.86	0.42	3.45	2.66	-	2.31	20.81	30.01	5.28
Ind#8	-	29.73	2.26	16.00	4.55	-	31.58	72.07	25.91	45.69
Ind#9	0.00	0.00	0.00	0.69	0.00	-	1.64	0.00	3.31	1.17
Ind#10	0.00	2.05	0.00	-	0.00	-	5.00	-	11.11	1.87
Ind#11	0.00	0.00	0.15	0.00	2.65	-	-	33.33	12.90	1.67
Ind#12	0.00	0.94	1.54	-	1.64	-	7.14	4.76	3.82	2.33
Ind#13	0.00	4.76	0.00	0.00	-	-	25.00	30.00	25.00	4.96
Ind#14	0.00	9.52	0.36	22.08	3.30	-	44.07	29.31	17.58	14.12
Ind#15	-	4.24	1.52	14.76	-	88.24	23.53	30.00	72.36	21.53
Ind#16	0.00	0.37	0.00	7.81	-	0.00	0.00	58.82	5.77	2.17
Ind#17	0.00	0.40	0.00	2.80	-	-	11.76	46.15	18.30	3.52
Ind#18	-	4.24	0.00	7.62	11.11	-	0.00	-	17.39	5.96
Ind#19	-	0.00	1.10	0.26	0.00	-	1.90	4.55	10.27	2.19
Ind#20	-	-	-	-	-	-	-	-	0.00	0.84
Ind#21	-	-	0.00	-	-	-	-	-	-	0.00

Total	5.11	1.98	0.70	3.18	2.65	89.40	15.69	24.66	27.07	14.22

Note: "-" means there no samples in the cell; Ind#1 = agriculture, forestry, and fishing; Ind#2 = mining and quarrying; Ind#3 = manufacturing; Ind#4 = electricity, gas, steam and water supply; Ind#5 = sewerage, waste management, materials recovery and remediation activities; Ind#6 = construction; Ind#7 = wholesale and retail trade; Ind#8 = transportation; Ind#9 = accommodation and food service activities; Ind#10 = information and communications; Ind#11 = financial and insurance activities; Ind#12 = real estate activities and renting and leasing; Ind#13 = professional, scientific and technical activities; Ind#14 = business facilities management and business support services; Ind#15 = public administration and defense, compulsory social security; Ind#16 = education; Ind#17 = human health and social work activities; Ind#18 = arts, sports and recreation related services; Ind#19 = membership organizations, repair and other personal services; Ind#20 = activities of households as employers; undifferentiated goods- and services- producing activities of households for own use; Ind#21 = Activities of extraterritorial organizations and bodies; Job#1 = manager; Job#2 = professionals and related workers; Job#3 = clerks; Job#4 = service workers; Job#5 = sales workers; Job#6 = skilled agricultural, forestry and fishery workers; Job#7 = craft and related trades workers; Job#8 = plant, machine operators and assemblers; Job#9 = elementary occupations

< Appendix Table 2.4> Number of FA Occurrences and Average RA_am by Cells

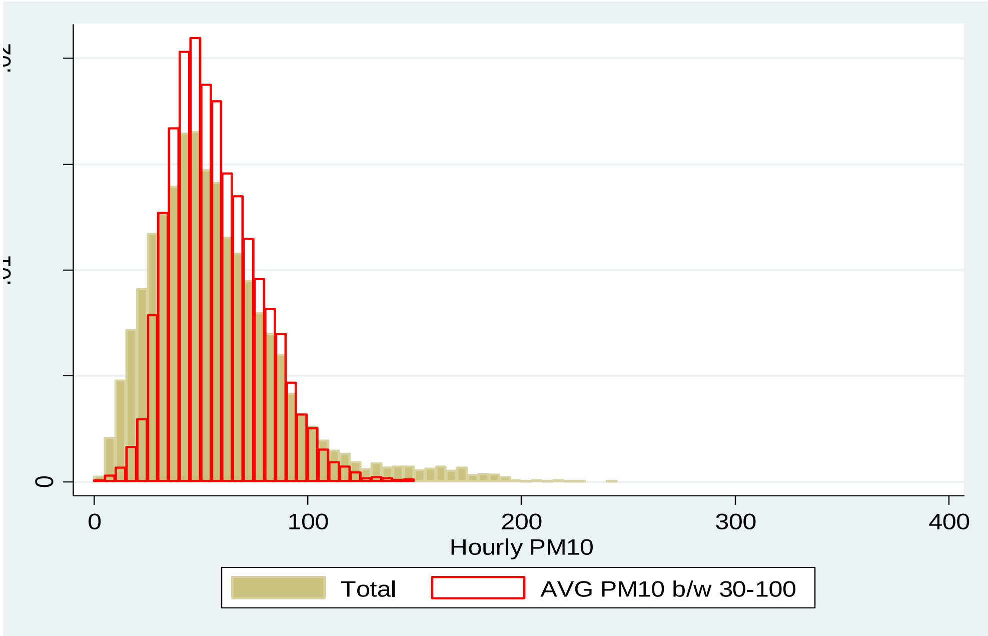
	Job#1	Job#2	Job#3	Job#4	Job#5	Job#6	Job#7	Job#8	Job#9	Total
Ind#1	- [-]	- [-]	1 [2.86]	0 [6]	- [-]	15 [1.49]	0 [0]	1 [5]	0 [0.33]	17 [1.49]
Ind#2	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]
Ind#3	0 [0.14]	8 [1.29]	10 [1.18]	0 [0.5]	3 [1.29]	0 [3]	10 [1.2]	19 [1.74]	4 [2.65]	54 [1.47]
Ind#4	- [0]	- [0]	- [0.63]	- [0]	- [-]	- [-]	- [5]	- [2]	- [0]	- [1.15]
Ind#5	- [-]	- [11]	- [5]	- [-]	- [-]	- [-]	- [0]	- [0.25]	- [1.5]	- [2.27]
Ind#6	1 [2.15]	0 [2.35]	7 [0.7]	0 [6]	0 [1.33]	1 [10]	17 [1.74]	1 [1.85]	0 [1.14]	27 [1.6]
Ind#7	0 [0]	4 [0.73]	9 [1.22]	0 [0]	26 [1.13]	- [-]	1 [1.65]	1 [0.09]	1 [1.65]	42 [1.16]
Ind#8	- [-]	1 [0]	2 [0.62]	0 [0]	0 [3.6]	- [-]	2 [5.67]	9 [1.94]	3 [2.04]	17 [1.74]
Ind#9	0 [0]	0 [0]	0 [0]	14 [1.92]	3 [1.22]	- [-]	0 [1.5]	0 [0]	4 [2.03]	21 [1.84]
Ind#10	0 [0]	9 [1.16]	3 [1.67]	- [-]	0 [3.8]	- [-]	0 [2.6]	- [-]	0 [0]	12 [1.41]
Ind#11	0 [2.4]	1 [1.08]	6 [1.36]	0 [0]	2 [1.79]	- [-]	- [-]	0 [3]	0 [0]	9 [1.55]
Ind#12	1 [0.42]	1 [1.77]	0 [3.07]	- [-]	0 [0.63]	- [-]	1 [3]	2 [0.71]	1 [0.33]	6 [1.46]
Ind#13	0 [0]	6 [1.38]	2 [2]	1 [0.33]	- [-]	- [-]	0 [0]	0 [0]	1 [0.6]	10 [1.38]
Ind#14	0 [0]	2 [2.09]	1 [1.38]	1 [0.25]	3 [0.4]	- [-]	1 [0.83]	0 [0]	6 [1.19]	14 [1.08]
Ind#15	- [-]	1 [2.11]	7 [1.89]	2 [1.28]	- [-]	0 [1.5]	0 [0]	0 [0.4]	4 [1.85]	14 [1.72]
Ind#16	0 [0]	12 [1.38]	3 [1.88]	1 [1.6]	- [-]	0 [0]	0 [3]	1 [3.2]	1 [0.92]	18 [1.45]
Ind#17	2 [4]	12 [1.66]	0 [2.4]	3 [2.19]	- [-]	- [-]	0 [7]	1 [2.29]	3 [2.14]	21 [1.91]
Ind#18	- [-]	2 [2.07]	3 [2.88]	2 [1.57]	1 [6]	- [-]	0 [0]	- [-]	1 [2]	9 [2.1]

Ind#19	- [-]	3 [0.95]	0 [1.05]	7 [2.1]	0 [0]	- [-]	3 [1.31]	1 [1.68]	7 [2.96]	21 [1.69]
Ind#20	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	3 [1.18]	3 [1.18]
Ind#21	- [-]	- [-]	1 [0]	- [-]	- [-]	- [-]	- [-]	- [-]	- [-]	1 [2]
Total	4 [1.23]	62 [1.43]	55 [1.42]	31 [1.83]	38 [1.27]	16 [1.53]	35 [1.52]	36 [1.73]	39 [1.64]	316 [1.52]

Note: The number in the table indicates the number of FA occurrences and the figure in square brackets represents the average RA_am; "-" means there no samples in the cell; Ind#1 = agriculture, forestry, and fishing; Ind#2 = mining and quarrying; Ind#3 = manufacturing; Ind#4 = electricity, gas, steam and water supply; Ind#5 = sewerage, waste management, materials recovery and remediation activities; Ind#6 = construction; Ind#7 = wholesale and retail trade; Ind#8 = transportation; Ind#9 = accommodation and food service activities; Ind#10 = information and communications; Ind#11 = financial and insurance activities; Ind#12 = real estate activities and renting and leasing; Ind#13 = professional, scientific and technical activities; Ind#14 = business facilities management and business support services; Ind#15 = public administration and defense, compulsory social security; Ind#16 = education; Ind#17 = human health and social work activities; Ind#18 = arts, sports and recreation related services; Ind#19 = membership organizations, repair and other personal services; Ind#20 = activities of households as employers; undifferentiated goods- and services- producing activities of households for own use; Ind#21 = Activities of extraterritorial organizations and bodies; Job#1 = manager; Job#2 = professionals and related workers; Job#3 = clerks; Job#4 = service workers; Job#5 = sales workers; Job#6 = skilled agricultural, forestry and fishery workers; Job#7 = craft and related trades workers; Job#8 = plant, machine operators and assemblers; Job#9 = elementary occupations

Appendix 2.2 – Distribution of Hourly PM10 concentration

< Appendix Figure 2.1> Histogram on Hourly PM10 by the Sample Restriction



When the daily concentration of PM10 is restricted to 30-100μg/m^3, the extreme value of the hourly PM10 concentration disappears a lot.

Appendix 2.3 – Linearity Check

< Appendix Table 2.5> Linearity Check for OR and RA

VARIABLES	Model 1	VARIABLES	Model 2
FA	4.841	FA	6.208
	(8.866)		(8.831)
FA * OR dummy	-12.61	FA * OR	-69.33**
(10-50%)	(19.23)		(29.35)
FA * OR dummy	-46.22*	RA (am) dummy (1-3)	12.40*
(50-100%)	(23.99)		(6.883)
RA	0.833	RA (am) dummy (4-6)	-4.322
	(0.968)		(10.61)
RA * OR dummy	-4.594***	RA (am) dummy (7-9)	19.81
(10-50%)	(1.770)		(14.15)
RA * OR dummy	-6.301**	RA (am) dummy	5.446
(50-100%)	(2.731)	(10-12)	(11.94)
		RA (am) dummy (1-3)	-3.233
		* OR	(24.57)
		RA (am) dummy (4-6)	-3.706
		* OR	(34.49)
		RA (am) dummy (7-9)	-137.4**
		* OR	(66.18)
		RA (am) dummy	-93.39**
		(10-12) * OR	(42.43)
Observations	4,023	Observations	4,023
R-squared	0.194	R-squared	0.195

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The study assumes that information has a linear impact on working hours according to the outdoor worker ratio. It is also assumed that one unit increase of RA_am has a constant impact on labor time. However, both variables may have a nonlinear relationship with working hours. Therefore, I checked the nonlinearity by replacing OR and RA_am to its interval dummies. The results of the analysis show that both variables have a nonlinear impact on working hours.

Appendix 2.4 – Replacing OR to Industry or Occupation Dummies

< Appendix Table 2.6> Effect of Information by Industries or Occupations

	(1)	
VARIABLES	Info = RA	Info = FA
Info * Ind#1	-2.559	-110.3***
	(3.096)	(32.36)
Info * Ind#3	-0.792	5.613
	(1.464)	(16.82)
Info * Ind#4	4.110	-
	(10.03)	
Info * Ind#5	-8.157	-
	(9.396)	
Info * Ind#6	-2.537	28.76
	(2.056)	(23.22)
Info * Ind#7	-0.149	18.99
	(1.870)	(18.49)
Info * Ind#8	-4.854*	48.05*
	(2.543)	(29.01)
Info * Ind#9	-3.327*	8.737
	(2.018)	(26.46)
Info * Ind#10	0.400	20.34
	(3.577)	(35.70)
Info * Ind#11	-1.334	26.31
	(3.337)	(40.04)
Info * Ind#12	-5.143	-31.44
	(3.701)	(47.50)
Info * Ind#13	4.474	32.63
	(3.411)	(37.07)
Info * Ind#14	-1.255	-49.18
	(3.801)	(32.52)
Info * Ind#15	1.635	-28.85
	(2.798)	(31.51)
Info * Ind#16	1.204	-52.03*
	(2.445)	(27.78)
Info * Ind#17	2.292	-55.38**
	(2.141)	(26.54)
Info * Ind#18	5.704	-23.77
	(5.405)	(51.48)
Info * Ind#19	4.726**	35.13
	(2.351)	(27.43)
Info * Ind#20	28.48	-142.1*
	(17.76)	(75.62)
Info * Ind#21	30.08	-
	(39.41)	
Observations	4,023	
R-squared	0.204	

	(2)	
VARIABLES	Info = RA	Info = FA
Info * Job#1	0.478	42.93
	(4.995)	(62.98)
Info * Job#2	1.664	-14.08
	(1.470)	(15.54)
Info * Job#3	0.0498	6.883
	(1.732)	(16.82)
Info * Job#4	-2.110	45.82**
	(1.735)	(21.94)
Info * Job#5	0.494	9.920
	(1.899)	(19.43)
Info * Job#6	-1.927	-82.95**
	(3.179)	(33.37)
Info * Job#7	0.200	26.79
	(1.718)	(20.69)
Info * Job#8	-1.852	-11.37
	(1.673)	(20.24)
Info * Job#9	-1.904	-44.00**
	(1.856)	(20.04)
Observations	4,023	
R-squared	0.196	

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Ind#1 = agriculture, forestry, and fishing; Ind#2 = mining and quarrying; Ind#3 = manufacturing; Ind#4 = electricity, gas, steam and water supply; Ind#5 = sewerage, waste management, materials recovery and remediation activities; Ind#6 = construction; Ind#7 = wholesale and retail trade; Ind#8 = transportation; Ind#9 = accommodation and food service activities; Ind#10 = information and communications; Ind#11 = financial and insurance activities; Ind#12 = real estate activities and renting and leasing; Ind#13 = professional, scientific and technical activities; Ind#14 = business facilities management and business support services; Ind#15 = public administration and defense, compulsory social security; Ind#16 = education; Ind#17 = human health and social work activities; Ind#18 = arts, sports and recreation related services; Ind#19 = membership organizations, repair and other personal services; Ind#20 = activities of households as employers; undifferentiated goods- and services- producing activities of households for own use; Ind#21 = Activities of extraterritorial organizations and bodies; Job#1 = manager; Job#2 = professionals and related workers; Job#3 = clerks; Job#4 = service workers; Job#5 = sales workers; Job#6 = skilled agricultural, forestry and fishery workers; Job#7 = craft and related trades workers; Job#8 = plant, machine operators and assemblers; Job#9 = elementary occupations

Model (1) in Appendix Table 2.6 interacts Industry dummies with the information variables (RA, FA) instead of the outdoor worker ratio (OR) to estimate the differential effect of information by industry. The results show that the industry is responding differently to forecasts and real-time information. Ind#1 shows a significant reduction in working hours in response to FA and it is the same results with the main results. On the other hand, one new finding is that workers in Ind#16, Ind#17, and Ind#20 decrease their working hours when FA appears even though they have low outdoor worker ratio. Since the main concern of this paper is outdoor workers, the reasons for this result will be examined through further research. Ind#8, one of the industries with a high outdoor worker ratio, shows that working hours increase when FA appears, while RA_am decreases working hours.

Model (2) shows the discriminatory effects of the information by occupations. In the case of Job#6 and Job#9, working hours decrease when the FA appears, while Job#4 is found that working hours increase in response to FA.

Appendix 2.5 – The effect of information on the decision of whether to work or not

The main analysis used the individuals who answered that the surveyed day was a workday and actually worked for more than 30 minutes.[18] However, there may be workers who decide not to work on that day based on information on PM. In this case, the results of the main analysis can under-estimate the reduction in working hours. Therefore, I analyzed the impact of information on labor decisions on the survey day.

<Appendix Table 2.7> Effect of Information on the Decision not to Work on Workdays

VARIABLES	(1) Zero Work w/ Sample Restriction	(2) Zero Work w/o Sample Restriction
FA	0.0077	0.00357
	(0.00968)	(0.00874)
FA * OR	-0.0189	0.0263
	(0.0316)	(0.0286)
RA_am	-0.00203*	-0.00105
	(0.00119)	(0.000640)
RA_am * OR	0.0128***	0.00916***
	(0.00413)	(0.00220)
Observations	4,089	5,248
R-squared	0.052	0.047

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[18] The main analysis of the study was based only on individuals whose work start and end time could be clearly identified; thus it did not include those who worked zero minutes.

The above analysis used a dummy variable, indicating whether a sample worked for 0 minutes or not even though it was a workday, as a dependent variable. Of those who responded that the surveyed day was the workday, about 1.5 percent worked zero minutes. The results of the analysis represent that Real-time information provided in the morning increases the probability not to work on workdays, while the forecasts did not.

Chapter 3

Air Pollution, Information, and Hospital Visits: Evidence from Korea

This study estimated the impact of particulate matter (PM) and PM information on the number of hospital visits due to respiratory diseases in Korea. The results showed that, if the forecast for PM appeared bad or very bad, then the number of hospital visits increased. This finding is in contrast to the results of some previous studies that reported that information on air pollution reduces hospital use by avoidance behavior. However, the results of this study confirmed that information can affect hospital use by channels other than avoidance behavior, such as sensitivity, and can thus increase hospital use.

3.1 Introduction

Particulate matter (PM) negatively affects not only health but also non-health aspects, such as cognitive ability, schooling, and labor productivity (Pope III and Dockery, 2006; Zweig et al., 2009; Sander, 2012; Lavy et al., 2014; Chang et al. 2016). Therefore, many countries enforce various policies, including information provision policy, to protect people from the risk. In general, policies on air pollution mean restrictions on emission sources. However, providing information can also protect public health because provided information induces people to adjust their behavior. Therefore, action guidelines are presented along with air pollution information to maximize the policy effect.

Several previous studies have shown that information, such as forecasts, alleviates the negative effect of air pollution (Neidell, 2009; Janke, 2014; Altindag et al., 2017). Some studies have estimated the effect of avoidance behavior on health by using hospital use, such as hospitalization or emergency admission, as a dependent variable and information on air pollution as a proxy variable of avoidance behavior. However, some factors which are not related to avoidance behavior but related to air pollution information and hospital use can exist and in this case, the estimated information effects do not coincide with the effect of avoidance behavior. For example, sensitivity can be affected by air pollution information and can affect hospital use in turn. In this case, the estimated effect of information contains not only the avoidance behavior effect but also the effect of other factors, such as sensitivity.

The current study investigates whether information on PM affects the number of daily hospital visits and whether other factors, other than avoidance behavior, exist between hospital use and air pollution information. This study uses the number of hospital visits as a dependent variable to clearly identify whether information affects hospital use by paths other than avoidance behavior. Hospital visits are more likely to be influenced by other factors, such as sensitivity, than by hospitalization or emergency admission, which is used in previous studies. In addition, Koreans are sufficiently sensitive to feel PM as a disturbing factor than North Korea’s nuclear capabilities (Jung et al. 2017). Moreover, in Korea, the cost of hospital visits is very low because people are required to sign up for the national health insurance system. Therefore, predicting the direction of information effect on hospital visits can be difficult.

In Korea, an air quality forecast system was introduced in 2014. This system has allowed people to check forecasted PM and O_3 one day before via news or online. Therefore, forecast information on PM is used in this study. The analysis period is from 2012 to 2015, and I focus on PM10, which is available throughout the entire analysis period among PM.[19]

3.2 Previous Research

Many studies have estimated the negative effects of PM on various aspects. As effectively summarized in Pope III and Dockery (2006), PM pollution causes respiratory and cardiovascular diseases. They also showed that PM negatively impacts health not only at a very high level but also at a relatively low level. Moreover, they reported that the negative effects of PM appear even with short exposure time and estimated that its exposure–response function is linear. Furthermore, recent studies have reported that PM is related to non-health aspects, such as cognitive skills, academic or labor market performance, and labor supply (Zweig et al., 2009; Sander, 2012; Lavy et al., 2014; Hanna and Olivia, 2015; Chang et al., 2016; Isen et al., 2017; Kim et al., 2017).

Most of the abovementioned studies have used ambient air pollution data to estimate the effects of PM. However, if people adjust their behavior depending on pollution levels, then ambient air quality data may overestimate the actual exposure,

[19] PM2.5 data were measured and published in 2015 in Korea.

and the effect of air pollution can be underestimated (Currie et al., 2014). Some studies have shown that people adjust their behavior when information on air pollution is provided and the negative effects of air pollution on their health are alleviated as a result of the adjustment. Neidell (2009) found that smog alerts announced in Southern California reduce the number of visitors to outdoor facilities and the asthma hospitalization of children. He also demonstrated that the effects of ozone on the hospitalization largely increase when the smog alert variable is included in the analysis model. Janke (2014) reported that alerts on air pollution cause avoidance behavior, but the alerts only mitigate the negative effect on asthma patients. Altindag et al. (2017) found that PM exposure during pregnancy negatively impacts infant health. However, that information, such as Asian dust alerts, eases the negative influence.

Several non-health studies have also found that air pollution causes avoidance behavior. Zhang and Mu (2018) and Liu et al. (2018) demonstrated that sales of product defending against PM increase when the level of PM pollution is high. Sheldon and Sankaran (2019) reported that domestic electricity demand increases on a day with poor air quality due to forest fire.

3.3 Data

National Sample Cohort data from the National Health Insurance Service are used to estimate the number of daily hospital visits. National Sample Cohort data is a panel data sampling of approximately one million within individuals with national health insurance from 2002–2015. The Korean government provides medical insurance, and the people are obliged to sign up for it. Therefore, individuals in the National Sample Cohort data are representatives of the Korean people. These data contain demographic information, economic status, medical utilization records, and health examination records. The number of daily hospital visits by county[20], age (four groups; 0–4, 5–19, 20–64, 65+), sex (two groups: men, women), and income (three groups: 1–3, 4–7, 8–10 in decile group) are obtained from the data. Hospital visits due to the total respiratory disease, acute respiratory disease, and asthma are considered in the analysis.

<Table 3.1> Considered Respiratory Diseases

	ICD-10 Codes
Respiratory Total	J00-J99, R05, R06
Respiratory Acute	J00-J22
Asthma	J45-46

Forecast data are obtained from www.airkorea.or.kr. In Korea, the forecast for air quality (PM, O_3) began in February 2014. The forecast on PM is provided for four times a day; 5 a.m., 11 a.m., 5 p.m., and 11 p.m. Among forecast information, the datum at 5 p.m. is used in the analysis because the information is announced on evening main news. Given that the forecast is provided at the province levels, PM10 forecast of a province is matched to a county within a province. The forecast is not provided as expected figures but as four levels only, namely, good, moderate, bad, and very bad. Therefore, the effect of the forecast is estimated by the dummy

[20] The largest regional classification in Korea is 16 provinces. The second largest regional classification is county, followed by more than 300 counties in Korea.

variable that indicates whether forecasted PM10 is bad or very bad.

Hourly air pollution data from the National Institute of Environmental Research (NIER) of Korea are used to generate county-level PM10 concentration and real-time information on PM. In Korea, approximately 300 air pollution monitoring stations are operated by the national or local governments, and they measure the pollution levels on PM, CO, O_3, NO_2, and SO_2 every hour. NIER collects the data from the stations and serves them to the public via their website (www.airkorea.or.kr). The analysis unit of this study is a county, whereas NIER provides the data at monitoring station levels. Therefore, matching the stations to counties is necessary. Monitoring stations in Korea are classified into four types, namely, urban, roadside, rural, and national background, depending on their purpose and location. Real-time information provided by the website or online at the county level is based on the urban monitoring stations. Therefore, the average value of the urban station data within a county is used as real-time information of the county. Real-time information is provided as the exact figures and categories at the same time; 0–30 is expressed as good, 31–80 as moderate, 81–150 as bad, and over 151 as very bad. Moreover, colors are assigned to each category to express the risk intuitively; blue is assigned to good, green to moderate, amber to bad, and red to very bad. Thus, people who want to avoid the risk can react to categories rather than figures. Therefore, the number of real-time bad or very bad occurrences in a day is included in the regression models. However, this variable is not expected to only capture the effect of real-time information because real-time PM10 concentration is correlated with body response and visibility. Therefore, the real-time information variable is used as a control variable in the analysis.

Contrary to the real-time information, pollution levels of counties are estimated using data from all types of stations because information based solely on urban stations may inaccurately reflect pollution levels of a county. The method of estimation is given as follows.

$$P_{ct} = \sum_j (\frac{P_{jt} \times W_{cj}}{\sum W_{cj}}) \ \ where \ \ W_{cj} = \frac{1}{(D_{cj} | D_{cj} \leq \sqrt{area_c})} \tag{1}$$

D_{cj} indicates the distance between the administrative office of county c and monitoring station j. The weighted mean of pollution levels of stations, which is within a distance closer than the square root value of the area of a county, is used as pollution of the county. The inverse of the distance is utilized as a weight. Square root values of county areas are adopted to reflect the differences in size between counties. Figure 1 presents the analyzed counties and the locations of monitoring stations. Table 2 shows the information on county-monitoring station matching.

Weather variables can be potential confounding factors to disturb estimation of information effects. Therefore, weather data obtained from the climate data open portal (data.kma.go.kr) operated by the Korea Meteorological Administration are used.

Summary statistics are shown in Table 3. Figures 2 and 3 present the monthly variations of the level of air pollutants and hospital visits due to respiratory diseases.

<Figure 3.1> Distribution of Counties and Monitoring Stations used for Analysis

Note: Shaded area indicate counties used in this study. Black dots represents locations of monitoring stations.

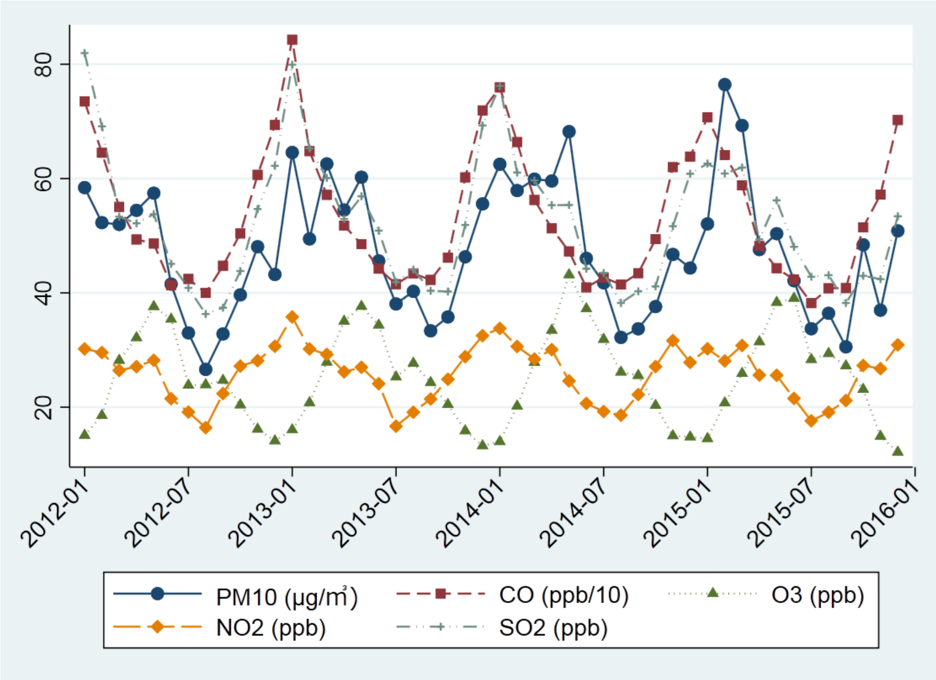
<Table 3.2> County and Monitor Matching

	Mean	Std. Dev.	Min	Max
# of Monitor matched to a County	6.89	5.03	1	33
Distance from County to Monitor	8.39	7.36	0.015	35.91
Square Root of Area of County	13.31	9.47	2.66	39.01

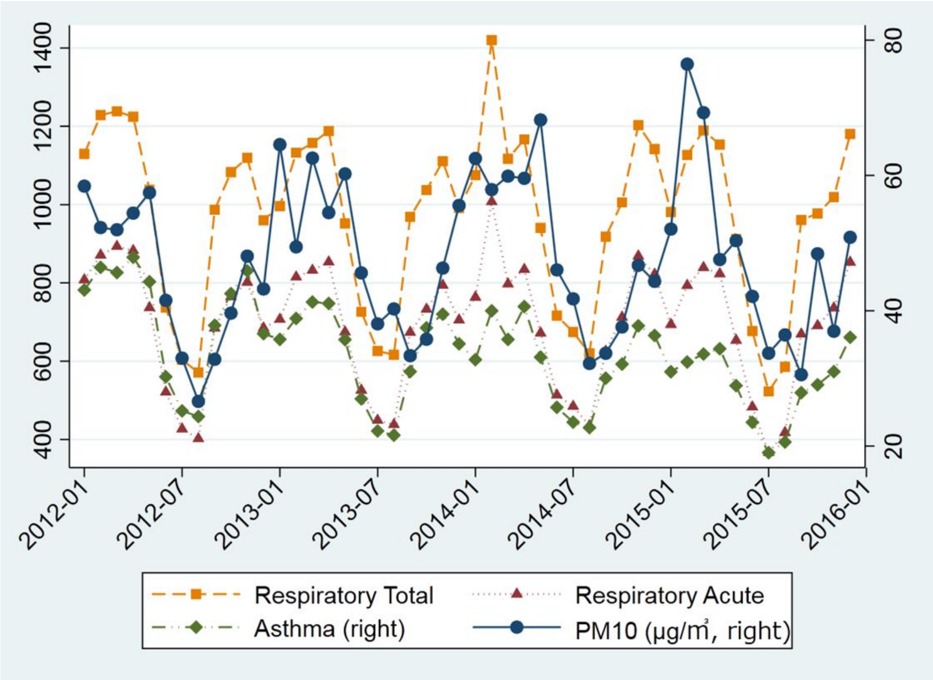
<Table 3.3> Summary Statistics

	Mean	Std. Dev.	Min	Max
Population	246.57	315.08	1	2298
Respiratory Total (per 100,000)	977.1	1497.21	0	200000
Respiratory Acute (per 100,000)	697.05	1249.69	0	200000
Asthma (per 100,000)	32.73	182.02	0	100000
PM10 (μg/㎥)	47.69	26.82	1.12	699.96
CO (ppm*10)	5.34	2.25	0.43	37.88
O3 (ppb)	25.08	12.43	0.66	93.80
NO2 (ppb)	25.87	13.40	0.99	130.03
SO2 (ppb)	5.24	2.55	0.17	46.63
Forecast Alert	0.36	0.187	0	1
True Forecast Alert	0.24	0.148	0	1
Real-time Alert	2.75	5.51	0	24
Temperature (℃)	13.24	10.09	-13.70	33.10
Precipitation (mm)	3.30	12.12	0.0	308.9
Wind Speed (m/s)	2.25	0.97	0.3	10.3
Humidity (%)	65.65	15.14	12.2	99.9
N	5,539,746			

<Figure 3.2> Monthly Variation of Pollutants



<Figure 3.3> Monthly Variation of Respiratory Diseases and PM10



3.4 Conceptual Framework

The study estimates the impact of PM and its information on hospital visits, which include hospital admissions and outpatients.

The effects of air pollution on health can be expressed as the following equation when considering the avoidance behavior:

$$\frac{dH}{dP} = \frac{\partial H}{\partial P} + \frac{\partial H}{\partial A} \cdot \frac{\partial A}{\partial P} \tag{2}$$

In the equation above, H, P, and A indicate health, air pollution, and avoidance behavior, respectively. The left side represents the total effect of air pollution on health. The first part of the right side is the direct effect of air pollution, and the second term is the effect through avoidance behavior. In general, the direct effect is expected to be negative, whereas avoidance behavior may positively affect health.

Several previous studies on avoidance behavior have used information variables as a proxy of the averting action and have shown that the action mitigates the adverse effects of air pollution on health (Neidell, 2009; Janke, 2014; Altindag et al., 2017). Some of these works have applied hospital use, such as hospitalization or emergency admission, as proxy variables for health. Then, the effects of air pollution on hospital use can be expressed as the following equation.

$$\frac{dHU}{dP} = \frac{\partial HU}{\partial H} \cdot \frac{\partial H}{\partial P} + \frac{\partial HU}{\partial H} \cdot \frac{\partial H}{\partial A} \cdot \frac{\partial A}{\partial PI} \cdot \frac{\partial PI}{\partial P} \tag{3}$$

HU and *PI* indicate hospital use and information on pollution, respectively. If *PI* affects *HU* only through avoidance behavior, then the equation above can be established. However, if other factors that are not associated with avoidance behavior but associated with *PI* and *HU* exist, then the equation may not be established. For example, the information on PM can increase people's sensitivity, which results in increased hospital visits. In this case, Equation 3 should be modified as follows.

$$\frac{dHU}{dP} = \frac{\partial HU}{\partial H} \cdot \frac{\partial H}{\partial P} + \left(\frac{\partial HU}{\partial H} \cdot \frac{\partial H}{\partial A} \cdot \frac{\partial A}{\partial PI} + \frac{\partial HU}{\partial OF} \cdot \frac{\partial OF}{\partial PI} \right) \cdot \frac{\partial PI}{\partial P} \tag{4}$$

Here, *OF* represents other factors. Both terms in the parenthesis of the right side of the equation show channels through which information can affect hospital use. The first term in the parenthesis is expected to be negative, whereas the direction of the second term is not fixed and can be positive. Therefore, the direction of the effect of information on hospital visits is difficult to predict. In addition, the information effect on hospital use must not be interpreted as avoidance behavior effects but as total information effects.

3.5 Econometric Specification

To estimate the information effect on hospital visits, the following fixed effect model is used.

$$Y_{ict} = \alpha + \sum_{j=0}^{4} \left[\beta_1 FA_{ct-j} + \beta_2 RA_{ct-j} + \beta_3 PM10_{ct-j} + \gamma OP_{ct-j} * + \delta W_{ct-j} \right]$$

$$+\theta X_i + \pi_{cs} + \rho_t + \epsilon_{ict}. \tag{5}$$

Y_{ict} is the number of hospital visits per 100,000 population of cell i, which is constituted on the basis of age, sex, and income, in county c on day t. *FA* is a dummy variable that indicates whether forecast alerts are given. *RA* is the number of the occurrence of real-time alerts on day *t* and controlled to eliminate the effect of real-time information, visibility, and body responses. *PM10* is the daily average PM10 concentration. *OP* and *W* are vectors of the other air pollutants (CO, O_3, NO_2, SO_2) and weather variables (minimum temperature, maximum temperature, precipitation, wind speed, and relative humidity), respectively. Not only contemporaneous values but also four lags of *FA*, *RA*, *PM10*, *OP*, and *W* are included in the model because previous air pollution and weather conditions can affect hospital visits of today.[21] *X* is a set of age, sex, and income dummy variables. County-season fixed effects are controlled to capture the unobserved but time–invariant characteristics of counties and seasonal effects by counties. Various time fixed effects (year, season, day of week, holiday, and MERS period) are also controlled in the model. Furthermore, each observation is weighted by the size of the cell population in the regression.

3.6 Results

The results in Table 4 report the sum of the coefficients of the contemporaneous and four lagged PM10 variables. The sum can be interpreted as the total effect of PM10 on the number of visits to a hospital on days from t to t+4. Each panel shows the results of the analysis on different diseases, and each column has a different set of control variables. Table 4 reports that PM10 increases the number of hospital visits for all types of respiratory diseases.

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[21] The lag structure coincides with those of Neidell (2009) and Janke (2014).

The results of the model that considers forecast information are presented in Table 5. In the table, FA largely increases the number of hospital visits; this finding is contrary to the result that can be expected from previous research. This situation shows the possibility that the information affects hospital visits through not only avoidance behavior but also other factors. Figure 4 graphically expresses the average number of predicted hospital visits by the average PM10 concentration of five days (today and past four days).[22] The five days' PM10 concentration is divided into intervals, and each value in the graph indicates an average value of within an interval. "Avg # of FA" represents the average number of FA occurrences in five days. "w/ FA" indicates the number of predicted hospital visits when FA has occurred more than once in five days, and "w/o FA" indicates the number of hospital visits when no FA has occurred for five days. This figure shows that systematically more hospital visits occur when the FA appears than when no FA is available.[23]

This study assumes that the effect of PM10 on the number of hospital visits is linear. However, if the assumption is incorrect, then the effects of PM10, which are not captured in linear PM10 variable, can be captured in FA. Therefore, Table 6 shows whether the coefficients of FA are robust to the functional form of PM10 variable by including PM10 interval dummies (20 intervals) instead of the linear

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[22] The predicted hospital visits are estimated by the regression model.

[23] In the data used, a case shows an average PM10 concentration of between 10–20 and the occurrence of FA in five days. However, in this case, the number of observations is very low, whereas the number of hospital visits is abnormally high. Thus, this case is excluded in the figure.

<Table 3.4> Effects of PM on Hospital Visits

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total							
PM10	3.98***	3.94***	0.338***	1.105***	0.172***	0.433***	0.639***
	(0.0332)	(0.0248)	(0.0276)	(0.0334)	(0.0324)	(0.0368)	(0.0552)
R-squared	0.0029	0.4453	0.4570	0.4689	0.53	0.5323	0.5323
Acute							
PM10	2.879***	2.838***	0.196***	0.776***	0.084***	0.299***	0.49***
	(0.028)	(0.0207)	(0.0232)	(0.0281)	(0.0278)	(0.0316)	(0.0474)
R-squared	0.0022	0.4437	0.4525	0.4607	0.5035	0.5058	0.5058
Asthma							
PM10	0.12***	0.12***	0.0107**	0.042***	0.024***	0.004	0.025**
	(0.0041)	(0.004)	(0.0045)	(0.0055)	(0.0056)	(0.0063)	(0.0096)
R-squared	0.0002	0.0404	0.0412	0.0421	0.0478	0.0499	0.0499
Demographic Info.		○	○	○	○	○	○
Weather			○	○	○	○	○
Other Pollutants				○	○	○	○
Time Fixed Effects					○	○	○
C-S Fixed Effects						○	○
Real-time Info.							○
Observations	5,524,582	5,524,582	5,524,582	5,524,582	5,524,582	5,524,582	5,524,582

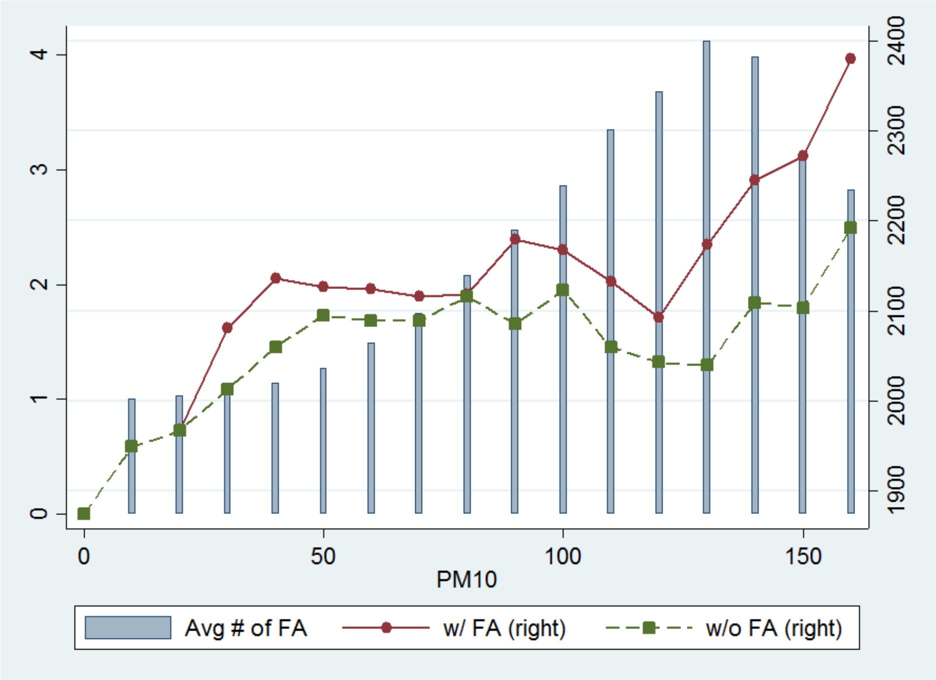
Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

<Table 3.5> Effects of PM and Information on Hospital Visits

VARIABLES	(1) *Total*	(2) *Acute*	(3) *Asthma*
Total Hospital Visit			
PM10	0.355***	0.295***	0.0243**
	(0.0565)	(0.0485)	(0.0097)
FA	105.19***	70.97***	0.0628
	(4.505)	(3.868)	(0.782)
Daily HV * 5	4985.13	3556.34	166.98
R-squared	0.5324	0.5058	0.0499
Outpatient			
PM10	0.344***	0.288***	0.022**
	(0.056)	(0.0481)	(0.0097)
FA	102.59***	71.22***	-0.0338
	(4.469)	(3.838)	(0.775)
Daily HV * 5	4932.13	3522.26	164.37
R-squared	0.5303	0.5034	0.0494
Hospitalization			
PM10	0.0102*	0.007	0.002
	(0.0061)	(0.0052)	(0.0013)
FA	2.6***	0.756*	0.097
	(0.4888)	(0.4156)	(0.1016)
Daily HV * 5	53	34.07	2.6
R-squared	0.0499	0.0494	0.0016
Observations	5,524,582	5,524,582	5,524,582

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

<Figure 3.4> Predicted Hospital Visits by PM10



Note: This figure shows the average number of hospital visitors by the average PM10 concentration of five days (today and past four days). The five days' PM10 concentration was divided into intervals and each value in the graph indicates an average value of within an interval. 'Avg # of FA' represents the average number of FA occurrences in five days. 'w/ FA' indicates the number of hospital visits when FA has occurred more than once in five days, and 'w/o FA' indicates the number of hospital visits when there is no FA in five days.

PM10 variable. The results indicate that the coefficient of FA is robust to the functional form of PM10.

The results of the sub-sample regressions by groups are reported in Table 7. The table shows that the effect of PM and FA vary by groups. The increasing trend of hospital visits in response to FA is large in young (under 19) and old (over 65) age groups. Moreover, FA increases the number of hospital visits more in the high-income group than in the low-income group.

In Table 8, I attempt to determine a possible mechanism through which FA

<Table 3.6> Linearity Check

VARIABLES	(1) *Total*	(2) *Acute*	(3) *Asthma*
Panel A - Linear			
FA	105.19***	70.97***	0.0628
	(4.505)	(3.868)	(0.782)
R-squared	0.5324	0.5058	0.0499
Panel B - Interval			
FA	100.1***	71.76***	0.103
	(4.687)	(4.023)	(0.814)
R-squared	0.5325	0.5059	0.0499
Observations	5,524,582	5,524,582	5,524,582

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; In *Panel A*, daily average PM10 is included as a linear function. While, in *Panel B*, interval dummy variables of PM10 (with 20 intervals) were used instead of daily PM10 concentration

increases hospital visits. In the model used in Panel A, the interaction term of FA and PM10 is included. Therefore, the coefficients of FA represent the impact of FA regardless of the level of air pollution, and the coefficients of the interaction team indicate changes in FA effect based on daily PM10 levels. The results show that, for total and acute respiratory diseases, FA increases the number of hospital visitors regardless of the level of pollution. This finding indicates that FA affects other factors that increase the visits other than avoidance behavior. The coefficient of the interaction term, which indicates the additional effect of FA based on the PM10 level, is negative. The additional effect can be interpreted as the impact of health improvement as a result of avoidance behavior because, even if someone adjusts his or her behavior on the basis of FA, health benefits can only occur when the actual air quality is bad.

<Table 3.7> Effects of PM and Information on Hospital Visits by Groups

VARIABLES	(1) a0004	(2) a0519	(3) a2064	(4) a65+	(5) Man	(6) Woman	(7) Low Income	(8) Mid Income	(9) High Income
PM10	1.542***	-1.448***	0.426***	1.794***	0.24***	0.467***	0.379***	0.336***	0.356***
	(0.3768)	(0.109)	(0.037)	(0.102)	(0.081)	(0.078)	(0.106)	(0.097)	(0.093)
FA	374.53***	287.54***	43.09***	103.44***	101.99***	108.2***	84.75***	95.18***	126.26***
	(29.91)	(8.683)	(2.958)	(8.158)	(6.429)	(6.26)	(8.453)	(7.743)	(7.413)
Daily HV * 5	26432	7021	2978.5	4758.5	4612.5	5352.5	4404	5093.5	5239.5
R-squared	0.2656	0.2979	0.4882	0.2421	0.5509	0.5184	0.3879	0.5793	0.5667
Observations	1,380,874	1,381,236	1,381,236	1,381,236	2,762,110	2,762,472	1,841,286	1,841,648	1,841,648

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

<Table 3.8> Differential Effects of FA by Pollution Levels of PM

	(1)	(2)	(3)
VARIABLES	*Total*	*Acute*	*Asthma*
Panel A - Linear			
PM10	0.604***	0.579***	0.0275**
	(0.693)	(0.0595)	(0.012)
FA	163.79***	137.98***	0.779
	(10.16)	(8.722)	(1.764)
FA * PM10	-0.592***	-0.669***	-0.0074
	(0.093)	(0.795)	(0.0161)
R-squared	0.5337	0.5071	0.0502
Panel B - Interval			
PM10	-	-	-
FA	220.23***	158.67***	2.718*
	(8.266)	(7.095)	(1.435)
True FA	-195.18***	-141.19***	-4.242**
	(11.173)	(9.59)	(1.939)
Daily HV * 5	4985.13	3556.34	166.98
R-squared	0.5325	0.5059	0.0499
Observations	5,524,582	5,524,582	5,524,582

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; In *Panel A*, daily average PM10 is included as a linear function. While, in *Panel B*, interval dummy variables of PM10 (with 20 intervals) were used instead of daily PM10 concentration. True FA means that daily average PM10 concentration was actually bad (81μg/m^3 or over) when FA appeared.

In Panel B of Table 8, the linear PM10 variable is replaced to PM10 interval dummies (20 intervals), and True FA are included. True FA is a dummy variable indicating that daily average PM10 concentration is actually bad (81 μg/m^3 or over) when FA appears. The results in Panel B also show that FA increases the number of hospital visits regardless of whether PM10 is actually bad. The additional effect of True FA, which occurs only when FA appears and actual PM10 is bad, has the opposite direction to FA effect and reduces the number of hospital visits. The results for total and acute respiratory diseases are consistent with the results of Panel A. However, the impact of the FA on asthma is inconsistent between panels.

Table 8 demonstrates that, when the information variable is used in the analysis, the coefficient of the information can represent the total effects of the information, including the effects of avoidance behavior and other factors that increase the number of hospital visits. Moreover, when the effects of the other factors are larger than those of avoidance behavior, FA can increase hospital visits.

Sensitivity can be one of the other factors that increase hospital visits. As mentioned above, Koreans treat PM as a more disturbing factor than North Korea's nuclear capabilities (Jung et al. 2017). In addition, the cost of hospital visits is very low due to the national health insurance system. Therefore, FA may have increased the number of hospital visits through sensitivity.

Table 9 shows the effect of FA on hospital expenditure per visit. The results show that the coefficients of the FA are negative, but this condition is insignificant in asthma. Thus, expenditures for hospital visits in response to the FA are smaller than the average expenditure of hospital visits. Moreover, the severities of patients who visit a hospital in response to FA are low.

In Table 10, the effects of PM and FA on hospital visits due to other diseases, such as conjunctivitis (ICD-10 codes H10-H13), injury (ICD-10 codes K00-K93), and digestive diseases (ICD-10 codes S00-T88) are estimated. The results show

<Table 3.9> Effects of PM and Information on Hospital Expenditure per Visit (log)

	(1)	(2)	(3)
VARIABLES	*Total*	*Acute*	*Asthma*
PM10 / 100	-0.01***	-0.01***	-0.03**
	(0.003)	(0.003)	(0.014)
FA / 100	-1.14***	-0.58***	-1.84
	(0.239)	(0.222)	(1.166)
R-squared	0.7981	0.8279	0.5738
Observations	3,832,017	3,394,003	410,693

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

<Table 3.10> Effects of PM and Information on Hospital Visits due to Other Diseases

	(1)	(2)	(3)
VARIABLES	*Conjunctivitis*	*Injury*	*Digestive Diseases*
PM10	-0.046***	-0.015	-0.011***
	(0.009)	(0.0193)	(0.018)
FA	-1.506**	-2.506	-5.881***
	(0.719)	(1.54)	(1.402)
Daily HV * 5	240.2	1394.3	1111.3
R-squared	0.0354	0.1208	0.1764
Observations	5,524,582	5,524,582	5,524,582

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Conjunctivitis means hospital visits with ICD-10 codes H10-H13; Injury means hospital visits with ICD-10 codes K00-K93; Digestive Diseases mean hospital visits with ICD-10 codes S00-T88;

that the effects of PM and PM information on different diseases are completely different from those on respiratory diseases.

Table 11 represents the change in the total effect of PM10 and FA by lag settings, and the changes are graphically shown in Figure 5. The table and figure indicate that the effects of PM10 are relatively stable even when the lag structure changes, whereas the effects of FA increase steadily.

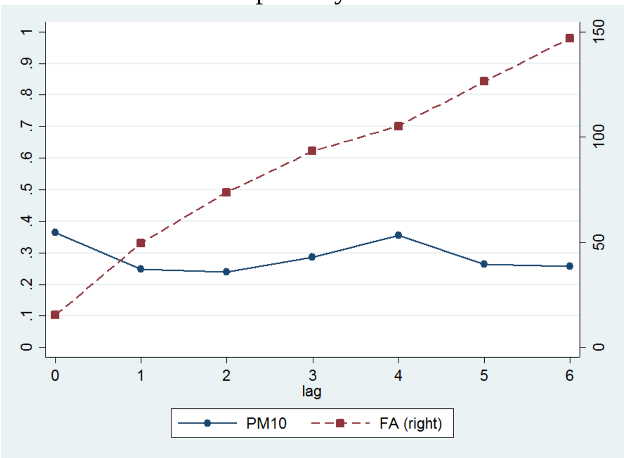
<Table 3.11> Effects of PM and Information on Hospital Visits with Various Lag Structures

	(1) Total		(2) Acute		(3) Asthma	
VARIABLES	PM10	FA	PM10	FA	PM10	FA
Lag 0	0.363***	15.34***	0.27***	11.45***	0.016***	-0.902**
	(0.033)	(2.639)	(0.028)	(2.264)	(0.006)	(0.458)
Lag 1	0.248***	49.74***	0.199***	35.33***	0.013*	-0.705
	(0.04)	(3.247)	(0.034)	(2.787)	(0.007)	(0.564)
Lag 2	0.239***	73.79***	0.203***	51.79***	0.021**	-0.114
	(0.047)	(3.697)	(0.040)	(3.174)	(0.008)	(0.642)
Lag 3	0.285***	93.29***	0.24***	64.58***	0.024***	0.031
	(0.052)	(4.132)	(0.045)	(3.547)	(0.009)	(0.717)
Lag 4	**0.355*** **	**105.2*** **	**0.295*** **	**70.97*** **	**0.0243** **	**0.0628**
	(0.0565)	**(4.505)**	**(0.0485)**	**(3.868)**	**(0.0097)**	**(0.782)**
Lag 5	0.263***	126.36***	0.228***	86.13***	0.024**	0.841
	(0.06)	(4.827)	(0.052)	(4.143)	(0.01)	(0.838)
Lag 6	0.258***	147.03***	0.229***	99.24***	0.028**	0.843
	(0.064)	(5.146)	(0.055)	(4.417)	(0.011)	(0.893)

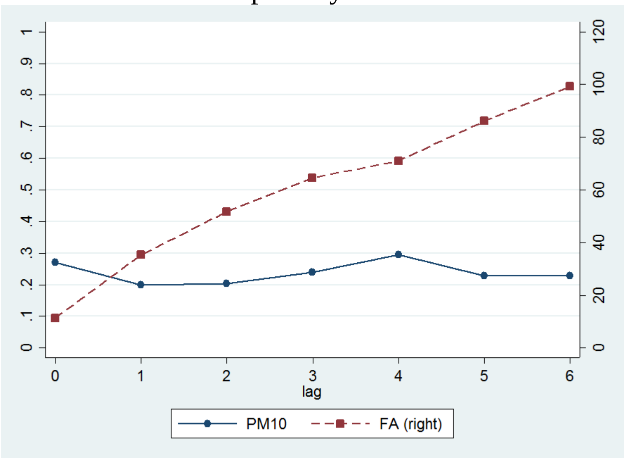
Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Contemporaneous and 4 lagged variables were used in the main analysis.

<Figure 3.5> Effects of PM and Information on Hospital Visits with Various Lag Structure

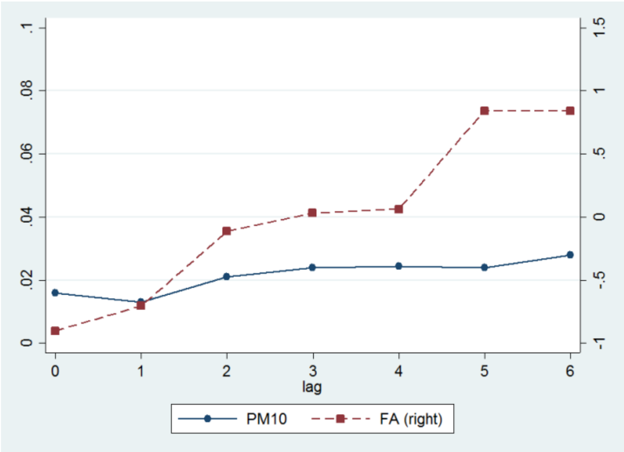
<Respiratory Total>



<Respiratory Acute>



<Asthma>



3.7 Conclusion

This study shows that air pollution information can increase the number of hospital visits. This finding represents that FA affects hospital use through other factors other than avoidance behavior. Forecasts for PM increase hospital visits due to respiratory diseases. I attempt to determine a possible mechanism through which FA increases hospital visits by adding the interaction terms of FA and PM10 or True FA variable. In this model, FA is found to increase the number of hospital visits regardless of the actual air quality. It means that information on PM influences hospital visits through other factors that are unrelated to health, such as sensitivity. The coefficient of the interaction term (FA×PM10) or True FA has the opposite direction to the FA effect and reduces the number of hospital visits. The additional effect can be interpreted as the effect of health improvement as a result of avoidance behavior.

This study demonstrates that previous research, which has interpreted that the influence of information on hospital use is caused only by avoidance behavior, can be incorrect. Specifically, information on air pollution may have affected hospital visits through channels other than avoidance behavior, such as sensitivity. Therefore, the information effects on the hospital use in previous studies may need to be interpreted not as avoidance behavior effects but as total effects of information.

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국문초록

대기오염에 대한 정보가 회피행동 및 병원이용에 미치는 영향

서울대학교 대학원

경제학부 경제학전공

유근식

많은 국가들이 대기오염에 대한 정책의 일환으로 정보를 제공하고 있다. 일반적으로 대기오염 정책은 배출원에 대한 규제를 의미하지만, 정보의 제공은 사람들의 행동을 변화시켜 국민건강을 지킬 수 있다는 점에서 정책으로써의 의의가 있다. 그리고 기술의 발달로 과거보다 더 많은 정보가 제공되고 사람들은 그 정보를 즉각적으로 습득할 수 있게 된 요즘, 정보는 과거 어느 때보다 중요해졌다. 하지만 아직도 정보가 사람들의 행동에 영향을 주고 있는지에 대한 충분한 연구는 부족한 실정이다. 따라서 이 학위논문은 미세먼지에 대한 정보가 사람들의 행동에 영향을 미치고 있는지 여부에 대해 다양한 관점에서 살펴보았다.

이 학위논문의 첫번째 챕터는 미세먼지에 대한 실시간 정보가 회피행동을 유발하였는지 여부를 살펴보고 있다. 실시간으로 정보의 제공과 습득이 이루어지는 환경에서 실시간 정보의 효과를 파악해 보는 것은 의미가 있다. 기존의 선행연구들은 사람들이 예보와 같은 정보를 바탕으로 행위를 조정하고 있음을 보인바 있지만 하지만 실시간 정보에 대한 분석은 아직 이루어지지 않았다. 이 챕터에서는 실시간 정보가 야구장 관중수에 영향을 주었는지를 분석하여 사람들이 실시간 정보에 반응하는지 여부를 살펴보았다. 분석의 결과 실시간 미세먼지 농도가 나쁨 또는 매우 나쁨인 경우 야구장 관중수가 약 7% 감소하는 것으로 나타났다. 그리고 이 효과의 크기는 미세먼지 예보가 관중수에 미치는 효과와 크게 다르지 않았다. 뿐만 아니라 실시간 정보의 효과는 2014년부터 나타난 것으로 분석되었는데 이는 사람들의 민감성 및 접근성의 증가로 인해 야기되었을 수 있다.

2번째 챕터는 야외근로자들이 미세먼지 정보에 반응하여 노동시간을 조정하고 있는지 여부를 살펴본다. 정보와 야외활동에 관한 선행연구들이 존재하지만 이 연구들이 살펴보고 있는 것은 대부분 야외 레저활동이며 야외근로자의 노동시간에 관한 연구는 존재하지 않는다. 분석의 결과 야외근로자들은 미세먼지의 예보와 실시간 정보에 반응하여 노동시간을 조정하는 것으로 나타났다. 노동시간의 조정은 출퇴근 시간의 조정을 통해 발생하며, 일을 하고 있던 중 정보에 즉각적으로 반응하여 노동시간

을 조정하지는 못하는 것으로 나타났다. 그리고 노동시간 감소는 대부분 농림어업 종사자로부터 나타나고 있으며, 출퇴근시간 조정에 대한 권한이 있거나, 자영업자(고용주)인 경우에만 노동시간 조정이 가능한 것으로 분석되었다.

3번째 챕터는 미세먼지에 대한 예보가 사람들의 병원 방문에 미친 영향력에 대해 분석하고 있다. 분석의 결과 미세먼지가 나쁨 또는 매우나쁨으로 예보되는 경우 병원 방문자수가 증가하는 것으로 나타났다. 이는 정보의 제공이 회피행동을 유발하며 그 결과로써 입원과 같은 병원이용을 감소시킨다는 기존 선행연구들의 결과와 반대된다. 이 연구의 결과는 대기오염에 대한 정보가 회피행동 뿐만 아니라 민감성과 같은 다른 경로를 통하여 병원 방문에 영향을 줄 수 있고, 결과적으로 병원 방문을 증가시킬 수 있음을 보여준다.

주요어: 대기오염, 미세먼지, 예보, 실시간 정보, 회피행동, 건강, 노동시간, 병원이용

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