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Effects of particulate matter (**PM**$_{10}$) on tourism sales revenue: A generalized additive modeling approach

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ABSTRACT

This study investigates the effects of PM_{10} concentration on tourism and recreational sales revenues through the case of Seoul, South Korea, from 2015 to 2017, using a twofold generalized additive modeling strategy. The finding confirms that PM_{10} exerts differing influences on such sales revenue by level. People begin to alter their consumption only after the PM_{10} level becomes worse than the "Bad" level. In the case of the present day's PM_{10} level, up to 41 μg/m^3 and 109 μg/m^3, respectively, each 10 μg/m^3 increase is associated with an incremental increase of sales revenue by 3.8% and by 0.3%; thereafter, the same increase is associated with an incremental decrease of sales revenue by −1.2%. A similar pattern is observed for the two-day lag of the PM_{10} level. Well-balanced standards should be sought to ensure a maximum level of health safety and not depress tourism businesses and industries.

1. Introduction

Particulate matter (PM) refers to particles suspended in the air. It is composed of liquid and solid components ranging widely from chemicals, elemental carbon, and mineral and metals to organic or biological particles (World Health Organization (WHO), 2016; WHO, 2013). In general, PM is categorized into two classes based on size; the coarser category, called PM_{10}, has a maximum aerodynamic diameter of 10 μm, while the maximum diameter of the finer category, called $PM_{2.5}$, is 2.5 μm (Kim, Kabir, & Kabir, 2015). Anthropogenic sources of PM include combustion of fuel for industrial and household uses and dust-generating operations at manufacturing, construction, transportation, and agricultural sites. Natural sources include natural hazards such as volcano eruptions, dust storms, and forest fires (Kim et al., 2015; WHO, 2013).

The increasing concentration of PM and its harmful effects on human health have brought worldwide attention. Exposure to PM has been recognized as a direct or indirect cause of premature or excess mortality (Atkinson, Fuller, Anderson, Harrison, & Armstrong, 2010; Hu et al., 2017a,b; Pascal et al., 2013). The commonly vulnerable parts of the human body are the cardiovascular and respiratory systems (WHO, 2006; Pascal et al., 2013; Garrett & Casimiro, 2011): approximately 3% of cardiopulmonary and 5% of lung cancer deaths have been attributed to exposure to PM globally (Cohen et al., 2004). Consequently, reduction of PM concentration would lead to increasing life expectancy between 0.35 and 1.37 years per 10 μg/m^3, depending on the country considered (Krewski, 2009).

Research on other impacts of PM has been less extensive than that conducted on the human health effects. The revealed economic impact of air pollution has not been comprehensive; rather, it is limited to the welfare costs incurred as a result of damaged health, such as healthcare costs and hospital expenditure, the value of human life, and the loss of labor productivity (Matus et al., 2012; Vrontisi, Abrell, Neuwahl, Saveyn, & Wagner, 2016). Plant physiologists have documented the harmful effects of gaseous pollutants, such as ozone, nitrogen dioxide, and sulfur dioxide, on crops and forests. Similar effects have been observed for PM; it would acidify soil and water sources and reduce the fertility of agricultural land (Agrawal, Rajput & Bell, 2003; Honour, Bell, Ashenden, Cape, & Power, 2009; Sett, 2017).

The impact of PM on other economic sectors, especially those involving human behaviors and activities, are less well studied. Tourism is one sector in which such research has been more frequently conducted, and it has become evident that tourists perceive PM as posing potential health risk or reduced utility and alter their travel plans (Looi & Anaman, 2000; Poudyal, Paudel, & Green, 2013; Qi, Gibson, & Zhang, 2009; Zhang, Zhong, Xu, Wang, & Dang, 2015). From this relevant literature, we can easily deduce that tourists and residents might alter their detailed plans and schedules and refrain from going out on a day of high PM concentration. This behavioral pattern would affect their consumption activities and perhaps lead to a significant economic

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disadvantage for retailers. While health problems occur occasionally and for a specific portion of the population, behavioral changes are more frequent and more sensitive reactions to PM among the general population. In spite of this magnitude, however, questions remain about how PM levels influence consumption patterns in the tourism and recreational sectors in an urban context.

Against this backdrop, we investigate the relationship between retail revenues and the level of PM_{10}, in the context of Seoul, South Korea for about two years from 2015 to 2017, using the time-series Generalized Additive Model (GAM). This research is the first attempt to decipher the effect of PM on tourism and the recreational retail industry. The level of PM in Korea has been continuously high, ranked as the first among 34 OECD member countries as of 2015 (Ministry of the Environment, 2016), or fifth among 178 countries in the world as of 2018 (Yale Center of International Law & Policy, 2018), justifying the site selection. We limited our analysis to restaurants and recreational businesses. Those businesses are the most ubiquitous retail trades in Seoul, and their sales revenue most promptly responds to various external factors beyond managerial control, such as market trends, government policies, seasonality, weather, and perhaps air quality (Camillo, Connolly, & Kim, 2008; Parsa, Self, Njite, & King, 2005). We excluded the accommodation businesses from the analysis, since daily PM level is almost unpredictable and would not prevent tourists from coming to the study site. Once they visit the city, they must pay for accommodations.

The rest of the text is structured as follows: the next section provides a brief background of PM issues in Seoul, South Korea and a review of PM-related studies. Analytical design and method are explained, followed by the results. The conclusion discusses policy implications.

2. Background and literature review

2.1. PM in Seoul, South Korea

In South Korea, the government began recognizing PM as one of the main air pollutants and established quality standards in 1995 (National Institute of Environmental Research, 2013). In most of the cities, the annual average levels of PM_{10} and $PM_{2.5}$ have substantially exceeded what is recommended by WHO: 20 and 10 μg/m^3, respectively. For example, in the seven major cities, such levels were 44.43 and 24.29 μg/m^3, respectively, in 2016 (National Institute of Environmental Research, 2017). Compared to other world cities, Seoul's PM level is higher by a large margin. As of 2014, the annual average PM_{10}level of Seoul is 46 μg/m^3, which is 1.5, 2.1, and 2.3 times higher than that of Los Angeles, Paris, and London, respectively. The reasons may be found in the high population density and the intense urbanization/industrialization that Korean cities have undergone. In addition, high atmospheric pressure formed around the Korean peninsula causes air congestion and accumulates PM in the region (Ministry of the Environment, 2016). Particularly in the Asian dust season, mainly in winter and spring, movement of yellow dust from the central Asian deserts is recognized as a major source of PM. Along the length of that long-range transportation, particles larger than 10 μm are dropped near the origin and those of smaller size continue farther to drop in Korea (Chun, Boo, Kim, Park, & Lee, 2001; Park et al., 2005). This pattern has substantially exacerbated the air quality problems of the country (Ahmed, Shon & Song, 2015).

In response to nationwide concerns, the Ministry of the Environment began reporting the level of PM through various media, such as TV, radio, websites, mobile applications, and text messages to inform citizens and minimize their exposure. Many people check the level of PM using smartphone applications (Ministry of the Environment, 2016). For PM_{10}, four grades are reported; Good (from 0 to 30 μg/m^3), Normal (from 31 to 80), Bad (from 81 to 150), and Very Bad (over 151 μg/m^3). When the levels exceed 150 μg/m^3 or 300 μg/m^3 continuously for more than two hours, public agencies and municipalities issue a watch or an alert, respectively. They also recommend reducing or avoiding outdoor activities in areas of high pedestrian and traffic volume. Public outdoor sports facilities are closed or posted with warning notices to discourage use. Schools are allowed to cancel physical education classes or shorten class time at their discretion (Ministry of the Environment, 2016).

2.2. Effects of PM

Negative effects of PM have been studied, and a large portion of the research investigates effects on human health. Two main strands constitute the majority of the research: cohort studies tracing the effects of long-term exposure and cross-sectional studies estimating the short-term effects.

For assessing the long-term effects, it is common to use hazard modeling with the number of deaths or disease outbreaks as the dependent variable. A 12-year cohort study, using a measured value of PM from the nearest monitoring station, reveals that the 3.4%–6.0% rise in lung cancer mortality is explained by the increment of PM_{10} by 10 μg/m^3 in China (Chen et al., 2016). A 19-year study in China has found similar results, using annual average levels estimated through remote sensing and global chemical transport models, in that the same increase of $PM_{2.5}$ is associated with the hazard ratio of 1.06 for urbanites (Guo et al., 2016). Seventeen cohort studies for nine European countries with an average study period of 12.8 years, using measured PM levels with nine monitoring stations and addressing spatial variation among regions with land use regression, also suggest a statistically significant relationship between the PM_{10} and lung cancer incidence with a hazard ratio of 1.22 (Raaschou-Nielsen et al., 2013). Another meta-analysis of 22 European cohort studies, following up to a 13.9-year period, suggests an increased hazard ratio of 1.07 per 5 μg/m^3 increase of $PM_{2.5}$ (Beelen et al., 2014). The result of a 25-year follow-up study conducted in France agrees with the aforementioned studies, in that hazard ratio of 1.09 for non-accidental mortality is associated with a PM_{10} increment of 2.2 μg/m^3. In this analysis, the CHIMERE chemistry-transportation model was used to recalculate the initial pollution level at 50-km resolution for European scale to 10-km resolution national scale, then mesh-refinement was applied to scale it down to 2-km resolution, using land cadaster and road network data (Bentayeb et al., 2015).

In assessing short-term effects, the generalized linear model (GLM) and GAM have frequently been used to address the distinct relationships between the count-based health-related dependent variables and the independent variables, which are convoluted and nonlinear in their effects (Dominici, McDermott, Zeger, & Samet, 2002). The dependent variables are more diverse, and include the count of disease outbreaks, the number of hospital admissions, the rates of mortality and morbidity, and life expectancy. Studies using GAM with Poisson distribution, with measured air pollution data from local monitoring stations, found that 10 μg/m^3 increases in PM_{10} and $PM_{2.5}$ are associated with the rise of mortality by 7.2% and 5.1%, respectively, during the summer in nine French cities (Pascal et al., 2014). A study in Lisbon, Portugal, using measured air pollution data from the Portuguese Environmental Agency, showed a 2.39% incremental increase of elderly cardiovascular mortality with a 10 μg/m^3 increase of $PM_{2.5}$ (Garrett & Casimiro, 2011). Studies often consider a time lag between the day of a high PM level and such health effects. A study investigating Austrian urban and rural areas, using measured air pollution data from one monitoring station at each site, suggested a 4.2% incremental increase per 10 μg/m^3 in the number of elderly persons admitted to hospitals due to respiratory symptoms after 2 and 10 days of high PM_{10} (Neuberger et al., 2004). A spatial analysis, conducted in Taiwan, reaffirmed the aforementioned results, in that an area that underwent a typhoon-triggered landslide had a significantly higher prevalence of pediatric pneumonia (by at least 2%) than an area of different conditions (Tu & Chen, 2017).

Beyond epidemiology, studies of PM effects have looked at tourism. Perceived threats to health or reduced satisfaction with travel could affect tourists' intention to visit certain sites. A time-series analysis on Great Smoky Mountain National Park, U.S., suggested that visibility conditions caused by air pollution influenced the number of visitors. Consequently, a 10% improvement of visibility would attract one million more visitors a year (Poudyal et al., 2013). Another time-series analysis, using daily averaged, measured pollution level data including PM_{10} and $PM_{2.5}$, analyzed with a Markov regime-switching model, suggested that the number of travelers to Sun Moon Lake in Taiwan decreased by 25,725 people a month for days of "Bad" air quality in the peak season (Chen, Lin, & Hsu, 2017). A study conducted in China, using a panel analysis of the number of tourists and the daily air-quality measurements in 11 cities, suggested that low air quality in the place of origin increased outbound tourism demand (Wang, Fang, & Law, 2018). In some studies, the basic premise for the relationship between the PM and outcome is reversed; it is believed that tourism activities are one of the sources of high PM concentration. Thus, on a day with a large number of tourists, the PM level becomes higher, rather than higher concentration of PM reducing the number of tourists. Using GAM with daily stock of people and observed value of air quality from two monitoring stations from the two cities, a study revealed that a 1% increase of tourists explains up to a 0.45% incremental increase of PM_{10} concentration level in Mallorca, Spain (Saenz-de-Miera & Rosselló, 2014).

The level of PM also affects other types of outdoor activities. A multilevel study investigating adults in the U.S. and linking their physical activities and the level of $PM_{2.5}$ proved that a 1 $\mu g/m^3$ increase in monthly average PM was associated with an increase of the odds of physical inactivity by 0.46%. To acquire a country-level PM concentration for nine years, the authors used modeled data using ground-level observed value and satellite imagery (An & Xiang, 2015). Using personal data collected from mobile exercise applications and multivariate analyses of variance, a study confirmed that a smaller number of people exercised on a day of bad air pollution, while the average duration of the exercise was unaffected for people who were already out for exercise (Hu et al., 2017a,b). A panel study conducted in Beijing, China, for college students concurred with the other studies, in that a $PM_{2.5}$ concentration higher by one standard deviation was associated with decreased outdoor activities, such as 7.3 min less walking, 10.1 min less vigorous exercise, and an increase of sleeping time by 1.07 h per week. The $PM_{2.5}$ level was measured at the monitoring station in the U.S. Embassy in Beijing (An & Yu, 2018).

2.3. PM data

The aforementioned literature necessitates air-quality data accurate enough to assess effects on health conditions on human behaviors. Four types of data-producing procedures have been widely used for exposure assessment: 1) measured data, 2) spatial interpolation, 3) regression modeling, and 4) air-quality or dispersion modeling.

Observed values have been most commonly employed for such studies (Jiang & Yoo, 2018; Sarnat et al., 2010). If monitoring networks are dense, a higher spatiotemporal resolution is consequently available even without modeling simulations and interpolations. In particular, near the monitoring stations, a measured value best reflects the actual exposure to air pollution (Bravo, Fuentes, Zhang, Burr, & Bell, 2012; Sarnat et al., 2006). The definition of "near" varies among studies, but it generally means locations where the monitored level of the pollutants extends homogeneously. Spatial homogeneity is expected in the distribution of particles rather than gaseous pollutants, in areas with regional secondary sources (Bell, Ebisu, & Peng, 2011; Jiang & Yoo, 2018). Ozone and PM are considered spatially homogeneous pollutants, but the exact extent of homogeneity has not been confirmed (Lippmann, Ito, Nadas, & Burnett, 2000). Röösli et al. suggested an extremely low spatial variability of PM_{10} in one of the urban areas in Swaziland, called Basel, monitored at 6 sites within its 36 km^2 area (2000). Sarnat et al. suggested that, in an urban context, associations between exposure and a health outcome would be robust if the distance between the monitoring station and the subject was less than 20 miles (2010). In Korea, spatial heterogeneity of PM has not been observed if the maximum distance from a monitoring station to a subject is 30 km (Son, Bell, & Lee, 2010). For the same reasons, exposure assessment farther from the monitoring station would be less accurate.

Second, using spatially interpolated data has been recommended when a monitoring network has a limited spatial and temporal coverage (Holland et al., 2003, pp. 31–35; Wong, Yuan, & Perlin, 2004). The idea of this strategy is to assign a value to a location without a measured record using average weighted values measured from neighboring stations. Nearest-neighbor, inverse-distance weighting (IDW) and kriging have been often used and compared. The definition of neighbors and the weighting schemes differ among methods (Wong et al., 2004; Xie et al., 2017). While the performance of such methods does not differ tremendously (Son et al., 2010; Wong et al., 2004), IDW and kriging are the most frequently used due to their sophistication in assigning spatial weights (Xu et al., 2014). In the former, weights are defined as an inverse function of the distances between the existing monitoring stations within a search radius, while in the latter weights are defined by the distance as well as the spatial autocorrelation (Ellen, 2004; Xie et al., 2017). Some researchers chose IDW over kriging (Azpurua & Ramos, 2010; Beckerman et al., 2012), and others did the opposite (Finkelstein, Jerrett, & Sears, 2005; Künzli et al., 2004) because performance differs largely by the local contexts (Xu et al., 2014). The disadvantage of this approach is the lack of consideration of environmental factors such as land use, traffic features, and the meteorological conditions of the surrounding areas (Xie et al., 2017).

Third, regression, especially land use regression (LUR) is a statistical strategy under an assumption that the local concentration of pollutants is affected by the locational characteristics (Marshall, Nethery, & Brauer, 2008; Xie et al., 2017). LUR has gained increasing popularity for studies of long-term health effects of air pollution in complex urban or neighborhood settings (Gulliver, de Hoogh, Fecht, Vienneau, & Briggs, 2011). To achieve modeling superiority in addressing detailed locational conditions, LUR requires intensive geographic data. Also, due to the multiple regression technique that LUR is based on, a small sample size or violations of the assumption of linearity would lead to biased results (Xie et al., 2017).

Last, atmospheric chemistry and transport models are used in predicting concentrations of pollutants. One of the most frequently used models is three-dimensional Community Multi-scale Air Quality (CMAQ), developed by the U.S. Environmental Protection Agency (EPA) in the 1990s. CMAQ simulates emission, transformation, and transportation of several air pollutants, such as ozone, nitrogen oxides, and PM (De Visscher, 2013); it thus requires meteorological, emission, and chemical transport modeling components coupled in system (U.S. EPA, n.d.; Marshall et al., 2008). The model produces grid-based predictions at various resolutions, ranging from 2 to 36 km, but there is no consensus on which performs better in assessing exposure. The strength of the method lies in its ability to consider weather conditions and to simulate interactions of multiple air pollutants simultaneously (Jiang & Yoo, 2018; Thompson & Selin, 2012).

3. Analytical design

3.1. Research questions

This study investigates whether (and if so, how much) the level of PM_{10} affected the sales revenue of restaurant and recreational businesses in Seoul, South Korea, from April 2015 to February 2017, using time-series GAM. We hypothesize that on a day of a higher PM_{10}level, people would reduce outdoor activities, which might result in less consumption at recreational and food retail business establishments.

3.2. Data and sample

The study site is in Seoul, the capital of South Korea. More specifically, we focused on 500-m buffer areas surrounding the PM monitoring stations in the city. One or two stations are located in each of the 25 wards, for a total of 39 (Air Korea, n.d.). The average distance between two neighboring stations is 2050 m, and the average coverage of a station is 11.69 km^2. We used measured data under the assumption that people tended to rely on the PM level reported at local monitoring stations when deciding whether they would refrain from going out.

In Korea, two datasets have been mainly used to draw the attention of the general population to the issue of PM level. For PM forecasting on TV or radio, modeled values (predicted value) are used. An air quality or dispersion modeling system called Korean Air Quality Forecasting System (KAQFS) is used to make predictions for four times each day (5 a.m., 11 a.m., 5 pm, and 11 pm), covering two consecutive days. While the spatial resolution is 3 km for Seoul Metropolitan Area, the forecasting is made with values aggregated at the city level (Anitech, n.d.). For the warning system, measured values are used. The measured value is aggregated to an average for a city or province, since those jurisdictional units announce the warning across the board. Finally, for real-time information provision, available from smartphone applications and the website of the Korean Environment Corporation, the measured data is used without interpolation (Air Korea, n.d.).

The measured data may be the best choice for our study's purposes, because it is reported to and understood by the general public through the aforementioned sources. Real-time information especially might be frequently accessed by the people. As of the end of 2017, 96% of the entire population in South Korea owned a smartphone (Poushter, Bishop & Chew, 2018), and the most frequently downloaded application in Korea is one related to PM (Lee, 2018). Also, measured data has the most fine-grained spatial and time resolution.

However, we did not rule out the possibility that people indeed reacted to the actual level of PM physically, as well as to the reported PM psychologically, and thus we limited our site to the 500-m buffer around the monitoring stations (Fig. 1). The area of homogeneous pollutant level varies by local contexts, as mentioned in the literature review section, and in some cases locations just 2 km apart display a substantially different air pollution condition (Wilson, Kingham, & Sturman, 2006). Conservatively, we limited the area of investigation to the 1000-m radius around each monitoring center and conducted sensitivity analyses for the four options 1000 m, 700 m, 500 m and 300 m. While the non-parametric PM_{10} plot of the first three different radii suggested pretty similar results, that of the 1000-m buffer displayed a different trajectory from the rest. We concluded that the customers' response to PM is homogeneous up to a 700-m distance. The fit is better with a smaller buffer radius; however, a larger buffer embraces more diversified food and recreational business establishments. Considering this trade-off, we chose the 500-m buffer.

The first primary dataset is the record of retail revenues collected by SK Telecom Geovision, a private telecommunication company. The data include the hourly transaction amounts of one major credit card for which the market share has not changed drastically within a short time. From this dataset, we used sales revenues incurred in restaurant and recreational business establishments in the aforementioned 500-m buffer areas around the stations. Recreational businesses include indoor and outdoor game rooms, sports facilities, museums, auditoriums, and theaters.

The second primary dataset is the record of air quality measured at 39 stations in Seoul, collected by Korea Environment Corporation. The air-quality data comprises hourly average levels of PM_{10}, along with ozone (O_3), nitrogen dioxide (NO_2), carbon monoxide (CO), and sulfur dioxide (SO_2). We also included weather information because of its effects on shopping activities as well as its interactive effects on PM. We obtained weather information, measured at 29 stations in Seoul, from the Korea Meteorological Administration. The weather data comprised hourly averages of temperature, wind speed, and precipitation.

4. Analytical plan and methods

4.1. Generalized additive model

The GAM is an extended version of the GLM to achieve precise predictions. Like the GLM, the GAM links the non-normal dependent variable with a linear combination of covariates, some or all of which are replaced by non-linear and non-parametric smooth functions. To enable estimations of parameters related to the question predictors, we can additionally mix those with parametric model terms (Wood, 2006).

The link function transforms the dependent variable in order to linearly relate it to the set of covariates; consequently, its type is determined by the probability distribution of the dependent variable. For continuous dependent variables, Gaussian, inverse Gaussian, and gamma distributions have been frequently assumed, each of which specifies a unique relationship between the mean and variance. The associated link functions are identity, log, inverse, or inverse-square (Ng & Cribbie, 2017).

The non-parametric function, also called the smooth function, is a flexible specification of a relationship between the dependent variable and the covariates without parametrization (Neuberger et al., 2004; Wood, 2006). Diverse types of smoothers are used to form the smooth function, among which two are tried here: thin plate regression splines and cubic regression splines. The former have been frequently chosen for their advantages in minimizing squared residuals and increasing precision in predictions. In addition, in cases without clear prior knowledge of their functional form and knot locations, this type finds an optimal solution balancing the fidelity to the data and smoothness of the function. The cubic regression spline, on the other hand, assumes a modest number of evenly distributed knots throughout the value of covariates, and it thus can confer advantages in computation (Wood, 2006).

4.2. Models and variables

We specify GAM models with gamma distribution and log link function. The spatial analytical unit is the smallest census unit, called *Soguyok* in Korean, and the time resolution is a day. The dependent variable is the total daily sales revenue of restaurants and recreational businesses incurred in the study sites, in Korean won, aggregated by the analytical unit (*Sales_Rev*). We excluded census units that contained fewer than 20 business establishments, as those are possibly in close proximity to residential areas, and using them would not involve substantial travel. The final sample size was 319,958. The revenue is skewed positively and has a variance increasing along with the value, which can be approximated with a gamma distribution (Fig. 2(1)). The main question variable is the daily maximum level of PM_{10} in increments of 10 µg per cubic meters, 10 µg/m^3 (PM_{10}). This level also follows a gamma distribution (Fig. 2(2)).

We also consider the time lags between the dependent and question variables. The sales revenue displays a strong weekly cycle, and cyclical changes might be falsely associated with the PM level. Therefore, we first excluded lags longer than seven days. We further excluded fourth- to sixth-lags due to their remoteness from the current time. It is hard to believe that bad air quality of four to six days ago would affect today's recreational and dining activities. We selected the first- and second-order lags for their relatively stronger serial correlation with the current level of PM, 0.411 and 0.251, respectively. Then we further excluded the first lag due to the lack of explanatory power in the modeling process. All of these preliminary analytical results are available upon

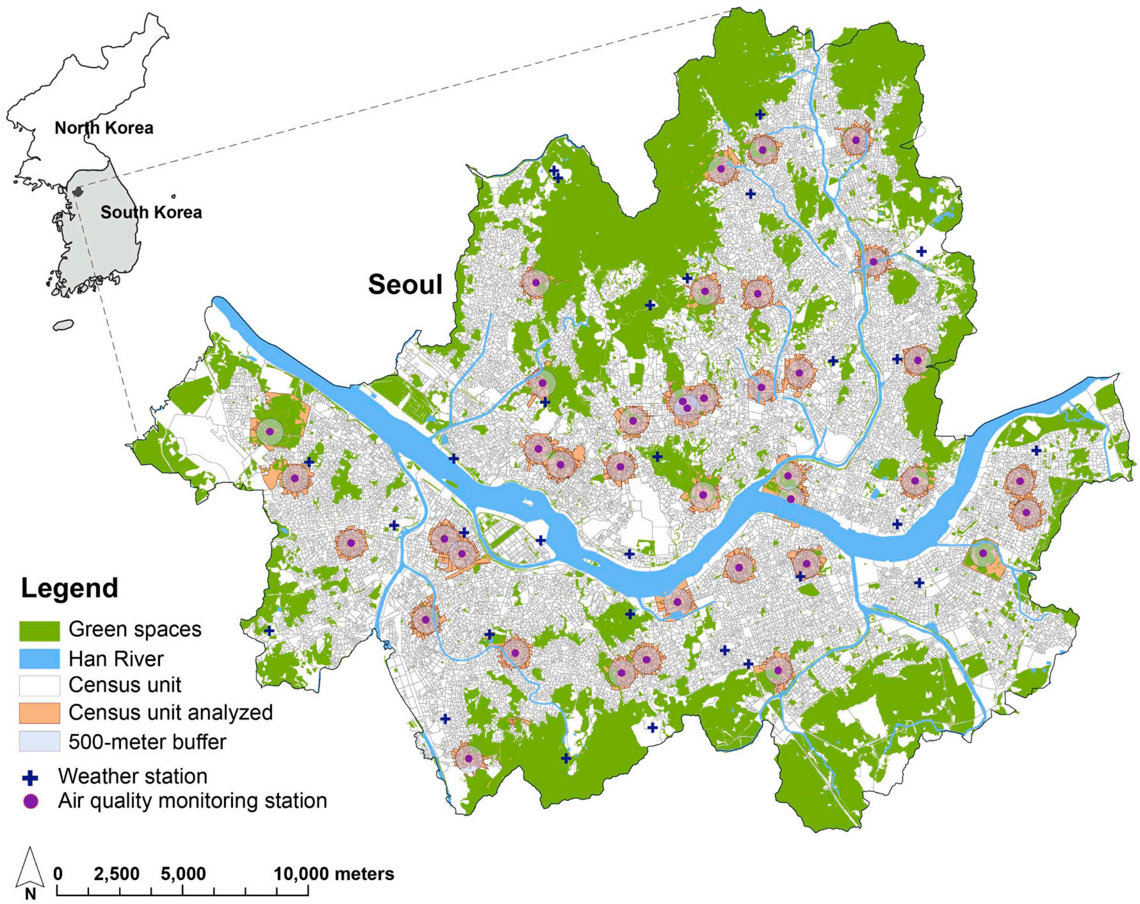

Fig. 1. The study site, showing the census units in the analyses and locations of weather and air-quality monitoring stations.

request from the corresponding author.

Other air pollutants considered together are ozone (PLT_1; ppm), sulfur dioxide (PLT_2; ppm), and carbon monoxide (PLT_3; ppm) because some of them are known as precursors of PM formation and exacerbate poor air quality by interactions with PM. Nitrogen dioxide is excluded for its strong correlation with carbon monoxide (0.705) and sulfur dioxide (0.577). Weather conditions included in the analysis are daily average temperature (WTH_1; Celsius), daily average wind speed (WTH_2; m/s), and total precipitation in a day (WTH_3; mm). For a time indicator, we specified the cumulative number of days from April 1, 2015, to February 28, 2017 (*TIME*). Also included are some of the widely known seasonality and weekly sales patterns as dummy variables: the day of a week from Thursday to Tuesday (DAY_1 to DAY_6; Wednesday is the reference) and the season of each year (spring, March to May; summer, June to August; fall, September to November; and winter, December to February; $TRND_2$ to $TRND_7$). To control for the retail location

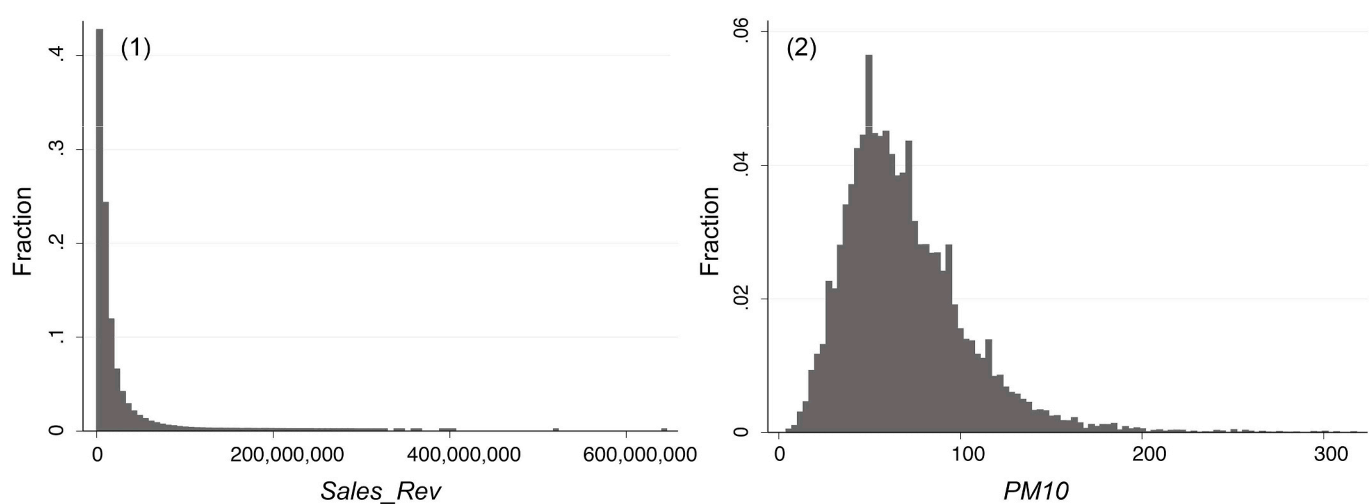

Fig. 2. Distribution of the PM concentration and sales revenue.

characteristics of each area defined by the 500-m buffer around the monitoring stations and the scale effects of retail agglomerations, we specified a variable indicating the total number of restaurants measured every month (*NUM_ REST*) as a proxy. Descriptive statistics are presented in Appendix A.

Without certainty about the nature of the relationships between PM_{10}-related variables and sales revenue, we adopted a twofold modeling process. In the first preliminary modeling, we relaxed linearity assumptions and specified PM_{10}-related variables as flexible smooth functions. In the second modeling, after gaining clues about the nature of the relationship, we constructed a parametric form with PM-related variables to interpret the magnitude and direction of their effects on the dependent variable. The air pollutant and weather variables were treated as smooth functions for the same reason but without further parametrization in the second modeling process to keep their roles as covariates. While the time variable is also specified as a smooth function, the day of a week and seasonality are also included in the model as dummy variables. The final two modeling strategies are presented below as Models (1) and (2); three versions of each are fitted using differing smoothers.

For a census unit (i) around the air pollution monitoring station (j) or weather station (h) and time (t),

Model (1)

$$\begin{aligned}\ln(E(Sales\_Rev_{ijt})) = {} & \beta_0 + f_1(PM_{10\,jt}) + f_2(L2\_PM_{10\,jt}) + \sum_{k=1}^{4} f_{k+3}(PLT_{kjt}) \\ & + \sum_{k=1}^{3} f_{k+7}(WTH_{kht}) + f_{11}(TIME_t) + \sum_{k=1}^{6} \beta_k DAY_{kt} \\ & + \sum_{k=1}^{7} \beta_{k+6} SEASON_{kt} + \beta_{14} NUM\_REST_{ijt}\end{aligned}$$

$Sales\_Rev_i \sim Gamma$

Under Model (1), Model (1-1), Model (1–2), and Model (1–3) are fitted using the thin plate regression spline smoother, cubic regression spline with 10 knots, and cubic regression spline with 20 knots, respectively.

Model (2)

$$\begin{aligned}\ln(E(Sales\_Rev_{ijt})) = {} & \beta_0 + \beta_1 PM_{10\,jt} + \beta_2 PM_{10}\_HIGH_{jt} + \beta_3 PM_{10\,jt} * PM_{10} \\ & \_HIGH_{jt} + \beta_4 L2\_PM_{10\,jt} + \beta_5 L2\_PM_{10}\_HIGH_{jt} \\ & + \beta_6 L2\_PM_{10} * L2\_PM_{10}\_HIGH_{jt} + \sum_{k=1}^{4} f_{k+3}(PLT_{kjt}) \\ & + \sum_{k=1}^{3} f_{k+7}(WTH_{kjt}) + f_{11}(TIME_t) + \sum_{k=1}^{6} \beta_k DAY_{kt} \\ & + \sum_{k=1}^{7} \beta_{k+6} SEASON_{kt} + \beta_{15} NUM\_REST_{ijt}\end{aligned}$$

$Sales\_Rev_i \sim Gamma$

Under Model (2), Model (2-1), Model (2-2), and Model (2–3) are fitted using the thin plate regression spline smoother, cubic regression spline with 10 knots, and cubic regression spline with 20 knots, respectively.

5. Results

5.1. PM as smooth functions

The fit statistics of the three models in Model (1) are presented in Table 1.

The results suggest that the model with a 20-knot cubic regression spline smoother (1–3) has the highest explanatory power (the highest deviance explained) and the best fit (the lowest AIC and GCV score) among the three, but it consumes the highest number of degrees of freedom, making the smooth function less legible and interpretable. The thin plate regression spline model (1-1) is ranked in the middle, and the model with a 10-knot cubic regression spline smoother (1–2) is the worst in terms of both criteria. Considering the small difference of the fit scores between Models (1-1) and (1–3) and the obvious advantages that come from the parsimonious model specification, we selected the thin plate regression spline smoother for the final model.

The results suggest non-linear relationships between the PM-related variables and the response variable. For the current level of PM_{10}, the relationship seems roughly like a cubic curve, although the degree of freedom is 6.72, representing that the curve wiggles more than a normal cubic curve (Fig. 3(1)). Sales revenue increases rapidly along with the increment of PM_{10} until the first inflection point, at around 41 μg/m^3, and it then again increases thereafter with a smaller rate. After 109 μg/m^3, revenue begins to decrease until 245 μg/m^3 and then curves up again. The 95% confidence interval (CI) becomes quite wide around 200 μg/m^3, calling the precision into question.

The two-day lag of PM_{10} has a similar but relatively less drastic effect on the revenue (Fig. 3(2)). The relationship could also be illustrated as a cubic curve, whereby the level of past PM_{10} is positively associated with sales revenue up to 121 μg/m^3, followed by the negative relationship up to 227 μg/m^3. Sales revenue then increases with a decreasing rate. However, as in the previous result, as the 95% CI grows wider and contains the zero point, the statistical significance of the result becomes uncertain for this segment.

5.2. PM as parametric terms

In the second model, we constructed parametric functional components with the PM-related variables and included them in the model. The trajectory of the relationship revealed in the previous models led us to explore a linear function with interaction terms at the prominent knots. As before, the three modeling options have been tried; for the same reasons, we select Model (2–1) as the final choice. The results are presented below in Table 2.

First, for the current effects, the PM_{10}, interaction, and binary terms for the point 41 and 109 μg/m^3 have a statistically significant relationship with the response variable at the 0.1 percent level while those related to the point 245 μg/m^3 do not, confirming the effect of PM changes at the first two junctions. When the PM_{10} level is lower than 41 μg/m^3, a 10 μg/m^3 increase of the daily highest PM_{10} is associated with an incremental increase of sales revenue by 3.8% (*Coeff. = 0.038, p = 0.00*), controlling for the factors of business, time, weather, and other pollutants. The increasing rate is much reduced on the segment between 41 μg/m^3 and 109 μg/m^3, in that every 10 μg/m^3 increase of

Table 1
Fit statistics of the three GAM models with PM_{10} variables as smooth functions.

Smoothers	*df*	Akaike Information Criterion (AIC)	Generalized Cross Validation score (GCV)	Deviance Explained
Model (1–1) Thin plate regression spline	86.077	11,062,709	0.903	33.9%
Model (1–2) Cubic regression spline (10 knots)	83.073	11,062,723	0.903	33.9%
Model (1–3) Cubic regression spline (20 knots)	166.679	11,062,168	0.902	34.1%

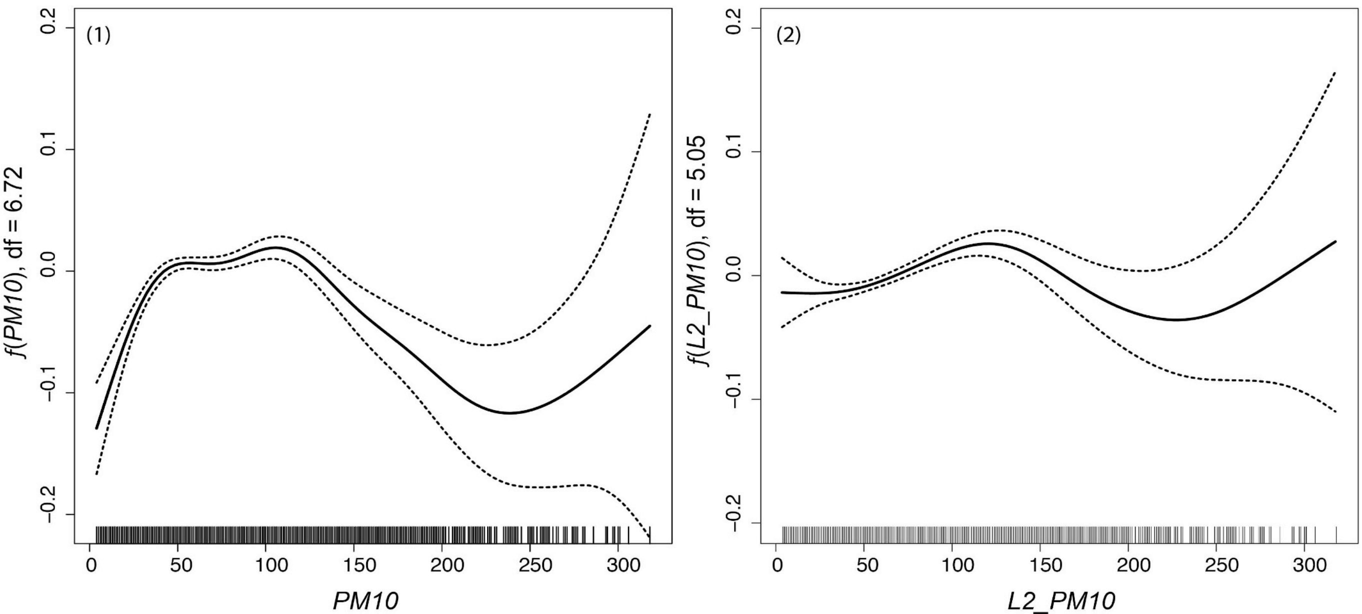

Fig. 3. Estimated smooth function and 95% CI of the current (PM_{10}) and past PM ($L2\_PM_{10}$) on retail revenue.

the daily highest PM_{10} is associated with an incremental increase of sales revenue by 0.3% (*Coeff. = 0.035, p = 0.00;* 0.038–0.035).

It is not intuitively clear why increasing revenues are associated with the increasing levels of PM. One plausible reasoning might be that the influences between those two variables are reciprocal. The increment of revenue might be a consequence of increasing PM_{10} levels while the latter is also a consequence of the former. Many studies including Saenz-de-Miera and Rosselló (2014 & 2013) corroborate this argument; a large volume of people contributed to the higher concentration of PM_{10}. Regardless of the applicability of the argument in this specific case, we can infer that, at least on average, people are indifferent about the PM_{10} concentration until the level gets worse than the "Bad" category (from 81 to 150 μg/m^3). This relationship changes after the PM_{10} level exceeds 109 μg/m^3. In that range, every additional 10 μg/m^3 increase of PM_{10} is associated with an incremental decline of sales revenue by −1.2% (*Coeff. = 0.05, p = 0.00;* 0.038–0.050). It can be inferred that from this point on, people begin to react and refrain from going out to eat and engaging in recreational activities.

Second, for the effect of PM_{10} two days prior to the sales revenue, a consistent pattern is observed, as previously. The past daily maximum PM_{10} level, interaction, and binary terms for the point 121 μg/m^3 have a statistically significant relationship with the response variable at the 0.1 percent level, while those factors related to 227 μg/m^3 do not, also confirming that the past PM_{10} exerts differing influences on sales revenue according to PM levels. Every 10 μg/m^3 increase of daily highest PM_{10} level of the two preceding days is associated with a 0.5% (*Coeff. = 0.005, p = 0.00*) higher sales revenue of today. When the daily highest PM_{10} level is over 121 μg/m^3, every 10 μg/m^3 increase of the PM_{10} level is associated with a −1.2% (*Coeff. = -0.012, p = 0.00;* 0.005–0.017) incremental decline of the revenue two days later. The sales revenue of the day after the high PM_{10}-level day might have been affected as well; however, due to the high serial correlation, we could not reveal such effects directly with our modeling. The moderate serial correlation of the PM_{10} and $L2\_PM_{10}$ makes it possible to apply the aforementioned reasoning in explaining the positive relationship with sales revenue in this case.

Although it is beyond the scope of this study to reveal why the effects of the current and past PM_{10} change direction at 109 μg/m^3 and 121 μg/m^3, respectively, we speculate that people rely on the quality criteria established by the government in taking action relative to ambient air pollution. Their belief might be that it would be safe to be outside until the concentration reaches the Bad level, and that they should be careful in doing outdoor activities once the quality becomes worse than the Bad level. It is also possible that people indeed worry and refrain from undertaking substantial outdoor activities even on a day of moderately Bad PM concentration, but they still conduct minor outdoor activities such as eating out. They might think that they do not stay outside long enough to be harmed, as they can be seated inside if they wish at almost any restaurant.

Other pollutants also affect restaurant sales revenue, possibly through changes in human behaviors. Ozone is the other ambient air pollutant about which the government issues warnings, along with PM_{10} and $PM_{2.5}$. Interestingly, a similar pattern was observed. The revenue increases along with the incremental increase of ozone concentration until the level reaches approximately 0.12 ppm; then it reverses direction and declines thereafter (Fig. 4(1)). Public alerts begin at the 0.12 ppm level.

Other covariates also affect sales revenue. First, timing matters. Sales revenues displayed an apparent seasonality over a year, with the highest value in July and August of 2015; revenues declined thereafter, reaching the lowest point on February of 2016 (Fig. 4(2)). One more cycle repeated the following year with a lesser amplitude. This finding reflects that restaurant and recreational businesses thrive during the summer in general and slow in the winter seasons (Higuera, 2018). Also, by including the time function in the model, we could successfully control such seasonal business effects. For that reason, five of the seven seasonal dummy variables present a statistically significant relationship with sales revenues. Weekend effects were also observed as 9.8% and 11.1% higher revenues on Saturday and Sunday than those on Wednesday. Second, as might be expected, the number of stores affects the amount of revenue. Each additional restaurant is associated with a 2.8% higher total revenue in a census unit (Table 2).

Third, weather conditions influence sales revenues as well. Fig. 4(3) illustrates that overall the restaurant businesses gain higher revenues on cold days than on warm days. This result conflicts with the results of previous findings that temperature is positively associated with the

Table 2
Parameter estimates, standard errors, and approximate p-values from the semi-parametric GAM models (Models (2–1) and (3–1)), describing the relationships between log of daily sum of sales revenue by the census unit and the daily maximum PM_{10} level.

Variable	Model (2–1)	Model (2-2)	Model (2–3)
	PM as parametric terms; Thin plate regression spline	PM as parametric terms; Cubic regression spline with 20 knots	PM as parametric terms; Cubic regression spline with 10 knots
Question Variable			
PM_{10}	0.038***	0.037***	0.038***
	(0.001)	(0.006)	(0.006)
PM_{10}_OVER41	0.125***	0.125***	0.124***
	(0.021)	(0.021)	(0.021)
Int_PM_{10}_OVER41	−0.035***	−0.034***	−0.034***
	(0.006)	(0.006)	(0.006)
PM_{10}_OVER109	0.291***	0.290***	0.294***
	(0.036)	(0.036)	(0.036)
Int_PM_{10}_OVER109	−0.050***	−0.049***	−0.050***
	(0.006)	(0.006)	(0.006)
PM_{10}_OVER245	−0.175	−0.176	−0.161
	(0.509)	(0.509)	(0.509)
Int_PM_{10}_OVER245	−0.029	−0.029	−0.029
	(0.020)	(0.020)	(0.020)
L2_PM_{10}	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
L2_PM_{10}_OVER121	0.218***	0.216***	0.208***
	(0.044)	(0.043)	(0.044)
Int_L2_PM_{10}_OVER121	−0.017***	−0.017***	−0.016***
	(0.003)	(0.003)	(0.003)
L2_PM_{10}_OVER227	0.047	0.041	0.012
	(0.376)	(0.375)	(0.375)
Int_L2_PM_{10}_OVER227	−0.005	−0.004	−0.003
	(0.014)	(0.014)	(0.014)
Business/time var.			
NUM_ REST	0.028***	0.028***	0.028***
	(0.000)	(0.000)	(0.000)
f(TIME)	8.750***	8.690***	18.560***
	(8.977)	(8.967)	(18.970)
$SEASON_2$	−0.130***	−0.127***	−0.048*
June to Aug. 2015	(0.018)	(0.018)	(0.027)
$SEASON_3$	−0.152***	−0.148***	−0.017
Sept. to Nov. 2015	(0.025)	(0.025)	(0.036)
$SEASON_4$	−0.075**	−0.076**	−0.072
Dec. 2015 to Feb. 2016	(0.031)	(0.031)	(0.047)
$SEASON_5$	−0.001	−0.002	−0.042
March to May 2016	(0.036)	(0.036)	(0.053)
$SEASON_6$	−0.028	−0.037	−0.092
June to Aug. 2016	(0.040)	(0.040)	(0.060)
$SEASON_7$	−0.121***	−0.121***	−0.201***
Sept. to Nov. 2016	(0.045)	(0.045)	(0.007)
$SEASON_8$	−0.116**	−0.122**	−0.202***
Dec. 2016 to Feb. 2017	(0.048)	(0.048)	(0.006)
DAY_1	0.006	0.006	0.009
Thursday	(0.007)	(0.007)	(0.007)
DAY_2	0.029***	0.030***	0.030***
Friday	(0.007)	(0.007)	(0.007)
DAY_3	0.098***	0.098***	0.100***
Saturday	(0.007)	(0.007)	(0.007)
DAY_4	0.111***	0.111***	0.113***
Sunday	(0.007)	(0.007)	(0.007)
DAY_5	−0.103***	−0.102***	−0.098***
Monday	(0.007)	(0.007)	(0.007)
DAY_6	−0.135***	−0.133***	−0.133***
Tuesday	(0.007)	(0.007)	(0.007)
Pollutant/weather var.			
f(PLT_1); ozone	7.328***	7.146***	17.760***
	(8.061)	(8.023)	(18.58)
f(PLT_2); sulfur dioxide	6.313***	6.726***	16.140***
	(7.702)	(7.611)	(17.400)
f(PLT_3); carbon monoxide	8.857***	8.217***	18.000***
	(8.987)	(8.655)	(18.650)
f(WTH_1); temperature	8.450***	8.065***	13.890***
	(8.919)	(8.766)	(16.190)
f(WTH_2); wind speed	8.535***	8.041***	18.190***
	(8.927)	(8.746)	(18.900)
f(WTH_3); precipitation	7.600***	6.595***	14.500***
	(8.370)	(7.554)	(16.450)
Intercept	15.430***	15.430***	15.430***
	(0.034)	(0.034)	(0.047)
Summary and Goodness-of-fit			
Observations	319,958	319,958	319,958
df	83.833	81.481	145.047
Deviance Explained	33.9%	33.9%	34.1%
AIC	11,062,704	11,062,721	11,062,205
GCV	0.903	0.903	0.902

Standard errors or degree of freedom in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

tourism-related sales revenues (Goh, 2012; Lise & Tol, 2002; Maddison, 2001; Wilton & Wirjanto, 1998), as well as the results of the current analysis for time and seasonality variables described above. Our unexpected results might be due not to substantive phenomenon in regard to restaurant businesses but to the statistical setting in this study. Due to the presence of some level of multicollinearity, the temperature effect might turn out to be the opposite of what it is in reality (Adeboye, Fagoyinbo, & Olatayo, 2014). To corroborate our claim, we tried another model without the seasonality variables and observed that the effect of temperature on sales revenue changed as have been expected; sales revenue increases with the increment of the temperature until 30 degrees Celsius (Maddison, 2001). Wind speed and restaurant sales revenue exhibit a non-linear relationship as well (Fig. 4(4)). The function resembles a parabolic curve, which agrees with the results of the study in Spain (Saenz-de-Miera & Rosselló, 2014). As reasoned in that study, strong wind would dissipate the dust accumulation. If people noticed this dissipation, they might believe that the negative effects of high PM_{10} concentration had been offset. Finally, precipitation negatively affects restaurant sales revenues in general, but in a non-linear fashion (Fig. 4(5)).

6. Conclusion and discussion

In this study, we examined the effects of PM_{10} concentration on tourism retail sales revenues, through the case of Seoul's restaurants and recreational service businesses from April 2015 to February 2017. We adopted a twofold GAM strategy; in the first exploratory modeling, we specified the PM-related variables as smooth functions and derived inflection points of the trajectories. In the second model, we parametrized the line segments with interaction terms to estimate the effects' size and direction.

The study confirms that the level of PM_{10} and sales revenues in the tourism industry exhibit a statistically significant relationship in a non-linear fashion. People begin to alter their consumption related to dining and recreation activities only after the PM_{10} level becomes worse than the “Bad” level. When the PM_{10} level is “Good” or “Normal” up to some low value of the “Bad” category, its concentration has a positive relationship with sales revenue. When the level exceeds that point, the relationship becomes negative. The turning points are at 109 $\mu g/m^3$ and 121 $\mu g/m^3$ for the PM_{10} level of today and the day before yesterday, respectively. In the case of today's PM_{10} level, every 10 $\mu g/m^3$ increase

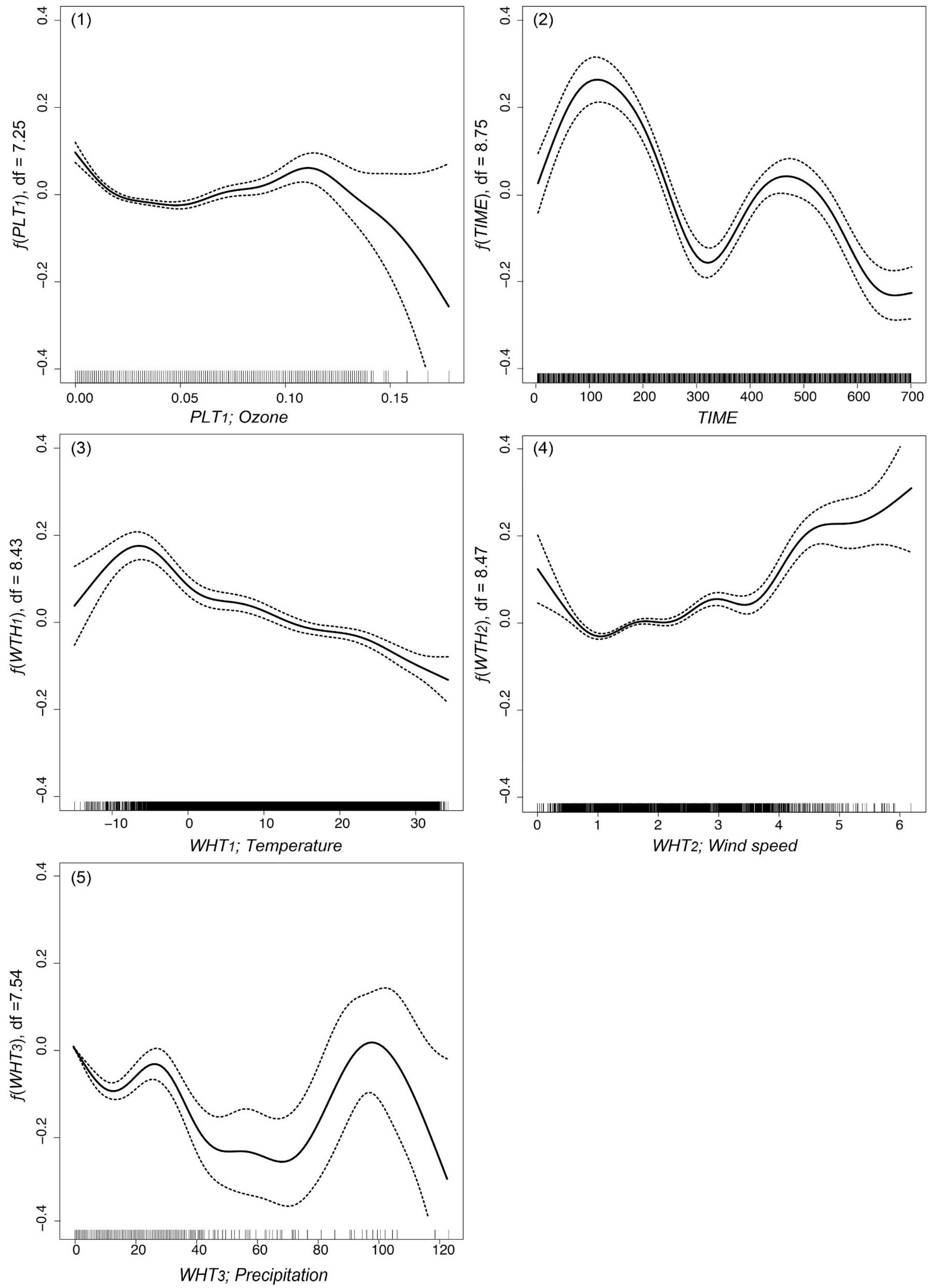

Fig. 4. Estimated smooth function and 95% CI of the time and weather covariates on retail revenue.

is associated with an incremental increase of sales revenue by 3.8% up to 41 μg/m^3 and by 0.3% up to 109 μg/m^3. Thereafter, the same increase is associated with an incremental decrease of sales revenue by −1.2%. In the case of a two-day lag in the PM_{10} level, every 10 μg/m^3 increase is associated with an incremental increase of sales revenue by 0.5% up to 121 μg/m^3. Thereafter, the same increase is associated with an incremental decrease of sales revenue by −1.2%.

This result contributes to the literature in two ways. First, while the effects of PM levels have been the topic of a large amount of research, this study was the first attempt to investigate those effects on retail sales revenues in the tourism industry at large. Second, the twofold modeling strategy enabled us to reveal a unique non-linear relationship between the PM level and sales revenues, which is new to the literature. In other relevant studies, the PM level has usually been treated as a parametric term as if its effect is constant throughout the entire level (An & Yu, 2018; Chen et al., 2017; Garrett & Casimiro, 2011). However, it might be more sensible to consider human factors in the mechanism of perceiving and responding to the risk and to design a statistical model accordingly. People may be aware of the threat in general, but the points at which they take appropriate adaptive behavior differs from individual to individual (Kalkstein & Sheridan, 2007). Collective behavioral patterns would generate a tipping point at which the counteraction becomes visible in the general population.

Such findings provide evidence for policy implications concerning air quality and monitoring systems. People do react to air quality in light of the quality standards established by the public authority. Given the analytical results of this study, it is possible that the Bad category is the threshold at which people begin altering some of their outdoor activities. However, it should be noted that there is no safe level of PM concentration to be exposed to, and even a low level of PM would cause adverse health effects (Cassee, Héroux, Gerlofs-Nijland, & Kelly, 2013; Zwozdziak et al., 2016). Especially in South Korea, relatively loose standards are applied. The Bad grade is from 81 to 150 μg/m^3 in Korea; however, the equivalent grade given by the WHO is from 51 to 100 μg/m^3 (Ministry of the Environment, 2016). A part of the Bad range—from 81 to 100 μg/m^3—in the world standards is considered normal by Korean standards. This discrepancy may give Korean people a false sense of safety about being outside on a day with such PM concentrations, which world standards do not consider safe. This gap holds for other countries under similar conditions.

It might be wise to impose air-quality criteria as strictly as possible if the health risk is the only concern. Although human health should be prioritized, other issues should also be considered in enacting policies. While numerical evidence on health effects is abundant, less evidence has been supplied to understand the effects on other economic sectors, simply due to the lack of analysis. Considering the entire sales revenue generated from all product and service types with all means of payments, the magnitude of the PM effects on the retail sector could be substantial. These effects should not be neglected in assessing the social cost incurred by PM. Well-balanced standards should be sought to ensure a maximum level of health safety and not depress tourism businesses and industries. Along with regulating emissions and the formation of PM, the improvement of public spaces should be accompanied by minimized exposure to ambient air and purified indoor and outdoor air (Kroeger, McDonald, Boucher, Zhang, & Wang, 2018), so people can keep enjoying tourism activities safely.

This study has some limitations. First, the gap between the actual PM_{10} level and the one monitored at the stations limits the inference of the analytical results to the people's response to the perceived risk of PM concentration. In the analyses, we assumed that the level of PM_{10} reported through media is the one that people would react to. Such a level, however, might have differed from the actual PM_{10} level that people are exposed to in the buffer around a station. With more advanced technologies in interpolation and simulation, we could analyze the effects of the actual PM_{10} level on sales revenues, since people may recognize the bad air quality through their own sensory experiences (Bickerstaff & Walker, 2001). Second, the causal direction between the PM level and amount of foot traffic is uncertain. Due to the reciprocal relationship, the revealed effect of PM level on sales revenue might be convoluted. Further study is warranted to investigate the function of impulse-response between those two time-series in finer time units.

Contribution

Heeyeun Yoon, the sole author of the manuscript, have conducted the entire research, from conceiving the idea, data collection and analysis, and writing the text.

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Appendix A. Descriptive statistics

Variable	Obs.	Unit	Mean	Std. Dev.	Min.	Max.
Sales_Rev	332,402	KRW	1.50e+07	2.81e+07	9590.25	6.46e+08
PM_{10}	332,402	10 μg/m^3	6.931	3.355	0.400	31.800
Ozone	331,142	ppm	0.037	0.024	0.000	0.178
Sulfur dioxide	329,764	ppm	0.007	0.002	0.000	0.030
Carbon monoxide	330,642	ppm	0.798	0.336	0.000	2.900
Temperature	332,402	Celsius	15.119	10.805	−14.964	34.279
Wind speed	332,402	m/s	1.692	0.741	0.000	6.186
Precipitation	332,402	mm/day	1.426	6.361	0.000	123
NUM_ REST	332,402	EA.	27.704	54.096	11	10,001
TIME	332,402	Day	360.551	200.282	1	700

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