Journal of Public Transportation 26 (2024) 100111

Contents lists available at ScienceDirect

Journal of Public Transportation

journal homepage: www.journals.elsevier.com/journal-of-public-transportation

Air pollution hindering a transit-oriented city: Examining the association of particulate matter concentration with public transit ridership and road traffic in Seoul, South Korea

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ARTICLE INFO

Keywords:
Particulate matter
Air pollution exposure
Compact city
Transit ridership
Modal shift
Seemingly unrelated regression

ABSTRACT

In high-density metropolitan areas prone to air pollution, public transit may be less preferred when air quality is poor due to the difficulty of avoiding outdoor air exposure during their use. By applying seemingly unrelated regression models, we examined the association of particulate matter (PM) with both public transit ridership and, as an alternative to sharing vehicular traffic demands, private car road traffic in Seoul from 2015 to 2018. To control for fluctuations in ridership and road traffic associated with seasonalities such as the day of the week, we used nine-term moving averages transformed into residual form. Results show that higher PM concentration was negatively associated with not only transit ridership, but also road traffic volume and congestion level; yet, the reduction in subway ridership was found to be larger than that in road traffic. This suggests that (1) when PM concentration is severe, people could reduce overall travel rather than change travel modes from public transit to private cars, thus implying that both modes are complementary rather than substitutionary in terms of responding to air pollution; and (2) public transit still seems more susceptible to air pollution than private cars. The findings help us understand the adverse effects of air pollution on public transit use as well as better predict and respond to demand for public transit in poor atmospheric conditions, thereby providing future policy directions for sustainable transportation planning.

1. Introduction

Among various air pollutants, airborne particulate matter (PM) has recently received attention due to its various adverse effects on human health (Kim et al., 2015a). Exposure to PM in the air through the respiratory system is a leading cause of asthma, chronic bronchitis, cardiovascular disease, and lung cancer, and may even reduce life expectancy (Bai et al., 2019; Deng et al., 2019; Strak et al., 2012; Tang et al., 2020). Accordingly, PM exposure can be particularly more problematic in high-density urban environments, where air pollutants become concentrated and many residents come to be affected during their daily activities and travels throughout the city.

Nonetheless, the degree of exposure to such PM in the city differs depending on the mode of travel. The exposure levels of private car users are generally lower than those of walkers, bicycle users, or public transit riders (Hernández et al., 2021; Singh et al., 2021). People who use non-motorized, active transportation modes (e.g., walking, cycling, etc.) are most unprotected from PM, being exposed to outdoor air during travel with minimal physical or spatial barriers when breathing. Although less exposed to outdoor air, subway users are also still exposed to PM while approaching/leaving stations, and bus users also while approaching/leaving and waiting at bus stops. In contrast, private car users are more protected from airborne PM because their first- and last-mile outdoor walking trips are usually shorter than those of other travel modes, especially when parking lots are set up indoors.

Urban researchers, practitioners, and policymakers have been encouraging active transportation modes and public transit over private cars to reduce road traffic and air pollutant emissions, and to ultimately achieve sustainable and good-quality urban life (Frank et al., 2006; Tal and Cohen-Blankshtain, 2011). However, when considering the adverse health effects of PM, ordinary city dwellers may contrarily prefer private cars which are less exposed to outdoor air than the other two

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https://doi.org/10.1016/j.jpubtr.2024.100111
Received 3 May 2024; Received in revised form 30 September 2024; Accepted 11 November 2024
Available online 19 November 2024
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alternatives, especially on days with or during periods of poor air quality. This can be a question of interest, particularly because there is a risk of a vicious cycle in which reduced use of active transportation modes and public transit due to deteriorating air quality may lead to an increased use of private cars instead, which then again exacerbates air quality.

In this regard, several studies have explored the issue concerning active transportation modes, showing that severe air quality actually discourages outdoor activities involving walking and/or cycling (An et al., 2019; Chung et al., 2019; Kim and Lee, 2019a; Li and Kamargianni, 2017; Saberian et al., 2017; Yoon, 2019). Unlike such non-motorized means of transportation, however, parallel examinations of motorized modes remain limited. Although several studies have addressed the effect of vehicular traffic on air quality deterioration (Tang et al., 2020; Wang et al., 2020), the potential other-way-around effect of poor air quality on vehicular traffic demand (both public transit and private cars) has not yet been discussed in depth. Though there is some related research on this topic regarding public transit, results are inconsistent, and investigations have not been conducted in terms of bus ridership. While Blanken et al. (2001) and Welch et al. (2005) asserted that air quality advisory programs do not influence the choice of transportation mode, Wu and Liao (2020) contrarily showed that poor air quality decreased subway ridership in Beijing; Ki and Lee (2019) also revealed that PM2.5 concentration was negatively associated with subway ridership in Seoul. Moreover, the impact of air pollution on public transit ridership may be greater in cities where the modal share of transit is large (Singh et al., 2021), but further empirical investigations (including on bus ridership) are needed. As for private cars, related studies seem harder to find, while the results remain mixed; analyzing the effects of PM2.5 and ozone alerts on daily vehicle traffic in Salt Lake and Davis counties, Tribby et al. (2013) found that traffic volume decreased in the center of the city but increased on the edges of the metropolitan area. Since the demands for different transportation modes are interdependent (Kim et al., 2015b) and there is a trade-off between private cars and public transit as an alternative long-distance means of travel (Sung et al., 2014), the effects of air quality on the use of cars should also be addressed alongside transit ridership. Reduced public transit use, potentially due to poor air quality, may affect the demand for personal vehicles – could public transit be substituted by private cars because people prefer travel modes that minimize exposure to outdoor air, or could the two modes show other forms of association?

Against this backdrop, this study aimed to examine the impact of air quality (represented by PM concentration, which has been problematic recently) on transit ridership, as well as on the use of private cars as an alternative to sharing vehicular traffic demands. Specifically, the following two research questions (RQ) are of interest within the context of high-density metropolitan areas:

RQ1. Does public transit ridership decrease as PM concentrations increase?

RQ2. If public transit ridership falls, is the reduced demand converted to private car use, leading to a substitutionary relationship between the two modes? That is, does private car use increase as PM concentrations increase?

To address such questions, we analyzed time-series data on daily PM concentration, public transit ridership and road traffic in Seoul from 2015 to 2018 by applying seemingly unrelated regression (SUR) models. The following section describes in detail the study area, variables, and statistical methods.

2. Methods

2.1. Study area and context

As of 2019, Seoul, the capital of South Korea, has approximately 10 million residents (about 19.4 % of the national population) over an area of 605 km^2 (0.6 % of the national territory) (Korean Statistical Information Service (KOSIS)). The city's sizable population density (17,013 people/km^2) makes public transit highly feasible (Kang, 2016), as exemplified by its 10 subway lines with 329 stations and 354 bus lines with 6254 stops (Seoul Open Data Platform, 2021a, 2021b, 2021c) supported by one of the most convenient and smartest transfer, payment, and information systems worldwide (Kim and Han, 2012; Lee, 2015). By virtue of this, the collective commuting modal share of public transit alongside walking and cycling was relatively high in 2019 at 77.8 % (Seoul open data platform, 2021).

At the same time, PM air pollution is severe in Seoul due to such high concentrations, with many people affected. The city's high population density and compact urban structure—which make it possible to provide good-quality public transportation—also lead to the accumulation of air pollutants and the congregation of victims within a limited area, and the city's basin topography worsens the situation by hindering the spread of PM. Accordingly, Seoul remains one of the most vulnerable countries to poor air quality in the world. In 2019, the mean population exposure to PM2.5 (27.4 $\mu g/m^3$) was the highest among the 37 member states of the OECD countries, and 99.4 % of the population was exposed to PM2.5 concentration, exceeding the levels mandated by the WHO (10 $\mu g/m^3$) (OECD Library, 2020). The air quality in Seoul is also worse than that in other cities in South Korea; no other city besides Seoul remained below this benchmark in 2020 (AirKorea, 2020; IQAir, 2020).

Additionally, in response to the recent surge in citizens' awareness of PM and its adverse health impacts (Fig. 1), Seoul is a city in a country where information on air pollution is publicly provided so that anyone can easily check the current real-time level of air pollution. Measuring, forecasting, and providing air quality alerts is regarded as an essential public service in South Korea, and people can access air quality information ubiquitously from two primary sources. The first one is short-term forecasting. Using various atmospheric dispersion modeling systems, the Korean Environment Corporation (KEC) and the Korea Meteorological Administration (KMA) (Korea Meteorological Administration, 2019) predict air quality over two consecutive days at a 1.5–3 km spatial resolution (Yoon, 2019; National Meteorological Super Computer Center). The prediction is officially announced four times each day (05:00, 11:00, 17:00, and 23:00) through numerous channels, including official public websites such as those of Air Korea, the KMA, and the Seoul Metropolitan Government (2018), in addition to privately operated mobile apps and other mass media. The second source consists of (quasi) real-time alerts and warnings. Air quality data covering PM10, PM2.5, SO_2, NO_2, CO, and O_3 are gathered from air quality monitoring stations (AQMSs) run by the KEC in real time, and their hourly average levels are published each hour through the aforementioned diverse channels (Chung et al., 2019). In combination with recent skyrocketing public concerns regarding PM, Seoul's citizens are thereby able to both proactively and immediately react to air pollution; short-term forecasting may help people plan their schedules, affecting their intention whether to go outside and travel as well as their corresponding choice of travel mode, while real-time alerts and warnings may be further taken into account when making final decisions (Chung et al., 2019).

Given these characteristics, Seoul has both spatial and social contexts as a high-density metropolitan area equipped with conditions in which air pollution can possibly affect people's choice of vehicular travel mode. These factors may lead to results distinctive from previous analyses, allowing for an examination of the relationship between air quality and public transit/private car ridership in urban environments vulnerable to air pollution.

2.2. Data and variables

2.2.1. Dependent variables and model specification

Using a four-year period (2015–2018) of daily travel time-series data from Seoul, we set two dependent variables each to address public

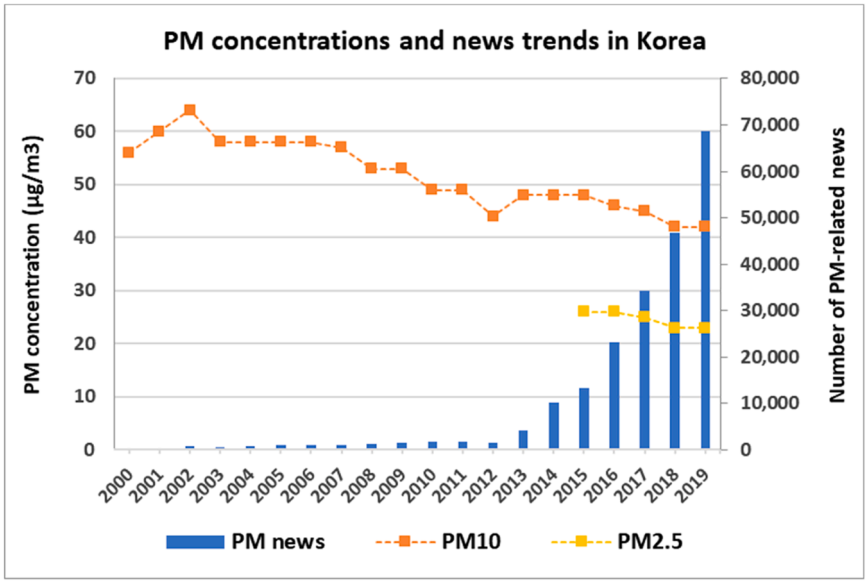


Fig. 1. Trends in PM concentration and media exposure frequency in South Korea (2000–2019).
Source: Authors' calculations using the data from AirKorea (OECD Library, 2020) and BigKinds (2021).

transit ridership and private car use (Table 1). The variables for public transit ridership were set as daily total subway and bus ridership, the latter being included in this study given its need for examination alongside the former, as identified in the introduction. Ridership data were acquired from the Seoul Big Data Campus (Seoul Big Data Campus, 2019) and the Seoul Open Data Platform (Seoul Open Data Platform, 2021b, 2021c), which consist of hourly ridership data from all subway stations (except for 38 stations along Line #9 run by a private company) and bus stops in Seoul collected via smartcards which are used by more than 99 % of Seoul's transit users (Lee, 2015). Meanwhile, private car use was operationalized as daily average road traffic volume and vehicle speed because public transit volume is nearly constant according to a set schedule; thus, any other variation or increase/decrease in traffic volume or speed can be considered due to the number of private cars on the road. Unlike ridership data, measuring the detailed daily average traffic volume and vehicle speed on all roads in Seoul is challenging. Hence, we measured both variables using sampled data automatically collected from 484 representative road segments and 135 survey spots managed by the Seoul Metropolitan Government and provided by the Seoul Transport Operation and Information Service (TOPIS) (2021a, 2021b).

To control for fluctuations in ridership and road traffic/vehicle speed associated with the day of the week, time of the year, and other trends over time, the four dependent variables into "residual" form by employing the approach of Kalkstein et al. (2009) and Singhal et al. (2014). For instance, the daily bus ridership residual as the percentage difference between a given day's actual and moving average ridership where, being consistent with Kalkstein et al., nine terms (i.e., the given day plus the days of the four weeks on either side of that day) were used to calculate the moving average and thereby compare a day's ridership to that of similar times of the year on the same day of the week. The nine-term moving average, $\bar{r}_t^{M.A.\pm4}$, was defined using the following formula, where r_t is the actual ridership:

$$\bar{r}_t^{M.A.\pm4} = \frac{\sum_{\tau=-4}^{4} r_{t+7\tau}}{9}. \quad (1)$$

Then, the daily bus ridership residual, e_t, was normalized in percentage terms using the following formula:

$$e_t = \frac{r_t - \bar{r}_t^{MA\pm4}}{\bar{r}_t^{MA\pm4}} \times 100. \quad (2)$$

However, because the four variables are likely to be mutually dependent, owing to travel demand constraints, we need to make the separate ordinary least squares (OLS) regression estimators more efficient by taking these interdependencies into account (Greene, 2008; Gujarati, 2003). If we relax the independence assumption and assume that the error terms follow a multivariate normal distribution, the equations can be analyzed using Zellner's (1962) SUR equation. The SUR equations estimated in this study, where the subscripts for individual cases are omitted for simplicity, are as follows (Gujarati, 2003; Jöreskog, 2004):

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{pmatrix} + \begin{pmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ 0 & 0 & X_3 & 0 \\ 0 & 0 & 0 & X_4 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix} + \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{pmatrix} \quad (3)$$

where y_i, α_i, X_i, β_i, and z_i represent the dependent variables, intercept terms, explanatory variables, regression coefficients, and error terms, respectively, for travel mode types $i = 1, 2, \ldots, 4$. The X_i and β_i are conformable vectors of length K_i, where $K_i$is the number of explanatory variables in the i th equation. It is assumed that z_i is independent of X_i and has a multivariate normal distribution with

$$E\begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{pmatrix} = 0 \text{ and}$$

$$Var\begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{pmatrix} = \begin{pmatrix} \psi_1^2 & & & \\ \psi_{12} & \psi_2^2 & & \\ \psi_{13} & \psi_{23} & \psi_3^2 & \\ \psi_{14} & \psi_{24} & \psi_{34} & \psi_4^2 \end{pmatrix}. \quad (4)$$

From the four-year daily travel data, we used only the data for 1068 days. Firstly, because we applied a nine-term moving average approach, data before January 30th, 2015 and after December 3rd, 2018, were excluded from the analysis for fair measurement. Additionally, the data had some missing values owing to reasons such as the loss of raw data or the partial failure of automatic devices. As the SUR model requires complete data for all dependent variables, data for days with missing values for even one dependent variable were excluded from the analysis. Finally, data for days affected by those missing values (i.e., the four

Table 1
Definitions of the variables.

Variable	Definition and description	Scale
Dependent variables*		
Daily subway ridership	Daily sum of Seoul subway lines 1–8	−100 to 100
Daily bus ridership	Daily sum of all buses registered within Seoul Metropolitan Government	−100 to 100
Daily average traffic volume	Daily average of 135 automatic survey spots	− 100 to 100
Daily average vehicle speed	Daily average of 484 road segments	− 100 to 100
Independent variables		
Test variables		
Daily PM10 concentration	Daily average of 25 AQMSs	$\mu g/m^3$
Daily PM2.5 concentration		
Control variables		
Weather conditions		
Daily average temperature	Daily average temperature	℃
Daily average wind speed	Daily average wind speed	m/s
Precipitation	Daily precipitation > 10 mm = 1	dummy
Snowfall	Daily snowfall > 0 mm = 1	dummy
Precipitation x Daily PM concentration	Interaction term between precipitation and PM concentration	
Economic factors		
Economically active population	Workers and job seekers in population, age 15 + (monthly statistic)	million
Daily average gasoline price	Daily average of regular gasoline prices of all gas stations in Seoul	USD/liter
Before transit fare increase	1 = Before Jun. 27th, 2015 (Seoul has maintained its public transit fare since raising it by about 20 % on that day)	dummy
Operation of transit fare-free program	1 = Dates of transit fare-free program (Jan. 15th, 17th, and 18th, 2018)	dummy
Year, season, and other special periods		
Year (2015, 2016, 2017, 2018)	2015 = Reference group	dummy
Season (spring, summer, fall, winter)	Spring = Reference group	dummy
Students' summer and winter vacations	1 = Jan., Feb., July, Aug.	dummy
Workers' peak holiday season	July 24th to Aug. 14th = 1	dummy
The start/end of the year	Dec. 25th to Jan. 7th = 1	dummy
Public holidays	All public holidays in South Korea (70 days for 4 years)	dummy

AQMSs = air quality monitoring stations, PM = particulate matter, USD = US dollars.

* All dependent variables were transformed into "residual" form (see Section 2.2.1.).

weeks on either side of the day) were also excluded.

2.2.2. Test variables and other control variables

The key test variables used in this study were the daily average concentrations of PM10 and PM2.5 (Table 1). In Seoul, PM10 and PM2.5 concentrations are measured from 25 AQMSs, with one station for each of Seoul's 25 boroughs. We gathered and averaged the data to obtain the daily average values.

We also controlled for various factors known to affect transit ridership and road traffic, such as weather conditions, economic factors, and seasonality effects (Table 1). Adverse weather conditions can act as a constraint on travel mode choice, especially in the selection and use of public transport. Rain/snowfall, strong winds, and low temperatures lead to a decline in subway and bus ridership; their impacts are generally greater on the latter (Arana et al., 2014; Choi et al., 2013; Guo et al., 2007; Lee and Jung, 2018; Shin and Choi, 2014; Stover and McCormack, 2012). As such, temperature, wind speed, precipitation, and snowfall were incorporated into the model. While temperature and wind speed variables are defined on a daily average basis, the amounts of precipitation and snowfall are applied as dummy variables based on the critical thresholds suggested by Shin and Choi (2014). All meteorological data were gathered from automated weather stations operated by the KMA and Seoul Metropolitan Government. Meanwhile, it is also possible that weather conditions such as precipitation may interact with PM concentration, where air quality may improve with rainfall due to its "washing" effect (Gao et al., 2019; McMullen et al., 2021; Ouyang et al., 2015). Hence, we included additional interaction terms between rainfall and PM concentrations in the model to control for such possible interaction effects.

As for economic factors, three main aspects were considered. First, economically active population was included to control for the number of people who could generate traffic. Second, following the general approach of studies examining public transit ridership (Stover and McCormack, 2012; Chen et al., 2011; Haire and Machemehl, 2007; Sung, 2017), the average daily gasoline price at all gas stations in Seoul was provided by the Oil Price Information Network (OPINET) (2019). Third, changes in transit fares during the four-year period were reflected in the model. Initially, because the fare increased once during this period, a dummy variable was defined as 1 = before the day of transit fare increase (June 27th, 2015). Next, another dummy variable was employed to address the execution of a transit fare-free program. This was a program which the Seoul Metropolitan Government started implementing in January 2018 during commuting hours on days with severe PM2.5 concentrations (> 50 $\mu g/m^3$) to encourage using public transit rather than private cars, but was suspended after only three days of operation due to its suggested negligible effect compared to its huge budgetary cost (Kim and Lee, 2019b). Nevertheless, bus and subway ridership had increased, and vehicle traffic had declined on the three days compared to the previous week (Seoul Metropolitan Government, 2018), so control for the program was still included.

Using several dummy variables, we also controlled for periodic trends stemming from a specific year, season, or other special period in South Korea. In addition, specific periods when travel demand was expected to fall were reflected as dummy variables, including students' summer and winter vacations, workers' peak summer holidays, periods marking the start and end of the year, and traditional public holidays such as Lunar New Year's Day and *Chusuk* (the Korean equivalent of Thanksgiving).

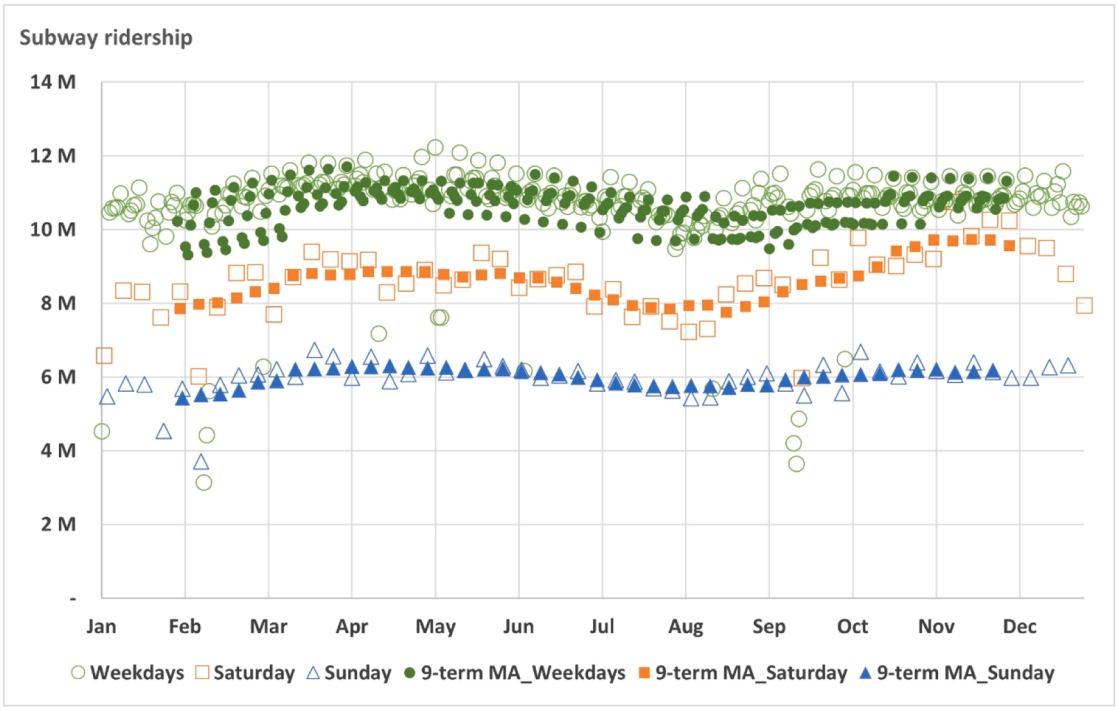
3. Results and discussion

3.1. Seasonality check of time-series dependent variables

3.1.1. Intra-year daily transit ridership trends

To check whether transit ridership data actually displayed seasonal and other types of fluctuations and whether the residual approach could alleviate them, we first observed in Figs. 2 and 3 the actual daily transit ridership trends on weekdays, Saturdays, and Sundays and their respective nine-term moving averages (top), and the ridership residuals in percentage terms (bottom) for subways and buses. In this seasonality check process, we only used data from 2016, the set without missing values. As shown in the top graphs, both subway and bus ridership on weekdays were considerably higher than on weekends. This trend can be regarded as "day of the week" seasonality. In addition, both figures demonstrate greater ridership in spring and fall than in summer and winter. This is "time of the year" seasonality.

The bottom graphs indicate the absence of "day of the week" seasonality and the much flattened "time of the year" seasonality, thus validating the residual approach. However, they still exhibit some peak fluctuations. For both buses and subways, daily ridership was at least 20 % less than the nine-term moving average on 10 occasions. These outliers were primarily affected by annual events. For example, in South Korea, there are two main national holidays, Lunar New Year's Day and



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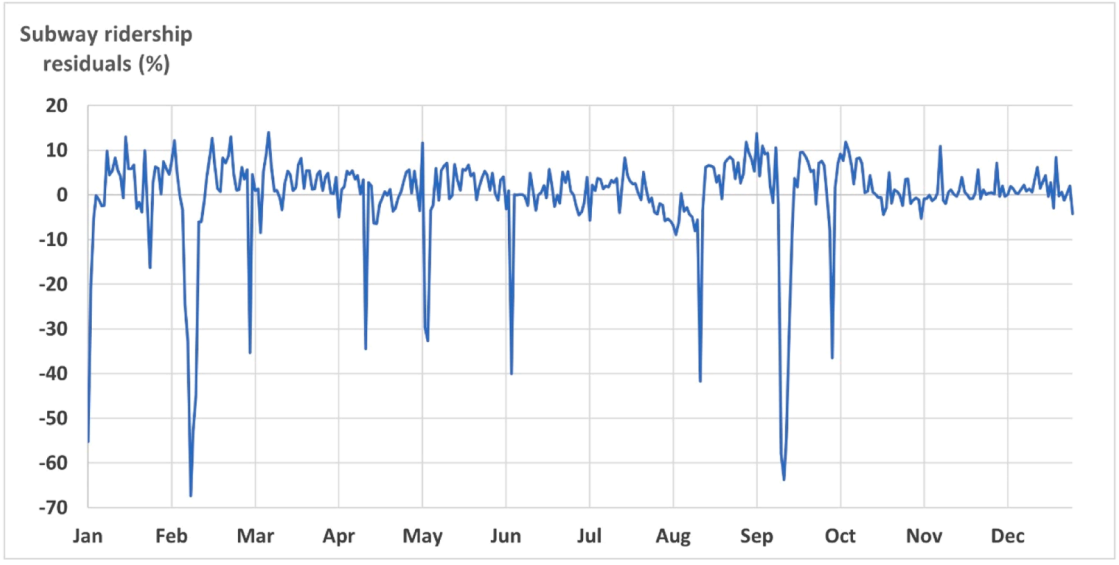


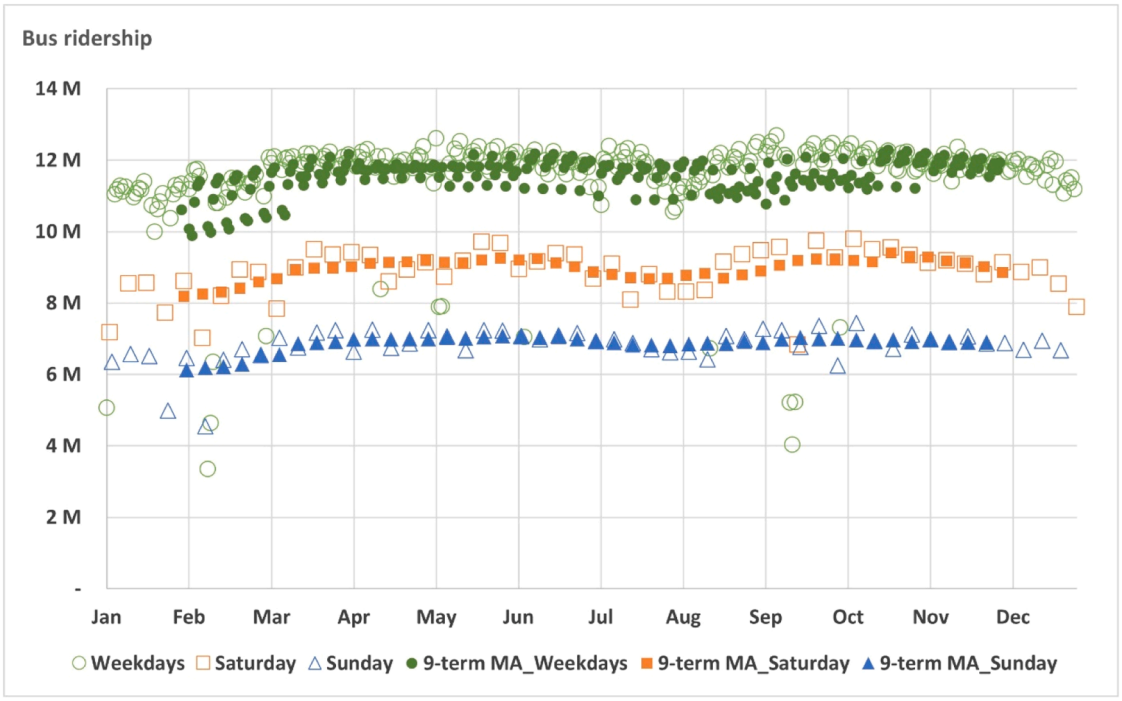
[b]

Fig. 2. Daily subway ridership trend in 2016: nine-term moving averages ([a]) and residuals ([b]).

Chusuk, during which daily ridership was as 60 % less than usual as many people leave Seoul to visit their hometowns. Other outliers are related to public holidays and special periods that affect travel demand. Accordingly, despite our residual approach, we controlled for these periods in the SUR models.

3.1.2. *Intra-year daily average traffic volume and vehicle speed trends*

Figs. 4 and 5 illustrate the same measures as those in Figs. 2 and 3 for daily average traffic volume and vehicle speeds. In detail, the two variables show somewhat different trends compared to those of transit ridership. First, while transit ridership was significantly lower on Saturdays than on weekdays, the average traffic volume and vehicle speed on Saturdays did not differ substantially from those on weekdays. Second, the differences between winter and the other seasons were more pronounced for traffic volume and vehicle speed than for transit ridership. Third, the average traffic volume rose distinctly during major holiday periods in contrast to transit ridership, suggesting that short-distance routine travel using public transit declined, whereas long-distance occasional travel using private cars increased during major holidays in Seoul. Fourth, the average vehicle speed shows greater variation by day of the week, even on weekdays (the highest on Monday and lowest on Friday), and this intra-weekday seasonality is prominent



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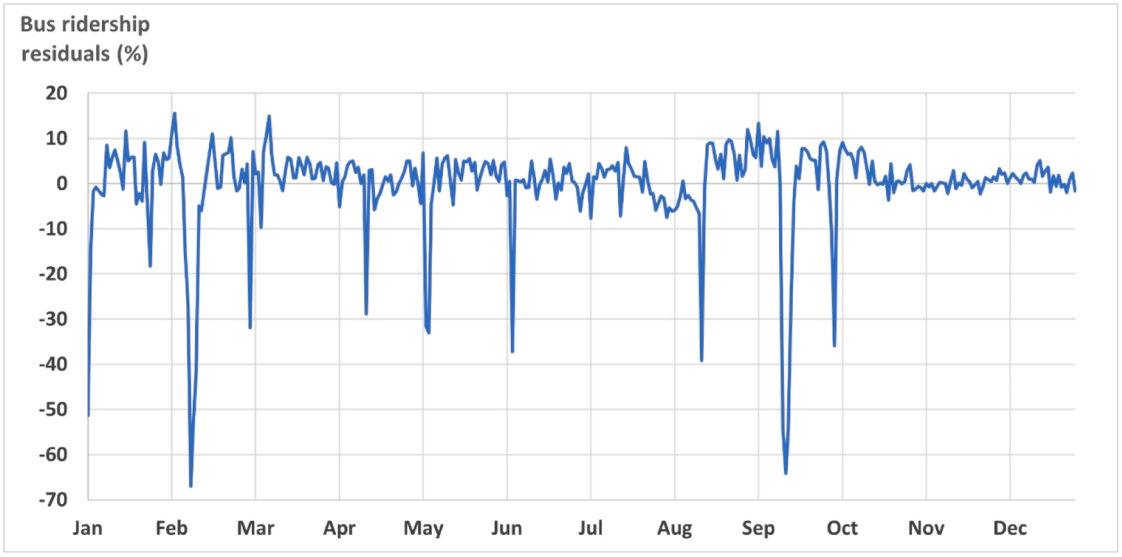


[b]

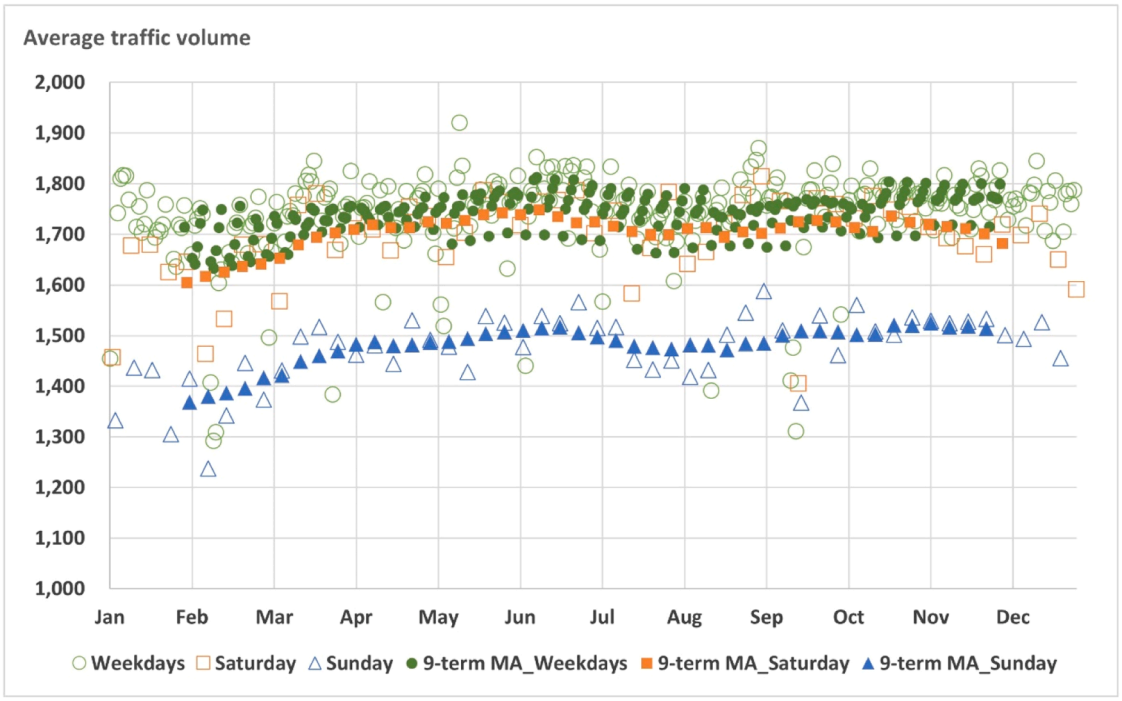
Fig. 3. Daily bus ridership trend in 2016: nine-term moving averages ([a]) and residuals ([b]).

in summer. Nevertheless, the two variables still demonstrate similar "day of the week" and "time of the year" seasonalities as transit ridership, and although our residual approach smoothed them, peak fluctuations during major holidays were not completely eliminated. This again indicates the need to control for these special periods in the SUR models.

3.2. SUR results

3.2.1. Negative associations between PM concentrations and travel demand

Tables 2 and 3 show that both PM10 and PM2.5 concentrations were significantly and negatively associated with daily subway and bus ridership at the 10 % probability level, as expected (RQ 1). Contrary to expectations, however, the PM concentrations were also negatively associated with the amount of travel and congestion levels in the major streets of Seoul. Given the context of the study area (see Section 2.1) that public concerns over PM are high, and that the city's advanced real-time air quality monitoring/alert system enables people to take immediate or planned steps to reduce PM exposure via travel rearrangements, tele-activities, or other behavioral modifications, this seems to indicate that people may reduce overall travel rather than change their travel modes from public transit to private cars (RQ 2) when PM concentration is severe. While previous studies that focused on the intra-household interaction of travel mode choice within a given budget constraint have generally supported a substitutionary relationship between public



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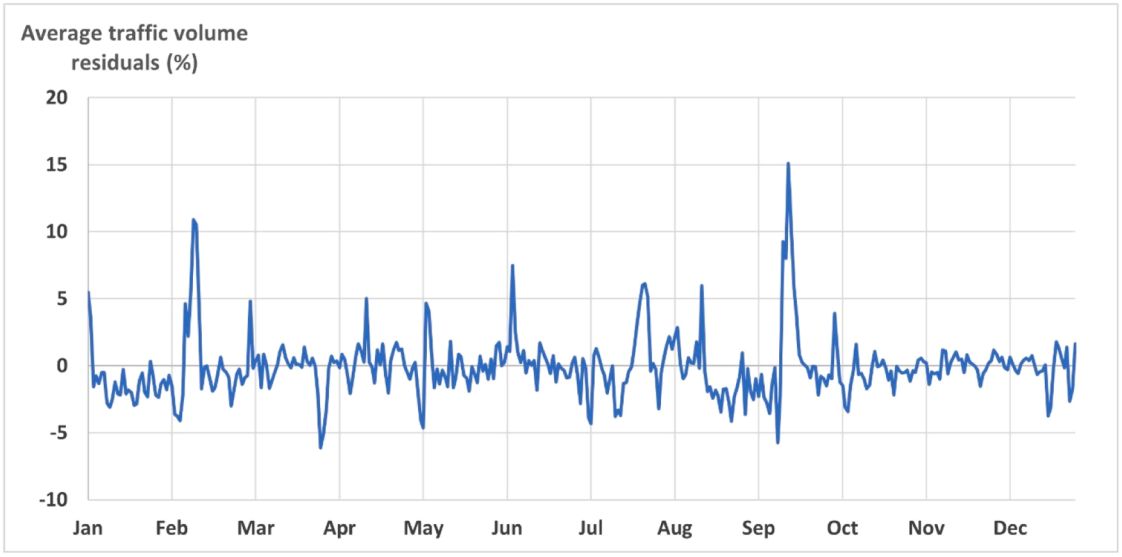


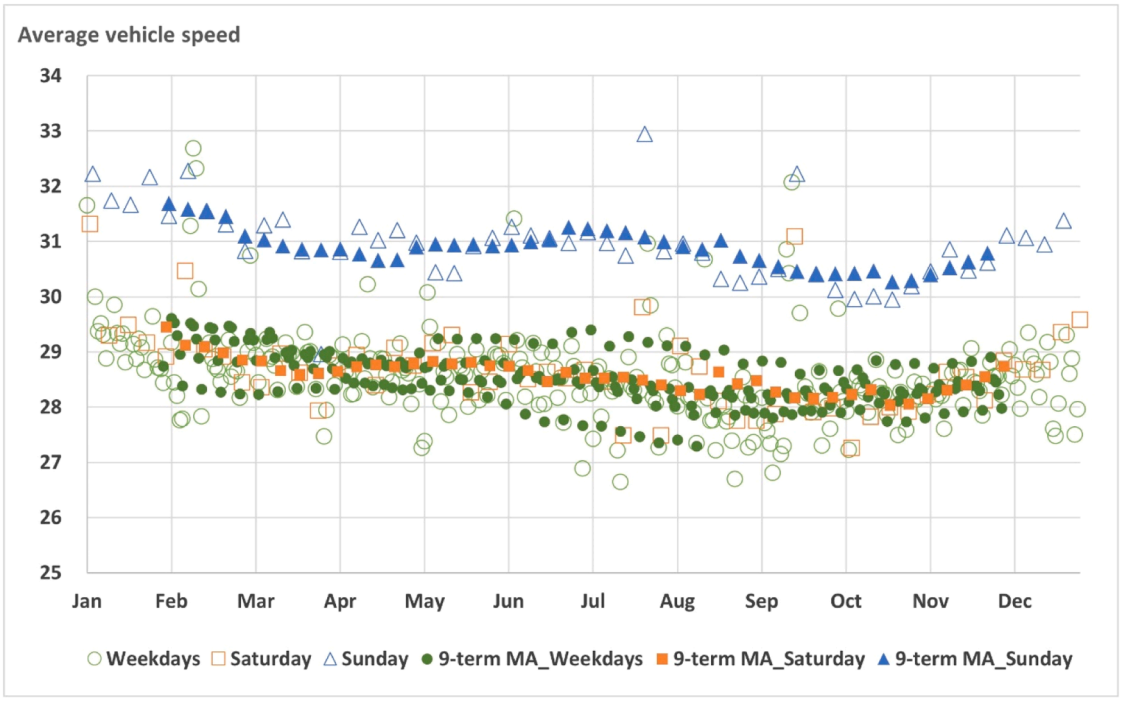
[b]

Fig. 4. Daily average traffic volume trend in 2016: nine-term moving averages ([a]) and residuals ([b]).

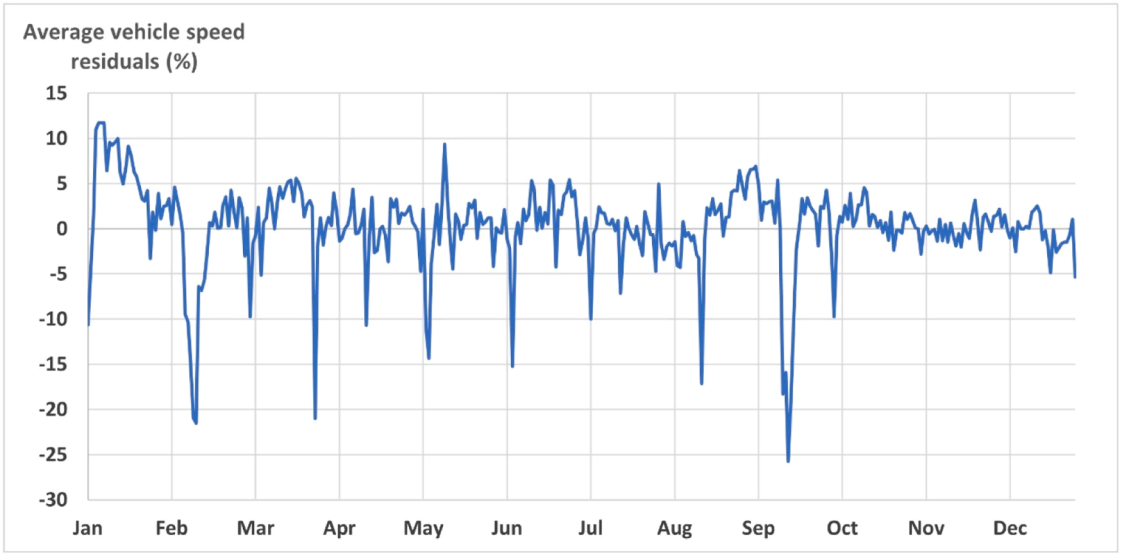
transit and private cars (Sung et al., 2014; Bieliński et al., 2021; Ceccato and Diana, 2021), our analysis using citywide daily travel data suggests that PM may reduce both transit ridership and vehicle traffic. This implies that public transit and private cars may be complementary rather than substitutionary in terms of people's responses to air pollution.

Meanwhile, while the size of the coefficients indicating the potential impact of PM varied across the models, the asymptotic *t*-test showed that the reduction in subway ridership associated with PM10 was statistically significantly larger than the reduction in road traffic ($Z = 1.954$, $p = 0.050$). This may stem from the fact that due to sparsely spaced stations, subway users are generally exposed to outdoor air for quite a long time while either approaching or leaving stations by foot, whereas private car users are accompanied by relatively short first- and last-mile walking trips. As such, this implies that the distance towards and away from transit stations/stops should also be considered when addressing the impact of air pollution on transit use.

Based on the statistical insignificance of the interaction terms between precipitation and PM concentration, the above associations between PM concentration and travel demand and related interpretations regarding their coefficients seem to hold independent of rainfall. While air quality may be affected by precipitation, its potential impact on public transit ridership and private car use seems viable, regardless of



[a]



[b]

Fig. 5. Daily average vehicle speed trend in 2016: nine-term moving averages ([a]) and residuals ([b]).

the latter's interaction.

3.2.2. Associations regarding other control variables

Though not the key test variables of this study, we briefly discuss the results of the other control variables to scan the overall acceptability of the SUR models, starting with weather condition variables. Consistent with previous studies (Arana et al., 2014; Shin and Choi, 2014; Stover and McCormack, 2012), both SUR models show that higher temperatures (reflecting milder weather) increase transit ridership, whereas higher winds (reflecting more inclement weather) decrease it. Meanwhile, the effects of rainfall and snowfall were mixed. On one hand, on both rainy and snowy days, vehicle speed did not increase, even though traffic volume fell. Since these two variables generally form an inverse relationship, the reduction in speed can be attributed to weather conditions. Bad weather conditions can be an obstacle to traveling, particularly for private cars, and rainfall and snowfall aggravate inconvenience during driving (e.g., congestion and collision risk), thereby both hindering traffic flow and discouraging private car owners from driving. On the other hand, while both transit ridership and vehicle traffic declined on rainy days, vehicle traffic decreased but the use of public transit rose during snowfall. Although bad weather makes travel inconvenient and thus usually acts as a constraint on all modes of travel, as implied by the results regarding rainfall, it may be possible that for mandatory trips, a stronger substitutionary effect of snowfall on public

Table 2
SUR models of PM10.

	Daily subway ridership		Daily bus ridership		Daily average traffic volume		Daily average vehicle speed	
	B	p	B	p	B	p	B	p
Air quality and weather conditions								
Daily PM10 concentration	− 0.035	0.000***	− 0.028	0.001***	− 0.013	0.061*	0.010	0.001***
Daily PM10 concentration x Precipitation	0.011	0.792	− 0.002	0.966	0.042	0.175	0.022	0.100
Daily average temperature	0.127	0.000***	0.133	0.000***	− 0.007	0.795	− 0.013	0.280
Daily average wind speed	− 0.569	0.036**	− 0.633	0.011**	− 0.125	0.538	0.081	0.358
Precipitation (1 = 10 mm or more)	− 3.962	0.004***	− 4.203	0.001***	− 4.713	0.000***	− 2.315	0.000***
Snowfall (1 = 0 mm or more)	1.636	0.058*	1.515	0.056*	− 1.826	0.005***	− 1.038	0.000***
Economic factors								
Economically active population	− 2.150	0.747	− 4.624	0.449	− 4.198	0.397	3.450	0.111
Daily average gasoline price	6.759	0.145	4.942	0.246	9.574	0.006***	− 1.459	0.334
Transit fare increase (1 = before increase)	− 6.159	0.000***	− 4.318	0.000***	0.024	0.980	0.291	0.503
Transit fare-free (1 = implementation)	6.375	0.060*	6.154	0.048**	2.606	0.303	0.397	0.720
Year, season, and other special periods								
Year_2016	0.179	0.786	0.003	0.997	1.928	0.000***	− 0.404	0.060*
Year_2017	− 0.557	0.390	− 0.587	0.324	0.914	0.058*	− 0.247	0.242
Year_2018	− 2.091	0.012**	− 1.859	0.015**	− 0.579	0.350	0.515	0.057*
Summer	− 3.658	0.000***	− 3.168	0.000***	− 1.389	0.030**	0.723	0.010**
Fall	− 1.516	0.019**	− 1.456	0.014**	− 0.325	0.499	0.088	0.676
Winter	0.465	0.586	0.276	0.725	− 1.217	0.056*	0.167	0.549
Students' summer and winter vacations	− 0.191	0.743	− 0.035	0.948	1.694	0.000***	− 0.666	0.000***
Workers' peak holiday season	− 5.967	0.000***	− 6.240	0.000***	− 2.163	0.001***	1.828	0.000***
The start/end of the year	− 2.090	0.035**	− 1.961	0.031**	− 1.497	0.043**	1.273	0.000***
Public holiday	− 41.460	0.000***	− 39.875	0.000***	− 13.576	0.000***	6.165	0.000***
(Constant)	6.329	0.865	22.128	0.517	8.843	0.750	− 16.896	0.163
Adjusted R^2		0.667		0.687		0.305		0.363

Note: number of observations = 1068; *p < 0.10, **p < 0.05, ***p < 0.01.

Table 3
SUR models of PM2.5.

	Daily subway ridership		Daily bus ridership		Daily average traffic volume		Daily average vehicle speed	
	B	p	B	p	B	p	B	p
Air quality and weather conditions								
Daily PM2.5 concentration	− 0.031	0.039**	− 0.025	0.065*	− 0.028	0.012**	0.015	0.002***
Daily PM2.5 concentration x Precipitation	0.008	0.893	− 0.018	0.739	0.051	0.255	0.028	0.156
Daily average temperature	0.123	0.001***	0.130	0.000***	− 0.007	0.788	− 0.011	0.325
Daily average wind speed	− 0.547	0.052*	− 0.625	0.015**	− 0.214	0.304	0.112	0.221
Precipitation (1 = 10 mm or more)	− 3.479	0.006***	− 3.676	0.001***	− 4.405	0.000***	− 2.237	0.000***
Snowfall (1 = 0 mm or more)	1.650	0.058*	1.524	0.056*	− 1.806	0.005***	− 1.048	0.000***
Economic factors								
Economically active population	− 0.589	0.930	− 3.300	0.590	− 3.583	0.469	2.874	0.185
Daily average gasoline price	8.525	0.066*	6.381	0.133	10.021	0.004***	− 1.914	0.203
Transit fare increase (1 = before increase)	− 6.379	0.000***	− 4.498	0.000***	− 0.029	0.977	0.347	0.424
Transit fare-free (1 = implementation)	6.018	0.080*	5.877	0.062*	3.094	0.224	0.273	0.806
Year, season, and other special periods								
Year_2016	0.203	0.759	0.023	0.970	1.930	0.000***	− 0.406	0.059*
Year_2017	− 0.668	0.304	− 0.678	0.256	0.866	0.072*	− 0.215	0.308
Year_2018	− 2.161	0.010**	− 1.923	0.012**	− 0.686	0.269	0.557	0.040**
Summer	− 3.219	0.000***	− 2.823	0.000***	− 1.407	0.026**	0.650	0.019**
Fall	− 1.134	0.076*	− 1.159	0.048**	− 0.366	0.440	0.032	0.877
Winter	0.683	0.425	0.461	0.557	− 1.155	0.068*	0.115	0.678
Students' summer and winter vacations	− 0.145	0.804	− 0.001	0.998	1.694	0.000***	− 0.679	0.000***
Workers' peak holiday season	− 5.894	0.000***	− 6.179	0.000***	− 2.127	0.001***	1.809	0.000***
The start/end of the year	− 2.106	0.035**	− 1.979	0.031**	− 1.439	0.052*	1.249	0.000***
Public holiday	− 41.449	0.000***	− 39.870	0.000***	− 13.652	0.000***	6.193	0.000***
(Constant)	− 5.904	0.874	11.923	0.727	5.199	0.851	− 13.056	0.280
Adjusted R^2		0.664		0.685		0.306		0.362

Note: number of observations = 1068; *p < 0.10, **p < 0.05, ***p < 0.01.

transit and private cars could exist. This can possibly be attributed to the geographic context of the study area. Seoul is a city where mountainous and hilly terrain is widely distributed in diverse places, thus making it difficult for vehicles to drive comfortably, particularly in snowy weather; it therefore seems to have triggered a modal shift from private cars to public transit to avoid the various inconveniences in driving. Overall, the results regarding weather conditions are generally reliable, being within the realm of reasonable interpretation.

The variables regarding economic factors showed somewhat different outcomes compared to those of previous studies (Chen et al., 2011; Haire and Machemehl, 2007). Both SUR models indicated lower transit ridership in the period before public transit fares increased (i.e., before June 2015). In contrast to prior studies (Stover and McCormack, 2012; Haire and Machemehl, 2007; Sung, 2017), the models also demonstrated that the higher the gasoline price, the greater the subway ridership (for the PM2.5 model) and vehicle traffic. This unexpected finding seems to be related to South Korea's economic situation. During the study period (2015–2018), the South Korean economy was in a

modest recovery phase, coinciding with a rise in gasoline prices. This means that the results may reflect the fact that the economic revival generated more economic activity and travel when public transit fares and oil prices were higher. Another possible interpretation is that the unexpected coefficient sign may be due to the low variability of the variables (Kennedy, 2008). During the study period, transit fares were raised only once, and the fluctuation in the daily average gasoline price was also quite stable, ranging from 1.416 to 1.774 USD/L.

The results also demonstrate that the transit fare-free program variable was positively associated with subway and bus ridership but not statistically significantly associated with traffic volume. Thus, we tentatively interpret that the transit fare-free program did not lead to a shift from private cars to public transit as intended; rather, it seems to have increased only latent demand for free public transit.

Finally, the special period variables successfully identified and controlled for specific travel patterns. First, during several short special periods in South Korea (workers' peak holiday season, the start/end of the year, and public holidays), people were more likely to reduce both public transit and private car use, thereby improving the average vehicle speed. Second, during students' vacations, vehicle traffic increased, thereby lowering the average vehicle speed.

4. Conclusion

Using a nine-term moving average approach and SUR models, this study examined the impact of PM concentrations on public transit ridership and private car use in Seoul. To the best of our knowledge, this is the first empirical study to investigate such relationships while considering the interdependencies between the two travel modes. The analysis showed that in Seoul, a higher PM concentration is not only negatively associated with public transit ridership but also with road traffic volume and congestion level. This suggests that when the PM concentration is severe, people are likely to reduce their overall travel rather than change travel modes from public transit to private cars, thus implying that both modes are complementary rather than substitutionary in terms of response to air pollution. Nonetheless, the reduction in subway ridership was larger than that in road traffic, also suggesting that public transit users are still more sensitive to air pollution than private car users. Taken together, these findings are expected to contribute to understanding the adverse effects of air pollution on public transportation use, and thereby to better predict and respond to demand for public transit. From a policy perspective, while efforts to expand public transit as an alternative to private cars and reduce the latter's use in response to poor air quality may not necessarily lead to ridership gains, measures that reduce the time one is exposed to outdoor air while using public transit (such as increasing station/stop density) may be more effective in reducing the reluctance to use public transit when the air is polluted.

Yet, it should be noted that our results—especially those regarding the negative relationship between PM concentration and total travel—do not imply that policy efforts to reduce air pollution are unnecessary. Rather, air pollution should be more regulated to maintain the viability of public transit and prevent a vicious cycle in which air quality further worsens. On days with or during certain periods of poor air quality, people seem to refrain from traveling altogether. However, avoiding air pollution exposure by reducing travel would only be a transitory measure valid for irregular or temporary air quality deterioration; such would be unsustainable if air quality continued to be poor, as reducing travel implies a contraction in economic activity. For primary breadwinners, reducing commuting travel is rarely an option in the first place (Zhao et al., 2018). Given these circumstances, if air quality continues to be poor, the damage to health and economic activity will inevitably slowly increase. It is likely that more people would then eventually resort to maintaining travel by owning private cars, and walking, cycling, and public transit may no longer be viable transportation modes because of worsened air quality. This is not a situation that should be allowed to happen.

This study has several limitations. First, we posited that citizens can accurately perceive air quality forecasts and, accordingly, act rationally. However, while some people may make decisions based on objective forecasts, others may rely on their own subjective experiences and/or senses. For instance, some people may judge air quality based on the color of the sky or the visibility of distant buildings, whereas others may simply judge air quality by breathing; people may perceive the same concentration level differently, which would eventually lead to bias. This topic warrants further investigation. Next, although the data used in this study are rooted in a time series, the selected analysis model (i.e., SUR) was not sufficiently robust to definitively establish causal relationships between air pollution, transit ridership, and road traffic. The estimated coefficients in our SUR models could be biased due to the possible endogeneity of the key variables; in particular, the effects of PM may be *over*estimated because the coefficients of the PM variables may partly capture causality in the opposite direction (travel-related variables influencing PM). Moreover, because people's trips and travel mode choices may be affected by the PM concentration level at a particular time rather than the daily average, further consideration of the granularity of data (the time interval between cause and effect) would be preferable. It is necessary to understand more precisely when people are made aware of PM concentrations and how this affects their decision to travel as there may be a time lag between recognizing air quality and taking action upon it (Riley et al., 2021). Hence, to further verify the potential causal relationships between the key variables demonstrated in this analysis, future studies should employ traditional simultaneous equations or mathematical causal verification methods (such as causal discovery and causal inference) while also using more granular, hourly data to examine the time lag between the awareness of air quality information and travel behavior decisions.

CRediT authorship contribution statement

Hyungkyoo Kim: Writing – original draft, Supervision, Conceptualization. **Youngha Joo:** Writing – review & editing, Visualization, Formal analysis, Methodology. **Sunwoo Jung:** Writing – original draft, Investigation, Formal analysis. **Seung-Nam Kim:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Funding

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2019S1A5A8036584). This work is also supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant RS-2022-00143404).

Declaration of interest

None.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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