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RESEARCH ARTICLE

Road traffic flow and air pollution concentrations: evidence from Japan

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Abstract

Vehicular emissions are a major global health concern. The aim of this study is to examine the short-term relationship between road traffic flows and air pollution concentrations in Japan. Our approach involves matching hourly data from the 2015 Road Traffic Census to data from nearby air pollution monitoring and meteorological stations and estimating a dynamic panel model. We focus on four pollutants designated under the vehicle emission standards of Japan: nitrogen oxides (NOx), carbon monoxide (CO), nonmethane hydrocarbons (NMHC), and fine particulate matter ($PM_{2.5}$). The standard estimates indicate that short-run pollution concentration-road traffic flow elasticities are 0.04–0.05 for NOx, CO, and NMHC, and insignificant for $PM_{2.5}$. Long-term effects are also estimated. We apply the estimates to a case study on the link between road traffic flows and meeting the new World Health Organization air quality guidelines.

Keywords Road traffic flow · Air pollution concentration · Dynamic panel model · Japan

Introduction

For reasons including seeking to reduce the adverse health effects of vehicular air pollution, major cities around the world have introduced various policies to reduce or manage road traffic flows. London, Milan, San Diego, and Stockholm

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have introduced road-pricing schemes. Some cities have also employed regulatory approaches, such as driving restrictions: the *Hoy No Circula* in Mexico City, the odd–even/1-day-per-week program in Beijing, the *Pico y Placa* in Quito, and low-emission zones in European cities.

Empirical evidence has revealed that these policies are effective in reducing road traffic flows; however, the sizes of their pollution-reducing effects remain ambiguous. For example, Gibson and Carnovale [7] analyzed Milan's road pricing policy, called "Area C", finding that it reduced entries of relevant vehicles into the priced area and the ambient carbon monoxide (CO) concentration in the area. However, no significant effect was observed on ambient fine particulate matter ($PM_{2.5}$). Green et al. [9] examined the London Congestion Charge Zone, finding that it reduced the annual vehicle miles driven by covered vehicles and ambient concentrations of CO and $PM_{2.5}$ in the priced area. However, they found that nitrogen dioxide (NO_2) levels in the priced areas increased as a result of the policy. These prior results raise the question of the size of the link between road traffic flows and air pollution.

This study aims to examine the relationship between road traffic flows and local air pollution concentrations in Japan. Examining the case of Japan is important for three key reasons. First, diesel vehicle driving restrictions were introduced in 2003 to improve air quality in Tokyo, with some prior work presenting evidence on their pollution-reducing effects [22, 27]. However, the links between road traffic flows and air pollution concentrations have yet to be estimated. Second, high-quality granular data on road traffic flows and air pollution concentration are available for Japan, making it a good setting to study. Third, Japan is a populous country and continues to seek to improve ambient air quality. Better understanding the causes of ambient air pollution may provide insights for policies to improve public health.

We use data for 24-h periods from the 2015 Road Traffic Census, matched to data from air pollution monitoring stations and meteorological stations. We focus on four pollutants designated under the vehicle emission standards of Japan: nitrogen oxides (NOx), CO, nonmethane hydrocarbons (NMHC), and $PM_{2.5}$. We estimate a dynamic panel model to obtain short- and long-run elasticities of pollution concentrations to road traffic flows for the four pollutants, separately. Knowledge on the short- and long-run elasticities are useful for informing the calibration of policy interventions to improve air quality through a reduction in road traffic flows. In this study, we demonstrate the usefulness of our estimates in quantitatively examining the potential that Japan could achieve the World Health Organization (WHO)'s new air-quality guidelines introduced in 2021, by reducing road traffic flow.

We identify short-run elasticities of pollution concentrations to motor vehicle flows of 0.04–0.05 for NOx, CO, and NMHC. Assuming that the dynamic relations observed over a 24-h period are able to be extrapolated, long-run elasticities for these pollutants are in the range 0.09–0.17. No significant evidence of pollution concentration-road traffic flow links is found for $PM_{2.5}$. We also investigate potentially heterogeneous pollution concentration-road traffic flow links by space, hour-of-day, and vehicle type.

This study contributes to the literature estimating the effects of road traffic flows on ambient air pollution [1, 4, 14, 18, 26].[1] First, our analyses cover a nationwide sample of air pollution monitoring stations, allowing us to exploit the substantial variation in road traffic flows and pollution levels. Previous studies have focused on single towns [14], municipalities [26], or counties [1, 4, 18]. We instead use data from the 2015 Road Traffic Census, which covers approximately 65,000 census points across the country.

Second, our approach allows us to identify traffic census points in close proximity to each pollution monitoring station (an average of 6 m). Aldrin and Haff [1], Coria et al. [4], and Rossi et al. [26] used traffic count data from the traffic monitoring station nearest to each fixed pollution monitoring station. However, this involved using distant traffic-monitoring stations in some cases. For example, in the study of Rossi et al. [26], the distances between road traffic monitoring stations and the two pollution monitoring stations in the sample were 570 m and 1.2 km respectively.

The third contribution of this study is the examination of short-run temporal dynamics. It is well known that emissions take time to influence pollution concentrations at nearby monitoring stations and that it also takes time for air pollutants to be reabsorbed or transformed by the environment [24]. However, prior research typically has not focused on the dynamic aspects of the pollution concentration-road traffic flow links. We do so by estimating a dynamic estimation model.

In 2021, the WHO introduced new air-quality guidelines [29]. The limits in terms of the 99th percentile values of 24-h averages in a given year were set at 25 μg/m^3 for NO_2, 4 mg/m^3 for CO, and 15 μg/m^3 for $PM_{2.5}$. As of 2019, approximately 86% of Japan's air monitoring stations were noncompliant with the standard for NO_2, 17% with the standard for CO, and 100% with the standard for $PM_{2.5}$ based on our dataset. Using our estimates, we explore whether reducing road traffic flows could make a sizeable contribution to achieving the new WHO air quality goals in Japan, assuming the composition of the current vehicle fleet remains unchanged. We find that traffic reduction policies are likely not sufficient to make much progress in achieving the new WHO targets across the country, thus, requiring a more comprehensive policy package. Other key approaches that would help include the adoption of emission-free vehicles.

The remainder of this paper is organized as follows. First, Sect. "Data" describes the construction and characteristics of the station-hour panel datasets. Sect. "Empirical approach" presents our modelling approaches. Sect. "Results" presents the estimation results and explores their robustness. Sect. "Meeting the new WHO guidelines" explores the implications of the results and discusses their policy implications. Section 6 concludes.

[1] See Appendix A for details. The appendix does not cover studies that use alternative measures of road traffic flows such as vehicle-kilometers traveled [12].

Data

We purchased hourly road traffic flow data from the 2015 Road Traffic Census, made available via the PAREA-Traffic dataset of the Japan Asia Group in shapefile form. The underlying data collector was Japan's Ministry of Land, Infrastructure, Transport, and Tourism. The dataset covers approximately 65,000 traffic census points across Japan and provides hourly traffic flow data past specific points during each hour on specific census days. Road traffic flow data are available for both standard vehicles (passenger vehicles and light trucks) and heavy vehicles (buses, heavy trucks, and special vehicles, such as ambulances, fire engines, and garbage trucks). Motorcycles and bicycles are excluded.

A notable feature of the study context is that the road traffic census points were each set up for only 1 day at each location from December 7, 2010, to December 18, 2015.[2] Appendix B displays the distributions of the road traffic census points by year, month, and hour. This shows that the majority of the census points were set up during the months of October and November 2015. It can also be seen that some census points did not record road traffic flows outside the hours of 7.00–18.00.

To match against the road traffic flow data, we obtained hourly air pollution data from the Environmental Statistics Database of the National Institute for Environmental Studies. Specifically, we collected data on ambient concentrations of NOx, CO, NMHC, and $PM_{2.5}$ as measured at each pollution monitoring station. We also collected air concentration data for NO_2, suspended particulate matter (SPM), sulfur dioxide (SO_2), and oxidants (Ox). Information on whether air pollution monitoring stations are in residential or roadside areas is also available. Air concentration data are measured using the average across all minutes in an hour.

Hourly meteorological data also were obtained from the Japan Meteorological Agency. We collected data on the temperature, precipitation, atmospheric pressure, humidity, wind speed, and wind direction measured at each meteorological station. Other than precipitation, these were all average hourly measurements.

Our station-hour panel dataset was constructed by matching each pollution monitoring station with the nearest road traffic census point and meteorological station.[3] Each pollution monitoring station was matched with a single traffic census point and a meteorological station. The average distance from each pollution monitoring station to the nearest roadside traffic census point was 6 m (0.2 m at minimum and 72 m at maximum). This was possible in part due to the granularity of the census points in the 2015 Road Traffic Census.

Our station-hour panel dataset is for a maximum of 24 h. However, given that we estimate a dynamic panel model with one-hour lagged dependent variable, the

[2] The 2015 Road Traffic Census includes data for years before 2015 because individual surveys on road traffic flows are also included, such as cases where highways and bridges were newly built.

[3] It might be more appropriate to measure total traffic volumes around each pollution monitoring station within a certain radius in order to account for the influence of the neighboring road network. However, the 2015 Road Traffic Census does not allow us to do so, as census days vary for different nearby census points.

Table 1 Summary statistics for estimation sample

	Mean	SD	Min	Max	Obs	Stations	Hours
(A) Air pollution concentration							
NOx, ppb	20.48	22.62	0	292	24,410	1077	22.7
CO, ppm	3.62	2.08	0	17	4466	197	22.7
NMHC, 10ppbC	14.05	12.51	0	472	7371	330	22.3
$PM_{2.5}$, µg/m^3	12.45	9.60	0	135	14,348	653	22.0
NO_2, ppb	13.75	11.07	0	110	24,410	1077	22.7
SPM, µg/m^3	16.19	12.07	0	125	25,106	1111	22.6
SO_2, ppb	1.75	2.02	0	34	14,590	645	22.6
Ox, ppb	25.56	15.08	0	96	17,076	754	22.6
(B) Road traffic flows							
ln standard vehicles	6.45	1.05	0.69	9.01	18,580	1231	15.1
ln heavy vehicles	4.30	1.38	0	8.01	18,407	1227	15.0
ln total	6.62	1.02	0.69	9.16	18,580	1231	15.1
(C) Meteorological variables							
Temperature, ℃	16.31	4.57	−1.4	34.7	28,236	1231	22.9
Precipitation, mm	0.11	0.79	0	38.0	28,223	1231	22.9
Pressure, hPa	1,012	11	952	1,035	27,781	1212	22.9
Humidity, %	67	17	18	100	27,777	1212	22.9
Wind speed, m/s	2.9	1.9	0	13.9	28,188	1230	22.9
Wind direction dummies							
NNE	0.12	0.33	0	1	28,313	1234	22.9
NE	0.08	0.26	0	1	28,313	1234	22.9
ENE	0.09	0.28	0	1	28,313	1234	22.9
E	0.04	0.21	0	1	28,313	1234	22.9
ESE	0.03	0.18	0	1	28,313	1234	22.9
SE	0.03	0.18	0	1	28,313	1234	22.9
SSE	0.04	0.19	0	1	28,313	1234	22.9
S	0.04	0.19	0	1	28,313	1234	22.9
SSW	0.03	0.17	0	1	28,313	1234	22.9
SW	0.04	0.20	0	1	28,313	1234	22.9
WSW	0.03	0.18	0	1	28,313	1234	22.9
W	0.04	0.21	0	1	28,313	1234	22.9
WNW	0.07	0.25	0	1	28,313	1234	22.9
NW	0.09	0.28	0	1	28,313	1234	22.9
NNW	0.10	0.30	0	1	28,313	1234	22.9
N	0.12	0.33	0	1	28,313	1234	22.9

The table presents summary statistics for hourly air pollution concentrations, road traffic flow, and meteorological variables in our station-hour panel dataset. Standard vehicles include passenger vehicles and light trucks. Heavy vehicles include buses, heavy trucks, and special vehicles. N, E, S, and W stand for North, East, South, and West. SD = standard deviation. Obs = Observations. Stations refers to pollution monitoring stations. Hours is the average number of hours per pollution monitoring station

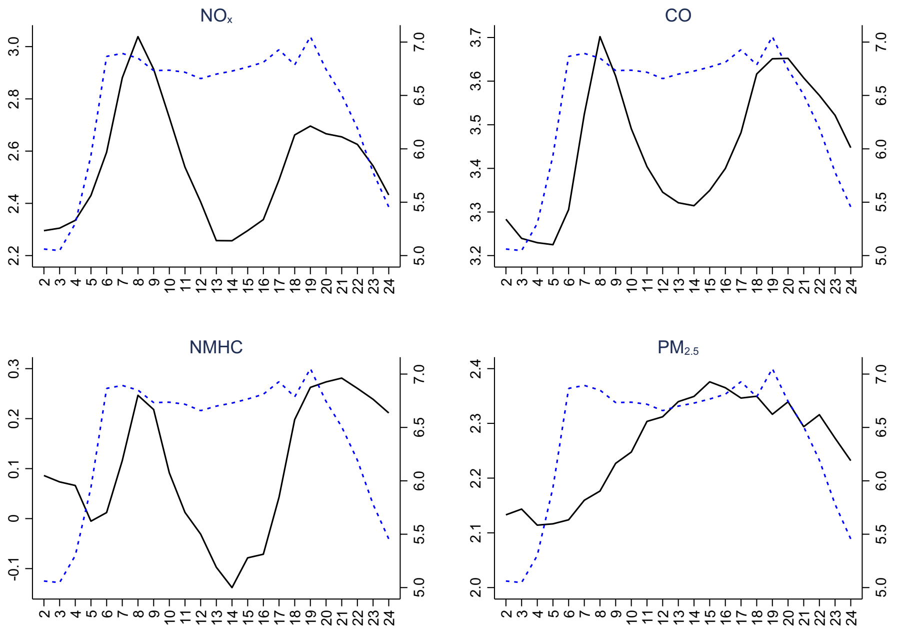


Fig. 1 Temporal variation in road traffic flow and vehicular air pollution concentration. These graphs show the temporal variations in the natural logarithm of the average hourly road traffic flow (blue dotted line, right axis) and the natural logarithm of the average hourly ambient concentrations of the four vehicular air pollutants (black line, left axis). NOx, nitrogen oxide; CO, carbon monoxide; NMHC, non-methane hydrocarbons; $PM_{2.5}$, fine particulate matter. The first hour of the day is omitted

first hour of the day is excluded from the estimations. This leaves a maximum of 23 h per panel unit.

In summary, our station-hour panel dataset is characterized by the following: (i) each panel unit is only in the sample for a maximum of one day during 2010–2015, (ii) the hours in the sample are between 2.00 and 24.00 in terms of the hour end time, (iii) the sample is highly concentrated in October and November of 2015, (iv) the panel is unbalanced, (v) the coverage varies among air pollutants, and (vi) the dataset includes both residential and roadside pollution monitoring stations in both rural and urban municipalities.

Table 1 shows summary statistics for the hourly air pollution concentrations, road traffic flow (in log), and meteorological variables for the station-hour panel dataset. The final two columns show the maximum coverage of each variable in terms of the number of air pollution monitoring stations and the average length of hours per station in the dataset. We observe that meteorological variables have fewer missing observations. The number of available pollution monitoring stations ranges from around 197 for CO to 1,111 for SPM because some pollution monitoring stations only measured selected pollutants. The average number of hours of road traffic flow was 15. This is because road traffic flows were not recorded outside 7.00–18.00 at some traffic census points (see Appendix B).

Figure 1 displays the temporal variation in the four vehicular air pollutants and road traffic flows during the day. The blue dotted line shows the log of the average road traffic flow per hour. The black line represents the log-averaged hourly ambient concentration of each air pollutant. The road traffic flow variable exhibits two peaks: one at 7.00 and the other at 19.00. The hourly ambient concentrations of NOx, CO, and NMHC appear to be correlated with hourly road traffic flows. In contrast, such an association cannot be observed for $PM_{2.5}$; hourly ambient concentrations of $PM_{2.5}$ peak at 15.00.[4]

There are many factors to consider when estimating pollution concentration-road traffic flow links. First, meteorological conditions are relevant, in particular because the air pollutants we are studying are not uniformly mixed [24].[5] Second, pollution concentrations for pollutants that are not pure flow pollutants are functions of both current and lagged emissions [24], making it important to consider dynamics. For instance, a vehicle passing a location in the final minute of an hour is likely to mostly affect the average pollution concentration in the next hour rather than the same hour. Finally, Fig. 1 may mask heterogeneous pollution concentration-road traffic flow links by location (e.g., roadside vs. residential). The next section explains our empirical approach for addressing these issues.

Empirical approach

Baseline specification

The average ambient concentration of a pollutant at a location in any hour is a function of the initial concentration, new emissions, and outflows resulting from natural processes. Given the importance of the initial concentration, we estimate the following dynamic panel model:

$$\ln P_{m,h} = \alpha_1 \ln P_{m,h-1} + \beta_1 \ln T_{m,h} + \boldsymbol{\gamma} \boldsymbol{C}_{m,h} + \delta_m + \theta_h + \varepsilon_{m,h} \tag{1}$$

where m is the air pollution monitoring station and h is the hour. P is the ambient concentration of either NOx, CO, NMHC, or $PM_{2.5}$. The inclusion of the h-1 lagged dependent variable as a regressor makes it an autoregressive model, specifically called the partial adjustment model. T is the road traffic flow as measured at the nearest road traffic census point. An h-1 lagged T is not included in Eq. (1) because we failed to reject the null hypothesis that the coefficient of the h-1 lagged T is zero for each pollutant. We take the natural logarithm, denoted by "ln," for P and T, as their distributions are heavily skewed and to produce direct estimates of elasticities.

[4] Appendix C shows temporal variation in road traffic flow and ambient concentrations for NO_2, SPM, SO_2, and Ox. The NO_2 levels appear to be correlated with hourly road traffic flows, while SPM, SO_2, and O_X do not.

[5] See Appendix D for how average meteorological variables tend to fluctuate across the day. For example, there tend to be higher wind speeds in the evening hours.

C in Eq. (1) is a vector of meteorological variables (temperature, precipitation, pressure, humidity, wind speed, and wind direction).δ is air pollution monitoring station fixed effects to capture unobserved time-invariant factors such as location.[6] θ is hour-of-day fixed effects, to remove the influence of hour-specific factors affecting all pollution monitoring stations in the same way, such as the ability of the environment to "ventilate" the pollution at any specific time of day [4, 10].[7] ε is an error term.

β_1 can be interpreted as the short-run or same-hour pollution concentration-road traffic flow elasticity: the % change in P with respect to a 1% change in T in the same hour. Equation (1) also enables us to obtain a long-run pollution concentration-road traffic flow elasticity using $\beta_1/(1-\alpha_1)$. This captures the summed effect of observed lagged responses based on holding the assumed functional form fixed in a long-run simulation [6]. Given that we use only a maximum of 23 h of pollution concentration data for any location in the estimation sample, we cannot utilize longer time series of data to obtain alternative estimates of long-run effects.

There are several identification challenges in estimating Eq. (1). The first is that the inclusion of air pollution monitoring station fixed effects (δ) does not eliminate dynamic panel bias given that the lagged P and ε mechanically move together and thus a regressor and the error are correlated [25]. The second is the fact that T might be correlated with ε. For example, vehicular emissions may positively co-move with emissions from stationary sources (e.g., power plants and industrial combustion) or other mobile sources (e.g., ships and airplanes). Third, some locations may have denser road networks, hence additional nearby vehicle traffic not measured at the traffic census point. Air pollution monitoring station fixed effects cannot fully exclude the bias emanating from potential measurement error.

To address the issues above, we apply a system GMM estimator to Eq. (1). The system GMM uses lagged differences and levels of the dependent variable as instrumental variables in a system of two equations and is known to have superior efficiency than the difference GMM estimator [3]. An assumption is that changes in the instruments are uncorrelated with the fixed effects [25]. In our one-step system GMM estimation, we regard the h-1 lagged P as predetermined but not strictly exogenous and the T and ***C*** as endogenous. Therefore, we put every regressor in Eq. (1) other than the station and hour-of-day fixed effects into the instrument matrix and took a collapsed form to limit the number of instruments, resulting in 574 instruments in our system GMM specifications. We applied the forward orthogonal deviations transform that subtracts the average of all available future observations, rather than the previous observation [2]. The Arellano-Bond tests reject the null hypothesis of no first-order serial correlation in first differences for the specification of each pollutant.[8]

[6] Roadside areas are physically more proximate to a key source of emissions, likely leading to higher ambient concentrations of pollutants. In addition, there might be time-persistent differences between rural and urban areas. For example, due to the greater intensity of economic activities, urban areas might have other activities that lead to pollution.

[7] Ventilation coefficients tend to be low during mornings and evenings as a result of higher humidity and slower wind speeds [8].

[8] Note that we failed to reject the null hypothesis of second-order serial correlation except for the model of $PM_{2.5}$, warning our GMM estimates may be imperfect. We do not discuss the Hansen tests for over-

Additionally, we adopt the following robustness check approaches. First, we include municipality-by-hour-of-day fixed effects to control for potential time-varying confounders at the municipal level. The second is to control for the hourly SO_2 concentration at the monitoring station level as a proxy for pollution from sources other than road transport. This is motivated by the fact that in 2015, other mobile sources accounted for 36% of the total anthropogenic SO_2 emissions in Japan, power stations contributed 26%, and industrial combustion accounted for 31%, leaving the contribution of the road transport sector at almost zero (Organization for Economic Cooperation and Development OECD, 2023).[9] The third is to estimate Eq. (1) with date-specific hour fixed effects to control for seasonality and unusual events, such as typhoons and earthquakes. This means the inclusion of a fixed effect for every hour in the calendar (i.e., hour-by-day-by-month-by-year) and is possible because multiple traffic census points were operated simultaneously.

There are two concerns over statistical inference. First, common shocks in the same municipality could cause model errors for each pollution monitoring station within the municipality to be spatially correlated. Second, model errors may be serially correlated. To address these issues, we report robust standard errors clustered by municipality. The number of clusters ranges from 156 to 610, depending on the air pollutant. This is sufficient for the reliability of the standard cluster adjustment.

Additional specifications

To analyze the extent to which pollution concentration-road traffic flow elasticities differ between residential and roadside areas, we estimate the following specification:

$$\ln P_{m,h} = \alpha_1 \ln P_{m,h-1} + \beta_1 \ln T_{m,h} + \beta_2 (\ln T_{m,h} \times Roadside_m) + \boldsymbol{\gamma} \boldsymbol{C}_{m,h} + \delta_m + \theta_h + \varepsilon_{m,h} \tag{2}$$

where *Roadside* is a dummy that takes the value of one if an air pollution monitoring station is located in a roadside area and zero otherwise. The other elements are identical to Eq. (1). $\beta_2 > 0$ would indicate that the short-run pollution concentration-road traffic flow elasticity is larger for roadside areas than residential areas. Based on the estimates, we also calculate the long-run elasticities for residential areas ($\beta_1 / \left(1 - \alpha_1\right)$) and roadside areas ($(\beta_1 + \beta_2) / \left(1 - \alpha_1\right)$).

We next estimate separate pollution concentration-road traffic flow elasticities for standard and heavy vehicles. To do so, we split road traffic flow (*T*) into flows of standard vehicles (*TS*) and heavy vehicles (*TH*). We estimate the following specification:

Footnote 8 (continued)

identifying restrictions here, because the “xtabond2” package in Stata did not allow us to obtain the results for some pollutants.

[9] Note that SO_2 also comes from natural sources such as volcanoes. It can react with other pollutants to form acid rain, particulate matter, and ozone [11].

Table 2 Baseline estimates

Dependent variable: Ln ambient concentration of air pollution				
	NOx	CO	NMHC	$PM_{2.5}$
	(1)	(2)	(3)	(4)
Ln road traffic flow	0.054***	0.043**	0.040*	– 0.036
	(0.016)	(0.018)	(0.023)	(0.029)
Temperature, ℃	– 0.015***	– 0.000	– 0.011	0.026***
	(0.005)	(0.006)	(0.007)	(0.007)
Precipitation, mm	– 0.004	– 0.002	– 0.004	0.005
	(0.005)	(0.003)	(0.004)	(0.009)
Pressure, hPa	0.004	0.002	0.000	0.011*
	(0.004)	(0.003)	(0.006)	(0.006)
Humidity, %	0.002**	0.001	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Wind speed, m/s	– 0.031***	– 0.025***	– 0.029***	– 0.017***
	(0.003)	(0.004)	(0.005)	(0.005)
Ln h-1 lagged dependent variable	0.680***	0.598***	0.574***	0.395***
	(0.009)	(0.019)	(0.020)	(0.020)
R^2	0.624	0.547	0.453	0.197
Station fixed effects	Yes	Yes	Yes	Yes
Hour-of-day fixed effects	Yes	Yes	Yes	Yes
Wind direction dummies	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1053	193	323	641
Municipalities	610	156	247	482
Observations	15,480	3052	4679	8835
Long-run pollution concentration-road traffic flow elasticity	0.17***	0.11**	0.09*	– 0.06

The table shows the results for estimating Eq. (1) for each vehicular pollutant. The R^2 is for within monitoring station units. All specifications use a station-hour panel dataset. Standard errors are robust to heteroscedasticity and clustered by municipality. For the long-run elasticity, standard errors are generated using the delta method

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively

$$\ln P_{m,h} = \alpha_1 \ln P_{m,h-1} + \beta_1 \ln TS_{m,h} + \beta_2 \ln TH_{m,h} + \boldsymbol{\gamma} \boldsymbol{C}_{m,h} + \delta_m + \theta_h + \varepsilon_{m,h} \qquad (3)$$

The long-run pollution concentration-road traffic flow elasticities can be calculated by $(\beta_1/(1-\alpha_1))$ for standard vehicles and by $(\beta_2/(1-\alpha_1))$ for heavy vehicles.

Finally, to examine time patterns for the same-hour pollution concentration-road traffic flow elasticity, we interact hour-of-day dummies (θ_h) for all hours in the sample with the log road traffic flow variable ($\ln T$):

$$\ln P_{m,h} = \alpha_1 \ln P_{m,h-1} + \sum_{h=2}^{24} \beta_h \left(\ln T_{m,h} \times \theta_h \right) + \boldsymbol{\gamma} \boldsymbol{C}_{m,h} + \delta_m + \theta_h + \varepsilon_{m,h} \tag{4}$$

β_h indicates the same-hour pollution concentration-road traffic flow elasticity for each of the 23 h. Knowing the elasticity at specific times of day could be useful for informing policy design, such as the timing of vehicle flow restrictions. It may also be of use for pollution modelling and prediction exercises.[10]

Results

Baseline estimates

Table 2 reports the baseline results for estimating Eq. (1) for each pollutant. All estimations control for the log h-1 lagged dependent variables, meteorological variables, station fixed effects, and hour-of-day fixed effects. To save space, we do not report the estimated coefficients for wind direction dummies. All estimations use the station-hour panel dataset. Data coverage varies among pollutants, leading to varying sample sizes that range from 3052 to 15,480 observations.

The first column of Table 2 finds a short-run pollution concentration-road traffic flow elasticity of NOx of 0.05. This is significantly different from zero at the 1% level, with the 95% confidence interval ranging from 0.02 to 0.09. The coefficient suggests that a 1% increase in road traffic flow, on average, leads to a 0.05% increase in the same-hour ambient NOx concentration at the local level. Our estimated positive elasticities for NOx are consistent with the prior work of Aldrin and Haff [1], Coria et al. [4], and Rossi et al. [26], who find a positive link between road traffic flows and ambient concentrations of NO, NO_2, and NOx. Prior research has not presented elasticity estimates, however.

The second and third columns of Table 2 report similar short-run elasticities for CO and NMHC. The coefficients suggest that a 1% increase in road traffic flow on average leads to a 0.04% increase in the same-hour ambient CO and NMHC concentrations. By contrast, we find that the estimated short-run elasticity for $PM_{2.5}$ is negative in point estimate terms and statistically indistinguishable from zero (column 4). The standard error reveals that it is also estimated less precisely than the elasticities for the other pollutants.

The base of Table 2 reports the long-run pollution concentration-road traffic flow elasticities for each pollutant. These are 0.17 for NOx, 0.11 for CO, and 0.09 for NMHC. These are larger than their short-run counterparts, likely due to lags in the conversion of emissions to pollution concentrations. No evidence of significant long-run pollution concentration-road traffic flow elasticity was found for $PM_{2.5}$.

[10] For example, the *Hoy No Circula* in Mexico City bans most drivers from using their vehicles one weekday per week between 5.00 and 22.00.

Table 3 Pollution concentration-road traffic flow elasticity: roadside vs residential areas

Dependent variable: Ln ambient concentration of air pollution

	NOx	CO	NMHC	$PM_{2.5}$
	(1)	(2)	(3)	(4)
Ln road traffic flow	0.053***	0.011	0.027	– 0.036
	(0.016)	(0.022)	(0.022)	(0.029)
Ln road traffic flow × Roadside dummy	0.034**	0.047***	0.052***	0.001
	(0.016)	(0.017)	(0.017)	(0.022)
R^2	0.624	0.548	0.454	0.197
Station fixed effects	Yes	Yes	Yes	Yes
Hour-of-day fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
Ln h-1 lagged dependent variables	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1053	193	323	641
Municipalities	610	156	247	482
Observations	15,480	3052	4679	8835
Long-run pollution concentration-road traffic flow elasticity for				
Residential stations	0.17***	0.03	0.06	– 0.06
Roadside stations	0.27***	0.14***	0.18***	– 0.06

The table shows the results for estimating Eq. (2) for each vehicular pollutant. All meteorological variables including wind direction dummies and the log h-1 lagged dependent variables listed in Table 2 are included in each model. The R^2 is for within monitoring station units. All specifications use a station-hour panel dataset. Standard errors are robust to heteroscedasticity and clustered by municipality. For the long-run elasticity, standard errors are generated using the delta method

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively

Small pollution concentration-road traffic flow elasticities are likely to emanate from the fact that there are multiple contributors to emissions. For example, as of 2015, road transport accounted for 21% of the total anthropogenic NOx emissions in Japan [23]—a ratio that is similar to the long-run elasticity estimate in Table 2. Another reason for low pollution concentration-road traffic flow elasticities is that during congested road conditions, traffic flow numbers may be low [30] but emissions high. Traffic density (vehicles per unit road area) data are unavailable.

Appendix E reports the estimation results of Eq. (1) for the other pollutants. We find that road traffic flows are positively associated with NO_2 levels and negatively associated with SPM levels, consistent with the results for NOx and $PM_{2.5}$ (Table 2). We find no evidence of either short- or long-run pollution concentration-road traffic flow links for SO_2 and Ox.

Wind speed is found to be negatively associated with the ambient concentrations of all pollutants in Table 2. This makes sense given that wind promotes the dispersion of air pollutants [1, 4, 26]. We also find that humidity is positively associated with the concentrations of NOx, NMHC, and $PM_{2.5}$, consistent with the fact that humidity increases the retention of harmful or toxic chemicals in the

Table 4 Pollution concentration-road traffic flow elasticity by vehicle type

Dependent variable: Ln ambient concentration of air pollution				
	NOx	CO	NMHC	$PM_{2.5}$
	(1)	(2)	(3)	(4)
Ln road traffic flow of standard vehicles	0.013	0.037**	0.042	– 0.036
	(0.017)	(0.015)	(0.027)	(0.025)
Ln road traffic flow of heavy vehicles	0.055***	0.008	0.027**	– 0.001
	(0.012)	(0.010)	(0.013)	(0.016)
R^2	0.626	0.549	0.457	0.198
Station fixed effects	Yes	Yes	Yes	Yes
Hour-of-day fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
Ln h-1 lagged dependent variables	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1,050	193	320	639
Municipalities	609	156	244	480
Observations	15,357	3038	4613	8762
Long-run pollution concentration-road traffic flow elasticity for				
Standard vehicles	0.04	0.09**	0.10	– 0.06
Heavy vehicles	0.17***	0.02	0.06**	– 0.00

The table shows the results for estimating Eq. (3) for each vehicular pollutant. All meteorological variables including wind direction dummies and the log h-1 lagged dependent variables listed in Table 2 are included in each model. Standard vehicles include passenger vehicles and light trucks. Heavy vehicles include buses, heavy trucks, and special vehicles. The R^2 is for within monitoring station units. All specifications use a station-hour panel dataset. Standard errors are robust to heteroscedasticity and clustered by municipality. For the long-run elasticity, standard errors are generated using the delta method

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively

air. The effects of other meteorological variables on air quality are either indistinguishable from zero or vary by pollutant type.

Appendix F reports the estimation results for the static panel model without the lagged dependent variable. The pollution concentration-road traffic flow elasticities for NOx, CO, and NMHC are between the short- and long-run elasticities from Table 2. By not specifically incorporating dynamics, static estimates typically represent an intermediate elasticity rather than a short- or long-run elasticity [16].

Heterogeneity

Table 3 reports results for Eq. (2) to examine the extent to which the pollution concentration-road traffic flow elasticity differs between residential and roadside areas. The first to third columns indicate that for NOx, CO, and NMHC, the same-hour elasticities for roadside monitoring stations are greater than those for residential monitoring stations. For the case of NOx, the point estimates suggest that the short-run elasticity for roadside monitoring stations is 64% (≈ (0.034/0.053) × 100) larger

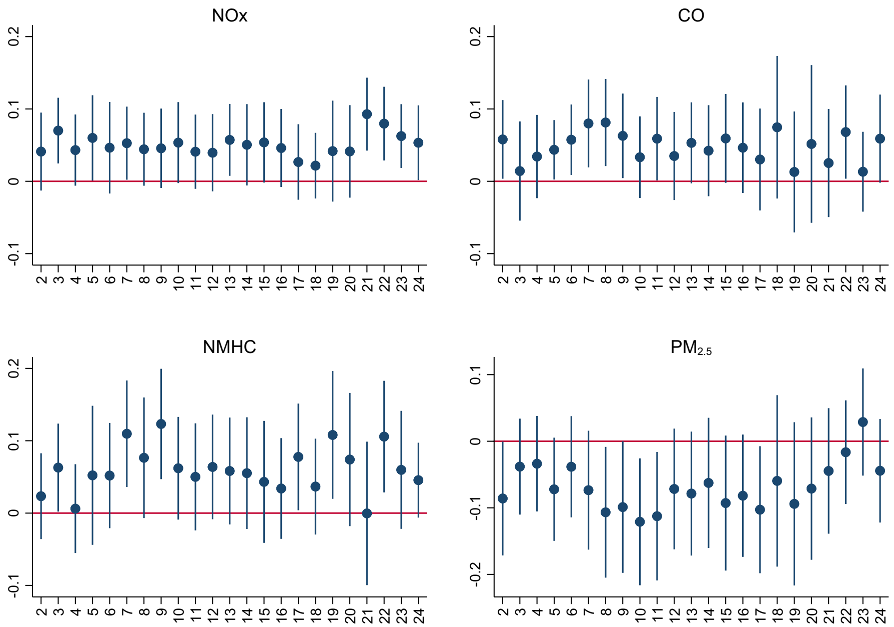


Fig. 2 Pollution concentration-road traffic flow elasticity by hour. The figures present the estimation results of Eq. (4) for each vehicular pollutant. All specifications use a station-hour panel dataset. The dots represent the point estimates, and the vertical bands represent the 95% confidence intervals. Standard errors are robust to heteroscedasticity and clustered by municipality. Hourly data for 1.00 were not included in the estimation sample. The first hour of the day is omitted

than for residential monitoring stations.[11] This makes sense given that it takes time for emissions to reach non-roadside areas. We find no significant evidence of heterogeneous pollution concentration-road traffic flow elasticities between roadside and residential monitoring stations for $PM_{2.5}$ (column 4).

Table 3 also reports the long-run pollution concentration-road traffic flow elasticities for residential and roadside stations. For residential stations, the long-run elasticity is 0.17 for NOx (significant at the 1% level). This is statistically indistinguishable from zero for the other pollutants. For the roadside stations, relatively large long-run elasticities are observed for NOx (0.27), CO (0.14), and NMHC (0.18). The effects remain similar and statistically insignificant for $PM_{2.5}$.

Table 4 reports results by vehicle type based on Eq. (3). We find that in the cases of NOx and NMHC, the pollution concentration-road traffic flow elasticities are positive and significant for heavy vehicles only (columns 1 and 3). In contrast, for CO the elasticity is positive and significant for standard vehicles only (column 2). These

[11] For the cases of CO and NMHC, the short-run elasticities for roadside monitoring station are 427% (≈ (0.047/0.011) × 100) and 193% (≈ (0.052/0.027) × 100) larger than for residential monitoring stations, respectively. Note that the elasticities for residential monitoring stations are insignificantly different from zero.

Table 5 Pollution concentration-road traffic flow elasticities based on different estimators, specifications, and samples

	NOx (1)	CO (2)	NMHC (3)	$PM_{2.5}$ (4)
(A) Adopting system GMM				
Short-run	0.07**	0.05*	0.05	– 0.09**
Long-run	0.28**	0.14*	0.13	– 0.18**
Observations	15,480	3,052	4,679	8,835
(B) Controlling for municipality-by-hour-of-day fixed effects				
Short-run	0.02***	0.02	– 0.00	– 0.01
Long-run	0.16***	0.17	– 0.01	– 0.04
Observations	9,065	772	1,462	3,182
(C) Adding ambient SO_2 concentration				
Short-run	0.04*	0.05	0.05	– 0.02
Long-run	0.12*	0.11	0.10	– 0.03
Observations	8,046	953	2,676	4,826
(D) Controlling for date-specific hour fixed effects				
Short-run	0.06***	0.04*	0.03	0.01
Long-run	0.19***	0.10*	0.07	0.01
Observations	15,480	3,052	4,679	8,835
(E) Clustering standard errors at the air pollution monitoring station level				
Short-run	0.05***	0.04**	0.04*	– 0.04
Long-run	0.17***	0.11**	0.09	– 0.06
Observations	15,480	3,052	4,679	8,835
(F) Using balanced panel				
Short-run	0.06***	0.04**	0.04	– 0.03
Long-run	0.22***	0.11**	0.11	– 0.06
Observations	6707	1630	2037	3766

All panels are based on Eq. (1) with a station-hour panel dataset. Panel A adopts system GMM. Panel B controls for municipality-by-hour-of-day fixed effects instead of station fixed effects and hour-of-day fixed effects. Panel C adds ambient SO_2 concentration to the model. Panel D controls for date-specific hour fixed effects instead of hour-of-day fixed effects. Panel E clusters standard errors at the air pollution monitoring station level instead of the municipality level. Panel F uses balanced panel data that keeps air pollution monitoring stations with 24-h data only. For the long-run elasticity, standard errors are generated using the delta method

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively

results are consistent with the fact that the main sources of vehicular NOx and CO emissions are trucks and passenger cars, respectively [17]. No significant evidence of differential pollution concentration-road traffic flow elasticities by vehicle type for $PM_{2.5}$ was found (column 4).

Figure 2 displays the time pattern of short-run pollution concentration-road traffic flow elasticities for each vehicular pollutant by hour of day from estimating

Eq. (4). For NOx, the same-hour effects of road traffic flows on air pollution concentrations are relatively stable over time, with point estimates ranging from 0.022 to 0.093 and a mean of 0.051. The largest effects are observed during night-time hours (21.00–23.00), perhaps because other contributors to ambient air concentration are lower. For CO and NMHC, the pollution concentration-road traffic flow elasticities are consistently positive and fluctuate over hour-of-day. For $PM_{2.5}$, the point estimates were negative for all hours except 23.00.

Robustness

Table 5 reports results for additional analyses. The panels are based on Eq. (1) but use different estimators, specifications, and samples. Panel A adopts the system GMM estimator. To account for unobserved time-varying factors, Panel B controls for municipality-by-hour-of-day fixed effects instead of separate hour-of-day fixed effects and station fixed effects.[12] Panel C adds the ambient SO_2 concentration to the model.[13] Panel D controls for date-specific hour fixed effects instead of hour-of-day fixed effects to account for seasonality and unusual events. Panel E clusters standard errors at the air pollution monitoring station level instead of the municipality level in order to allow for heterogeneous serial correlation among the air pollution monitoring stations. Panel F uses a balanced panel, retaining only the air pollution monitoring stations for which 24 h of data are available.

The first column of Table 5 reports short- and long-run pollution concentration-road traffic flow elasticities for NOx that are positive and statistically significant at the 10% level or below, regardless of the estimator, specification, or sample used. The same-hour and long-run elasticities range from 0.02–0.07 to 0.12–0.28 respectively, which encompasses our baseline estimates of 0.05 and 0.17 respectively. The second and third columns indicate that the pollution concentration-road traffic flow elasticities for CO and NMHC vary somewhat by estimator, specification, and sample.

To explore whether the different results in panel B of Table 5 relative to the base estimates in Table 2 are due to the additional controls or the reduced sample, we re-estimated the base model with the same samples as in Panel B. Appendix G reports the results, suggesting that the inclusion of the additional controls is the main factor. For example, in the case of NOx, using the same sample in Panel B the specification but without controlling for municipality-by-hour-of-day fixed effects generates a short-run elasticity of 0.07. This is 250% greater than when municipality-by-hour-of-day fixed effects are included and 40% greater than our baseline estimate.

Our baseline estimate indicates a lack of a significant positive pollution concentration-road traffic flow link for $PM_{2.5}$. The fourth column of Table 5 is consistent

[12] This is possible to do with the "reghdfe" package in Stata. However, the Stata package automatically drops all municipalities that have only a single air pollution monitoring station from the sample [5], substantially reducing the number of observations in panel B.

[13] The number of observations in panel C substantially decreases given that the number of air pollution stations measuring ambient SO_2 levels simultaneously is lower.

with this finding. Levy et al. [14] and Rossi et al. [26] also found an absence of short-run pollution concentration–road traffic flow links for $PM_{2.5}$. There are at least three potentially relevant factors here. First, there are many sources of particulate pollution, including power plants, the industrial sector, construction, and agriculture. Second, the diffusion process of $PM_{2.5}$ differs from gases (NOx, CO, and NMHC) given the heavier nature of particulates.[14] Third, some $PM_{2.5}$ forms via chemical reactions in the atmosphere and may be subject to long lags and/or may occur in a location far from the source due to the effects of winds.

Meeting the new WHO guidelines

In 2021, the WHO [21] announced new air quality guidelines (AQG) for key air pollutants. The AQG limit values in terms of the 99th percentile value of 24-h averages in a given year were set at 25 μg/m^3 for NO_2, 4 mg/m^3 for CO, and 15 μg/m^3 for $PM_{2.5}$, meaning that more than five exceedance days per year are regarded as non-compliant.[15] Based on scientific evidence of the harmful effects of $PM_{2.5}$ on human health at even lower concentrations than previously understood, the new $PM_{2.5}$ limit value was lowered by 40% from the 2005 value (25 μg/m^3). Short-term limit values for NO_2 and CO were newly introduced.

Table 6 shows the number of air pollution monitoring stations that were noncompliant with the WHO's new AQG limit values for NO_2, CO, and $PM_{2.5}$ in 2019, for each prefecture.[16] For NO_2, the number of non-compliant stations was 1,420 nationwide, accounting for 86% of the total number of NO_2 monitoring stations. Exceedance rates vary from 32% in Fukui prefecture to 100% in Kanagawa, Shiga, Nara, Kagawa, and Ehime prefectures. For $PM_{2.5}$, the exceedance rate was 100% except in Hokkaido. The exceedance rates for CO were much lower than those for NO_2 and $PM_{2.5}$ at both the prefecture and national levels. Overall, the results imply that harmful concentrations of NO_2 and $PM_{2.5}$ continue to exist.

Holding the vehicle mix constant, would a reduction in road traffic flows be useful in achieving the new WHO air quality targets? The answer is that this is unlikely given the small pollution concentration-road traffic flow elasticities that we have found. For example, utilizing the estimated long-run pollution concentration-road traffic flow elasticity for NO_2 in Appendix E (0.09), we calculated the changes in exceedance days for each pollution monitoring station if road traffic flows around each pollution monitoring station decreased by half. It was found that only 20

[14] The negative and statistically significant short- and long-run elasticities for $PM_{2.5}$ in Panel A of Table 5 may perhaps be because ambient $PM_{2.5}$ concentration increases when roads are congested, when traffic flows can decline. However, traffic density data are unavailable. The effect is insignificant in other estimations, however.

[15] The long-term AQG limit values were set at 10 μg/m^3 for NO_2 and 5 μg/m^3 for $PM_{2.5}$ in terms of annual averages in a given year. The WHO did not introduce a long-term AQG limit value for CO.

[16] The latest available year of hourly air pollution data was 2020 at the time of writing this paper. We avoided using 2020 data to avoid the influence of COVID-19.

Table 6 Air pollution monitoring stations that were not in compliance with the new WHO air quality guidelines limit values in 2019

	NO_2		CO		$PM_{2.5}$	
	Non-compliant stations	Share (%)	Non-compliant stations	Share (%)	Non-compliant stations	Share (%)
Hokkaido	55	72	1	17	24	96
Aomori	13	76	0	0	5	100
Iwate	13	93	0	0	10	100
Miyagi	30	83	1	25	28	100
Akita	10	63	0	0	7	100
Yamagata	9	56	0	0	14	100
Fukushima	11	48	0	0	11	100
Ibaraki	36	82	1	14	21	100
Tochigi	23	85	0	0	14	100
Gunma	20	91	1	11	11	100
Saitama	75	94	1	6	66	100
Chiba	120	98	7	32	59	100
Tokyo	88	99	3	10	87	100
Kanagawa	91	100	7	37	68	100
Niigata	21	84	2	67	17	100
Toyama	8	53	0	0	13	100
Ishikawa	9	43	2	33	16	100
Fukui	6	32	0	0	9	100
Yamanashi	10	91	0	0	6	100
Nagano	21	95	1	50	13	100
Gifu	16	76	0	0	17	100
Shizuoka	51	88	2	15	36	100
Aichi	101	99	1	9	56	100
Mie	26	93	0	0	25	100
Shiga	14	100	1	25	12	100
Kyoto	27	87	0	0	29	100
Osaka	101	99	1	7	56	100
Hyogo	94	95	6	23	65	100
Nara	12	100	0	0	9	100
Wakayama	12	48	0	0	14	100
Tottori	4	80	2	67	4	100
Shimane	2	40	0	0	8	100
Okayama	53	93	1	14	27	100
Hiroshima	34	94	0	0	25	100
Yamaguchi	24	86	0	0	20	100
Tokushima	15	83	0	0	10	100
Kagawa	19	100	0	0	13	100
Ehime	13	100	0	0	17	100
Kochi	4	57	0	0	6	100

Table 6 (continued)

	NO_2		CO		$PM_{2.5}$	
	Non-compliant stations	Share (%)	Non-compliant stations	Share (%)	Non-compliant stations	Share (%)
Fukuoka	54	98	2	29	39	100
Saga	9	60	1	50	12	100
Nagasaki	12	57	0	0	18	100
Kumamoto	14	61	0	0	28	100
Oita	18	69	0	0	17	100
Miyazaki	11	73	0	0	15	100
Kagoshima	4	33	1	50	10	100
Okinawa	7	78	2	100	5	100
Total	1,420	86	47	17	1,092	100

The new WHO air quality guideline levels are 25 μg/m^3 for NO_2, 4 mg/m^3 for CO, and 15 μg/m^3 for $PM_{2.5}$ in terms of the 99th percentile value of 24-h averages in a given year, meaning that more than 5 exceedance days per year are regarded as non-compliant. These are short-term levels

pollution monitoring stations out of 1,420 would switch from non-compliant to compliant across the country.

The key implication is that more specific road sector pollution reduction policies are required rather than targeting road traffic flow numbers alone. The adoption of clean vehicles, including battery electric vehicles (BEV) and fuel cell vehicles (FCV), is a promising method for improving air quality. Another alternative is to use diesel vehicle registration restrictions and low-emission zones. Diesel vehicle restrictions have already been adopted by some prefectures to reduce ambient concentrations of NOx and $PM_{2.5}$ by keeping polluted diesel trucks and buses away from designated areas.[17] Nishitateno and Burke [20, 21] have presented evidence that these interventions have been effective in improving local air quality.

An additional policy implication is that efforts beyond road transport are likely to be needed. An important reason for the inelastic effect sizes obtained in this study is that the road sector is only one contributor to pollution. Indeed, as of 2019, road transport accounted for only approximately 21% of total anthropogenic NOx emissions in Japan (1.2 million tonnes), whereas the contributions of other mobile sources, power stations, and industrial combustion were 25%, 15%, and 32%, respectively [23].[18] There is substantial scope for energy efficiency, electrification, and low-emission fuel switching across non-road sector activities.

[17] The diesel vehicle registration restrictions were introduced under the Automobile NOx/PM Law in Tokyo, Saitama, Chiba, Kanagawa, Osaka, and Hyogo prefectures in 1992 and Aichi and Mie prefectures in 2001. The low-emission zones were introduced in Tokyo, Saitama, Chiba, and Kanagawa in 2003, Hyogo in 2004, and Osaka in 2009.

[18] In addition, over the past three decades, NOx emission reductions in these sectors were slower than in road transport. NOx emissions from road transport decreased by 60% between 1990–2019. The reductions were 20% for other mobile sources and power plants and 35% for industrial combustion [23].

Conclusion

The objective of this study was to estimate the effects of road traffic flows on ambient concentrations of NOx, CO, NMHC, and $PM_{2.5}$ in Japan. To this end, we constructed an hourly panel dataset for a nationwide sample of air pollution monitoring stations from 2010 to 2015. Road traffic flows near each pollution monitoring station were accurately measured by leveraging the granularity of census points placed across Japan for the 2015 Road Traffic Census. Estimating a dynamic panel model, we found estimates of short-run pollution concentration-road traffic flow elasticities are 0.04–0.05 for NOx, CO, and NMHC. The long-run elasticities for these pollutants are 0.09–0.17.

Many Japanese citizens are currently exposed to concentrations of air pollution in excess of the WHO's short-term air quality targets introduced in 2021. The key policy implication of our findings is that traffic flow reduction policies are likely not on their own sufficient to make much progress in achieving the new WHO targets given the relatively small pollution concentration-road traffic elasticities that we have found. The small elasticities may perhaps be explained by factors including (i) complex chemical and other processes, (ii) multiple contributors to emissions, including non-road sector contributors, and (iii) some times of congested road conditions when traffic flow numbers may be low but emissions high. More specific road sector pollution reduction policies, such as promoting the adoption of emission-free vehicles and use of diesel vehicle registration restrictions and/or low-emission zones are likely required rather than relying on targeting of road traffic flow numbers alone.

Electric vehicles are highly promising for pollution reduction.[19] However, the Japanese market for clean vehicles remains fledgling. As of March 2022, the total number of clean passenger vehicles registered in Japan was 319,537, accounting for only 1% of all passenger vehicles [19]. Further support for electric charging and hydrogen fueling stations may be necessary, noting that Li et al. [15] found that a 10% increase in the number of charging stations in the United States increased the demand for BEVs by 8.4%. Government support often plays a significant role in the initial stages of technological adoption.

In contrast to other pollutants, this study found no evidence of pollution concentration-road traffic flow links for $PM_{2.5}$. Kunugi et al. [13] undertook ex-ante simulations of how control measures on stationary sources would affect $PM_{2.5}$ concentrations in the Tokyo metropolitan area. Research has yet to undertake an ex-post assessment of this issue. Examining the links between fluctuations in the operation of stationary sources and ambient concentrations of $PM_{2.5}$ and other pollutants is a promising topic for future research.

[19] Electric vehicles do not however eliminate all pollution from road transport, as particulates pollution from tyres and the road surface is still generated [28].

Appendix A

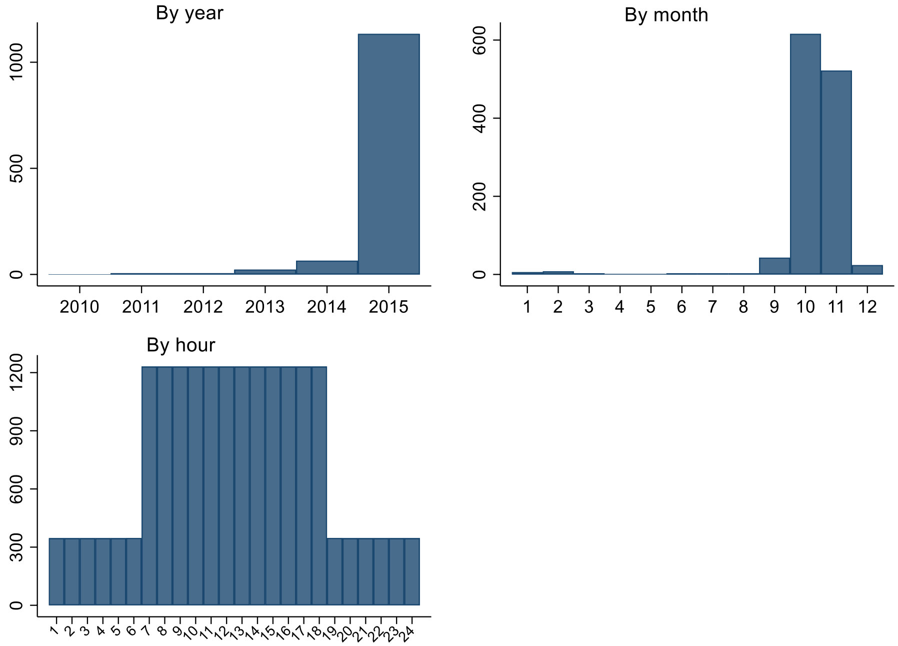
Summary of related studies

Authors	Locations	Air pollutants	Data	Places of road traffic flow measurements	Meteorological variables	Estimation methods	Pollution concentration-road traffic flow links
Levy et al. [14]	USA/Roxbury, Massachusetts	PAH, ultrafine PM, $PM_{2.5}$	9 air pollution monitors/9:30–16:30 for 12 days during July and August in 2001, 10-min average	Co-locate with air pollution monitors	Temperature, humidity	Mixed effects model	Negative link is found for ultrafine PM/No evidence is found for PAH and $PM_{2.5}$
Aldrin and Haff [1]	Norway/Oslo	PM_{10}, $PM_{2.5}$, NO_2, NOx	4 air pollution monitoring stations (Manglerud, Loren, Furuset, Alnabru)/1 November 2001–31 May 2003, hourly average	The same municipality for air pollution monitoring stations in Manglerud and Loren. The different municipality (Karihaugen) for those in Furuset and Alnabru	Temperature, wind directions and speeds, humidity, precipitation, snow cover, hour of day, day number	Ordinary least squares (OLS)	Positive links are found for all pollutants/The link is particularly stronger for NOx
Coria et al. [4]	Sweden/Stockholm	NO_2, PM_{10}	1 air pollution monitoring station/2002–2010, hourly average	The same county as air pollution monitoring station	Wind speed	Nonlinear least squares	Positive links are found for both NO_2 and PM_{10}

Authors	Locations	Air pollutants	Data	Places of road traffic flow measurements	Meteorological variables	Estimation methods	Pollution concentration-road traffic flow links
Rossi et al. [26]	Italy/Padova	NO, NO_2, NOx, PM_{10}	2 air pollution monitoring stations/8 March–30 April for 2017, 2018 and 2020, daily average	570–1170 m away from air pollution monitoring stations	Temperature, wind directions and speeds, precipitation, solar radiation, number of hours with thermal inversion	OLS	Positive links are found for NO, NO_2 and NOx/No evidence is found for PM_{10}
Munjal et al. [18]	India/Gurgaon, Faridabad, Hapur, SAS Nagar	PM_{10}, $PM_{2.5}$, PM_1	4 toll plazas/5 days during September-December 2020, hourly	Co-locate at the same toll plazas	Wind speed, humidity, pressure, solar radiation	OLS	Positive links are found for all pollutants

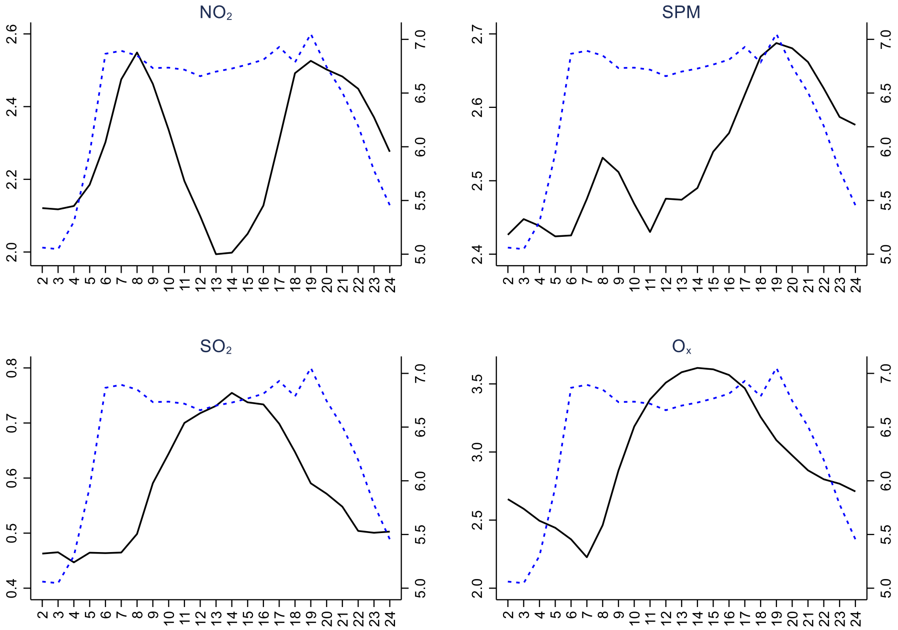
PAH stands for polycyclic aromatic hydrocarbon. No information on exact distance between air pollution and road traffic monitoring stations are provided in Aldrin and Haff [1] and Coria et al. [4]

Appendix B



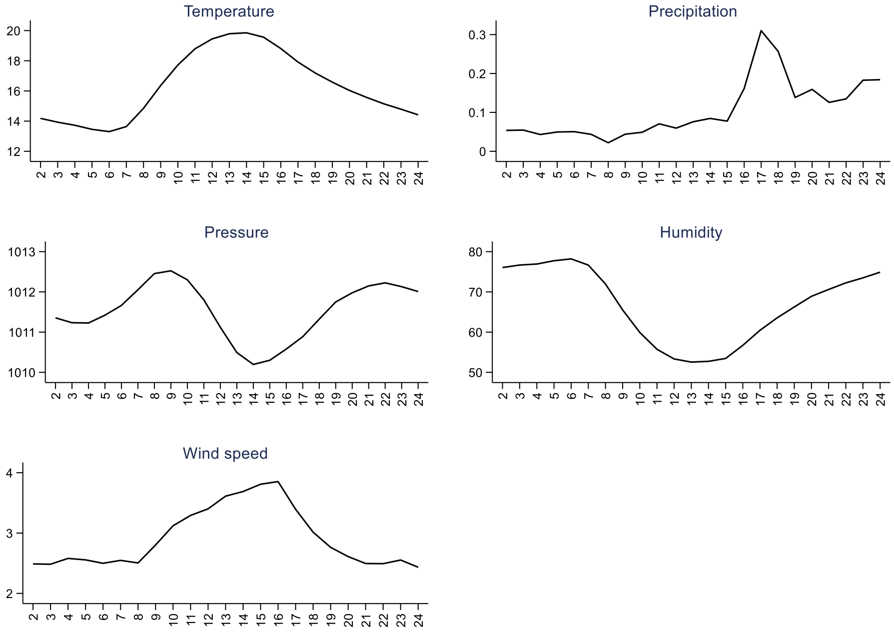
Distribution of road traffic census points by year, month, and hour. The y-axis of all figures shows the number of road traffic census points. The first hour commences at 12:00

Appendix C



Average hourly road traffic flow and other air pollution. The figure shows the co-movements of the natural logarithm of the average hourly road traffic flow (blue dotted line, right axis) and the logarithm of the average hourly ambient concentrations of nitrogen dioxide (NO_2), suspended particulate matter (SPM), sulfur dioxide (SO_2), and oxidants (Ox) (black line, left axis). The first hour of the day is omitted

Appendix D



Average diurnal variation in hourly meteorological conditions. The figure shows the average diurnal variations in the hourly meteorological conditions. The units of measurement for each meteorological variable were Celsius for temperature, millimeters for precipitation, hectopascals for pressure, percent for humidity, and meters per second for wind speed. The first hour of the day is omitted

Appendix E

Pollution concentration-road traffic flow elasticities: other pollutants

Dependent variable: Ln ambient concentration of air pollution				
	NO_2 (1)	SPM (2)	SO_2 (3)	Ox (4)
Ln road traffic flow	0.028**	– 0.041**	– 0.012	0.000
	(0.014)	(0.019)	(0.017)	(0.022)
R^2	0.614	0.147	0.473	0.822
Station fixed effects	Yes	Yes	Yes	Yes
Hour-of-day fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
Ln h-1 lagged dependent variables	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1053	1084	571	736

Dependent variable: Ln ambient concentration of air pollution				
	NO_2 (1)	SPM (2)	SO_2 (3)	Ox (4)
Municipalities	610	616	390	539
Observations	15,453	15,285	6981	10,471
Long-run pollution concentration-road traffic flow elasticities	0.09**	– 0.06**	– 0.03	0.00

The table shows the results for estimating Eq. (1) for each pollutant. All meteorological variables listed in Table 2 (including wind direction dummies) and the log h-1 lagged dependent variables are included in each model. The R^2 is for within monitoring station units. All specifications use a station-hour panel dataset. Standard errors are robust to heteroscedasticity and clustered by municipality. For the long-run elasticity, standard errors are generated using the delta method.

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively

Appendix F

Pollution concentration-road traffic flow elasticity: static panel model

Dependent variable: Ln ambient concentration of air pollution				
	NOx	CO	NMHC	$PM_{2.5}$
	(1)	(2)	(3)	(4)
Ln road traffic flow	0.152***	0.105***	0.081*	–0.033
	(0.035)	(0.032)	(0.045)	(0.040)
R^2	0.265	0.292	0.172	0.051
Station fixed effects	Yes	Yes	Yes	Yes
Hour-of-day fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
Ln h-1 lagged dependent variables	No	No	No	No
Air pollution monitoring stations	1,057	193	325	642
Municipalities	611	156	248	482
Observations	15,937	3,168	4,834	9,292

The table shows the results for estimating Eq. (1) without the log h-1 lagged dependent variables. All meteorological variables (including wind direction dummies) are included in each model. The R^2 is for within monitoring station units. All specifications use a station-hour panel dataset. Standard errors are robust to heteroscedasticity and clustered by municipality.

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively

Appendix G

Pollution concentration-road traffic flow elasticities based on reduced sample

	NOx (1)	CO (2)	NMHC (3)	$PM_{2.5}$ (4)
Short-run	0.07***	– 0.02	0.04	– 0.04
Long-run	0.20***	– 0.03	0.07	– 0.06
Observations	9,065	772	1462	3182

The table shows the results for estimating Eq. (1) for each pollutant, with the sample samples as in Panel B of Table 5.

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

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Research data policy and data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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