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Road Traffic Flow and Air Pollution Concentrations: Evidence from Japan*

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Abstract

Vehicular emissions, being a major global health concern, have gathered worldwide attention and necessitated extensive research to gain deeper insights. The aim of this study was to estimate the effects of road traffic flow on the local ambient concentrations of nitrogen oxides (NOx), carbon monoxide (CO), non-methane hydrocarbons (NMHC), and fine particulate matter ($PM_{2.5}$) in Japan. We constructed an hourly panel dataset of nationwide samples of air pollution monitoring stations from 2010–2015. By estimating a dynamic panel model with station-hour panel data, short-run pollution-road traffic elasticities of 0.04–0.05 for NOx, CO, and NMHC, and long-run elasticities of 0.09–0.17 were observed; however, no significant evidence was found for $PM_{2.5}$. We used these estimates to understand the potential effects of reducing road traffic flow to meet the World Health Organization's new air quality guidelines.

Keywords: Road traffic flow, air pollution, dynamic panel model

JEL codes: Q53, R41, Q52

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1. Introduction

Due to the adverse health effects of vehicular air pollution, major cities around the world have introduced various policies to reduce road traffic flows. London, Milan, San Diego, and Stockholm 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/one-day-per-week program in Beijing, the *Pico y Place* in Quito, and low-emission zones in European cities and Tokyo.

Empirical evidence has revealed that these policies are effective in reducing road traffic flow; however, their pollution-reducing effects remain ambiguous. For example, Gibson and Carnovale (2015) analyzed Milan's road pricing policy, called "Area C", finding that it reduced entries of relevant vehicles into the priced area and also the ambient carbon monoxide (CO) concentration in the area. However, no effect was observed on fine particulate matter ($PM_{2.5}$). Green et al. (2020) 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* after the introduction of the policy, likely because of substitution effects, given the exemptions available for many diesel vehicles.

This study aimed to estimate the effects of road traffic flow on air quality in Japan. To this end, we constructed an hourly panel dataset for nationwide sampling of air pollution monitoring stations from 2010–2015. Specifically, we collected hourly data from air pollution monitoring stations for the ambient concentrations of four pollutants designated under the vehicle emission standards of Japan: nitrogen oxides (NOx), CO, nonmethane hydrocarbons (NMHC), and $PM_{2.5}$. We also collected hourly road traffic flow counts as measured at the census points set from the 2015 Road Traffic Census and utilized data on weather conditions from the meteorological stations.

We estimated a dynamic panel model to obtain the short- and long-run elasticities of pollution concentration with respect to traffic flows for each of the four vehicular pollutants. We found that the short-run elasticities are 0.04–0.05 for NOx, CO, and NMHC, and long-run elasticities obtained by utilizing the 24 hours of data for each traffic point are 0.09–0.17. No significant evidence of pollution-road traffic links was found for $PM_{2.5}$. We confirmed that our estimates for NOx and $PM_{2.5}$ are robust to various estimators, specifications, and samples. We also investigated heterogeneous pollution-road traffic 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 (Levy et al., 2003; Aldrin and Haff, 2005; Coria et al., 2015; Rossi et al., 2020; Munjal et al., 2022).[1] First, our analyses covered a nationwide sample of air pollution monitoring stations, allowing us to exploit the substantial variations in air-road traffic flows and pollution levels. Previous studies focused on single towns, municipalities, or counties. We used data from the 2015 Road Traffic Census, which covers approximately 65,000 census points across the country.

Second, our approach allowed us to identify traffic census points in close proximity to each pollution monitoring station (an average of 6 m). Aldrin and Haff (2005), Coria et al. (2015), and Rossi et al. (2020) used traffic count data from the traffic monitoring station nearest to each fixed pollution monitoring station. However, distant traffic-

[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 (Kim and Guldmann, 2011).

monitoring stations have been used in some cases. For example, in a study by Rossi et al. (2020), the distances of the two pollution monitoring stations in the sample from the corresponding road traffic monitoring stations were 570 m and 1.2 km respectively.

The third contribution of this study is the importance of temporal dynamics in estimating the effects of road traffic flow on pollution concentrations. It is well known that emissions may take time to reach pollution concentrations. It also takes time for air pollutants to be reabsorbed or transformed by the environment due to lags and constraints in their assimilative capacity (Perman et al, 2011). This means that past ambient pollution levels are highly likely to matter for the current level; these are not pure "flow" pollutants. However, no prior research has accounted for lagged pollution concentration.

In 2021, World Health Organization (WHO) introduced new air-quality guidelines (WHO, 2021). The short-term limit values were set at 25 μg/m^3 for NO_2, 4 mg/m^3 for CO, and 15 μg/m^3 for $PM_{2.5}$ in terms of the 99th percentile values of 24-h averages in a given year. As of 2019, approximately 86% of Japan's air monitoring stations were noncompliant with NO_2, 17% with CO, and 100% with $PM_{2.5}$. Based on our estimates, we explored whether reducing road traffic flow could make a sizeable contribution to achieving the WHO's new air quality goals, given the composition of the current vehicle fleet.

The remainder of this paper is organized as follows: Section 2 describes the construction and characteristics of the station-hour panel datasets. Section 3 presents the dynamic panel model and additional specifications. Section 4 presents the estimation results and explores their robustness. Section 5 presents the application of the results and discusses their policy implications. Section 6 provides a conclusion that summarizes the main findings of the study and potentially identifies areas for further research.

2. Data

We used the hourly road traffic flow data from the 2015 PAREA-Traffic dataset of the Japan Asia Group. These came in the form of a shapefile for the 2015 Road Traffic Census made available by the Ministry of Land, Infrastructure, Transport, and Tourism. The dataset covers approximately 65,000 census points across Japan and provides hourly traffic flow data past specific points during each hour on specific census days. Road traffic flows 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 were excluded.

A notable feature of the study context is that the road traffic census points were each set up for only one day at each location from December 7, 2010, to December 18, 2015. 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 from October to November 2015. It can also be seen that some census points did not record road traffic flows outside 7 am–6 pm.

We obtained hourly air pollution data for 2010–2015 from the Environmental Statistics Database of the National Institute for Environmental Studies. Specifically, we collected ambient concentrations of NOx, CO, NMHC, and $PM_{2.5}$, which were measured at each pollution monitoring station. For additional analyses, we collected air concentration data for nitrogen dioxide (NO_2), suspended particulate matter (SPM), sulfur dioxide (SO_2), and oxidants (Ox). Information on whether air pollution monitoring stations are located in residential or roadside areas was also available. Air concentration was measured as the average across all minutes in an hour.

Hourly meteorological data for 2010–2015 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 a meteorological station. 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 because of the granularity of the census points in the 2015 Road Traffic Census.

We obtained data for a maximum of 24 h at each road traffic census point. However, given that we estimate a dynamic panel model where a lagged dependent variable is included, the 12–1 am hour is excluded from the estimations. This leaves a maximum of 23 h per panel unit.

Table 1 shows the 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 observed that meteorological variables had fewer missing observations. The number of available pollution monitoring stations ranged around 197 for CO to 1,111 for SPM because some pollutants were not covered by the pollution monitoring stations. The average number of hours of road traffic flow was 15. This is because road traffic flows were not recorded outside 7 am–6 pm at some traffic census points (see Appendix B).

In summary, our station-hour panel dataset is characterized by the following features: (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 am and 12 pm (in terms of their end point), (iii) the sample is highly concentrated in October and November of 2015, (iv) the panel is unbalanced, (v) the coverage substantially differs among air pollutants, and (vi) the dataset includes both residential and roadside pollution monitoring stations in both rural and urban municipalities.

Table 1: Summary statistics for estimation sample

	Mean	S.D.	Min	Max	Obs.	Stations	Hours
A. Air pollution concentration							
NOx, ppb	20.48	22.62	0	292	24,410	1,077	22.7
CO, ppm	3.62	2.08	0	17	4,466	197	22.7
NMHC, 10ppbC	14.05	12.51	0	472	7,371	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	1,077	22.7
SPM, μg/m^3	16.19	12.07	0	125	25,106	1,111	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	1,231	15.1
ln heavy vehicles	4.30	1.38	0	8.01	18,407	1,227	15.0
ln total	6.62	1.02	0.69	9.16	18,580	1,231	15.1
C. Meteorological variables							
Temperature, ℃	16.31	4.57	−1.4	34.7	28,236	1,231	22.9
Precipitation, mm	0.11	0.79	0	38.0	28,223	1,231	22.9
Pressure, hPa	1,012	11	952	1,035	27,781	1,212	22.9
Humidity, %	67	17	18	100	27,777	1,212	22.9
Wind speed, m/s	2.9	1.9	0	13.9	28,188	1,230	22.9
Wind direction dummies							
NNE	0.12	0.33	0	1	28,313	1,234	22.9
NE	0.08	0.26	0	1	28,313	1,234	22.9
ENE	0.09	0.28	0	1	28,313	1,234	22.9
E	0.04	0.21	0	1	28,313	1,234	22.9
ESE	0.03	0.18	0	1	28,313	1,234	22.9
SE	0.03	0.18	0	1	28,313	1,234	22.9
SSE	0.04	0.19	0	1	28,313	1,234	22.9
S	0.04	0.19	0	1	28,313	1,234	22.9
SSW	0.03	0.17	0	1	28,313	1,234	22.9
SW	0.04	0.20	0	1	28,313	1,234	22.9
WSW	0.03	0.18	0	1	28,313	1,234	22.9
W	0.04	0.21	0	1	28,313	1,234	22.9
WNW	0.07	0.25	0	1	28,313	1,234	22.9
NW	0.09	0.28	0	1	28,313	1,234	22.9
NNW	0.10	0.30	0	1	28,313	1,234	22.9
N	0.12	0.33	0	1	28,313	1,234	22.9

Notes: 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. S.D. = standard deviation. Obs. = Observations. Stations refers to pollution monitoring stations. Hours is the average number of hours per pollution monitoring station.

Figure 1 displays the temporal variations in the four vehicular air pollutants and road traffic flow 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 exhibited two peaks: one at 7 am and the other at 7 pm. Whether air pollution peaks occur during peak hours of road traffic flow depends on the pollutants. The hourly ambient concentrations of NOx, CO, and NMHC appear to be associated 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 3 pm when roads are less congested during the daytime.[2]

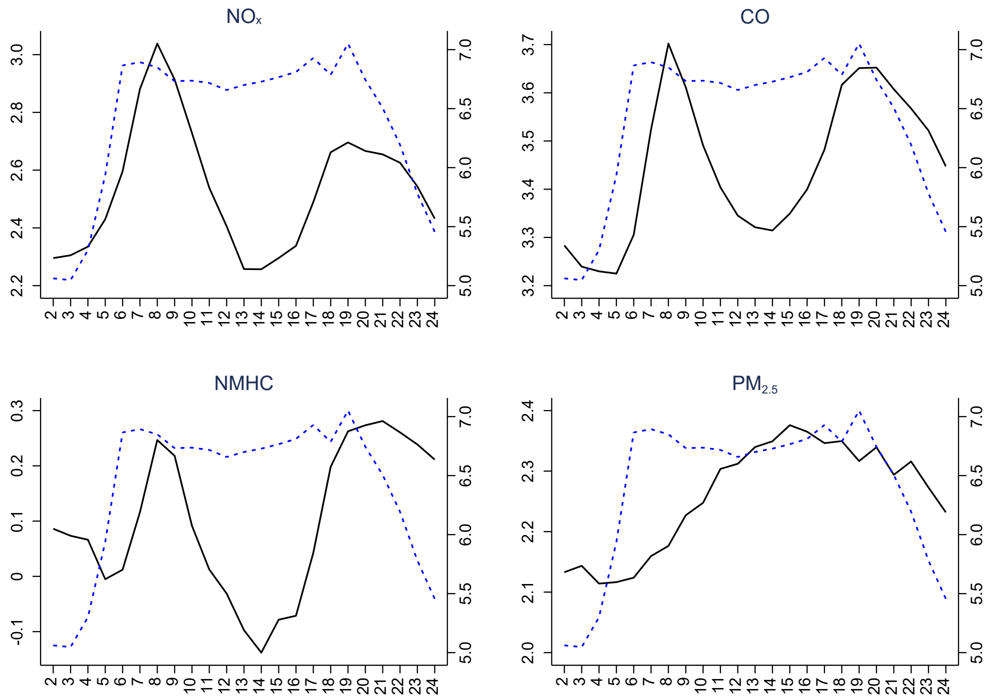

Figure 1. Temporal variations in road traffic flow and vehicular air pollution

Notes: 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.

There are many factors to consider when estimating pollution-road traffic links. First, meteorological conditions must be considered because vehicular air pollutants are not uniformly mixed (Perman et al., 2011).[3] Second, pollution concentrations are likely to be functions of both current and lagged emissions (Perman et al, 2011). Therefore, it is important to consider the dynamic nature of pollution. Finally, Figure 1 may mask

[2] Appendix C shows temporal variations 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.

[3] 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.

heterogeneous pollution-road traffic links by location (e.g., roadside vs. residential). The next section explains our empirical approach for addressing these issues.

3. Empirical approach

3.1. Baseline specification

Pollution concentrations at any hour are functions of the initial concentration, new emissions, and outflows resulting from natural processes. Given the importance of initial concentration, we estimate the following dynamic panel model:

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

where m is the air pollution monitoring station and h is the hour. P is the ambient concentration of NOx, CO, NMHC, or $PM_{2.5}$ (in separate regressions). The inclusion of the 1-h lagged dependent variable as a regressor makes it an autoregressive model. T is road traffic flow around each pollution monitoring station. $\boldsymbol{C}$ is a vector of meteorological variables (temperature, precipitation, pressure, humidity, wind speed, and wind direction). δ is station fixed effects to capture unobserved time-invariant factors such as the location of an air pollution monitoring station.[4] θ is hour fixed effects that removes the influences of hour-specific events affecting all pollution monitoring stations in the same way, such as the ability of the environment to "ventilate" the pollution (Coria et al., 2015; Huang et al., 2021).[5] ε is an error term. We take the natural logarithm, denoted by

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[4] Roadside areas are physically more proximate to a key source of emissions, likely leading to higher ambient concentrations of vehicular 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 while also having larger road traffic flows.

[5] Ventilation coefficients tend to be low during mornings and evenings as a result of higher humidity and slower wind speeds (Goyal et al., 2006).

"ln," for P and T, as their distributions are heavily skewed and to produce direct estimates of the elasticity.

β_1 can be interpreted as the short-run or same-hour pollution-road traffic elasticity: the % change in P with respect to a 1% change in T in the same hour. Eq. (1) also enables us to obtain a long-run pollution-road traffic flow elasticity using $\beta_1/(1-\alpha_1)$ (De Boef and Keele, 2008).[6] Careful attention should be paid to the interpretation of the long-run elasticity in this study context. Given that we used only a maximum of 23 h of pollution concentration data in the estimation sample, this is not likely to be a full long-run effect.

An identification issue arises in that ε might be correlated with T. Vehicular emissions may co-move with emissions from stationary sources (e.g., power plants and industrial combustion) or other mobile sources (e.g., ships and airplanes). If this is the case, β_1 could be biased upward.

We adopted the following additional approaches to address this issue: The first was to apply a system GMM estimator to Eq. (1) (Arellano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2009). Second, we included municipality-hour fixed effects to control for potential time-varying confounders at the municipal level. The third was 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

[6] Additional lags of T have effects that are statistically indistinguishable from zero for the four air pollutants and so are not included. Results available on request.

the contribution of the road transport sector at almost zero (Organization for Economic Cooperation and Development OECD, 2023).[7] The fourth was to estimate Eq. (1) with date-specific hourly fixed effects to control for seasonality and unusual events, such as typhoons and earthquakes.

There are two concerns over statistical inference. First, common shocks in the same municipality could cause model errors for each pollution monitoring station to be correlated within the municipality. Second, model errors for each pollution monitoring station may be serially associated. To address these issues, we reported robust standard errors clustered by municipality.[8] The number of clusters ranged from 156 to 610, depending on the air pollutant. This was sufficient for the reliability of the standard cluster adjustment.

3.2. Additional specifications

To analyze the extent to which pollution-road traffic elasticity differs between residential and roadside areas, we estimated the following specification:

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

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 were identical to those in Eq. (1). $\beta_2 > 0$ would indicate that the short-run pollution-road traffic

[7] 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 (Jain et al., 2016).
[8] We also report results clustering robust standard errors at air pollution monitoring stations in Table 5.

elasticity is larger for roadside areas than residential areas. Based on the estimates, we also calculate the long-run elasticities for residential areas ($\beta_1/(1-\alpha_1)$) and roadside areas ($(\beta_1+\beta_2)/(1-\alpha_1)$).

Next, we estimated separate pollution-road traffic elasticities for the flows of 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 specifications:

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

The long-run pollution-road traffic 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 the time patterns of the same-hour pollution-road traffic elasticity, we interact hour-of-day dummies (θ_h) for all hours in the sample with the log road traffic flow variable (ln*T*):

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

β_h indicates the same-hour pollution-road traffic elasticity for each of the 23 h.

4. Results

4.1. Baseline estimates

Table 2 reports the baseline results for estimating Eq. (1) for each pollutant. All estimations control for 1-h lagged dependent variables, meteorological variables, hour fixed effects, and station fixed effects. We do not report the estimation results for wind direction dummies to save space. All estimations use the station-hour panel dataset. Data coverage varies among pollutants, leading to varying sample sizes that range from 3,052 to 15,480 observations.

Table 2: Baseline estimates

Dependent variable: Ln ambient concentration of air pollution				
	NOx (1)	CO (2)	NMHC (3)	$PM_{2.5}$ (4)
Ln road traffic flow	0.054*** (0.016)	0.043** (0.018)	0.040* (0.023)	–0.036 (0.029)
Temperature, °C	–0.015*** (0.005)	–0.000 (0.006)	–0.011 (0.007)	0.026*** (0.007)
Precipitation, mm	–0.004 (0.005)	–0.002 (0.003)	–0.004 (0.004)	0.005 (0.009)
Pressure, hPa	0.004 (0.004)	0.002 (0.003)	0.000 (0.006)	0.011* (0.006)
Humidity, %	0.002** (0.001)	0.001 (0.001)	0.003** (0.001)	0.003** (0.001)
Wind speed, m/s	–0.031*** (0.003)	–0.025*** (0.004)	–0.029*** (0.005)	–0.017*** (0.005)
Ln 1-h lagged NOx	0.680*** (0.009)			
Ln 1-h lagged CO		0.598*** (0.019)		
Ln 1-h lagged NMHC			0.574*** (0.020)	
Ln 1-h lagged $PM_{2.5}$				0.395*** (0.020)
R^2	0.624	0.547	0.453	0.197
Hour fixed effects	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Wind direction dummies	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1,053	193	323	641
Municipalities	610	156	247	482
Observations	15,480	3,052	4,679	8,835
Long-run pollution-road traffic elasticity	0.17***	0.11**	0.09*	–0.06

Notes: 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.

The first column of Table 2 shows the short-run pollution-road traffic elasticity of NOx at 0.05. This was significantly different from zero at the 1% level, with the 95%

confidence interval ranging from 0.02–0.09. 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. The second and third columns report similar short-run elasticities for CO and NMHC. By contrast, we find that the estimated short-run elasticity for $PM_{2.5}$, although statistically indistinguishable from zero, is negative in point estimate terms (column 4).

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

Small pollution-road traffic elasticities could emanate from the fact that there are multiple contributors to emissions. Given that Eq. (1) controls for a lagged dependent variable, the elasticity of road traffic flows approximately represents the proportional contribution of road vehicle flows to pollutant emissions. For example, as of 2015, road transport accounted for 21% of the total anthropogenic NOx emissions in Japan (OECD, 2023). The pollution-road traffic elasticities may also be low, given the mitigated theoretical link between traffic flows and emissions during traffic jams. Traffic flow numbers may be low during traffic congestion (Zhang and Burke, 2020), but emissions are high. Traffic density (vehicles per unit road area) is theoretically the most relevant variable; however, traffic density data is unavailable.

Appendix E reports the estimation results of Eq. (1) for the other pollutants. We found that road traffic flows were 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 found no evidence of either short- or long-run pollution-road traffic links for SO_2 and Ox.

In addition to the effect of road traffic flow, wind speed was negatively associated with the ambient concentrations of all pollutants, likely because faster wind speeds promote the dispersion of air pollutants (Aldrin and Haff, 2005; Coria et al., 2015; Rossi et al., 2020). We also found that humidity was positively associated with the concentrations of NOx, NMHC, and $PM_{2.5}$, which is consistent with the fact that humidity increases the retention of harmful or toxic chemicals in the air. The effects of other meteorological variables on air quality are either indistinguishable from zero or vary according to the pollutant type.

Appendix F reports the estimation results for the static panel model with no lagged dependent variables. The pollution-road traffic elasticities for NOx, CO, and NMHC were between the short- and long-run elasticities, as reported in Table 2. By not allowing dynamic effects, static estimates may represent intermediate elasticity rather than either short- or long-run elasticity (Lin and Prince, 2013).

4.2. Heterogeneity

Table 3 reports results for Eq. (2) to examine the extent to which the pollution-road traffic 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% larger than that for residential monitoring stations. This makes sense, given that it takes time for emissions to reach non-roadside areas. We found no significant evidence of heterogeneous pollution-road traffic elasticities between roadside and residential monitoring stations for $PM_{2.5}$ (column 4).

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

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

Dependent variable: Ln ambient concentration of air pollution				
	NOx (1)	CO (2)	NMHC (3)	$PM_{2.5}$ (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
Hour fixed effects	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
1-h lagged dependent variables	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1,053	193	323	641
Municipalities	610	156	247	482
Observations	15,480	3,052	4,679	8,835
Long-run pollution-road traffic elasticity for:				
Residential stations	0.17***	0.03	0.06	–0.06
Roadside stations	0.27***	0.14***	0.18***	–0.06

Notes: The table shows the results for estimating Eq. (2) for each vehicular pollutant. All meteorological variables including wind direction dummies and the 1-h 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.

Table 4 reports results by vehicle type based on Eq. (3). We found that in the case of NOx and NMHC, the pollution-road traffic elasticities are positive and significant for heavy vehicles only (columns 1 and 3). In contrast, CO elasticity is positive and significant for standard vehicles only (column 2). These results are consistent with the fact that the main sources of vehicular NOx and CO emissions are trucks and passenger cars, respectively (Ministry of Environment, 2020). No significant evidence of differential pollution-road traffic elasticities by vehicle type for $PM_{2.5}$ was found (column 4).

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

Dependent variable: Ln ambient concentration of air pollution				
	NOx (1)	CO (2)	NMHC (3)	$PM_{2.5}$ (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
Hour fixed effects	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
1-h lagged dependent variables	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1,050	193	320	639
Municipalities	609	156	244	480
Observations	15,357	3,038	4,613	8,762
Long-run pollution-road traffic elasticity for:				
Standard vehicles	0.04	0.09**	0.10	–0.06
Heavy vehicles	0.17***	0.02	0.06**	–0.00

Notes: The table shows the results for estimating Eq. (3) for each vehicular pollutant. All meteorological variables including wind direction dummies and the 1-h 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.

Figure 2 displays the time pattern of short-run pollution-road traffic elasticities for each vehicular pollutant from the estimates of Eq. (4). For NOx, the same-hour effects of road traffic flow on air pollution concentrations were relatively stable over time, with point estimates ranging from 0.022 to 0.093 and a mean of 0.051. The largest effects were observed during night-time hours (9–11 pm). For CO and NMHC, the pollution-road traffic elasticities were consistently positive and fluctuated over time. For $PM_{2.5}$, the point estimates were negative for all hours except 11 pm.

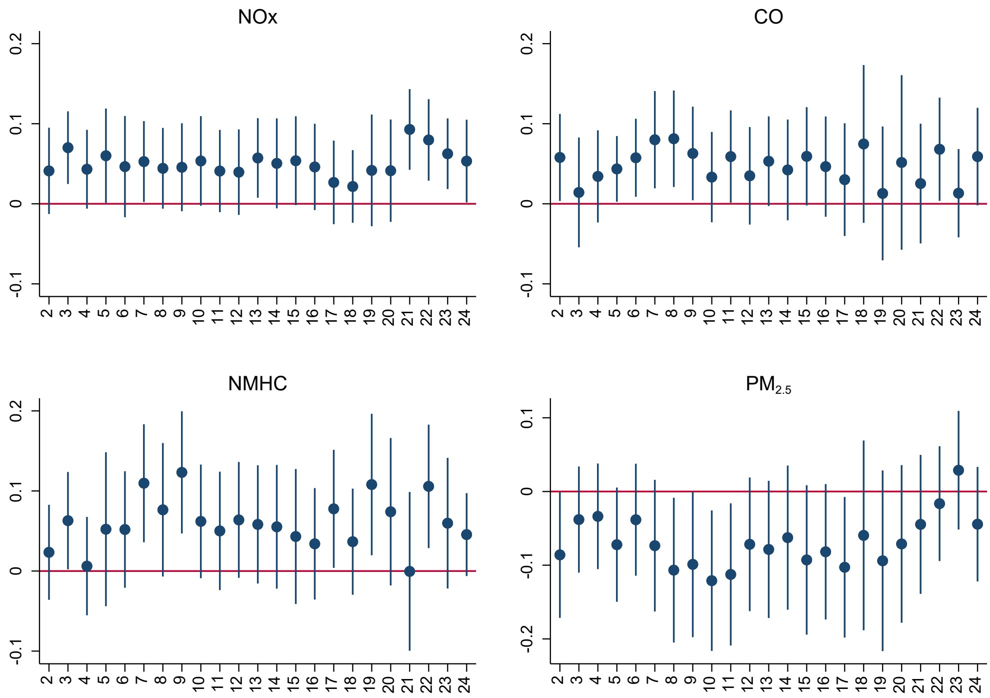

Figure 2. Pollution concentration-road traffic flow elasticity by hour

Notes: 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 am were not included in the estimation sample.

4.3. 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, with regressors in levels instrumented with suitable lags of their own first differences. We put every regressor in Eq. (1), except for the hour and station fixed effects, into the instrument matrix that takes a collapsed form to limit the number of instruments. To account for unobserved time-varying factors, Panel B controls for municipality-hour fixed effects instead of separate hour fixed effects and station fixed effects.[9] Panel C adds the ambient SO_2 concentration to the model.[10] Panel D controls for date-specific hour fixed effects instead of hour 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 account 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 (although noting that the first hour is excluded when the estimation sample is formed).

The first column of Table 5 shows the short- and long-run pollution-road traffic 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 and 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-road traffic flow elasticities for CO and NMHC vary somewhat by estimator, specification, and sample.

Our baseline estimate suggests no significant positive pollution-road traffic link for $PM_{2.5}$. The fourth column of Table 5 is consistent with this finding. These contrasting results for $PM_{2.5}$ can likely be explained by the fact that there are many sources of particulate pollution, including power plants, the industrial sector, construction, and agriculture. Some $PM_{2.5}$ also forms via chemical reactions in the atmosphere and thus may be subject

[9] 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 (Correia, 2015), substantially reducing observations in panel B.

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

to long lags and/or may occur in a location far from the source due to the effect of winds. Levy et al. (2003) and Rossi et al. (2020) also found an absence of short-run pollution–road traffic flow links for $PM_{2.5}$.

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-hour 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	6,707	1,630	2,037	3,766

Notes: All panels are based on Eq. (1) with a station-hour panel dataset. Panel A adopts system GMM. Panel B controls for municipality-hour fixed effects instead of hour fixed effects and station fixed effects. Panel C adds ambient SO_2 concentration to the model. Panel D controls for date-specific hour fixed effects instead of hour 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.

5. Policy implications

In 2021, the WHO announced new air quality guidelines (AQG) for key air pollutants. The short-term AQG limit values were set at 25 μg/m^3 for NO_2, 4 mg/m^3 for CO, and 15 μg/m^3 for $PM_{2.5}$ 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.[11] 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.[12] 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 among prefectures, from 32% in Fukui to 100% in Kanagawa, Shiga, Nara, Kagawa, and Ehime. 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 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 WHO's new air quality targets? The answer is that this is unlikely, given the small pollution-road traffic flow elasticities that were found. For example, utilizing the estimated long-run pollution-road traffic 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

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[11] 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.

[12] 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.

only 20 pollution monitoring stations (out of 1,420) would switch from non-compliant to compliant across the country.

The key policy implication for achieving the WHO's new air quality goals across Japan is that more specific road sector pollution reduction policies are required rather than targeting road traffic flows alone. The adoption of clean vehicles, including battery electric vehicles (BEV), plug-in hybrid vehicles (PHV), 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 PM2.5 by keeping polluted diesel trucks and buses away from designated areas. Nishitateno and Burke (2020, 2021, 2022) found that these interventions were effective in improving local air quality.

An additional policy implication is that policy packages beyond road transport are likely to be needed to achieve the WHO air quality goals. An important reason for the inelastic effect sizes obtained in this study is that the road sector is not the only contributor to pollution. Indeed, as of 2019, road transport accounted for only approximately 21% of the 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 (OECD, 2023). There is substantial scope for energy efficiency, electrification, and low-emission fuel switching across non-road sector activities.

Table 6: Air pollution monitoring stations that were not in compliance with the WHO's new 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
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

Notes: 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.

6. Conclusion

The objective of this study was to estimate the effects of road traffic flow 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 2010–2015. The novelty of our panel data is that road traffic flow near each pollution monitoring station was accurately measured by leveraging the granularity of census points placed across Japan for the 2015 Road Traffic Census. By estimating a dynamic panel model with the newly constructed station-hour panel dataset, we found that the short-run pollution-road traffic elasticities are 0.04–0.05 for NOx, CO, and NMHC and the long-run elasticities are 0.09–0.17.

Many Japanese citizens are currently exposed to high concentrations of air pollution, relative to the WHO's short-term air quality targets introduced in 2021. The key policy implication drawn from this study is that traffic flow reduction policies are likely not sufficient to make much progress in achieving WHO's new targets across the country. Instead, a more comprehensive policy package is required.

Electric vehicles are highly promising for pollution reduction.[13] However, the Japanese market for clean vehicles remains fledging. 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 (Next Generation Vehicle Promotion Center, 2023). Li et al. (2017) found that a 10% increase in the number of charging stations in the United States increased the demand for electric vehicles (BEV+PHV) by 8.4%. Given that the lack of

[13] Although they do not eliminate all pollution from road transport, as particulates pollution from the road surface is still generated (Timmers and Achten, 2016).

charging infrastructure is a key barrier to clean vehicles, further financial support for electric charging and hydrogen fueling stations is necessary. 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-road traffic links for $PM_{2.5}$. Kunugi et al. (2019) 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.

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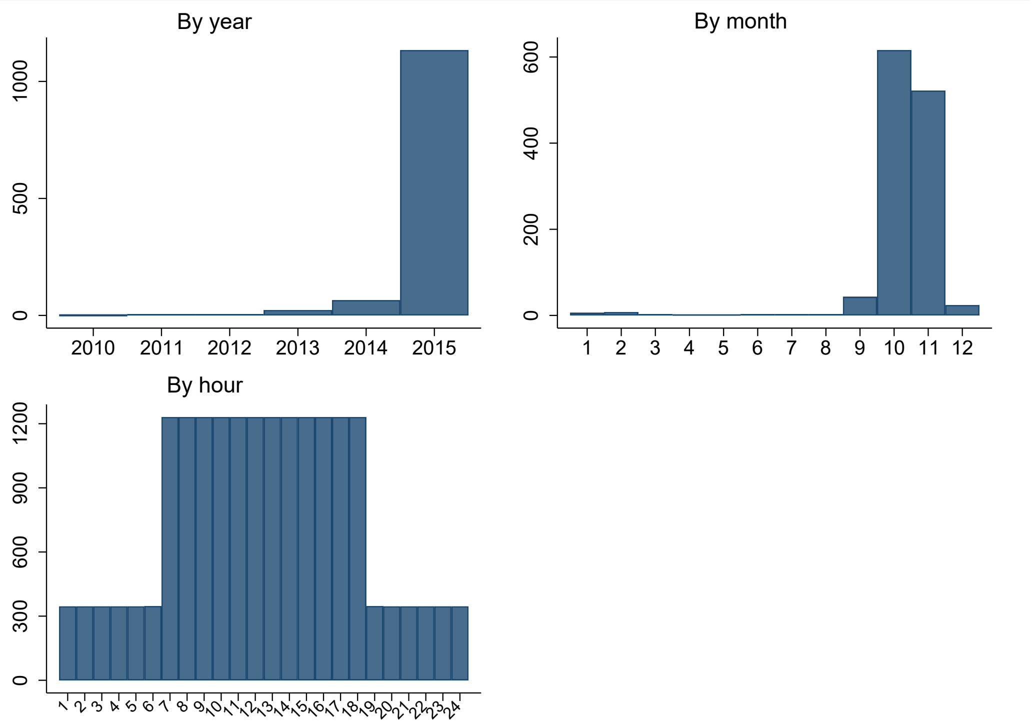
Appendix A. Summary of related studies

Authors	Locations	Air pollutants	Data	Places of road traffic flow measurements	Meteorological variables	Estimation methods	Pollution-road traffic links
Levy et al (2003)	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 (2005)	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 (2015)	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}
Rossi et al (2020)	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 (2022)	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

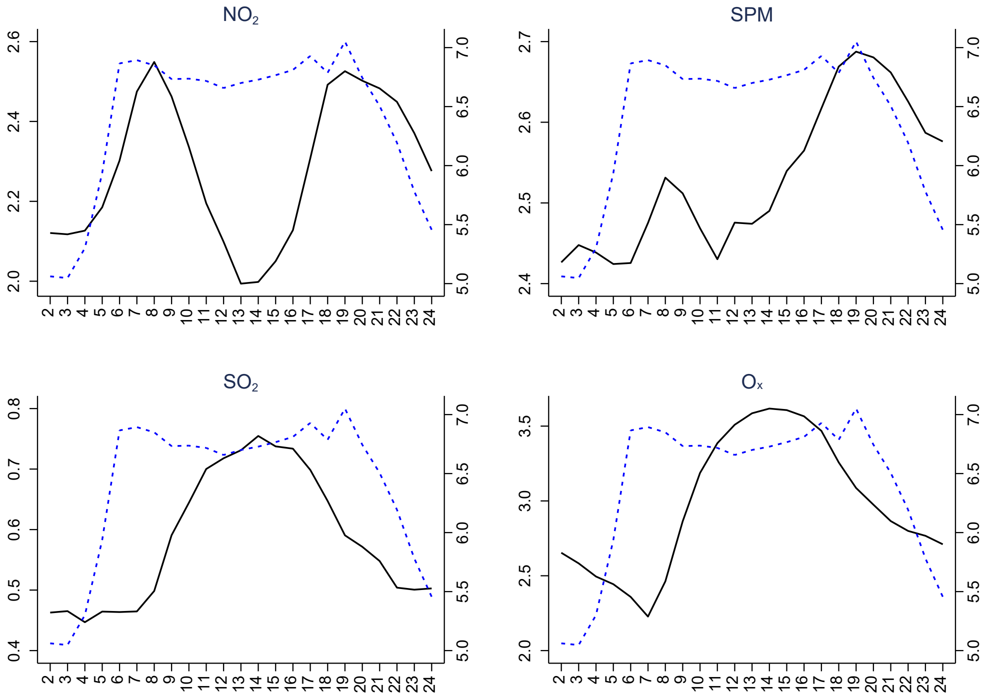
Notes: PAH stands for polycyclic aromatic hydrocarbon. No information on exact distance between air pollution and road traffic monitoring stations are provided in Aldrin and Haff (2005) and Coria et al (2015).

Appendix B. Distribution of road traffic census points by year, month, and hour



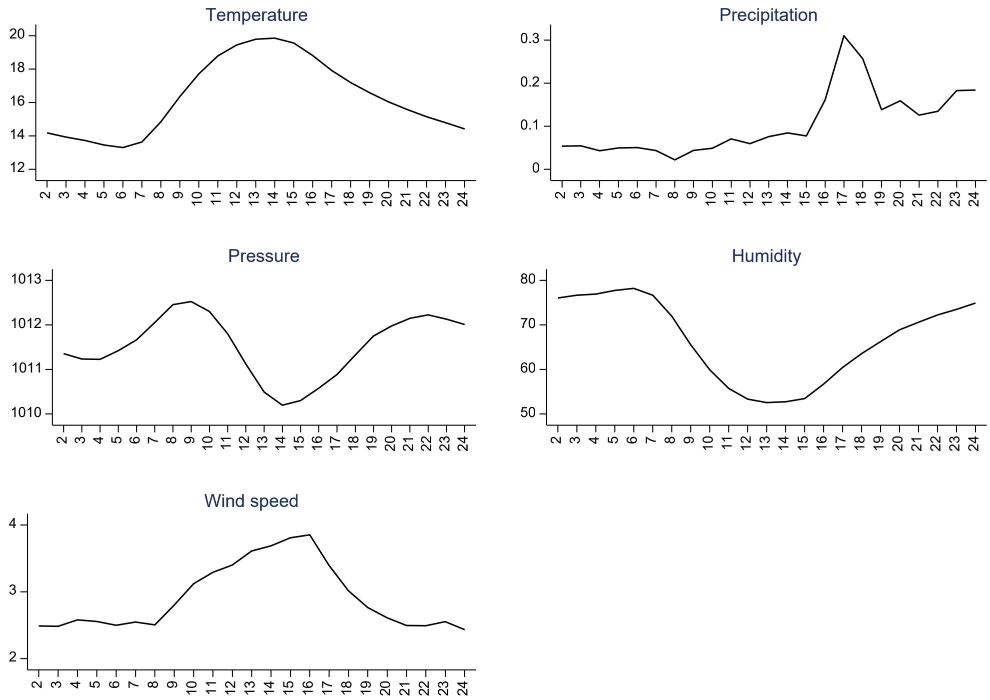
Notes: The y-axis of all figures shows the number of road traffic census points.

Appendix C. Average hourly road traffic flow and other air pollution



Notes: 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).

Appendix D. Average diurnal variation in hourly meteorological conditions



Notes: 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.

Appendix E. Pollution concentration-road traffic flow elasticities: other pollutants

Dependent variable: Ln ambient concentration of air pollution				
	NO_2	SPM	SO_2	Ox
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
Hour fixed effects	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
1-year lagged dependent variables	Yes	Yes	Yes	Yes
Air pollution monitoring stations	1,053	1,084	571	736
Municipalities	610	616	390	539
Observations	15,453	15,285	6,981	10,471
Long-run pollution-road traffic elasticities	0.09**	–0.06**	–0.03	0.00

Notes: The table shows the results for estimating Eq. (1) for each pollutant. All meteorological variables listed in Table 2 (including wind direction dummies) and 1-h 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
Hour fixed effects	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes
Meteorological variables	Yes	Yes	Yes	Yes
1-h 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

Notes: The table shows the results for estimating Eq. (1) without 1-h 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.