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Environmental consequences of fuel price shocks in China

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ABSTRACT

This study investigates the environmental consequences of fuel price shocks, using a rich dataset from the Chinese megacity of Hangzhou. Our identification strategy is mainly aided by instrumenting fuel price using exogenous global oil prices. We find that a 10% increase in fuel price leads to a 10.29%–11.45% decrease in driving demand, reflected by road congestion index, and a 17.6%–20.27% decrease in industrial activities, measured by electricity consumption. The decreases in driving demand and industrial activities are indeed correlated with air quality improvement and decline in major pollutant concentrations. While the findings shed light on the short-term environmental outcomes of price-based measures, the negative effects of fuel price increases on industrial activities may generate undesirable impacts on macroeconomy in the long-term perspective. Despite ample evidence demonstrating that drivers respond to fuel price changes, considerably fewer studies investigate their environmental and economic consequences. This study addresses this gap in the literature and contributes to a better understanding of the effects of fuel price shocks on air pollution and economic activities.

1. Introduction

Transportation is a crucial aspect of daily life and is responsible for a considerable share of pollutant emissions in many countries worldwide (Gillingham & Munk-Nielsen, 2019). Previous studies, including Sun, Zheng, and Wang (2014), Lu, Sun, and Zheng (2017), Han, Liu, and Lu (2020), and Rivers, Saberian, and Schaufele (2020), have demonstrated the causal effects of transportation on air pollution. To reduce transport-related fuel consumption, which aims to lower pollutant emissions and address energy security concerns, fuel price is typically used as a market-based measure (Banzhaf & Kasim, 2019).

In the case of passenger vehicles, rational consumers can react to fuel price shocks through three channels: (i) a utilization effect that relates to changes in driving behavior, (ii) a compositional effect that relates to vehicle purchasing decisions, and (iii) a location effect that relates to choices about where to reside. These three channels can influence air pollution by determining the number of vehicles on the road. For example, if people choose to drive less, delay owning a vehicle, or live closer to their place of work, traffic flows are expected to decrease with an increase in fuel price. Consumers' response to fuel price shocks could have environmental implications by affecting their driving demand due to traffic-related air pollution. Environmental policy has therefore made it a central goal to reduce vehicular emissions through fuel prices, such as taxes. However, it is unclear whether a rising fuel price reduces driving demand and the associated air pollution. Furthermore, in response to fuel price changes, industrial firms may adjust their production schedules and/or outputs when marginal costs shift (Jessoe & Rapson, 2015). The extent to which rising fuel prices affect the economic activities of industrial firms is also unclear. The environmental impacts of fuel price shocks are therefore theoretically ambiguous and

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require empirical investigation. This paper's focus is on the short-term response to fuel price shocks on driving behaviors and industrial activities, which could provide new evidence on the environmental consequences of such responsiveness. However, we will not discuss responses in the longer term, such as car purchases and residential/workplace choices.

Fig. 1 illustrates the framework for how fuel price shocks affect driving demand and industrial activities, which subsequently leads to environmental consequences through fuel combustion. The figure highlights that the environmental consequences heavily rely on the response of driving demand to fuel price changes. Not surprisingly, there is a vast literature aimed at estimating the price elasticity of driving demand and the associated fuel demand (e.g., Coglianese, Davis, Kilian, & Stock, 2017; Gillingham, 2014; Levin, Lewis, & Wolak, 2017). Comparing to the United States and European Union, the price elasticity in developing countries is expected to be larger because the share of fuel cost in total expenditures is typically higher in developing countries (Li & Sun, 2018). In the case of China, this paper therefore estimates how driving demand responds to fuel price shocks at first. Using hourly-frequency data, we find that driving demand, as measured by congestion index, is rather elastic to price changes. This implies significant environmental outcomes due to the response of drivers, and we provide new evidence to further support this claim.

One empirical concern when exploiting high-frequency price variations is that drivers may not fill up their oil tanks daily, and it is therefore necessary to understand what constitutes rational behavior in this data setting. A myopic decision-making process assumes that drivers only respond to the price they actually paid during their last oil tank fill-up, while a forward-looking model of consumer behavior would be more rational. Suppose there is a price increase; an informed consumer knows that for each additional unit of fuel consumed (even if only in the tank), they will have to pay a higher price for their next fill-up. A rational consumer will take into account the increased opportunity cost of fuel consumption today and, as a result, is expected to respond to the price change immediately, even if they only need to fill up their oil tank a few days later. For example, Levin et al. (2017) find high-frequency evidence on gasoline demand at the daily level. In this sense, drivers would adjust their behavior based on price shocks, regardless of how frequently they fill up their oil tanks, allowing us to exploit price variations at the daily frequency.

Estimating the environmental effects of fuel price shocks presents a critical challenge due to the endogeneity of fuel price. In the literature, fuel price shocks are typically not randomly assigned and are often confounded with other factors. To address this challenge, we leverage the plausibly exogenous adjustments of fuel price in China. Since 2013, the Chinese government has initiated and approved adjustments of gasoline and diesel prices every ten days based on a rule that is tied to crude oil prices in the global market. As a result, price shocks of gasoline and diesel in China are arguably exogenous and as good as randomly assigned. However, some may be concerned that the Chinese government has flexibility to decide the adjustment of fuel price based on macroeconomic factors. To address this concern, we instrument for fuel price using global oil price, which helps to mitigate the possibility of endogeneity caused by policy implementation.

We make several contributions to the literature. First, we utilize a rich dataset from various sources at an hourly frequency in a natural experiment setting to investigate how consumers respond to fuel price shocks by adjusting their driving behavior. Our study adds to the growing body of research on fuel price responses in driving. For instance, Gillingham (2014) estimates the elasticity of driving for new vehicles in California and finds a medium-run elasticity of -0.22. The responsiveness increases with income, which may be due to within-household switching of vehicles. Gillingham and Munk-Nielsen (2019) study the fuel price elasticities of drivers with different commuting distances in Denmark and find that drivers who commute very little and drivers with long commutes are more responsive to fuel price changes, while households that are not in these two tails tend to be much more inelastic. The estimated elasticities range from -0.05 to -0.85. Using hourly-frequency data from New South Wales in Australia, Zhang and Burke (2020) also find a negative price elasticity of traffic flows. These studies have used observations from developed countries and produced mixed findings on the magnitude of fuel price elasticities of driving. However, energy demand characteristics in the developing world may differ substantially (Wolfram, Shelef, & Gertler, 2012), particularly as the share of fuel expenditure in total expenditure is higher (Molloy & Shan, 2013), implying a larger fuel price response (Li & Sun, 2018). Therefore, our paper contributes to the scarce evidence on fuel price responses in driving in the developing world.

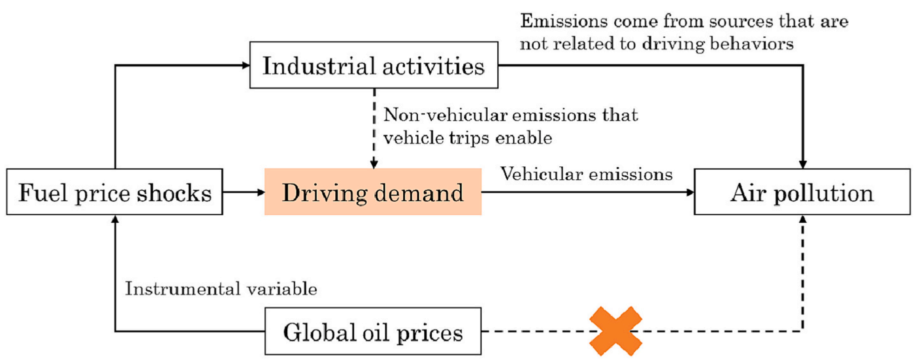

Fig. 1. How fuel price shocks generate environmental outcomes.
Note: The dashed line between industrial activities and driving demand represents the activities enabled by vehicle trips. For instance, if an increase in fuel prices leads to higher transportation costs for production, industrial activities may slow down. Consequently, pollutant emissions from industrial activities enabled by vehicle trips would also decrease with an increase in fuel price.

Second, we present novel evidence on how fuel price shocks result in environmental consequences due to behavioral adjustments and therefore extend the recent literature studying the fuel price response in driving. Previous studies, such as Sipes and Mendelsohn (2001) and Auffhammer and Kellogg (2011), investigate the impact of gas prices on air quality through driving behaviors. Several other studies have analyzed behavioral adjustments to fuel price changes in a broader context. Molloy and Shan (2013) estimate the differential impact of gasoline price changes on the price and quantity of housing in locations with varying commuting distances. Banzhaf and Kasim (2019) explore how households with high vehicle utilization change their vehicles' fuel economy when fuel prices rise compared to those with low utilization. Zhang and Burke (2022) find that higher gasoline prices lead to a relative decline in suburban housing prices in China due to rising transportation costs. In contrast to prior research, our study provides evidence of the environmental consequences of fuel price shocks due to behavioral responses.

Finally, our work contributes to the growing literature on identifying the impacts of energy and environmental policies. Related studies include low-emission zones (Ye, Qin, & Chen, 2021), road pricing (Gibson & Carnovale, 2015), public transit (Adler, Liberini, Russo, & Ommeren, 2021; Chen & Whalley, 2012), speed limits (Ang, Christensen, & Vieira, 2020), fuel standards (Li, Lu, & Wang, 2020), driving restrictions (Viard & Fu, 2015), and fuel-blended policies (Salvo & Geiger, 2014; Salvo & Wang, 2017). This paper adds to this literature by demonstrating the broad environmental consequences of fuel price shocks, and the findings of this paper are anticipated to inform well-informed decisions in energy pricing policy to achieve the benefits of environmental improvement.

The remainder of this paper is organized as follows. In Section 2, we briefly introduce the pricing mechanism of gasoline and diesel in China. Section 3 describes the data and estimation strategy, while Section 4 presents the empirical analysis. Finally, Section 5 concludes the study.

2. Gasoline and diesel prices in China

Gasoline and diesel are the primary refined oil products used for transportation in China. The National Development and Reform Commission (NDRC) highly regulates and controls the prices of refined oil in China. When setting prices, the crude oil price is the primary determinant, and NDRC adjusts the prices of refined oil, such as gasoline and diesel, based on fluctuations in global crude oil prices. Since China imports over 70% of its crude oil demand from global markets, the government guide prices for gasoline and diesel are adjusted every 10 workdays based on the moving average price of the global oil market, following several rounds of reforms. The adjustments are subject to a ceiling price of 130 USD/barrel and a floor price of 40 USD/barrel. For a more detailed description of the pricing mechanism for refined oil products in China, see Chen, Zhang, Mclellan, and Zhang (2020).

Fig. 2 illustrates the historical trends of gasoline and diesel prices in China and compares them with the crude oil price in the global market. Brent oil, which is the leading global price benchmark and is used to set the price of two-thirds of the world's internationally traded crude oil supplies, is used to measure the global oil price in this study (Kilian, 2016). The figure highlights the strong relationship between fuel prices and crude oil prices. However, NDRC has cancelled downward price adjustments for several rounds when the crude oil price plummeted in the name of protecting the environment and ensuring energy security.[1] As a result, the relative prices of gasoline and diesel with respect to crude oil price have become much higher in recent years. This situation raises concerns that the strategic decisions on adjusting refined oil prices may introduce endogeneity in identifying the environmental and economic impacts of fuel price shocks. Therefore, in this study, we use the global oil price as the instrumental variable (IV), which can be expected to be a strong instrument.[2] A similar method has been used in previous studies, such as Gillingham (2014).

3. Data and method

This study utilizes rich data from Hangzhou, a megacity in China with over 10 million residents. We focus on Hangzhou due to the availability of high-frequency monitoring data of on-road congestion, which enables us to capture driving demand variations in response to fuel price shocks. A direct measure of driving demand is the total vehicle-miles for a given period, while such data at high-frequency is not available in the present case. As a substitute, we use congestion index to measure driving demand. Congestion index in Hangzhou is calculated based on the real-time speed of vehicles on the road collected from taxis and street monitors. It is weighted by the length, width, classification, traffic volume of each road segment to determine the overall congestion index of road network in Hangzhou.[3] In the study by Gu, Jiang, Zhang, and Zou (2021), congestion is also measured based on speed.

Table 1 explains the values of the congestion index, which range from 0 to 10, with 0 indicating no congestion and 10 representing complete gridlock, based on a widely used definition in China's cities, including Beijing (Zhong, Cao, & Wang, 2017). The scale of the congestion index does not affect the parameter interpretation as it enters the model in logarithmic form, allowing us to interpret the coefficients as elasticities. Higher congestion index values indicate greater demand for driving on the road network, as more vehicles

[1] An example is available at: https://www.bbc.com/zhongwen/simp/business/2015/12/151230_china_petro_price_suspended (accessed at May-14, 2022).

[2] An alternative method to construct the IV is to use China's formula between prices of crude oil and gasoline/diesel. There are two obstacles to use this method. First, international oil categories that the domestic oil price linked to are not transparent, and the categories are adjusted according to imported crude oil structure and international oil market (Chen, Zhang, et al., 2020). Second, the randomly delayed adjustment of refined oil prices in China makes it infeasible to use the formula to construct the IV.

[3] The definition of congestion index is explained on a local semi-official news website in Hangzhou: https://hznews.hangzhou.com.cn/chengshi/content/2013-05/22/content_4745252_4.htm, which is co-operated by a municipal government agency of Hangzhou (accessed at April-8, 2023).

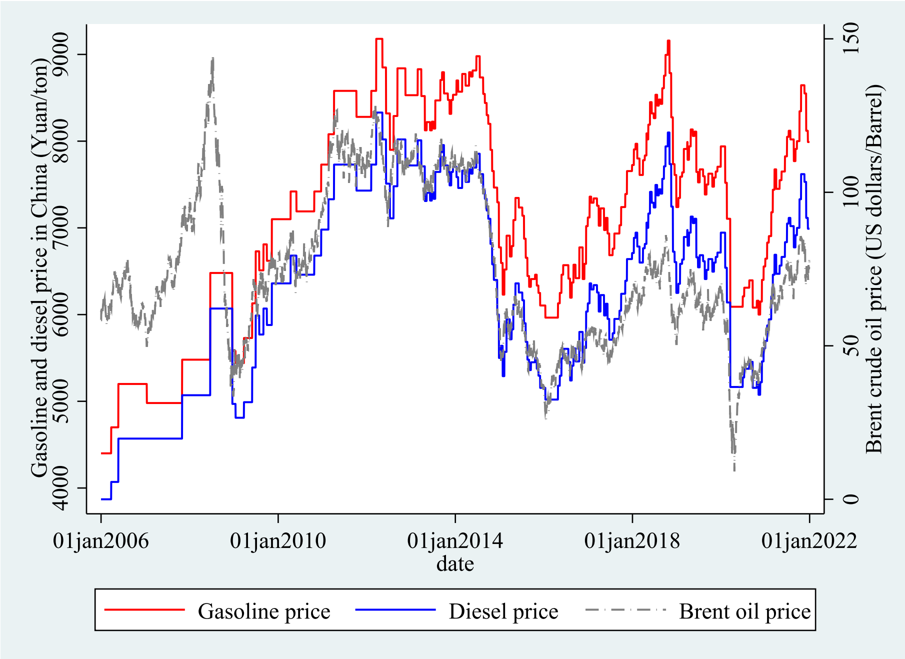

Fig. 2. Refined oil prices in China and crude oil price in global market.
Note: The data on gasoline and diesel prices are obtained from Wind database, and data on crude oil price of Brent are obtained from the website of the U.S. Energy Information Administration (EIA).

Table 1
Categories of congestion index.

Congestion index	Congestion level	Congestion conditions
0–2	I	Free-moving
2–4	II	Almost free-moving
4–6	III	Slightly crowded
6–8	IV	Moderately crowded
8–10	V	Heavily crowded

Note: The category is available from: https://hzjtydzs.com:801/ (accessed at October-12, 2022).

are competing for limited road space, resulting in slower speeds and longer travel times. We therefore argue that the congestion index is a suitable indicator of short-term driving demand given the road infrastructure. We obtain the congestion data from the Platform of Hangzhou Transport Monitoring, which is available at 5-min frequency, and we take the hourly average.

The second dataset consists of daily price data on gasoline, diesel, and Brent oil. Gasoline and diesel prices are obtained from the Wind Database, while Brent oil price is from the website of the EIA. The data is at an hourly frequency and includes the air quality index (AQI) and various pollutants, such as Nitrogen Dioxide (NO_2) and Particulate matter (PM_{10} and $PM_{2.5}$), which are tightly related to road traffic. The fourth dataset pertains to economic activities. The challenge here is that there is no official data to measure high-frequency information on economic activities, such as industrial production. To measure industrial production, we rely on restricted-access records on hourly electricity consumption of industrial firms. The main advantage of using electricity records is their high-quality measurement of industrial activities at high frequency.

As control variables, data on weather at hourly frequency in Hangzhou is collected from the U.S. National Oceanic and Atmospheric Administration, while information on holiday is obtained from the website of Chinese central government. We combine the data from the various sources to generate a final dataset. The sample period is from January 1, 2017, to December 31, 2021, the former of which is the first date that congestion data is available in Hangzhou. The data is at hourly frequency, and there are substantial diurnal variations in traffic congestion and air pollution (see Fig. A1 in Appendix A), which allows us to exploit the diurnal patterns for more precise estimation by exploiting hourly variations. Table 2 presents the summary statistics of the dataset used in this study.

We first estimate the environmental consequences of fuel price shocks. The following equation is used to estimate the relationship between fuel prices and air pollutant concentrations:

$$\begin{aligned} ln(Air_{ti}) = \beta ln(price_t) + \gamma weather_{ti} + holiday_t \\ +year_t + month_t + dow_t + hour_i + \varepsilon_{ti} \end{aligned} \tag{1}$$

Table 2
Summary statistics.

Variable	N	Mean	Std. Dev.	Median	Units
Panel A: Fuel prices					
Gasoline price	42,371	7450.82	736.18	7595.00	Yuan/ton
Diesel price	42,371	6461.75	706.09	6600.00	Yuan/ton
Brent price	42,371	60.30	13.70	62.60	USD/barrel
Panel B: Driving demand denoted by congestion index					
Congestion	42,365	1.85	1.65	1.37	–
Panel C: Air pollution					
AQI	42,215	59.54	31.11	54.00	–
NO_2	42,215	39.27	19.66	36.00	$\mu g/m^3$
PM_{10}	42,215	62.92	38.69	53.00	$\mu g/m^3$
$PM_{2.5}$	42,215	35.63	24.55	29.00	$\mu g/m^3$
Panel D: Electricity to measure economic activities					
Electricity consumption	8760	679.96	126.77	706.39	MWh
Panel E: Control variables on weather and holiday					
Temperature	42,371	184.26	91.17	190.00	°C
Wind speed	42,370	26.14	14.90	20.00	mm
Precipitation	42,371	2.77	21.96	0.00	m/s
Holiday = 1	42,371	0.06	0.24	0.00	–

where Air_{ti} is the air pollutant concentration on date t and hour i, which reflects the level of air pollution; $price_t$ includes the prices of gasoline and diesel on date t. We include a dummy for holidays to reflect the possible difference in air pollution during holidays. We also include weather variables, including air temperature in linear and quadratic terms, precipitation, and wind speed to account for effects of weather on the air pollution. Finally, we include the fixed effects of the year, month of the year, day of the week, and the hour of the day to account for unobserved common shocks to air pollution in a given year, month, weekday, and hour. Year fixed effects capture the secular changes of air pollutant concentrations and refined oil prices (such as escalation of the Russo-Ukrainian War in 2022), while month fixed effects account for their seasonal shocks (such as China's Spring Festival). Year-by-month fixed effects are not included because they would reduce or eliminate the effects from the swings of oil prices, which often last few months (as shown in Fig. 2). Similarly, such setting and argument on fixed effects can be seen in Sheldon and Sankaran (2017).

The coefficient of interest is β, which represents the elasticity of air pollutant concentrations with respect to fuel prices. However, the estimation in Eq. (1) may suffer from endogeneity problems since the strategic decisions in fuel price adjustments. For instance, a positive macroeconomic shock may lead to additional air pollutant emissions, allowing the government to postpone downward adjustments in fuel prices in the name of environmental protection. The simple fixed effects model in Eq. (1) would overestimate the elasticity. To further address this problem, we apply the two-stage least squares (2SLS) estimation in Eq. (2).

$$\begin{aligned} ln(price_t) &= \alpha ln(crudeoil_t) + \delta weather_{ti} + holiday_t \\ &+ year_t + month_t + dow_t + hour_i + \eta_{ti} \end{aligned} \tag{2}$$

$$\begin{aligned} ln(Air_{ti}) &= \beta ln(\widehat{price_t}) + \gamma weather_{ti} + holiday_t \\ &+ year_t + month_t + dow_t + hour_i + \varepsilon_{ti} \end{aligned} \tag{3}$$

In the first stage, we use global crude oil price to predict the gasoline and diesel prices in China, as specified in Eq. (2). Then, we utilize the estimated values of gasoline and diesel prices in the second-stage regression, as shown in Eq. (3). The variation in fuel prices in the second stage is therefore attributed to exogenous shocks in global oil price. The standard conditions for consistent estimation of β in the context of our 2SLS estimator are that $\alpha \neq 0$ in Eq. (2) and global oil price affects short-term air pollution in Hangzhou only through fuel prices. Global oil price is unquestionably the primary determinant of fuel prices in China, and thus the first condition clearly holds, which will be further tested in the subsequent sections. While the second condition is not explicitly testable, it seems plausible that the only way that crude oil prices influence air pollutant concentrations in a Chinese city is indirectly through local price of fuels such as gasoline and diesel, in which case the exclusion restriction would hold (Gillingham, 2014). Accordingly, the global oil price is expected to be a strong and valid instrumental variable for fuel prices, which enables a consistent estimator of β through 2SLS estimation.

The environmental consequences of fuel price shocks largely depend on the responses in driving demand. With the same validity assumption of instrumenting fuel price through global oil price, 2SLS estimation in Eq. (4) is applied to estimate the effects of fuel price change on driving demand:

$$
\begin{aligned}
ln(Congestion_{ti}) = \kappa ln(\widehat{price_t}) + \lambda weather_{ti} + holiday_t \\
+ year_t + month_t + dow_t + hour_i + \varepsilon_{ti}
\end{aligned}
\tag{4}
$$

To solve the potential concern on serial correlation of our time-series data, we follow Sheldon and Sankaran (2017) to estimate Newey-West standard errors robust to serial correlation in all regressions of 24th orders at hourly frequency (i.e., 24 h of a day) and of 7th orders at daily frequency (i.e., 7 days of a week). For estimates using instrumental variable, both the first and second stages are conducted by Newey-West standard errors robust to serial correlation.[4]

4. Results

In order to investigate the environmental consequences of fuel price shocks, Table 3 presents the impact of fuel price shocks on ambient air pollution. We estimate the elasticities of air pollutant concentrations with respect to gasoline and diesel prices while including a comprehensive set of control variables and fixed effects. For brevity, we only report coefficients of interest. To address potential concerns about serial correlation, we estimate Newey-West standard errors that are robust to serial correlation. We also report standard errors in the normal way for comparison purposes. To overcome the endogeneity of fuel prices, we further use global oil price as the instrumental variable.

Panels A and C of Table 3 present the ordinary least squares (OLS) estimates of the relationship between air pollutant concentrations and fuel prices. According to the OLS estimates, each 10% increase in either gasoline or diesel prices is associated with a reduction in air pollutant concentrations ranging from 3% to 13%. Panels B and D of Table 3 display the corresponding IV estimates of the causal effect of fuel prices on air pollution. The F-statistics in the first stage of the IV estimates rule out a weak instrument, and estimates by the IV method are significant at the 1% level except for $PM_{2.5}$, indicating that an increase in refined oil price is associated with a decrease in air pollution. For example, a 10% increase in gasoline prices is associated with a 5.3% decrease in AQI, a 10.6% decrease in NO_2, an 8.8% decrease in PM_{10}, and a 4.1% decrease in $PM_{2.5}$. The impact on NO_2 is the largest, which is consistent with previous findings that NO_2 is most closely related to vehicular emissions. The impacts on $PM_{2.5}$ are smaller than those on PM_{10} and are statistically insignificant using Newey-West standard errors robust to serial correlation, since PM_{10} is more directly related to traffic while $PM_{2.5}$ includes both primary emissions from traffic and secondary emissions through chemical reaction of other gaseous pollutants.

To exploit cross-city variation in fuel price for estimation, we further assemble fuel price data covering all capital cities in China and merge it with air pollution data from corresponding monitor stations, and we present the results in Table C1 of Appendix C, indicating that fuel price is still negatively associated with air pollutant concentrations.[5]

To uncover the mechanisms at work linking environmental consequences and fuel price shocks through traffic, Table 4 shows the results from estimating the price elasticity of driving demand in eq. (4). As discussed, we use congestion index to capture driving demand. The elasticities of congestion with respect to gasoline and diesel prices are both estimated, as shown in panel A of Table 4. The estimates of OLS in columns (1) and (3) indicate a gasoline price elasticity of −2.797 and a diesel price elasticity of −2.526. When using global oil price as instrumental variable in columns (2) and (4), the elasticities change to −1.398 and − 1.255, respectively.

The IV estimates are much smaller than OLS estimates, suggesting that OLS estimation may suffer from significant bias in estimating driving demand. This indicates the importance of considering the plausible endogeneity due to strategic decisions in fuel price adjustments. We regard results in columns (2) and (4) as our preferred estimates, in which the point estimates on price elasticity of driving demand measured by congestion index using IV method are larger than 1 but the difference is not significant statistically because of the large standard errors after considering serial correlation.[6] In addition, the elasticity to gasoline price is larger than elasticity to diesel price, which is reasonable since diesel is used more in commercial vehicles such as trucks and thus the price response of driving is expected to be more inelastic.

It is important to validate the estimated coefficients to ensure that they indeed capture the impact of fuel price changes on air pollutant concentration through changes in driving behaviors. Using the variation in distance to major roads across monitoring stations is an effective way to address this concern. In our study, there are 11 monitoring stations in Hangzhou, and Fig. 3(a) shows their locations in relation to the road network. As noted, 10 of these monitoring stations are located in the downtown area, which has a dense road network, while the remaining station (1225A) is situated at Qiandao Lake, where the road density is much lower. Table A1 in Appendix A also shows the density of road networks surrounding each monitoring station with various radius. It confirms that the road density around the Qiandao Lake station is significantly lower than the other stations, with no roads within 1 km. We used the global crude oil price as an instrumental variable to estimate the effects of fuel price changes on air pollutant concentrations at each

[4] To address the issue of serial correlation, an alternative approach is to use weekly data. Therefore, we have also aggregated our datasets to the weekly level and re-estimated all the results presented in this paper. The corresponding results are presented in Tables B1-B3 in Appendix B. These results demonstrate that our findings hold even when using weekly data, although some coefficients cannot be estimated precisely due to the significant reduction in sample size from over 40,000 observations at the hourly level and 1817 observations at the daily level to only 260 observations at the weekly level.

[5] In later estimates, we are not able to exploit cross-city variations because of data unavailability on key variables in other cities.

[6] The price elasticity of driving demand larger than unity has important implications since it indicates that the expenditure on driving is expected to decrease when the price of fuel increases. As such, the expenditure on other commodities and services is going to increase with people substituting away from driving because it is easy for individuals to react to fuel price changes by adjusting their demand for public transit and non-driving personal consumption through substitution. This implies outcomes on public transits and non-driving personal consumption.

Table 3
Environmental consequences of fuel price shocks.

	Log (AQI)	Log (NO_2)	Log (PM_{10})	Log ($PM_{2.5}$)
	(1)	(2)	(3)	(4)
Panel A: Impact of gasoline price on air pollution (OLS)				
ln (gasoline price)	−0.397***	−1.264***	−0.703***	−0.343*
	(0.145)	(0.112)	(0.176)	(0.180)
	[0.037]	[0.033]	[0.044]	[0.046]
Weather covariates	✓	✓	✓	✓
N	42,214	42,214	42,214	42,214
Panel B: Impact of gasoline price on air pollution (IV)				
ln (gasoline price)	−0.531***	−1.058***	−0.879***	−0.409
	(0.243)	(0.202)	(0.313)	(0.314)
	[0.059]	[0.052]	[0.071]	[0.074]
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	259.115	259.115	259.115	259.115
N	42,214	42,214	42,214	42,214
Panel C: Impact of diesel price on air pollution (OLS)				
ln (Diesel price)	−0.359***	−1.140***	−0.634***	−0.312*
	(0.130)	(0.101)	(0.158)	(0.162)
	[0.033]	[0.029]	[0.040]	[0.042]
Weather covariates	✓	✓	✓	✓
N	42,214	42,214	42,214	42,214
Panel D: Impact of diesel price on air pollution (IV)				
ln (Diesel price)	−0.477***	−0.950***	−0.789***	−0.368
	(0.218)	(0.181)	(0.281)	(0.282)
	[0.053]	[0.047]	[0.064]	[0.066]
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	259.230	259.230	259.230	259.230
N	42,214	42,214	42,214	42,214

Note: Newey-West standard errors robust to serial correlation are in parentheses and standard errors are in brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of holiday, year, month, day-of-week, and hour are all controlled for.

Table 4
Fuel prices and driving demand.

	Panel A: Regression with ln (Congestion) as dependent variable			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
ln (gasoline price)	−2.797***	−1.398***		
	(0.138)	(0.354)		
	[0.040]	[0.065]		
ln (Diesel price)			−2.526***	−1.255***
			(0.124)	(0.317)
			[0.036]	[0.058]
Weather covariates	✓	✓	✓	✓
First-stage F		259.925		260.034
N	42,364	42,364	42,364	42,364

Note: Newey-West standard errors robust to serial correlation are in parentheses and standard errors are in brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of holiday, year, month, day-of-week, and hour are all controlled for.

monitoring station. The results are shown in Fig. 3(b) for gasoline price and Fig. 3(c) for diesel price. The lack of significant effects on air pollutant concentrations around the monitoring station at Qiandao Lake provides further evidence that driving behavior is the primary mechanism driving our results on environmental outcomes.

After reassuring that air pollution is affected by fuel price changes, we next estimate how the change in driving demand affects air pollution. Using OLS estimation, panel A of Table 5 shows that air pollution (AQI) and various pollutant concentrations (NO_2, PM_{10}, and $PM_{2.5}$) are all increasing with more congested traffic. One possible concern is the endogeneity of congestion because it is possible that driving demand is also affected by air pollution when, for example, people choose to stay indoor in order to avert ambient pollution outside (Chen, Chen, Lei, & Tan-Soo, 2020; Zhong et al., 2017). The empirical challenge we face here is that global oil price is not a valid instrumental variable of congestion because global oil price could affect air pollution through other channels rather than

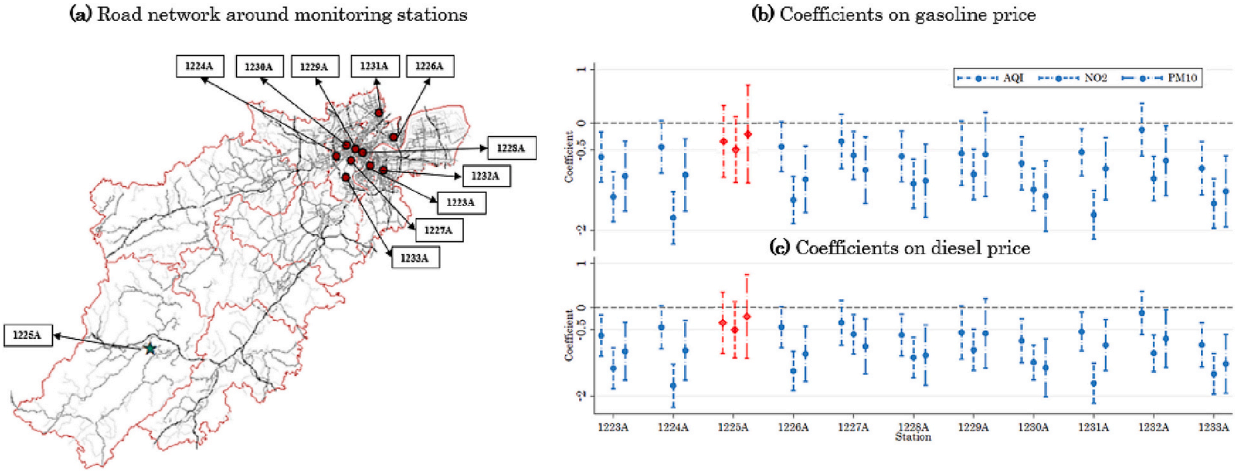

Fig. 3. Road networks around monitoring stations and the associated estimates by stations.
Note: The monitoring station of Qiandao Lake is denoted by the pentagram in Fig. 3(a), while the results of air pollutant concentrations measured in Qiandao Lake are shown as red lines in Fig. 3(b) and (c), in which the confidence intervals are estimated with Newey-West standard errors robust to serial correlation.

Table 5
Driving demand and air pollution.

	Log (AQI)	Log (NO_2)	Log (PM_{10})	Log ($PM_{2.5}$)
	(1)	(2)	(3)	(4)
	Panel A: OLS (all sample)			
ln (Congestion)	0.058***	0.201***	0.098***	0.077***
	(0.013)	(0.010)	(0.015)	(0.016)
	[0.004]	[0.004]	[0.005]	[0.005]
Weather covariates	✓	✓	✓	✓
N	42,208	42,208	42,208	42,208
	Panel B: IV (time windows around SW holiday)			
ln (Congestion)	0.787***	1.001***	1.045***	1.062***
	(0.164)	(0.116)	(0.196)	(0.214)
	[0.050]	[0.047]	[0.060]	[0.063]
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	85.900	85.900	85.900	85.900
N	11,089	11,089	11,089	11,089
	Panel C: OLS (time windows around SW holiday)			
ln (Congestion)	0.048**	0.149***	0.078***	0.054*
	(0.024)	(0.019)	(0.028)	(0.030)
	[0.011]	[0.009]	[0.012]	[0.013]
Weather covariates	✓	✓	✓	✓
N	11,089	11,089	11,089	11,089

Note: Newey-West standard errors robust to serial correlation are in parentheses and standard errors are in brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of holiday, year, month, day-of-week, and hour are all controlled for. "SW" is the abbreviation of "summer and winter".

only congestion. As we will show later, industrial activity could be another channel. The exclusion restriction of IV method is therefore violated.

To solve the potential endogeneity, following Lu et al. (2017), we use the repeated exogenous shocks on traffic demand from the start and end dates of winter and summer school holidays in Hangzhou, which provide us a source of instrumental variable for driving demand. The absence of school bus system in China generates a considerable amount of school trips via decentralized private driving, which is also the case in Hangzhou. Therefore, the validity of this instrumental variable is that there is a sharp reduction in driving demand during winter and summer school holidays while the start and end dates of school holidays are not directly related to air pollution. To exclude unobservable covariates during a long period, we restrict the study period to a narrow time window of 14 days (i.e., two weeks). We find that, all else being equal, school holidays experience a sharp decline in traffic congestion by 32% comparing to that of non-school-holidays.

Panel B of Table 5 presents the results of regression using instrumental variable, which shows that congestion has a significant positive effect on all indicators of air pollution. A 10% increase in congestion is associated with a 7.9% increase in AQI, a 10.0% increase in NO_2, a 10.5% increase in PM_{10}, and a 10.6% increase in $PM_{2.5}$. These coefficients using IV estimates in Panel B are larger than those in OLS estimates in Panel A, indicating that endogeneity in congestion may lead to substantial underestimation. To address concerns that the difference between OLS and IV estimates is caused by different samples, Panel C replicates OLS estimates using the same sample as Panel B and obtains comparable results to those in Panel A. Overall, the results in Table 5 provide evidence of the possible mechanisms linking fuel price shocks and environmental consequences through driving demand.

Given that a significant portion of air pollutant emissions comes from sources other than vehicular emissions (Zheng et al., 2018), changes in fuel prices may affect not only vehicular emissions but also pollutants from industrial activities, which are major sources of air pollution and fuel consumers. Specifically, industrial firms may respond to changes in fuel prices by adjusting their production schedules and/or outputs because fuel costs usually account for a significant portion of their total costs and also constitute a large share of their marginal costs (Liu, Du, & Li, 2019). When fuel price changes shift marginal costs, profit-maximizing firms are expected to adjust their production schedules and/or outputs by equating marginal benefit and marginal cost (Jessoe & Rapson, 2015). To test this plausible channel, we use hourly electricity consumption of industrial firms in Hangzhou as a proxy for measuring industrial activity. Previous studies have shown that electricity consumption is a good indicator of economic activity at high frequencies (e.g., Ai, Zhong, & Zhou, 2022). We obtain electronic records of firms' electricity consumption over the entire year of 2017, when Hangzhou first started monitoring road congestion. We estimate the association between fuel prices and industrial activities, as measured by electricity consumption. Since we only have access to electricity consumption data at high frequencies in 2017, global oil prices are not a strong predictor of refined oil prices in a single year, and we only have a weak instrumental variable. Therefore, we use OLS estimates to conduct the correlation analysis. Columns (1)–(2) of panel A in Table 6 show the results, which suggest that fuel prices are negatively associated with industrial activities.

Industrial activities are intertwined with traffic demand, and a change in fuel price may impact pollutants generated by industrial activities facilitated by vehicular trips (Zhong et al., 2017). For instance, if fuel prices rise and transportation costs increase, production in the industrial sector may become hampered. To isolate this component, we include traffic demand as a control variable in our regression analysis of industrial activities, presented in columns (3)–(4) of Table 6 in Panel A. As expected, traffic demand has a positive association with industrial activities, and the net effect of fuel prices becomes smaller after accounting for traffic demand. Nonetheless, the net impact of fuel prices on industrial activities remains statistically significant at the 5% level, and the coefficients are sizeable in magnitude. This association indicates that fuel price increases may have negative impacts on industrial activities, which are orthogonal to traffic demand.

The economic outcomes of fuel price shocks on industrial activities may also have environmental implications. Panel B of Table 6 establishes a positive relationship between industrial activities and air pollution. The findings demonstrate that a 10% increase in industrial activities is associated with a 1.8% increase in AQI, a 4.9% increase in NO_2, and a 2% increase in PM_{10} and $PM_{2.5}$. Therefore, a rise in fuel prices may also lead to a decrease in air pollution by curbing industrial activities. Our results indicate that fuel price shocks could trigger economic outcomes by prompting a response in industrial activities due to the impact on production costs.

5. Discussion and conclusions

This paper examines the environmental consequences of fuel price shocks by focusing on a Chinese megacity, Hangzhou. Global oil price is used as the instrumental variable of fuel price in order to address the possible endogeneity caused by strategic decisions in fuel price adjustments. We first show that fuel price increase results in a significant improvement in overall air quality and reduce major pollutant concentrations. We further find that the environmental outcomes of rising fuel prices could be partly attributed to the significant reduction in driving demand reflected by congestion index. The elasticities of driving demand with respect to gasoline price and diesel price are potentially larger than one, suggesting elastic responses to fuel price shocks. Moreover, an increase in fuel price is negatively associated with industrial activities which could be another channel at work reducing air pollution. Our results shed lights into understanding the behaviors of drivers in a broad way and thus help policymakers taking informed decisions on energy and environmental matters.

The findings of this paper are important for two reasons. First, they are particularly relevant for the pricing mechanisms of refined oil in China. Gasoline and diesel prices in China are closely tied to global oil prices, but sometimes the price adjustments are not fully implemented to protect the environment and ensure energy security, which has sparked public debate. This study enhances our understanding of this issue by quantifying the responses of drivers to fuel price increases, demonstrating how the reduced driving demand has improved air quality and reduced transport-related pollutant concentrations. However, the negative impact on industrial activities suggests that it is important to consider the broader macroeconomic impacts of fuel price increases.

Second, the large price response in driving suggests that price-based policies such as gasoline taxes could be effective measures to address energy and environmental concerns such as global warming, air pollution, and energy security. Particularly, substitution towards public transits provides alternatives to meet traffic demand such as commuting in a low-carbon and sustainable way. Access to public transit allows them to substitute away more readily from driving, thereby reducing their financial burden induced by price-based measures. Moreover, adopting cleaner vehicles such as electric vehicles may be another worthy alternative. Future research, when data becomes available, is encouraged to explore the adaption of drivers in a broader perspective.

Table 6
Fuel price and industrial activities measured by electricity consumption.

	Panel A: Dependent variable: Log (electricity demand)			
	(1)	(2)	(3)	(4)
Log (gasoline price)	−2.145**		−2.027***	
	(0.878)		(0.779)	
	[0.190]		[0.178]	
Log (diesel price)		−1.854**		−1.758**
		(0.790)		(0.700)
		[0.171]		[0.160]
Log (congestion)			0.216***	0.216***
			(0.015)	(0.015)
			[0.006]	[0.006]
Weather covariates	✓	✓	✓	✓
N	8593	8593	8593	8593
	Panel B: Environmental consequences of industrial activities			
	Log (AQI)	Log (NO_2)	Log (PM_{10})	Log ($PM_{2.5}$)
Log (electricity demand)	0.180**	0.491***	0.200**	0.200**
	(0.076)	(0.053)	(0.086)	(0.094)
	[0.020]	[0.017]	[0.023]	[0.025]
Weather covariates	✓	✓	✓	✓
N	8585	8585	8585	8585

Note: Newey-West standard errors robust to serial correlation are in parentheses and standard errors are in brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of holiday, year, month, day-of-week, and hour are all controlled for.

Data availability

Data will be made available on request.

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Appendix A. Additional information on data

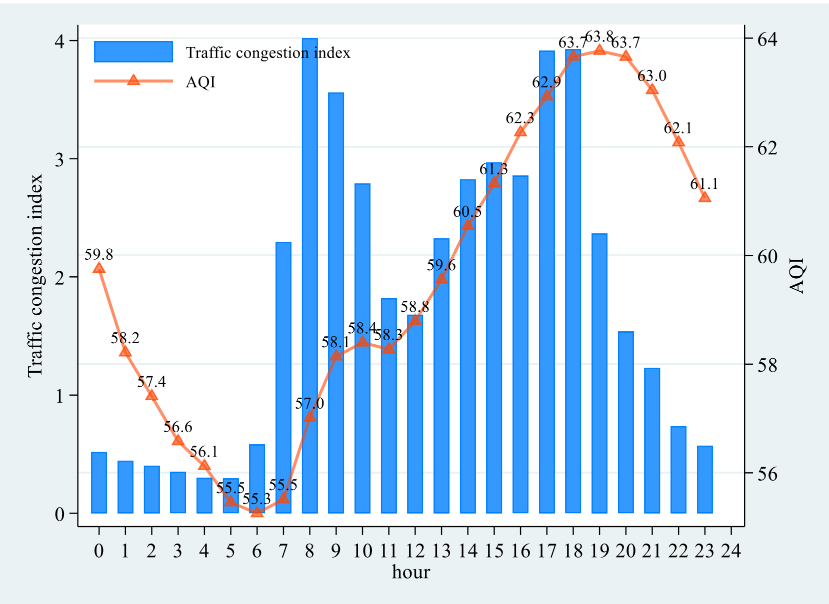

Fig. A1. Hourly variation of traffic congestion and air pollution.

Table A1
Road density around monitoring stations.

Labels of monitoring stations	Road density with various cycle radius (km/km^2)			
	1 km	2 km	5 km	10 km
1223A	42.97	37.78	40.11	31.00
1224A	4.17	13.45	26.24	26.02
1225A (Qiandao Lake)	**0.00**	**3.77**	**5.14**	**3.85**
1226A	30.78	32.51	24.49	26.59
1227A	14.77	13.02	23.89	30.91
1228A	38.81	42.84	42.43	35.07
1229A	35.03	43.58	42.98	32.62
1230A	24.68	37.59	40.07	32.69
1231A	36.46	30.32	26.96	20.72
1232A	27.93	33.78	35.62	28.91
1233A	2.92	12.62	14.76	19.03

Note: The bold tyle indicates the road density around Qiandao Lake station.

Appendix B. Additional results collapsing to weekly level

Table B1
Environmental consequences of fuel price shocks: weekly data.

	ln (AQI)	ln (NO_2)	ln (PM_{10})	ln ($PM_{2.5}$)
	(1)	(2)	(3)	(4)
Panel A: Impact of gasoline price on air pollution (IV)				
ln (gasoline price)	−0.285	−1.149***	−0.622*	−0.173
	(0.301)	(0.304)	(0.348)	(0.348)
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	173.186	173.186	173.186	173.186
N	260	260	260	260
Panel B: Impact of diesel price on air pollution (IV)				
ln (Diesel price)	−0.256	−1.032***	−0.558*	−0.155
	(0.271)	(0.273)	(0.312)	(0.312)
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	173.712	173.712	173.712	173.712
N	260	260	260	260

Note: Newey-West standard errors robust to serial correlation are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of year and month are all controlled for.

Table B2
Fuel prices and driving demand: weekly data.

	Regression with ln (Congestion) as dependent variable			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
ln (gasoline price)	−2.705***	−1.204**		
	(0.396)	(0.603)		
ln (Diesel price)			−2.442***	−1.082**
			(0.356)	(0.542)
Weather covariates	✓	✓	✓	✓
First-stage F		173.186		173.712
N	260	260	260	260

Note: Newey-West standard errors robust to serial correlation are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of year and month are all controlled for.

Table B3
Economic consequences of fuel price shocks: weekly data.

	Regression with Baidu index as dependent variable			
	Transit	Non-transport	Transit	Non-transport
	(1)	(2)	(3)	(4)
ln (gasoline price)	0.118	0.364***		
	(0.187)	(0.135)		
ln (Diesel price)			0.106	0.327***
			(0.168)	(0.121)
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	173.186	173.186	173.712	173.712
N	260	260	260	260

Note: Newey-West standard errors robust to serial correlation are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of year and month are all controlled for.

Appendix C. Additional results exploiting cross-city variations

Table C1 presents the corresponding IV estimates of Table 3 with the samples of all capital cities in China. After exploiting cross-city variation, the IV estimates imply still that fuel price is negatively associated with air pollutant concentrations, except for $PM_{2.5}$. As discussed, $PM_{2.5}$ is emitted from primary source and secondary source through chemical reactions with other gaseous pollutants by meteorological conditions (Zhong et al., 2017). The mixed sources may introduce correlation between $PM_{2.5}$, other gaseous pollutants, and weather (Deryugina, Heutel, Miller, Molitor, & Reif, 2019), which could be quite large in some cities and thus bias the estimates. Compared with the estimates in Hangzhou (as shown in Table 3), the nationwide average impacts are smaller in magnitude. A potential explanation is that vehicle ownership per capita in Hangzhou is the largest in China's capital cities.

Table C1
Environmental consequences of fuel price shocks exploiting cross-city variations.

	AQI	NO_2	PM_{10}	$PM_{2.5}$
	(1)	(2)	(3)	(4)
Log (gasoline price)	−0.119*	−0.567***	−0.554***	0.160*
	(0.062)	(0.056)	(0.072)	(0.082)
	[0.014]	[0.014]	[0.017]	[0.019]
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	6817.412	6817.397	6797.319	6817.294
N	1,043,455	1,043,452	1,036,413	1,043,405
Log (Diesel price)	−0.108*	−0.517***	−0.505***	0.146*
	(0.057)	(0.051)	(0.066)	(0.075)
	[0.013]	[0.013]	[0.016]	[0.017]
Weather covariates	✓	✓	✓	✓
F-value in the first-stage	6812.433	6812.417	6792.397	6812.311
N	1,043,455	1,043,452	1,036,413	1,043,405

Note: Newey-West standard errors robust to serial correlation are in parentheses and standard errors are in brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with Newey-West standard errors. Fixed effects of city, holiday, year, month, day-of-week, and hour are all controlled for.

References

Adler, M. W., Liberini, F., Russo, A., & Ommeren, J. N. V. (2021). The congestion relief benefit of public transit: Evidence from Rome. *Journal of Economic Geography, 21*(3), 397–431.
Ai, H., Zhong, T., & Zhou, Z. (2022). The real economic costs of COVID-19: Insights from electricity consumption data in Hunan Province, China. *Energy Economics, 105*, Article 105747.
Ang, A., Christensen, P., & Vieira, R. (2020). Should congested cities reduce their speed limits? Evidence from São Paulo, Brazil. *Journal of Public Economics, 184*, Article 104155.
Auffhammer, M., & Kellogg, R. (2011). Clearing the air? The effects of gasoline content regulation on air quality. *American Economic Review, 101*(6), 2687–2722.
Banzhaf, H. S., & Kasim, M. T. (2019). Fuel consumption and gasoline prices: The role of assortative matching between households and automobiles. *Journal of Environmental Economics and Management, 95*, 1–25.
Chen, S., Chen, Y., Lei, Z., & Tan-Soo, J. S. (2020). Impact of air pollution on short-term movements: Evidence from air travels in China. *Journal of Economic Geography, 20*(4), 939–968.
Chen, S. Y., Zhang, Q., Mclellan, B., & Zhang, T. T. (2020). Review on the petroleum market in China: History, challenges and prospects. *Petroleum Science, 17*(6), 1779–1794.
Chen, Y., & Whalley, A. (2012). Green infrastructure: The effects of urban rail transit on air quality. *American Economic Journal: Economic Policy, 4*(1), 58–97.
Coglianese, J., Davis, L. W., Kilian, L., & Stock, J. H. (2017). Anticipation, tax avoidance, and the price elasticity of gasoline demand. *Journal of Applied Econometrics, 32*(1), 1–15.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review, 109*(12), 4178–4219.
Gibson, M., & Carnovale, M. (2015). The effects of road pricing on driver behavior and air pollution. *Journal of Urban Economics, 89*, 62–73.
Gillingham, K. (2014). Identifying the elasticity of driving: Evidence from a gasoline price shock in California. *Regional Science and Urban Economics, 47*, 13–24.
Gillingham, K., & Munk-Nielsen, A. (2019). A tale of two tails: Commuting and the fuel price response in driving. *Journal of Urban Economics, 109*, 27–40.
Gu, Y., Jiang, C., Zhang, J., & Zou, B. (2021). Subways and road congestion. *American Economic Journal: Applied Economics, 13*(2), 83–115.
Han, Q., Liu, Y., & Lu, Z. (2020). Temporary driving restrictions, air pollution, and contemporaneous health: Evidence from China. *Regional Science and Urban Economics, 84*, Article 103572.
Jessoe, K., & Rapson, D. (2015). Commercial and industrial demand response under mandatory time-of-use electricity pricing. *Journal of Industrial Economics, 63*(3), 397–421.
Kilian, L. (2016). The impact of the shale oil revolution on US oil and gasoline prices. *Review of Environmental Economics and Policy, 10*(2), 185–205.
Levin, L., Lewis, M. S., & Wolak, F. A. (2017). High frequency evidence on the demand for gasoline. *American Economic Journal: Economic Policy, 9*(3), 314–347.
Li, J., & Sun, C. (2018). Towards a low carbon economy by removing fossil fuel subsidies? *China Economic Review, 50*, 17–33.
Li, P., Lu, Y., & Wang, J. (2020). The effects of fuel standards on air pollution: Evidence from China. *Journal of Development Economics, 146*, Article 102488.
Liu, H., Du, K., & Li, J. (2019). An improved approach to estimate direct rebound effect by incorporating energy efficiency: A revisit of China's industrial energy demand. *Energy Economics, 80*, 720–730.
Lu, M., Sun, C., & Zheng, S. (2017). Congestion and pollution consequences of driving-to-school trips: A case study in Beijing. *Transportation Research Part D: Transport and Environment, 50*, 280–291.
Molloy, R., & Shan, H. (2013). The effect of gasoline prices on household location. *Review of Economics and Statistics, 95*(4), 1212–1221.
Rivers, N., Saberian, S., & Schaufele, B. (2020). Public transit and air pollution: Evidence from Canadian transit strikes. *Canadian Journal of Economics, 53*(2), 496–525.
Salvo, A., & Geiger, F. M. (2014). Reduction in local ozone levels in urban São Paulo due to a shift from ethanol to gasoline use. *Nature Geoscience, 7*(6), 450–458.
Salvo, A., & Wang, Y. (2017). Ethanol-blended gasoline policy and ozone pollution in São Paulo. *Journal of the Association of Environmental and Resource Economists, 4*(3), 731–794.
Sheldon, T. L., & Sankaran, C. (2017). The impact of Indonesian forest fires on Singaporean pollution and health. *American Economic Review, 107*(5), 526–529.
Sipes, K. N., & Mendelsohn, R. (2001). The effectiveness of gasoline taxation to manage air pollution. *Ecological Economics, 36*(2), 299–309.
Sun, C., Zheng, S., & Wang, R. (2014). Restricting driving for better traffic and clearer skies: Did it work in Beijing? *Transport Policy, 32*, 34–41.
Viard, V. B., & Fu, S. (2015). The effect of Beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics, 125*, 98–115.
Wolfram, C., Shelef, O., & Gertler, P. (2012). How will energy demand develop in the developing world? *Journal of Economic Perspectives, 26*(1), 119–138.
Ye, J., Qin, Z., & Chen, X. (2021). Adapt by adopting cleaner vehicles?—Evidence from a low-emission zone policy in Nanchang, China. *China Economic Review, 66*(C).
Zhang, T., & Burke, P. J. (2020). The effect of fuel prices on traffic flows: Evidence from New South Wales. *Transportation Research Part A: Policy and Practice, 141*, 502–522.
Zhang, T., & Burke, P. J. (2022). The effect of gasoline prices on suburban housing values in China. *China Economic Review, 72*, Article 101762.
Zheng, B., Tong, D., Li, M., Liu, F., Hong, C., Geng, G., … Zhang, Q. (2018). Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. *Atmospheric Chemistry and Physics, 18*(19), 14095–14111.
Zhong, N., Cao, J., & Wang, Y. (2017). Traffic congestion, ambient air pollution, and health: Evidence from driving restrictions in Beijing. *Journal of the Association of Environmental and Resource Economists, 4*(3), 821–856.