Do Chinese Drivers Respond to Gasoline Price Changes?

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Abstract

Vehicle emissions contribute to air pollution. One tool that policymakers have to regulate traffic and reduce emissions is the driving cost. This paper uses data from 577 sensors on city expressways in Shanghai from January 2011 to March 2013 to estimate the short-run causal impact of unanticipated government gasoline price adjustments on traffic flow. Results show that traffic flow does respond to gasoline price changes. This impact dissipates in three days, with an estimated average elasticity of traffic flow to the price of gasoline of -0.26. Given baseline traffic, this estimate implies that a one percent increase in gasoline price would reduce daily average traffic flow by 104 vehicles per sensor. The impact varies with types of price changes and is greater for price increases than price decreases.

Keywords: gasoline prices, traffic, price elasticity, China, transportation, emissions

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1 Introduction

Air pollution in China is a severe problem. Among the 155 cities where hourly air pollutants are monitored by the Chinese Environmental Protection Agency (EPA), thirty-six percent of them have annual concentrations of particulate matters ($PM_{2.5}$ and PM_{10}) above the World Health Organization's guideline value of annual limits (Han et al., 2018). Vehicle emission is a major contributor to air pollution in major cities in China.[1] Any policy lever that can reduce the number of vehicles on the road could reduce vehicle emissions and thus reduce air pollution (Currie and Walker, 2011; Knittel, Miller, and Sanders, 2016) and improve health (Pui, Chen, and Zuo, 2014; Chen et al., 2013; Ebenstein et al., 2017).

This paper focuses on the impact of gasoline prices on traffic flow. The Chinese government has the ability to change the price of gasoline. If increased gasoline prices significantly reduce traffic flow, then gasoline price manipulation offers one way to reduce air pollution in China.

The existing literature outlines the primary identification problem in studying the effect of gasoline prices (e.g., Hughes, Knittel, and Sperling, 2008; Levin, Lewis, and Wolak, 2017). Simply regressing traffic flow on gasoline prices yields a biased estimated elasticity due to confounding factors. For example, a positive economic shock would both boost gasoline prices as well as gasoline demand through the income effect.

To solve this problem, I rely on unanticipated gasoline price shocks generated by a national policy in place in China from 2011 to March 2013. Under the policy, drivers cannot predict before government announcements how much gasoline prices will change. The NDRC (National Development and Reform Commission, a government department) regulates gasoline price ceilings in response to fluctuations in global crude oil markets. Once the NDRC announces a change in the price ceiling, all retailers are required to add the same change to their retail prices at midnight on the announcement day. Drivers cannot predict price changes by referring to global oil markets, since the NDRC relied on a publicly unknown rule for changing prices, announcing price changes whenever the price of a particular weighted basket of global oil markets changed by more than four percent in the past 22 business days.

The NDRC's price adjustments should be plausibly exogenous to traffic flow, allowing one to identify a causal impact. To ensure this is the case, I focus on the impact of unanticipated

[1] The Ministry of Ecology and Environment of the People's Republic of China (2018) finds that a major source of air pollution in Beijing, Hangzhou, Guangzhou, Shenzhen, and Shanghai is motor vehicles.

price changes on traffic flow, holding traffic flow's response to current gasoline price fixed. For example, if current gasoline price is high, then a small price decrease might not have an impact on traffic flow. Using a regression discontinuity in time framework (Hausman and Rapson, 2017), I examine whether there is a change in traffic flow for gasoline price changes, with a given level of current gasoline price, in a short window before and after price changes.[2] Limiting the comparison to a short window allows me to avoid possible systematic impacts on traffic flow and gasoline price changes. For example, a positive economic shock could affect both price changes and traffic flow, but is less likely to happen in a short period near price adjustments. In the robustness check, I use the daily stock price index of the Shanghai Stock Exchange Market as a measure of unobserved economic shocks to test whether it correlates with gasoline price changes in the short window.

Results show that traffic flow does respond to unanticipated gasoline price adjustments. The preferred short-term price elasticity of traffic flow is -0.26. Responses are asymmetric and are greater to price increases (-0.45 price elasticity of traffic flow) than to price decreases. The impact of gasoline price changes on traffic flow dissipates in six days after the price change.

In an extension, I study the impacts of announced price changes from April 2013 to 2014. In this period, the price change announcement policy changed, and price changes could be anticipated. In this setting, I find little short-term response to price changes.

Given the estimated impacts of gasoline price adjustments on traffic flow, I then analyze the social impact of gasoline price increases. I conduct a back-of-the-envelope analysis based on estimates of the impact of traffic flow on NO_2 concentrations in the United States (Zhang and Batterman, 2014). I calculate that a ten percent increase in gasoline prices reduces hourly NO_2 concentrations by 0.19 $\mu g/m^3$. Using the finding in Chen et al. (2008), I calculate that the reduction in NO_2 concentrations reduces daily mortality of 0.44 percent in Shanghai.

This paper contributes to two strands of literature. First, it is aligned with a broad literature that has studied impacts of gasoline prices. There is an existing literature that studies the impact of gasoline prices on driving, but most work focuses on the impact of gasoline prices on gasoline sales (Dahl and Sterner, 1991; Goodwin, 1992; McRae, 1994; Espey, 1998, Small and Van Dender, 2007; Hughes, Knittel, and Sperling, 2008; Park and Zhao, 2010). This literature

[2] I focus on the comparison of the impact of gasoline prices on traffic flow within one to six days before and after the NDRC's price adjustments. Details of the selection of lengths of days can be found in Section 5.2.4.

generally finds that gasoline consumption decreases in response to increases in gasoline prices. However, the elasticity of traffic flow is smaller than the elasticity of gasoline demand both in the short-run (within a year) and the long-run (about 5 years) (Goodwin, Dargay, and Hanly, 2004).

To the best of my knowledge, this is the first paper that estimates the elasticity of traffic flow with respect to gasoline prices in China. Previous studies in China use vehicle meters traveled (VMT) as a measure of traffic, but their data are either at the national or provincial level (He et al., 2005; Lin et al., 2009; Lin and Zeng, 2013). The most closely related paper is Lin and Zeng (2013). They use annual provincial data on traffic volume of trucks and buses from 2003 to 2009 to calculate vehicle meters traveled and to estimate the VMT price elasticity. Due to data limitations, Lin and Zeng (2013) are unable to account for unobserved confounding factors like economic growth and have coarse annual data rather than daily data.

Second, this paper contributes to the literature on how government regulations can reduce traffic congestion and pollution. De Grange and Troncoso (2011) find that temporary driving restrictions on vehicles with and without catalytic converters imposed on days with poor air quality in Santiago reduce traffic flow, and Troncoso et al. (2012) find these temporary restrictions reduce air pollution on weekdays. Two studies (Chen et al., 2013; Viard and Fu, 2015) on the driving restriction related to Beijing 2008 Olympic Games find reductions in air pollution, although this result remains controversial in a relatively long-term (within a year) studies (Ma and He, 2016). Even though my finding is a short-run price impact on traffic flow, it is consistent with evidence on the driving restriction in showing that changes in driving costs can help reduce traffic flow, which in turn reduces traffic congestion and air pollution; and that the impact of changes in driving cost dissipates with time.

The paper is organized as follows: Section 2 provides background on gasoline price policies as well as a description of alternative transportation modes in Shanghai. Section 3 describes the data, Section 4 describes the empirical model, and Section 5 presents the main results. Section 6 presents an extension, examining the impact of the announcement itself, before price changes actually occur, comparing the policy regime from 2011-2013 in which price change announcements were unanticipated to the policy regime from 2013-2014 in which price change announcements could be anticipated. Section 7 conducts a back-of-the-envelope analysis of gasoline price increases on vehicle emissions and health; Section 8 concludes.

2 Background

This section presents essential background information. Section 2.1 provides detail on gasoline price regulations in China. Section 2.2 discusses the alternatives to driving in Shanghai that allow residents to substitute away from driving as gasoline prices increase.

2.1 Gasoline Prices in China

The National Development Reform Commission (NDRC) oversees the oil market in China and has offices at the national and local levels. The NDRC national administration adjusts the wholesale crude oil price between producers and retailers according to fluctuations in global oil markets. Local city NDRC offices adjust local retail gasoline price ceilings based on the wholesale price of crude oil and local economic costs. For example, cities with higher costs of transporting gasoline have higher retail gasoline prices than cities with lower transportation costs.

The NDRC calculates their desired price for retail gasoline and makes occasional announcements to set the price ceiling. Their method for calculating their desired price is not publicly available. Both the NDRC's central and local administrations announce new price levels at the same time, and gasoline retailers must comply at midnight of that day. The gasoline price change largely affects private drivers because the operating costs of public transportation and taxi drivers are subsidized.

Since 2011, gasoline price change announcements have operated under two policy regimes. Before March 2013, the NDRC changed prices whenever a weighted index of global oil prices rose or fell by more than four percent in the past 22 business days. The index included the Brent Crude Oil Market, Dubai Crude Oil Market, and Minas Oil Market, among others, but the weight on each market was undisclosed, so consumers could not predict price adjustments.[3] I refer this policy period as *Unanticipated* Price Change.

The NDRC revised their policy on March 27th, 2013. Under the new policy regime, the

[3] In Appendix A, I present two media reports on consumers' opinions on future price changes, showing that consumers were unable to predict price changes accurately.

NDRC announces price changes (if any) every ten business days. Consumers know when NDRC announcements will be made. The NDRC also removed the four-percent criterion. Under the new policy, when the weighted average global oil price increases or decreases by more than 50 yuan per ton, the NDRC adjusts prices. Consumers can predict whether there will be a price increase/decrease by examining global oil price trends in past business days. I refer to this new price policy as *Anticipated* Price Change.

Under the Anticipated Price Change policy regime, gasoline prices change more frequently and by smaller amounts than under the Unanticipated Price Change policy. The gasoline price only changed 13 times from 2011 to March 2013 but changed 31 times from April 2013 to 2014. The average percentage change in gasoline prices was four percent from 2011 to March 2013 under Unanticipated Price Change but was less than two percent under Anticipated Price Change.

My identification strategy relies on the unanticipated nature of price changes, and so in this paper, I focus primarily on the Unanticipated Price Change era. In Section 6.2, I compare the impact of price changes under the two price policies.

Figure 1 shows the price of gasoline in Shanghai as set by the NDRC against crude oil prices in the Brent Crude Oil market from 2011 to March 2013.[4] The NDRC's gasoline prices closely follow fluctuations of the Brent Crude Oil price.

Since the NDRC's retail gasoline price is a price ceiling, gasoline retailers do have the option to sell gasoline at lower prices. Retail prices at Shanghai gasoline stations are not observed. However, in conversation with retailers at some gasoline stations in Shanghai, I learned that retailers must file an application to the oil company to get permission to sell at a price lower than the ceiling. This application is only approved if the retailer can provide evidence that their neighborhood has an exceptionally competitive gasoline market. The authorized retailer receives permission to charge the NDRC price minus a fixed discount.

Given the difficulty of offering discounts, it is likely that most gasoline is sold at the price ceiling. Further, since discounts are fixed relative to the NDRC price, even discounted gasoline prices should respond to NDRC announcements. I checked whether discounted gasoline prices respond to NDRC announcements by using the website Youke to track three gasoline stations

[4]I use the Brent Crude Oil price as a measure of global oil prices because the NDRC weighted the Brent Crude oil market more than the other two major oil markets in an old price policy from 2008 to 2009.

approved to offer discounts from July to August 2017.[5] Over this period, the price ceiling increased by 0.14 yuan/liter. The prices at all three gasoline stations increased by exactly 0.14 yuan/liter as well, keeping their discounts unchanged in absolute terms.

2.2 Alternative Transportation Modes in Shanghai

The Shanghai metro system is the second largest system in the world and is the top substitute for driving in the city. According to the Shanghai Transportation Annual Report (2016), metro ridership accounted for 51 percent of public transportation rides in Shanghai in 2016. Other modes of transportation include buses, which do not reduce travel time because they do not avoid traffic, and bikes or motorbikes, which are only useful for short distances. In the following comparison of transportation costs between driving and an alternative mode, I illustrate it using the metro fare.

To illustrate the difference of transportation costs between driving and non-driving modes, I conduct a simple calculation to compare the difference between driving and riding the metro without considering other costs of traveling, such as time and parking fees. The average amount of gasoline for private vehicles to run one hundred kilometers is 7 liters/100km.[6] The metro fare in Shanghai is 3 yuan for distances less than 6km. The average gasoline price was 7.74 yuan/liter from 2011 to March 2013. For travel distances less than 6 km, the gasoline cost can be as high as 3.25 yuan, which is more expensive than the metro fare of 3 yuan. The metro fare increases by 1 yuan for each additional 10 km, and so remains cheaper for longer distances.

The availability of the metro ensures that there is a low-cost alternative to driving that Shanghai citizens can substitute towards if gasoline prices increase. This alternative travel mode makes it possible for traffic flow to respond to changes in gasoline prices.

3 Data Descriptions

In this section, I describe the two main types of data used in this analysis: (1) dates and magnitudes of gasoline price adjustments, and (2) daily traffic flow.

[5] Youke (*www. ok619. com*) is a website where consumers report information on gasoline stations and retail gasoline prices.

[6] Details of gasoline consumed per one hundred kilometers for each type of vehicles in China can be found on `http://chaxun.miit.gov.cn/asopCmsSearch/`.

3.1 Gasoline Price Adjustments

The NDRC does not offer systematic historical gasoline price adjustment data on its public website. So I use Baidu, a Chinese online search engine, to collect organized records of price adjustments from sources that have tracked and compiled NDRC announcements. I use the search term "Fa Gai Wei You Jia Tiao Zheng," which translates to "NDRC's gasoline price adjustments."

To confirm the accuracy of historical price adjustment data collected from Baidu, I compare the information to news posted on the NDRC's official website.[7] From Baidu search results, I collect dates of historical price adjustments from 2011 to March 2013. I enter these dates together with the term "You Jia Tiao Zheng" ("the oil adjustment") to find NDRC posts about gasoline price adjustments on the official website. I match all dates of price adjustments from the Baidu search to the NDRC's official posts.

Table 1 presents summary statistics on characteristics of the NDRC's retail gasoline prices in Shanghai under the Unanticipated Price Change regime from 2011 to March 2013. The average gasoline price was 7.74 yuan per liter. The lowest price was 7.25 yuan per liter, and the highest price was 8.27 yuan per liter. Using an annual exchange rate of 6.461 yuan per dollar in 2011 from the World Bank database, the corresponding average price was 4.53 dollars per gallon. The lowest price was 4.25 dollars per gallon, and the highest price was 4.85 dollars per gallon.

3.2 Traffic Flow Data

This study focuses on traffic flow, measured as the number of vehicles passing a given sensor, from city expressways in Shanghai because of availability of traffic flow data from sensors. The traffic flow data is from the Shanghai Road Administration Bureau. Sensors are placed at exits, entrances, and intersections of expressways; they report observed traffic flow at their location.

I construct a panel data set of daily traffic flow at each sensor. Each sensor records the number of vehicles passing it every half hour. I aggregate the half-hour measurements of traffic flow to the daily level since the gasoline price adjustment is by day.

Sensor location is coded by the name of the expressway it is on, and the nearest non-

[7] http://www.ndrc.gov.cn/

expressway road. I associate each sensor with an approximate location using Google Maps. I enter road names into Google Maps to find possible locations of sensors. Then I enlarge the map to find the exit, entrance, or intersection of the corresponding expressway in the area to obtain the latitude and longitude of the sensor location. Since adjacent expressway entrances and exits are no more than 1km apart, error in sensor location is no more than 1km.

Shanghai is organized into two circles. Areas in the inner circle are highly populated with expensive housing areas and financial districts. Areas in the middle circle are newly developed commercial areas with rising housing prices and population density, as are areas right outside the middle circle. Areas far away from the middle circle are suburban areas with lower population density and housing prices. City expressways do not extend into these suburban areas.

Figure 2 illustrates the locations of these sensors. There are 577 sensors in the study, including 290 within the inner circle of Shanghai, and 213 sensors within the city's middle circle but outside the inner circle. There are 74 sensors outside the middle circle. Areas outside the coverage of sensors do not have expressway access and most of them are suburban areas. 179 of the sensors in the data set, which was collected in 2015, are for roads that had not been opened in the period of analysis. These sensors are dropped.

The Shanghai government imposes driving restrictions on expressways. Vehicles not registered in Shanghai and vacant taxis cannot use expressways during peak hours. Trucks registered outside Shanghai cannot enter the outer circle of the city until 8 pm. When these restrictions are in place, the only vehicles allowed are those that are likely to have gasoline purchased in Shanghai.

These driving restrictions apply to all expressways in the data set except areas of the Hongqiao Airport. For expressways near the airport, there are no driving restrictions, and so some vehicles may not be subject to Shanghai gasoline prices. Therefore, I exclude the 96 sensors in the Hongqiao Airport area from the main analysis. I examine data from these sensors in Section 5.3.2.

Driving regulations are also suspended during national holidays. Travel patterns on national holidays are different and include tourists from cities subject to different gasoline prices. Data collected during national holidays are excluded from my analysis. In results available upon request, I find no relationship between gasoline price change announcements and national holidays.

3.3 Additional Variables

Weather conditions influence traffic flow and thus the ability for NDRC price adjustments to affect traffic flow. I collect daily weather data from the China Weather Center with a weather monitor north-east of Shanghai.[8] The data set includes daily minimum, average, and maximum temperature, daily precipitation, average wind speed (measured every ten minutes), maximum wind speed (the maximum ten-minute-average wind speed in a day), superior wind speed (measured every second), directions of maximum wind speed, and directions of superior wind speed. There are statistically significant correlations between gasoline price adjustments and the weather conditions of rain, temperature, and wind. Moreover, weather conditions influence the costs of transporting gasoline. Since local retail gasoline price ceilings depend on changes in wholesale oil prices and transportation costs, they are correlated with weather conditions.

Because the NDRC's gasoline price ceiling responds to global oil markets, information from the global crude oil market may influence drivers' expectations of future price changes and their driving decisions. I collect the daily Brent Crude oil price from the Energy Information Administration (EIA).[9]

I use the daily stock price index of the Shanghai Stock Exchange (SSE) to test whether there might be unobserved economic impacts occurring when gasoline price changes. I collect the daily SSE market opening and closing price indices. For days when the SSE is closed, I use market price indexes from the previous day.

4 Estimation Model

In this section, I present an estimation model that identifies the elasticity of traffic flow with respect to gasoline price changes. I begin with a naïve model and then introduce my strategy of using NDRC announcements to identify the gasoline price elasticity of traffic flow.

[8] `http://www.cma.gov.cn/`

[9] `http://www.eia.gov/`. Missing daily prices are filled in with lagged values because the expectation of future gasoline price changes depends on global oil prices in the past.

4.1 General Price Elasticity Estimation

A basic log-log model can provide a naïve estimate of the elasticity of traffic flow with respect to gasoline price. Following Bento, Hughes, and Kaffine (2013), I present a model regressing log daily traffic flow at sensor i on day d ($\ln \mathrm{Traffic}_{id}$) on log gasoline prices on day d ($\ln \mathrm{P}_d$) and a set of controls.

$$\ln \mathrm{Traffic}_{id} = \alpha_0 + \alpha_1 \ln \mathrm{P}_d + f(Weather_d) + \gamma_w + \phi_j + \lambda_{my} + \sigma_i + \epsilon_{id} \tag{1}$$

where $f(Weather_d)$ is a quadratic function of weather variables, σ_i is a sensor-level fixed effect to control for time-invariant location characteristics, γ_w is a fixed effect for the day of the week, ϕ_j is a date of the month fixed effect; and λ_{my} is a month-year fixed effect. ϵ_{id} is the error term clustered at the week and district level.

The coefficient of interest, α_1, measures price elasticity of traffic flow with respect to current gasoline prices under the assumption that $\ln \mathrm{P}_d$ and ϵ_{id} are independent conditional on the controls in the model.

However, conditional independence may not hold because of unobserved factors that are correlated with current gasoline prices and traffic flow. Local NDRC decisions about city-level gasoline prices are responsive to the city's economic conditions. Cities with higher gross domestic product per capita have higher retail gasoline prices. Variation across time in economic conditions will then be correlated with both prices and traffic, biasing the estimate of α_1.

Previous researchers have tried to find instrumental variables to solve the endogeneity problem between gasoline prices and gasoline demand (e.g., Hughes, Knittel, and Sperling, 2008), such as the global price of oil or the price of other fuels. However, the validity of these and other instruments are controversial (Levin, Lewis, and Wolak, 2017). The NDRC's price adjustments in China provide a quasi-experiment that allow the causal effect of gasoline prices on traffic flow to be identified without the use of an instrument.

4.2 Using the NDRC's Price Changes to Identify Elasticity

I use a Regression Discontinuity in Time (RDiT) framework to examine whether there is a change in traffic flow among days before and after the NDRC's price adjustments.

The main assumption of this identification strategy is that the conditional covariance between the NDRC's gasoline price adjustments and unobservables is zero within a short window of days before and after price adjustments. This assumption is likely to hold because of the unanticipated nature of gasoline price change announcements. I introduce a set of additional covariates to account for other factors that are correlated with price changes and may also influence traffic flow.

The set of control variables includes all controls listed in Equation (1) as well as global oil prices.

$ln(P_d)$, from Equation (1), is included as a control because any new price ceiling will be positively correlated with the current price ceiling. The current price ceiling will also be correlated with current traffic since travelers make driving decisions based on current gasoline prices.

Weather conditions, $f(Weather_d)$ in Equation (1) are included as controls. As discussed in Section 3.3, weather conditions are correlated with the NDRC's gasoline price adjustments. Weather conditions also influence traffic flow. For example, traffic is more congested on a rainy day. If gasoline price announcements are more likely to happen under bad weather conditions, then the relationship between price announcements and traffic flow will be confounded.

Fluctuations in global oil markets correlate with future gasoline price ceilings and influence traffic flow as well. Since the NDRC's price adjustment is in response to global oil trends, the global oil price is positively correlated with the NDRC's price adjustment. Also, if travelers consistently observe increases in global oil prices, to prepare for possible price increases in the future, they might adjust their driving plans, for example by purchasing more fuel-efficient vehicles or getting used to public transport.

Gasoline prices, global oil prices, and weather conditions are observed confounding factors. However, there exist unobserved confounding factors as well. Seasonality and location are important determinants of traffic flow. Traffic flow might be greater on Friday because travelers are leaving for vacations for the coming weekend. Workers receive payments on the 5th or 15th of each month and bonuses on the 25th of the month. They might drive more on or after the payment day because they have relatively more disposable income to spend than they do on other days of the month. Furthermore, the number of vehicles in Shanghai has increased over time. Time fixed effects for day of the week, date of the month, and month-year fixed effects consider these confounding factors. Time-invariant location characteristics influence traffic flow as well. For example, traffic flow might be greater in central business areas than less developed areas. Sensor fixed effects capture this time-invariant confounding factor.

To further address the problem of unobserved confounding factors, I select pairs of s-day comparison windows before and after the NDRC's price adjustments. In these short windows, variation is more likely to be limited to just the effect of the NDRC's announcements and the controlled factors. The inclusion of a window before the price announcement acts as a placebo test for the identification strategy. If price changes are truly unanticipated, they should not affect traffic flow before they are announced.

Lengths of comparison windows range from within one day to six days before and after the NDRC's price adjustments. I limit the comparison no more than six days before and after the price adjustments for two reasons. First, the six-day window is the widest window without any overlap between two consecutive price adjustments in the range of the available traffic flow data from 2011 to 2014. Second, the more days included in the comparison, the higher the probability that there might exist unobserved confounding factors correlated with both gasoline price changes and traffic flow. To examine whether there are any unobserved economic activities correlated with gasoline price adjustments within one to six days before and after price changes, in Section 5.3.1 I conduct a robustness check using the daily stock market closing index in Shanghai as a measure of unobserved economic shocks.

I incorporate short windows around the NDRC's price adjustments with the list of controls discussed above into an econometric model. Let $T_{pre(s)}$ be a dummy variable that equals one in the s days before the NDRC's price adjustments and let $T_{post(s)}$ be a dummy variable that equals one in the s days after the NDRC's price adjustments. The announcement day itself is the last day before the NDRC's price adjustments and hence is included in $T_{pre(s)}$. The relevant regressions are:

$$\begin{aligned}\ln \text{Traffic}_{id} = \alpha_0 + \alpha_1 T_{pre(s)} + \alpha_2 T_{pre(s)} \times \ln \text{PNew}_d \\ + \alpha_3 T_{post(s)} + \alpha_4 T_{post(s)} \times \ln \text{PNew}_d \\ + \alpha_5 \ln \text{Global Oil}_d + \alpha_6 \ln \text{P}_d + f(Weather_d) + \gamma_w + \phi_j + \lambda_{my} + \sigma_i + \epsilon_{id} \quad (2)\end{aligned}$$

$$s = 1, 2, ..., 6$$

where PNew_d is the NDRC's new gasoline price ceiling. It equals the NDRC's new gasoline price within s days before and after gasoline price changes and zero for days outside the s-day window. Global Oil_d is the daily Brent Crude oil price on day d. Table 2 gives a description of each variable.

The coefficients of interest are α_2 and α_4. I run separate regressions for different values of s. α_2 estimates an average short-run price elasticity of traffic flow within s days before price changes. α_4 estimates an average short-run price elasticity of traffic flow within s days after price changes.

In all analyses, I cluster error terms at the district-week level to capture spatial and serial correlations. Sensors located within the same district area might share similar characteristics. For example, sensors located within a one-kilometer interval might be tracking the same cars. Clustering at the district level accomodates this possibility.[10] There may also be serial correlation due to traffic flows being correlated across time. To test the serial correlation of errors, I regress $\hat{\epsilon_{id}}$ on its daily lags, finding evidence of autocorrelation up to the second lag. Given this lag length, the district-week clustering mitigates problems of spatial and serial correlations.

4.3 Traffic Flow Responses to Price Increases vs. Price Decreases

While elasticities track responsiveness both to price increases and price decreases, the policy question of interest is whether price increases can reduce traffic flow. Therefore, I identify impacts from gasoline price increases and gasoline price decreases separately. I adopt binary variables of the direction of price changes in the estimation. INC is a binary variable that equals one when the price adjustment is a price increase and zero if it is a price decrease. The form of the equation to estimate heterogeneous effects of gasoline price increases and decreases on traffic flow is as follows:

[10]There are 13 districts in the sample.

$$\begin{aligned}
\ln \text{Traffic}_{id} = \beta_0 &+ \beta_1 T_{pre(s)} \times INC + \beta_2 T_{pre(s)} \times INC \times \ln PNew_d \\
&+ \beta_3 T_{post(s)} \times INC + \beta_4 T_{post(s)} \times INC \times \ln PNew_d \\
&+ \beta_5 T_{pre(s)} \times (1 - INC) + \beta_6 T_{pre(s)} \times (1 - INC) \times \ln PNew_d \\
&+ \beta_7 T_{post(s)} \times (1 - INC) + \beta_8 T_{post(s)} \times (1 - INC) \times \ln PNew_d \\
&+ \beta_9 \ln \text{Global Oil}_d + \beta_{10} \ln \text{P}_d + f(Weather_d) \\
&+ \gamma_w + \phi_j + \lambda_{my} + \sigma_i + \epsilon_{id} \quad (3)
\end{aligned}$$

$$s = 1, 2, ..., 6$$

Coefficients of interest in Equation (3) are β_2, β_4, β_6, and β_8. These coefficients measure the short-run price elasticity in the short window before and after a price change, and in response to a price increase or decrease, respectively. Control variables are the same as in Equation (2).

4.4 Measurement Error in Gasoline Prices

Some gasoline retailers set retail prices below the NDRC's gasoline price ceilings. Therefore, equating the NDRC's price ceilings with retail gasoline prices would generate measurement error. As discussed in Section 2.1, retailers with permission to sell gasoline at lower prices than the price ceilings have fixed discount amounts. If the true retail gasoline price discount is time-invariant at each sensor station, i.e., a fixed amount of discount at each location, a sensor fixed effect removes this measurement error in gasoline prices.

If true retail gasoline price is time-invariant at the gasoline station level but not the sensor level, using the NDRC's price ceilings as retail gasoline prices yield a non-classical measurement error, u_{id}, with the following relationship between the true retail gasoline price (P^*) and price ceiling (P):

$$P^*_{id} = P_{id} + u_{id}, \text{with } u_{id} \leq 0 \tag{4}$$

My estimates of the coefficients of interest are not biased by this discount for two reasons. First, conditional on current gasoline price ceilings, my identification strategy identifies the impact of changes of gasoline price ceilings on traffic flow, and price changes are the same at all gasoline stations. As discussed in Section 2.1, all gasoline retailers must change retail prices by the same amount regulated by the NDRC. Second, the NDRC's price ceiling is an upper bound on true retail gasoline prices, which is not correlated with the measurement error. Hyslop and Imbens (2001) find that the measurement error in a regressor that is correlated with true value but uncorrelated with observed value does not lead to a bias.

5 Empirical Results

This section begins with a discussion of estimation results from a simple log-log regression. It then presents results from the main identification strategy. It ends with tests of validity and robustness checks.

5.1 Simple Regression Result

Table 3 presents an estimate of the basic log-log model shown in Equation (1). For simplicity of presentation, I omit estimates for control variables. The estimated coefficient on gasoline price is positive and statistically significant at the one percent level.

Even though retail gasoline prices are regulated by the NDRC, simply regressing traffic flow on gasoline prices yields a biased estimate due to unobserved confounding factors. To address the bias, I implement the identification strategy discussed in Section 4.2. Results are presented in the following section.

5.2 Main Results

This section presents estimates of Equations (2) and (3). I begin with an estimate of the effect of price changes on traffic flow and then examine whether traffic flow responds differently to gasoline price increases and decreases. To find a preferred length of days to compare, I then conduct a regression to examine the impacts of price changes for sub-intervals of up to six days before and after gasoline price changes. Finally, I compare my findings with the existing literature in China and developed countries.

5.2.1 Existence of Changes in Traffic Flow

To motivate the identification of differences in traffic flow in days before and after gasoline price changes, I first show that traffic flow does respond to price changes. I conduct t-tests comparing the means of traffic flow in the six days before a price change to the six days after. Table 4 presents means of natural logarithms of traffic flow, and t-tests comparing them before and after price changes. I also compare residual traffic flow after controlling for sensor, day of the week, date of the month, and month-year fixed effects in columns 4 and 9, and residual traffic flow controlling for weather variables, current gasoline prices, and crude oil prices, in addition to the fixed effects, in columns 5 and 10.

For gasoline price increases, columns 3 and 4 show that traffic flow in days before gasoline price increases are statistically significantly smaller than traffic flow in days after gasoline price increases at the conventional significance levels. Column 5 shows that the sign of the difference reverses after controlling for weather conditions.

Columns 6 through 10 repeat the analysis of columns 1 through 5 but for price decreases. Columns 8 and 9 do not show any statistically significant differences in traffic flow between the days before and the days after gasoline price decreases. When including all control variables in column 10, the signs of the differences reverse and become significant.

Results from Table 4 show that there is a change in traffic flow before and after gasoline price changes. The estimated direction of this change depends on which controls are included, with the addition of controls for current gasoline prices, weather, and global oil prices seeming to yield the expected effect. In the following subsection, I estimate the magnitude of the impact of gasoline price changes on traffic flow.

5.2.2 Price Elasticity of Traffic Flow from Price Changes

To show the impact of the NDRC's price changes on traffic flow, I present an estimate of Equation (2). Figure 3 graphs estimated coefficients of α_2 and α_4 from Equation (2) for the six different observation windows. The vertical axis shows effects within one to six days before and after gasoline price changes. Each color represents a pair of estimated α_2 and α_4 coefficients from one estimation of Equation (2). In a pair of estimated coefficients, the upper dot is the estimate of α_2, and the lower dot is the estimate of α_4.

Results show that traffic flow does not respond to price changes before the prices are changed: α_2 is insignificant for all six analyses. These estimates match the hypothesis that the NDRC's gasoline price adjustments are unanticipated, and help justify the identification strategy, since any unobserved time-varying factors correlated with price changes would be likely to affect the period before the price change announcement as well, but there is no such effect found here. Drivers did not change their driving behavior in the lead-up to price changes. One remaining question regards the impact of gasoline price changes on traffic flow on the announcement day. I will examine this impact in Section 6.1.

Traffic flow does respond to gasoline price changes after the prices actually change. Estimated α_4s within one to six days after gasoline price changes range between -0.3 and -0.2. All estimates are statistically significant at the five percent significance level.

5.2.3 Heterogeneous Responses to Price Increases and Price Decreases

Does traffic flow respond differently to price increases than to price decreases? Figure 4 graphs estimates of Equation (3). Figure 4a presents estimated coefficients of β_2 and β_4 from Equation (3) for NDRC price increases. Estimated average price elasticities of traffic flow within one to four days before gasoline price increases are statistically insignificant. Within one to six days after gasoline price increases, estimates are statistically significant at the five percent level. Estimates within five to six days before gasoline price increases are consistently significant for every sample window. This raises a question of the selection of lengths of comparison windows before and after gasoline price changes. I conduct a test to select a preferred length of window in the following section.

Figure 4b graphs estimated coefficients of β_6 and β_8 from Equation (3) for NDRC price decreases. Traffic flow does not statistically significantly respond to new price ceilings in the days before and after gasoline price decreases.

This lack of an effect of price decreases is unsurprising in the extensive margin of driving given the discussion in Section 2.2. The metro is an alternative transportation mode in Shanghai and is already cheaper than driving. Since I focus on a short-run impact of gasoline price changes, other costs such as time cost might not change. If a traveler chose to drive instead of taking the metro before a gasoline price decrease, the traveler will still drive after price decreases. On the other hand, for travelers who choose to take the metro before price decreases, they might still choose to take the metro, i.e., because they do not own a vehicle.[11]

In summary, these results show that traffic flow responds more strongly to gasoline price increases than it does to gasoline price decreases. However, the traffic flow data does not allow me to discern impacts of price changes between the intensive margin, i.e., drivers drive less, and the extensive margin, i.e., drivers switch to other travel modes.

5.2.4 Window Selection

The use of six days as a maximum does not specify which response window is optimal. To answer this question, I conduct one regression including dummies for each day before and after gasoline price adjustments and interact them with new gasoline price ceilings:

$$\begin{aligned}\ln \text{Traffic}_{id} = \alpha_0 &+ \sum_{k=-6}^{-1} \Theta_k T_{pre_k} + \sum_{k=-6}^{-1} \beta_k T_{pre_k} \times \ln \text{PNew}_d \\ &+ \sum_{n=0}^{5} \rho_n T_{post_n} + \sum_{n=0}^{5} \psi_n T_{post_n} \times \ln \text{PNew}_d \\ &+ \alpha_1 \ln \text{Global Oil}_d + \alpha_2 \ln \text{P}_d + f(Weather_d) + \gamma_w + \phi_j + \lambda_{my} + \sigma_i + \epsilon_{id} \quad (5)\end{aligned}$$

where T_{pre_k} is a dummy variable equal to one when it is the kth day before price adjustments, and T_{post_n} is a dummy variable equal to one when it is the nth day after price adjustments.

Figure 5 presents the estimates of Equation (5). Each dot represents traffic flow response to new price ceilings on the corresponding day. For days before gasoline price changes, only the sixth day before a gasoline price change is statistically significant. Confounding factors might exist on the sixth day before price changes. For example, when global oil prices keep increasing, drivers might change their driving behavior with the expectation that the NDRC is going to increase gasoline price. In general, price announcements are unanticipated: Appendix A presents a news report that drivers thought the NDRC was going to increase gasoline prices but

[11] To test this interpretation, I calculate the density of metro availability, which is the number of metro stations within 1km of each sensor divided by the geographic area. I create a dummy variable equal one for sensors where the density of metro availability is greater than the median. I interact this dummy variable with price increases and decreases. I do not find that price elasticity of traffic flow is related to metro accessibility. This result suggests that there are other factors such as non-gasoline costs of driving that influence travelers' choices of travel modes.

it did not, and suddenly increased the price three days later. However, the six-day comparison window might be too wide to identify a causal impact of gasoline price changes on traffic flow.

For days after gasoline price changes, impacts of gasoline price changes on traffic flow are strongest immediately after the price change and then dissipate. Impacts of price changes on traffic flow on the first, the second, and the third day are statistically significant with magnitudes decreasing towards zero. Estimates beyond the third day are not statistically significantly different from zero. Since the impact of price changes on traffic flow dies out on the fourth day after price changes, I refer to the average estimated effects within three days after price changes as my preferred specification in following discussions. The reason I use average impact instead of impact by each day is that the average impact is more important for policy decisions.[12]

5.2.5 Comparisons to Findings in Existing Literature

The estimated average price elasticity of traffic flow within three days after price changes is -0.26. This estimate is greater than recent findings in the United States. Using sensor-week traffic flow in Los Angeles from 2000 to 2007, Bento, Hughes, and Kaffine (2013) find that short-run (weekly) gasoline price elasticities of traffic flow range between -0.083 and -0.050. A study by the Congressional Budget Office (CBO) between 2003 and 2006 uses daily traffic flow on freeways in California and estimates a short-run price elasticity of traffic flow of -0.035 with respect to weekly gasoline price fluctuations. Both studies used a log-log regression, which might contain confounding factors between traffic flow and gasoline prices that attenuate their estimates, while my study identifies a causal impact of price changes.

Another reason for the difference might be that consumers in Shanghai are less wealthy than consumers in California but face higher gasoline prices. The annual average gasoline price from 2011 to 2013 in Los Angeles (L.A.) is 3.96 dollars per gallon.[13] The annual average gasoline price ceiling in Shanghai from 2011 to 2013 is 4.63 dollars per gallon.[14] Considering the Gross

[12]As discussed in the introduction, vehicle emissions contribute to air pollution which affects human health. Policymakers are interested in regulations of traffic to improve air quality. Since air pollution is auto-correlated (Pèrez, Trier, and Reyes, 2000) and has a cumulative impact on human health (Kan et al., 2007), the average price elasticity of traffic flow is more helpful for policy design purposes.

[13]Annual average gasoline prices (unleaded regular) in Los Angeles in 2011, 2012, and 2013 are 3.85, 4.09, and 3.95 dollars per gallon, respectively. Data is available from the Los Angeles Almanac: `http://www.laalmanac.com/energy/en12.php`

[14]The average gasoline price ceiling from 2011 to 2013 is 7.74 yuan per liter. Using the annual average exchange rate (6.46 yuan per dollar in 2011 and 6.20 yuan per dollar in 2013) between CNY and USD from the

Domestic Product (GDP) per capita in L.A. is \$60,693 in 2013,[15] four times the GDP per capita in Shanghai (\$14,547 in 2013, Shanghai Statistical Yearbook, 2014), the retail gasoline price in Shanghai is a relatively heavier burden to consumers in Shanghai than it is to consumers in L.A., and so they may respond more strongly to price increases.

My finding, however, is close to that in a study in Denmark. Using vehicle-level average daily vehicle kilometers traveled (VKT) and average daily fuel prices in Denmark from 1998 to 2011, Gillingham and Munk-Nielsen (2016) find an elasticity of -0.3. Their estimate is similar to my estimate of -0.26.

The estimated elasticity in this study is smaller than the estimate in Lin and Zeng (2013). They use annual provincial data to estimate an intermediate-run price elasticity of vehicle miles traveled (VMT) ranging between -0.579 and -0.882 from 2003 to 2009. Since my study estimates a short-run elasticity, it is reasonable that my estimated price elasticity is smaller than theirs, since consumers have less time to adjust to the price change.

5.3 Validity and Robustness Check

In this section, I conduct a validity test of my identification strategy. A major threat to the identification strategy is that there might exist unobserved confounding factors that are correlated with gasoline price changes and traffic flow. Without considering these factors, I might find a spurious relationship of changes in traffic flow in response to price adjustments. I also conduct a robustness test by including observations from sensors located in the area of Hongqiao airport, where relaxed driving restrictions allow non-Shanghai drivers on the road.

5.3.1 Stock Price Indexes: A Measure of Impacts from Other Economic Activities

To test whether unobserved economic activity acts as a confounder in the identification strategy, I use the daily Shanghai Stock Exchange (SSE) closing market price index to examine the correlation between gasoline price changes and the stock market price. The daily stock price index reflects contemporary economic activities. I use SSE closing market price index as the dependent variable. I follow the form of Equation (2), dropping the sensor fixed effect. I

World Bank Exchange Rate data set, the annual average gasoline price in Shanghai is $7.74\times 3.78541 \div 6.33 \approx 4.63$ dollars per gallon.

[15]Open Data Network: `https://www.opendatanetwork.com/`

cluster the error term by week.

Table 5 presents results of impacts of gasoline price changes on the stock market. Within one to six days before and after gasoline price changes, none of the estimated coefficients of interest are statistically significant at conventional levels. Therefore, I do not find a strong correlation between the NDRC's price adjustments and influential economic activities within one to six days before and after gasoline price changes.

5.3.2 Sensors in the Hongqiao Airport Area

In the main analysis, I exclude sensors near the Hongqiao airport because drivers in this area might come from adjacent cities with different gasoline prices. I include these sensors in this section as a robustness check of sample selection. If traffic flow is changing in response to gasoline prices, then responsiveness should be smaller near Hongqiao, where only a portion of drivers is exposed to the changes.

Figure 6 presents results of impacts of gasoline price changes on traffic flow before and after price changes including traffic flow detected near Hongqiao airport. Magnitudes of estimated average price elasticity of traffic flow within one to six days after price changes are smaller than magnitudes found in the main analysis, as might be expected if a portion of the drivers near Hongqiao is not affected by Shanghai gasoline price changes. The inclusion of sensors near Hongqiao airport attenuates estimates, as would be expected under the identification strategy.

6 Extension

The main analysis of this paper focuses on price changes that cannot be anticipated. However, under the Unanticipated Price Change policy, drivers know about an upcoming price change between its announcement in the morning and its enactment at midnight that same day. Under the Anticipated Price Change policy, drivers know that an NDRC announcement will come every ten days. In the following sections, I evaluate the response of traffic flow to gasoline price changes under these two conditions.

6.1 Announcements of Unanticipated Gasoline Price Changes

Under the Unanticipated Price Change policy, drivers might change driving behavior when they learn information of price change to be enacted at midnight that evening. To identify this impact, I divide days before gasoline price changes into the announcement day and days before the announcement to evaluate the impact of price changes in these two windows separately:

$$\begin{aligned}\ln \mathrm{Traffic}_{id} = \alpha_0 + \alpha_1 T_{pre(k)} + \alpha_2 T_{pre(k)} \times \ln \mathrm{PNew}_d \\ + \alpha_3 T_a + \alpha_4 T_a \times \ln \mathrm{PNew}_d \\ + \alpha_5 T_{post(k)} + \alpha_6 T_{post(k)} \times \ln \mathrm{PNew}_d \\ + \alpha_7 \ln \mathrm{Global\ Oil}_d + \alpha_8 \ln \mathrm{P}_d + f(Weather_d) + \gamma_w + \phi_j + \lambda_{my} + \sigma_i + \epsilon_{id} \quad (6)\end{aligned}$$

$$k = 2, ..., 6$$

where $T_{pre(k)}$ is a dummy variable equal to one in the two to six days before a price change, excluding the announcement day. T_a is equal to one on the announcement day. $T_{post(k)}$ is a dummy variable equal to one in the two to six days after a price change. The coefficients of interest are α_2, α_4 and α_6, which measures traffic flow response to price changes before an announcement, on the day of an announcement, and after a price change.

Table 6 presents estimates from Equation (6). Price elasticities of traffic flow on the announcement day are negative across all lengths of days in each specification but are statistically insignificant. Coefficients on days before the announcement and after the price change are similar to findings from Figure 3.

To test for heterogeneous impacts of announcements of price increases and price decreases, I divide days before gasoline price increases and gasoline price decreases into the announcement day and days before the announcement with the following specification:

$$
\begin{aligned}
\ln \text{Traffic}_{id} = \beta_0 &+ \beta_1 T_{pre(k)} \times INC + \beta_2 T_{pre(k)} \times INC \times \ln PNew_d \\
&+ \beta_3 T_a \times INC + \beta_4 T_a \times INC \times \ln PNew_d \\
&+ \beta_5 T_{post(k)} \times INC + \beta_6 T_{post(k)} \times INC \times \ln PNew_d \\
&+ \beta_7 T_{pre(k)} \times (1 - INC) + \beta_8 T_{pre(k)} \times (1 - INC) \times \ln PNew_d \\
&+ \beta_9 T_a \times (1 - INC) + \beta_{10} T_a \times (1 - INC) \times \ln PNew_d \\
&+ \beta_{11} T_{post(k)} \times (1 - INC) + \beta_{12} T_{post(k)} \times (1 - INC) \times \ln PNew_d \\
&+ \beta_{13} \ln \text{Global Oil}_d + \beta_{14} \ln \text{P}_d + f(Weather_d) \\
&+ \gamma_w + \phi_j + \lambda_{my} + \sigma_i + \epsilon_{id} \qquad (7)
\end{aligned}
$$

$$k = 2, ..., 6$$

Table 7 presents the results. For brevity, I only present estimates of the coefficients of interest, β_4 and β_{10}. Results show that traffic flow statistically significantly responds to gasoline price increases on the announcement day but not to gasoline price decreases. These results reflect findings in the main estimation where traffic flow is more responsive to gasoline price increases.

6.2 Impact of Anticipated Price Changes on Traffic Flow

Using the form of Equation (3), I conduct a parallel analysis of the impact of NDRC price adjustments on traffic flow from April 2013 to 2014, under the Anticipated Price Change regime. Figure 7 presents results in the same format as Figure 4. Overall, estimates within six days before and after price increases are not statistically significantly different from zero. Estimates within three to five days before price decreases are statistically significantly positive at the five percent level.

Why is the impact of gasoline price changes on traffic flow with anticipated price changes different from the finding with unanticipated price changes? Given that these two policies are different in aspects discussed in Section 2.1, the primary reason might be due to consumers' anticipations. Hennessy and Strebulaev (2015) structurally show that anticipations might bias treatment effects or have the wrong sign. That is, the identification strategy is valid only when the policy is unexpected.

7 Welfare Analysis: Air Pollution and Health

While the estimated effect of gasoline price changes on traffic flow is greater in China than it is in the United States, it remains unclear how beneficial the reduction in traffic flow is to air pollution and health. To evaluate the impact of gasoline price changes on air pollution, I conduct a back-of-the-envelope analysis of the effect that the reduction in traffic flow has on vehicle emissions and human health.

How much does the reduction in traffic flow contribute to air pollution reduction? Due to the lack of studies on the impact of traffic flow on air pollution in China, I refer to a study conducted in the United States to evaluate a possible impact. Zhang and Batterman (2014) estimate the impact of traffic volume during peak hours on vehicle emission of NO_2 (Nitrogen Dioxide). According to their findings, there is a piecewise linear relationship between traffic flow and NO_2 concentrations. When the traffic flow is less than 4000 vehicles per hour (vph), the ratio between NO_2 concentration per hour and traffic flow per hour is 0.0025:1.

The average traffic flow in Shanghai is 1671 vph from January 2011 to March 2013. Using the estimated elasticity of traffic flow with respect to price increases in three days, -0.45, assuming the Chinese government imposes a policy of increasing gasoline prices by ten percent, then the average traffic flow is reduced by 75 vph.[16] This reduction leads to a decrease in hourly NO_2 concentrations of 0.19 $\mu g/m^3$ (micrograms per cubic meter).[17]

These estimated impacts are based on findings from the United States. Results in China might be different. Vehicle emissions in China are greater than they are in the United States due to lower emissions standards and poorer gasoline quality (Walsh, 2004; He, Yao and Zhang, 2010)). Therefore, the estimated impact on air pollution provides a lower bound on the effect.

I calculate an acute health effect based on the reduction in NO_2 concentrations. Chen et al. (2008) study the relationship between air pollution and daily mortality in Shanghai from 2001 to

[16] The estimated price elasticity of traffic flow is -0.45 within three days after price increases. The corresponding reduction in traffic flow is $1671\times(-0.45\%\times10)\approx75$.

[17] One percent increase in gasoline price decreases daily traffic flow by -0.45 percent. Given the average traffic flow of 1671 vph and the ratio between traffic flow and NO_2 concentration, a ten percent increase in gasoline price would lead to a reduction in hourly NO_2 concentration of $1671\times(-0.45\%\times10)\times0.0025\approx0.19$.

2004 and find that each 10 $\mu g/m^3$ increase in a 2-day moving average of NO_2 is associated with an increase of total daily mortality of 0.96 percent. Assuming a linear relationship between daily mortality and NO_2 concentrations, based on their finding, a ten percent increase in gasoline price leads to a reduction of total daily mortality of 0.44 percent.[18] This estimated impact might be a lower bound since vehicle emissions not only affect NO_2 concentrations but other air pollutants that influence human health as well.

8 Conclusions

Do Chinese drivers respond to gasoline price changes? This paper finds that they do. Using an Unanticipated Price Change policy setting as a quasi-experiment, I find that price changes do cause changes in traffic flow. In the preferred specification, the price elasticity of traffic flow in response to price changes is -0.26, which is larger than estimates for the United States. However, the impact only lasts for a very short term, specifically three days.

Comparing the effect of price increases versus price decreases, I find that gasoline price increases are effective in reducing traffic flow, while traffic flow does not respond to gasoline price decreases. In the winter of 2015, when air pollution in China was more severe than in other seasons, global oil prices declined sharply. Drivers in China were waiting for a corresponding gasoline price decrease, but the NDRC did not change the price on the announcement day, arguing that they intended to protect air quality.[19] Based on my findings, the NDRC's plan to protect the environment might not be effective by only avoiding a decrease in gasoline price.

The estimated price elasticity of traffic flow in response to price increases, -0.45, provides a benchmark for policymakers when designing policies to reduce traffic congestion, vehicle emissions, and air pollution. Other policies for reducing traffic flow have had mixed effects. For example, as previously discussed, a permanent driving restriction in Beijing, in which only vehicles with specific numbers of license plates were allowed on the road, was not effective in reducing traffic due to citizens' response to purchase additional vehicles (Wang, Xu, and Qin, 2014). Recently, the Chinese government has considered imposing congestion fees to discourage travelers from driving to other modes of transportation. Congestion fees are, like gasoline prices,

[18]Given the reduction of hourly NO_2 concentration of 0.19 $\mu g/m^3$, a ten percent increase in gasoline price leads to a reduction of total daily mortality by $0.19 \times 24 \div 10 \times 0.96 \approx 0.44$.

[19]See report: `http://www.xinhuanet.com//2015-12/16/c_1117471771.htm`

one method for policymakers to regulate traffic by changing the costs of driving (Arnott and Small, 1993; Santos, 2005; Litman, 2005; de Palma and Lindsey, 2011). Studies find that road pricing is efficient in reducing traffic and air pollution (Vikery, 1963; Arnott, De Palma, and Lindsey, 1993; Gibson and Carnovale, 2015). Knowing drivers' responses to gasoline prices, a major driving cost, helps policymakers set congestion fees to reduce traffic congestion.

This study suggests two further extensions. First, a further study will be encouraged to use monitor-level daily air pollution data to examine the impact of unanticipated gasoline price adjustments on air pollution and, if possible, the acute effect on human health. Second, gasoline price changes could be combined with sale information from gasoline stations to estimate the elasticity of gasoline demand.

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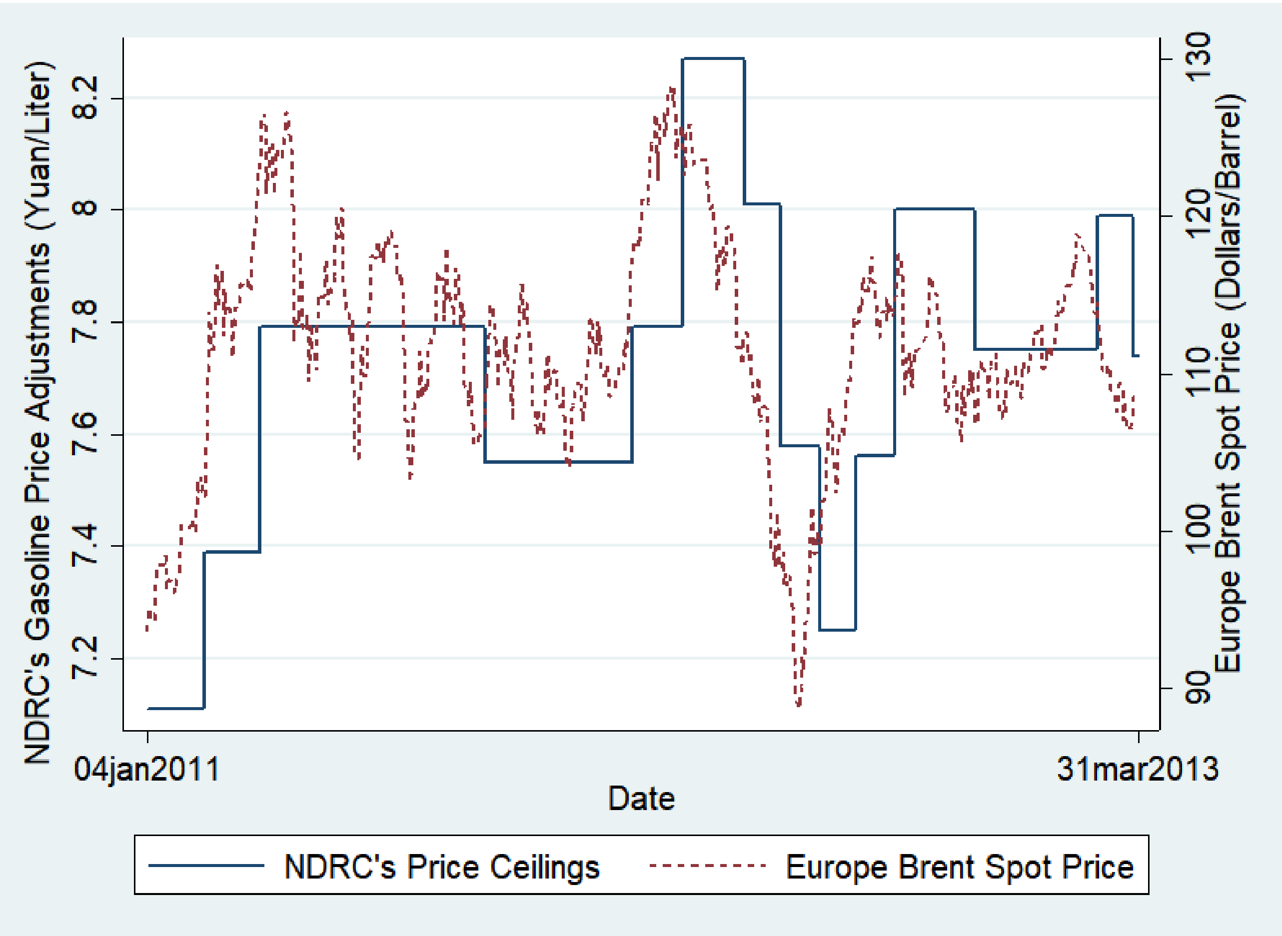
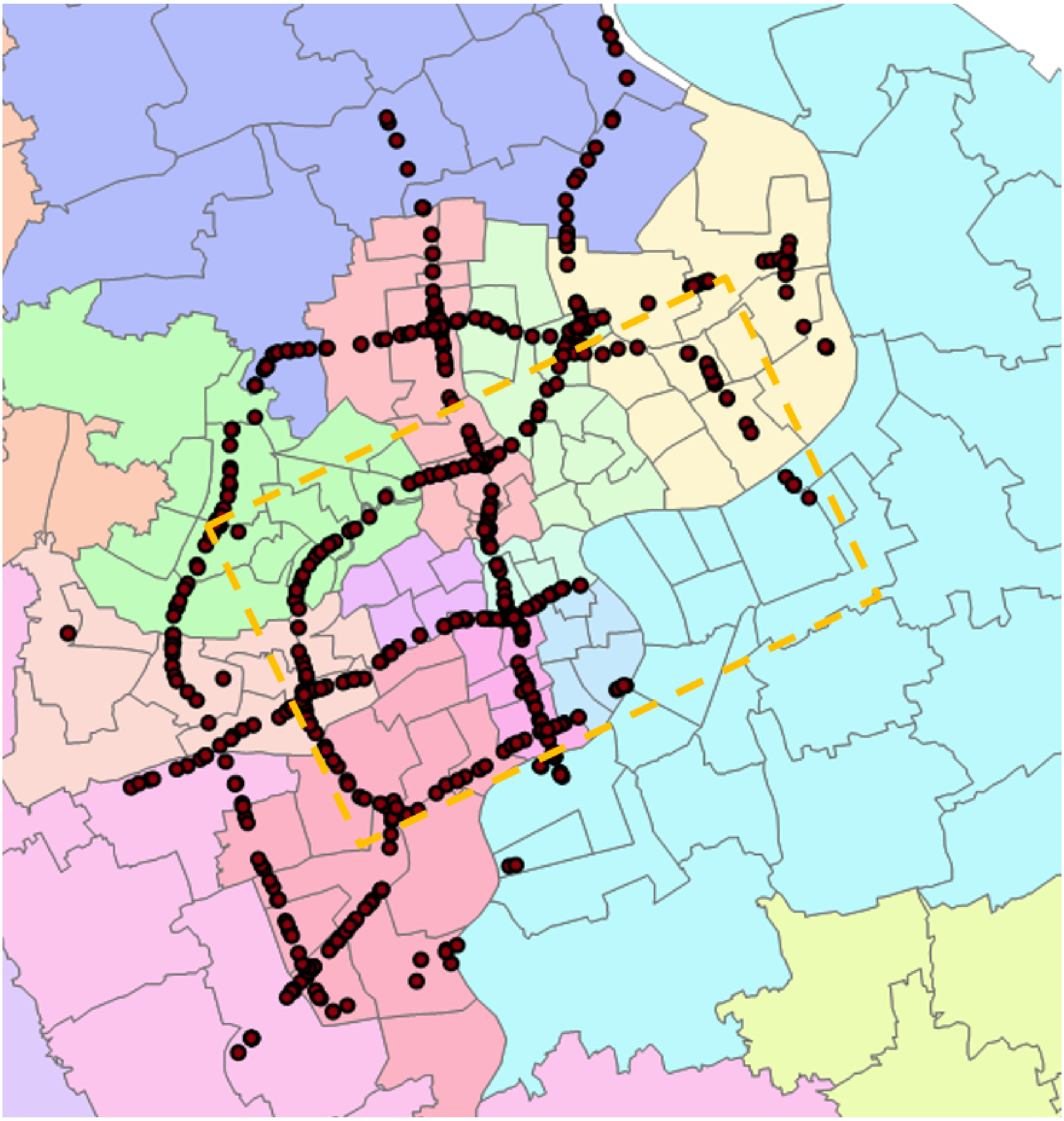
Figure 1: Shanghai Gasoline Price Ceiling vs. Brent Crude Oil Price



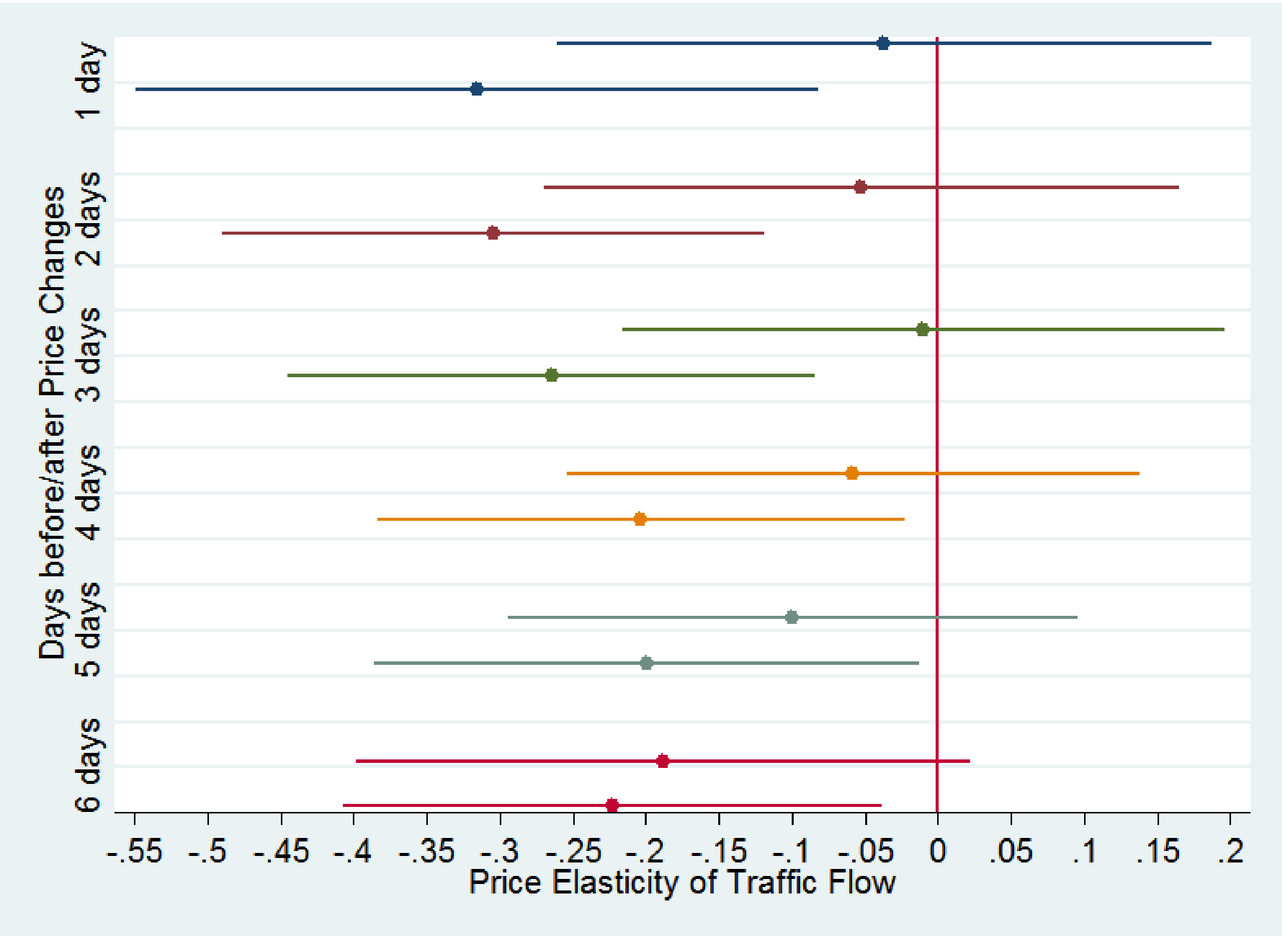
Note: The blue line shows the NDRC's gasoline price ceilings in Shanghai from January 2011 to March 2013. The red dashed line shows the price on the Brent Crude Oil market, from the Energy Information Administration over the same period

Figure 2: Locations of Sensors on Shanghai Expressways



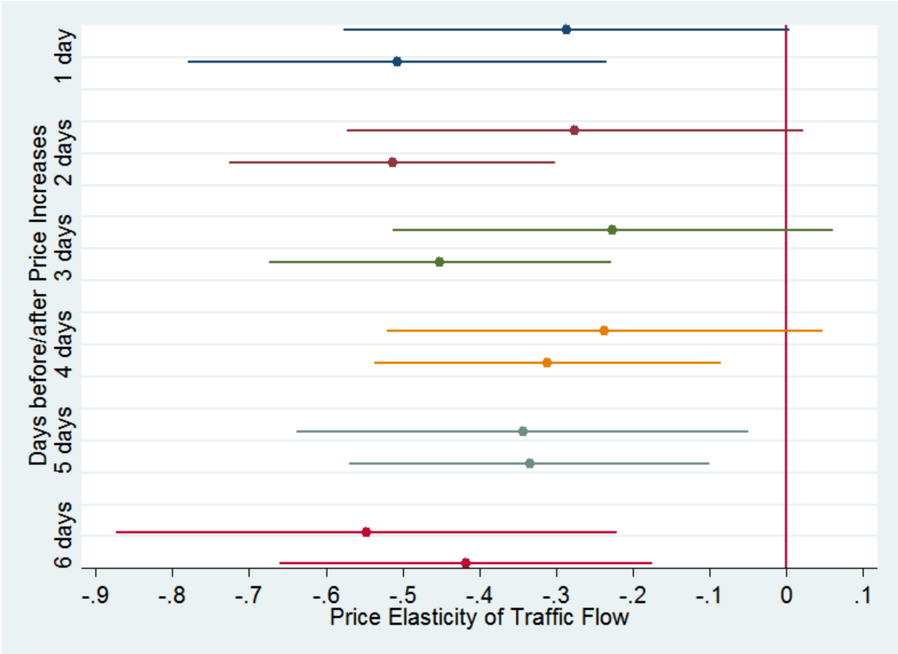
Note: Each polygon represents a neighbourhood in Shanghai, and each color represents a district. Red dots in the figure are locations of sensors on city expressways. Sensors inside the yellow square are located in the inner circle of the city, which includes the financial district. Outside the yellow square is the middle circle including newly developed commercial centers and residential areas. Neighbourhoods not covered by sensors are suburban areas.

Figure 3: Price Elasticities of Traffic Flow for Price Changes

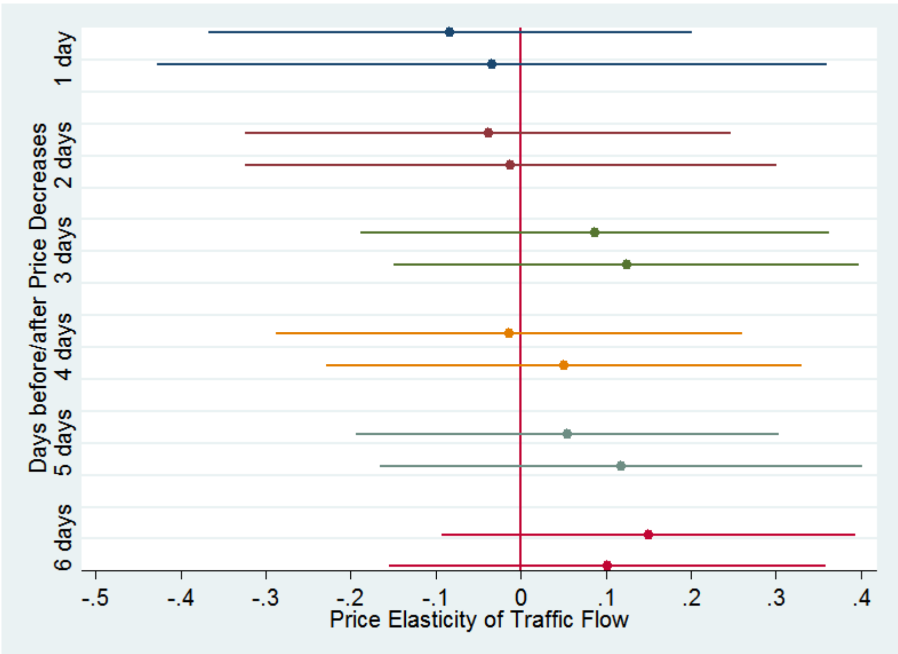


Note: Each color represents the results from one pair of estimates of Equation (2). 95% confidence intervals are shown. For each same-color pair of estimates, the upper dot shows the estimated price elasticity of traffic flow before gasoline price changes, and the lower dot shows the estimated price elasticity after price changes. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow. The estimation period is from January 2011 to March 2013.

Figure 4: Price Elasticities of Traffic Flow for Price Increases/Decreases



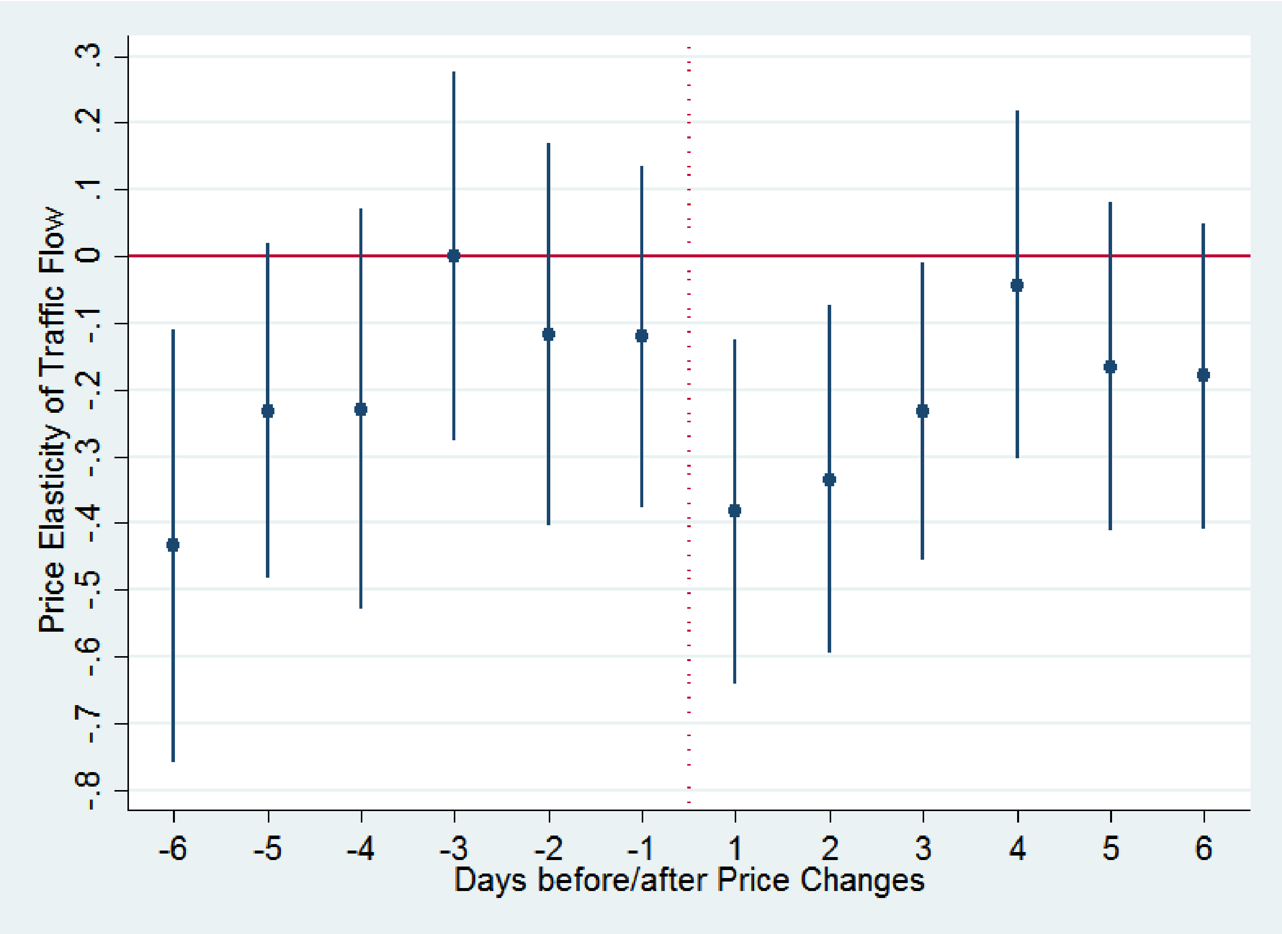
(a) Price Elasticity of Traffic Flow for Price Increases



(b) Price Elasticity of Traffic Flow for Price Decreases

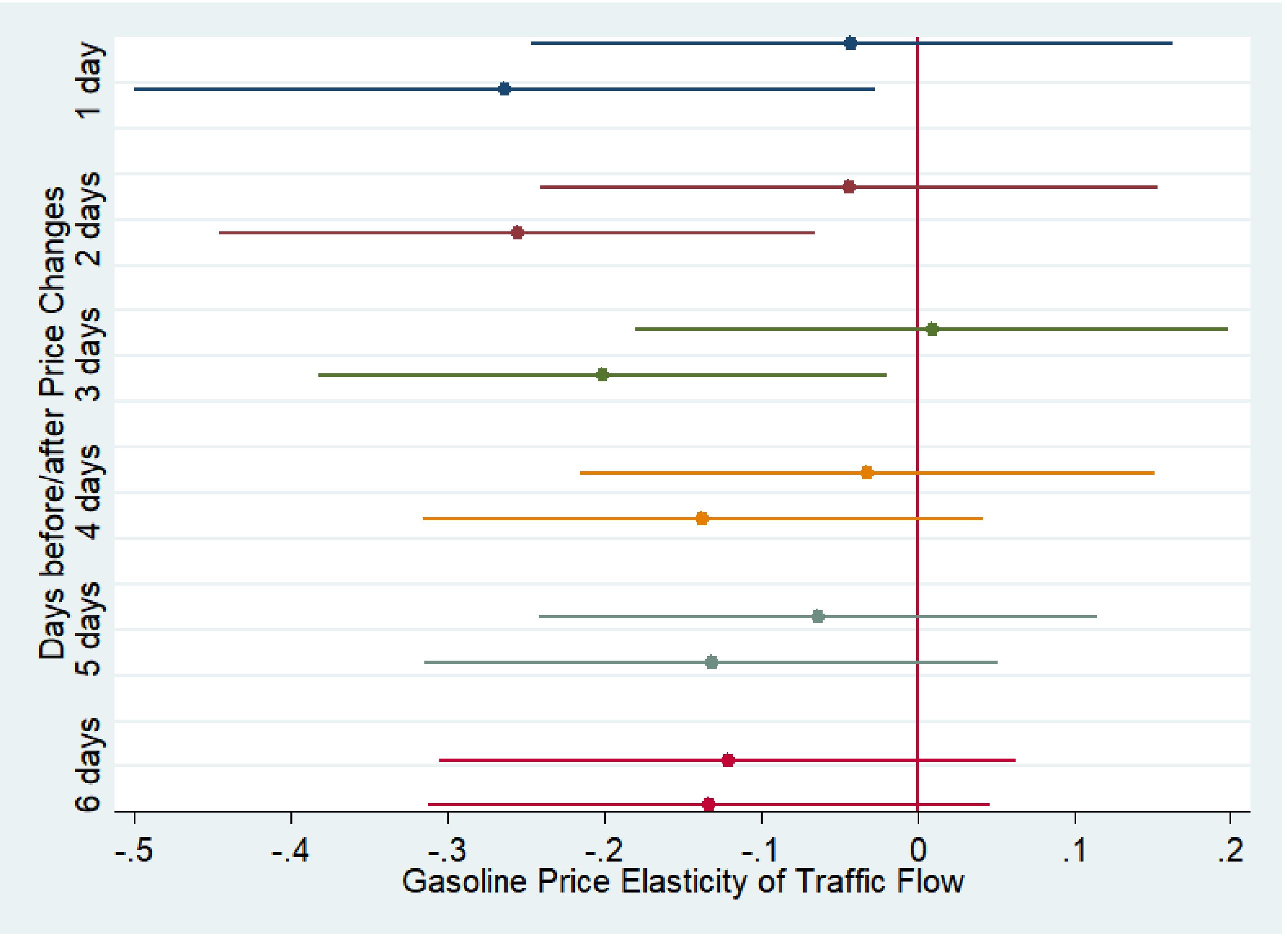
Note: Each color represents the results from one regression of Equation (3). 95% confidence intervals are shown. For each same-color pair of estimates, the upper dot shows the estimated price elasticity of traffic flow before gasoline price changes, and the lower dot shows the estimated price elasticity after price changes. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow.The estimation period is from January 2011 to March 2013.

Figure 5: Price Elasticities of Traffic Flow by Days



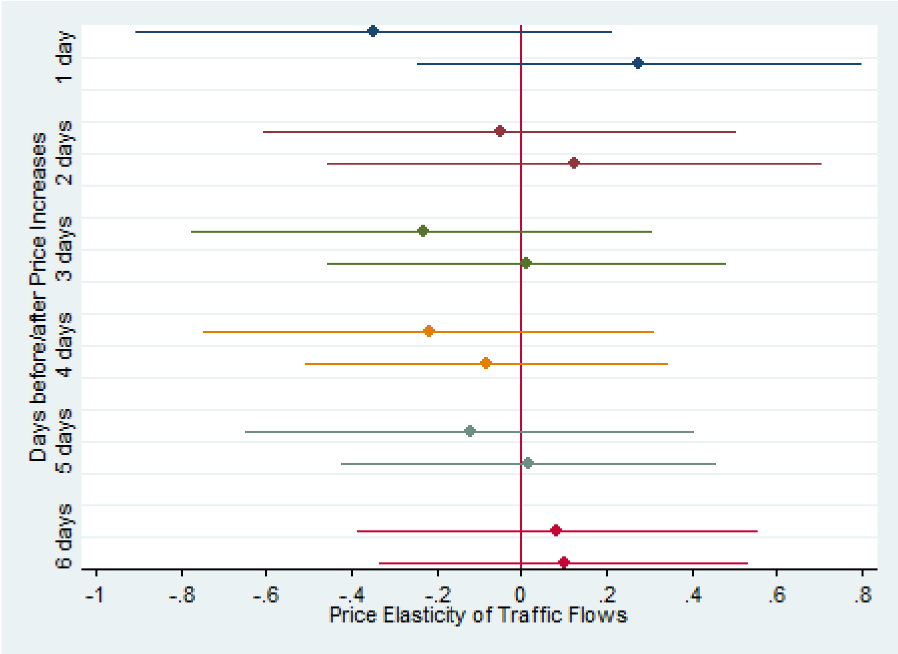
Note: Each dot shows an estimated price elasticity of traffic flow on a specific number of days before/after a price change. 95% confidence intervals are shown. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow. The estimation period is from January 2011 to March 2013.

Figure 6: Price Elasticities of Traffic Flow including Sensors near Hongqiao Airport

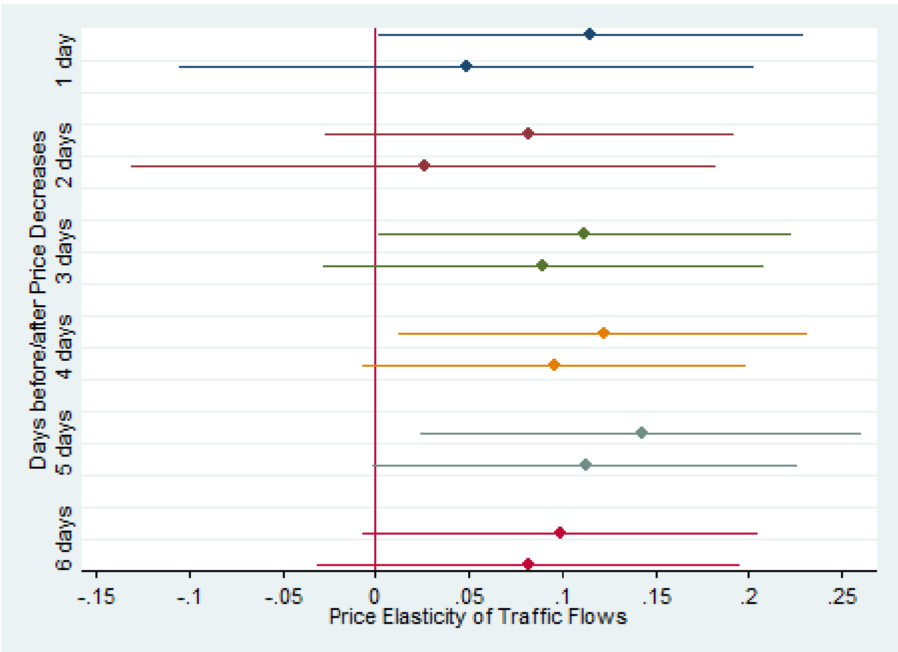


Note: Each color represents the results from one pair of estimates of Equation (2). 95% confidence intervals are shown. For each same-color pair of estimates, the upper dot shows the estimated price elasticity of traffic flow before gasoline price changes, and the lower dot shows the estimated price elasticity after price changes. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow. The estimation period is from January 2011 to March 2013. Sensors near Hongqiao airport are included.

Figure 7: Price Elasticities of Traffic Flow for Anticipated Price Increases/Decreases



(a) Price Elasticity of Traffic Flow for Price Increases



(b) Price Elasticity of Traffic Flow for Price Decrease

Note: Each color represents one regression of Equation (3). All estimates are drawn at the 5% significance level. For each same-color pair of estimates, the upper dot shows estimated price elasticities of traffic flow within one to six days before gasoline price increases/decreases, and the lower dot shows estimated price elasticities of traffic flow within one to six days after gasoline price increases/decreases. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow. The estimation period is from April 2013 to 2014.

Table 1: Gasoline Price Changes in Shanghai under Unanticipate Price Change Policy

Variable	# Price Changes	Mean	Std. Dev.	Min	Max
Regular Gasoline Retail Price (yuan/liter)	13	7.74	0.28	7.25	8.27
Regular Gasoline Retail Price (Increase)	7	7.83	0.29	7.39	8.27
Regular Gasoline Retail Price (Decrease)	6	7.65	0.25	7.25	8.01
Percentage Change (in absolute value)	13	4.12%	1.08%	3%	5.8%

Table 2: Description of Variables in the Estimation

Variable	Description
Traffic_{id}	daily traffic flow at sensor i on day d
$T_{pre(s)}$	dummy variable equal to one in the s days before a price change
$T_{post(s)}$	dummy variable equal to one in the s days after a price change
INC	dummy variable equal to one if the price adjustment is a price increase and zero if it is a price decrease
PNew_d	the new gasoline price ceiling
P_d	the current gasoline price ceiling
Global Oil_d	daily Brent Crude Oil prices
$f(Weather_d)$	quadratic function of weather variables including precipitation, temperature, wind speed, and wind direction
γ_w	fixed effect for day of the week
ϕ_j	fixed effect for date of the month
λ_{my}	month-year fixed effects
σ_i	sensor fixed effects
ϵ_{id}	error term

Table 3: Simple Regression Result

	(1)
Ln(Gasoline Price)	0.370***
	(0.079)
Quadratic Weather Function	YES
Sensor FE	YES
Month × Year FE	YES
Day of the Week FE	YES
Date of the Month FE	YES
N	417,079
R^2	0.908

Note: Standard errors are clustered by week and district to allow for serial and spatial correlations of traffic flow.*** p<0.01, ** p<0.05, * p<0.1

Table 4: Comparisons of Means of Ln(Traffic Flow) in Days Near Gasoline Price Changes

	Price Increases					Price Decreases				
In Days before and after Price Change	Before	After	(1)-(2) t-stat	FE t-stat	All Controls t-stat	Before	After	(6)-(7) t-stat	FE t-stat	All Controls t-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	10.30	10.32	-1.04	-1.71	4.78	10.36	10.34	1.21	0.51	-1.13
	(0.013)	(0.013)				(0.014)	(0.15)			
2	10.27	10.33	-4.95	-10.16	2.95	10.36	10.34	1.86	1.34	-2.45
	(0.010)	(0.010)				(0.011)	(0.010)			
3	10.27	10.33	-5.50	-10.39	2.42	10.34	10.34	0.306	0.492	-4.2894
	(0.008)	(0.008)				(0.009)	(0.008)			
4	10.28	10.33	-5.14	-10.66	2.60	10.33	10.33	0.08	0.41	-4.58
	(0.007)	(0.007)				(0.008)	(0.007)			
5	10.28	10.32	-4.67	-10.06	3.34	10.34	10.33	0.36	0.43	-4.64
	(0.006)	(0.006)				(0.007)	(0.007)			
6	10.28	10.32	-4.78	-13.07	1.51	10.33	10.34	-0.35	0.65	-4.65
	(0.006)	(0.005)				(0.006)	(0.006)			
Average Traffic Flow per Day	40,113									
Total Observations	417,079									

Note: Columns 1, 2, 6, and 7 show the mean of the natural logarithm of traffic flow within 1 to 6 days before and after gasoline price increases and decreases, respectively. Columns 3 and 8 present the t-statistic for the difference between traffic before and after a price change. Columns 4 and 9 present the t-statistic for the before-after difference of means of residuals from regressions logged traffic flow on sensor, day of the week, date of the month and month-year fixed effects. Columns 5 and 10 also control for current gasoline prices, Brent Crude oil prices, and a quadratic functions of weather variables.

Table 5: Correlation between Gasoline Price Changes and Shanghai Stock Market Index

	(1)	(2)	(3)	(4)	(5)	(6)
1 Day Before Price Changes	86.68					
	(377.1)					
1 Day After Price Changes	-333.2					
	(225.9)					
2 Days Before Price Changes		96.72				
		(334.1)				
2 Days After Price Changes		-340.2				
		(235.2)				
3 Days Before Price Changes			-108.5			
			(299.2)			
3 Days After Price Changes			-297.1			
			(224.6)			
4 Days Before Price Changes				-148.2		
				(272.9)		
4 Days After Price Changes				-258.4		
				(203.3)		
5 Days Before Price Changes					-213.4	
					(240.1)	
5 Days After Price Changes					-242.4	
					(198.6)	
6 Days Before Price Changes						-207.6
						(229.4)
6 Days After Price Changes						-161.7
						(203.4)
Quadratic Weather Function	YES	YES	YES	YES	YES	YES
Month × Year FE	YES	YES	YES	YES	YES	YES
Day of the Week FE	YES	YES	YES	YES	YES	YES
Date of the Month FE	YES	YES	YES	YES	YES	YES
N	755	755	755	755	755	755
R^2	0.976	0.976	0.976	0.976	0.976	0.976

Note: Standard errors are clustered by week to allow for serial correlation of daily stock price index.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Price Elasticities of Traffic Flow, Separating Announcement Day

	(1)	(2)	(3)	(4)	(5)
Announcement Day	-0.0538	-0.0556	-0.0583	-0.0746	-0.112
	(0.117)	(0.119)	(0.121)	(0.126)	(0.129)
Two Days Before	-0.0446				
	(0.132)				
Two Days After	-0.305***				
	(0.0942)				
Three Days Before		0.0149			
		(0.115)			
Three Days After		-0.264***			
		(0.0917)			
Four Days Before			-0.0553		
			(0.108)		
Four Days After			-0.202**		
			(0.0919)		
Five Days Before				-0.101	
				(0.102)	
Five Days After				-0.197**	
				(0.0952)	
Six Days Before					-0.196*
					(0.111)
Six Days After					-0.221**
					(0.0938)
Constant	9.257***	9.283***	9.296***	9.297***	9.322***
	(0.250)	(0.250)	(0.249)	(0.249)	(0.247)
N	417,079	417,079	417,079	417,079	417,079
R-squared	0.908	0.908	0.908	0.908	0.908
Station FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
Day of the Week FE	YES	YES	YES	YES	YES
Date of the Month FE	YES	YES	YES	YES	YES

Note: The dependent variable is the natural logarithm of traffic flow at sensor i on day d. The estimation period is from January 2011 to March 2013. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Price Elasticities of Traffic Flow on the Announcement Day

	2 Days	3 Days	4 Days	5 Days	6 Days
Price Increase					
Announcement Day	-0.314**	-0.332**	-0.344**	-0.398**	-0.482**
	(0.155)	(0.159)	(0.166)	(0.175)	(0.187)
Price Decrease					
Announcement Day	-0.0878	-0.0636	-0.0584	-0.0258	-0.0156
	(0.154)	(0.159)	(0.157)	(0.162)	(0.164)
N	417,079	417,079	417,079	417,079	417,079
R-squared	0.908	0.908	0.908	0.908	0.908
Station FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
Day of the Week FE	YES	YES	YES	YES	YES
Date of the Month FE	YES	YES	YES	YES	YES

Note: The dependent variable is the natural logarithm of traffic flow at sensor i on day d. Each column presents estimated result of one regression of Equation (7) when k=2,3,...,6. Standard errors are clustered by week and district to allow for serial and spatial correlations of daily traffic flow. The estimation period is from January 2011 to March 2013. *** p<0.01, ** p<0.05, * p<0.1

Appendices

A Media reports on the NDRC's Price Adjustments

In this section, I present two media reports on consumers' expectations of the NDRC's gasoline price adjustments under the Unanticipated Price Change regime.

Figure A.1 shows a report on gasoline price increase on June 3rd, 2009.[20]

At the beginning of the second paragraph, it says that car owners thought the gasoline price was going to increase on May 28th, 2009, but the price did not change. However, the price finally went up on June 1st when car owners thought the price was not going to increase (as shown in the highlighted sentence).

Figure A.2 shows a report on a gasoline price decrease on May 10th, 2012.[21] The first sentence in the last paragraph quotes a comment on the price decrease from a taxi driver in Shanghai. The driver told the reporter that he expected that the price was going to decrease but did not anticipate that the NDRC would adjust the price so late.

In summary, both reports provide evidence that the NDRC's price adjustments were unanticipated by consumers.

[20] http://auto.sina.com.cn/news/2009-06-03/0753496463.shtml
[21] http://district.ce.cn/newarea/roll/201205/10/t20120510_23311000.shtml

Figure A.1: Car Owners' Unanticipated Price Increase

6. 1成品油价格全面上涨 中石化90号油优惠继续

http://www.sina.com.cn 2009年06月03日 07:53 汽车007周报

端午假期前发改委暂不调整油价的信息发出后不到三天，国内油品价格上调。而同时，上海地区的90号油优惠促销还在继续，只是调价后，油站的90号油却一点货都没了。另外，今秋上海的所有机动车都将“喝”上符合国IV要求的汽柴油，届时上海油价可能再次上涨。

文/许诚玮

“今天加油了吗？快去加油。”端午来临前夕，坊间“5月28日油价上涨”的消息闹得车主们人心惶惶。当日零点，各加油站风平浪静，涨价之说自然平息。与此相对应的是，记者在上海部分加油站看到90号汽油的优惠措施。就在车主们以为涨价离自己还远时，三天后，即6月1日零点，国内油价今年第三次调整。

Figure A.2: Taxi Drivers' Unanticipated Price Decrease

成品油价格下调 沪加油站限时优惠油不取消

2012年05月10日 11:23　　来源：东方网

[推荐朋友] [打印本稿] [字号 大 中 小]

国家改革委昨天发布关于降低成品油价格的通知，决定自5月10日零时起下调国内成品油价格，汽油下调330元/吨，折合93号汽油下调0.27元/升，97号汽油下调0.28元/升；柴油下调310元/吨，折合0.27元/升。东方网记者看到，10日零点刚过，在上海成都北路的一家中石化加油站内，工作人员就忙着换牌子，驾车族最常使用的93号汽油从8.27元调为8.01元，0号柴油由8.19元降为7.92元。

尽管93号汽油仍然停留在“8元时代”，但对于有车一族来说，油价下调还是为他们省下一笔可观的开支。不仅如此，成都北路的这家加油站，仍然实行“晚上7点至次日早上7点93号汽油便宜0.2/升”的限时优惠让利，因此零点刚过，这家加油站93号汽油显示价格为7.81元/升，不少下班的出租车司机都赶来加油。

“这次油价下调在预料之中，但是来得晚了些。”大众出租车司机胡师傅告诉东方网记者，油价下调后，对于他们来说“能省不少”。他当场为记者算了一笔账，平日他们一天就要加一次油，加满大约在300元左右，如今油价下调后，大约每天能省10元左右，加限时优惠油每天则能省上18元。