Environmental Protection or Local Protectionism?

Evidence from Tailpipe Emission Standards in China*

Shanjun Li Danxia Xie Hui Zhou

October 6, 2019

PRELIMINARY & INCOMPLETE

Abstract

Many cities in China adopted tailpipe emissions standards from 2008 under the stated goal of improving local air quality. This city-level policy restricted the import of used vehicles from other cities that do not meet the local emission standard. By leveraging the staggered roll-out of the policy across cities and the universe of new and used vehicles registration, this paper examines the impacts of the policy on local air pollution, intercity trade of used vehicles, and new vehicle market to shed light on the policy choices by local governments. The analysis shows that the policy significantly reduced the intercity trade of used vehicles that do not meet the standard. However, there is no evidence that the policy improved air quality. Importantly, the policy dramatically increased the sales of locally produced brands. Our findings point to local governments engaging in practices of local protectionism in the name of environmental protection.

Keywords: Vehicle Emission Standards, Trade Restriction, Local Protectionism

*Li: Dyson School of Applied Economics and Management, Cornell University & NBER, email: sl2448@cornell.edu; Xie: School of Social Sciences, Tsinghua University, email: xiedanxia@tsinghua.edu.cn; Zhou: Dyson School of Applied Economics and Management, Cornell University, email: hz423@cornell.edu.

1 Introduction

It has long been established that trade liberalization can promote economic growth and increase social welfare through efficient allocation of resources across trading partners (Rivera-Batiz and Romer, 1991; Edwards, 1993; Krueger, 1998). Notwithstanding this premise, nations and local jurisdictions have incentives to protect particular industries that are deemed to be important to the national or local economy but vulnerable to outside competition. As tariffs are usually limited or prohibited by trade agreements, non-tariff barriers are often used to protect local interest and industries. Technical barriers to trade (TBT) alone impacts more than 30 percent of product lines and almost 70 percent of the world trade in 2018 (UN, 2019). Many practices of alleged non-tariff barriers are implemented with the stated intent of environmental protection (Runge, 1990; Copeland and Taylor, 2004; Ederington, 2001; Ederington and Minier, 2003). Article XX of the General Agreement on Tariff and Trade (GATT) allows WTO members to adopt environmental measures on their own jurisdiction, but not in a manner of "a disguised restriction on international trade" (UN, 2003). However, this type of "environmental protectionism" is often hard to detect and prove.

This paper examines vehicle emission standards adopted by cities in China and the impact of the policy on intercity trade of used vehicles and its stated goal of improving air quality. This is a good setting to study environmental protectionism and its impacts for several reasons. First, the dramatic increase in vehicle ownership during the past 20 years is a key contributor to China's pressing air pollution challenge. Tailpipe emission standards is an important policy tool to address air pollution. Second, due to its potentially large contribution to local employment and GDP, the automobile industry is considered a pillar industry by local governments and a frequent target for government protection(Barwick et al., 2018).[1] Third, although China has been the largest market of new vehicle sales starting

[1]Automobile production in China is spatially dispersed and exists in 22 out of 31 provinces. During China's 11th Five Year Plan from 2005 to 2010, all of these provinces designated the automobile industry as a strategic industry that enjoy tax benefits and various other government support.The industry was reported as the third most protected industries according to a survey administered by the Development Research Center of the State Council (Li et al., 2004).

from 2009, the used vehicle market in China is small and much less developed. This is partly driven by the fact that the vehicle stock is still relatively new in China. The local restriction policies based on emission standards may have played a role in hindering the development of the used vehicle market.

China implemented its first national vehicle emission standards in 2001, and has been tightening the standards every several years, from level one to level six. Starting from 2008, some cities started to restrict used vehicles that do not meet certain emission standard to be imported to the city in order to protect local air quality. Over time, more cities adopted this practice and the standards also tightened up often following the changes in national standards. In this study, we aim to understand the incentives of local governments by examining three questions: (1) How does the policy change the intercity trade flow of used vehicles? (2) What is the impact of the policy on local air pollution? (3) What is the impact of the policy on new vehicle sales?

We estimate a gravity equation with the triple difference design to examine the policy impact on intercity trade flows of used vehicles (intercity sales). The analysis is based on the universe of used vehicles registration data during 2013-2015 and the staggered roll-out of the policy across cities in China. The gravity equation allows the policy to differentially affect the intercity trade flows (i.e., used vehicles imported from other cities) and local sales (i.e., used vehicle transactions from one city resident to another). The regressions control for a rich set of fixed effects including city-pair fixed effects, origin by time (i.e., quarter of sample) fixed effect, and destination by time fixed effects. The last two sets of fixed effects control for time-varying unobservables at the origin and destination, respectively. They should alleviate the potential endogeneity of policy adoption across cities and over time.[2] However, if the time-varying unobserved demand shocks affect intercity sales and local sales differently, they would confound the policy impact. To address this concern, we construct an IV based on the

[2]For example, if the policy adoption by a city at a given time is a response to (time-varying) demand shocks for used vehicles in that city, this should be controlled for by the destination by time fixed effects as long as the shocks affect intercity sales and local sales in the same manner.

share of the automobile sector in tax revenue in 2010. Cities that rely more on automobile production for local tax are more likely to adopt the policy. The identification assumption is that the pre-determined tax revenue share is unlikely to be correlated with unobserved shocks that affect intercity sales and local sales differently.

The results from both the OLS and IV regressions suggest that the restriction policy based on tailpipe emissions standard dramatically reduced the intercity trade flow of dirty vehicles (i.e., used vehicles that do not meet the emissions standard adopted by the destination city) relative to the local sales of used vehicles. While the current specification allows us to control for time-varying unobservables separately for origin and destination cities, we are not able to identify the net impact on local sales as well as on the aggregate sales of used vehicles. In the near future, we plan to examine those margins of impacts.

Next we examine whether the impact on the trade flow of used vehicles translate to an improvement on local air quality. We aggregate the hourly ambient air pollution data ($PM_{2.5}$, PM_{10}, CO, and NO_2) from more than 1000 monitoring stations into the city-day level. We control for local weather condition by matching each city with its closest weather station. Both the OLS and IV regressions show no significant changes in any of the pollutants after the policy, suggesting that the policy has not achieved its stated objective of improving local air quality. Although the policy reduced the inflow of dirty used vehicles from other cities, it could have prolonged the lifetime of local dirty vehicles which now face less competition in the used vehicle market.

Our last set of analyses focuses on the policy impact on the new vehicle market. We divide the vehicle brands into two categories: locally brands (if the brand has a plant in the city), and non-local brands. Using the universe of new vehicle sales data by city by model by quarter during 2013-2015, we find that the restriction policy has led to a significant increase in the sales of local brands by 36.6%, but no significant effect on non-local brands.

This study contributes to the literature in the following three dimensions. First, this study provides a first analysis on the the environmental impact of vehicle emission standards and the trade restriction policy. There is a large body of literature studying the impact of different environmental policies, such as gasoline content regulation (Auffhammer and Kellogg, 2011), driving restrictions (Davis, 2008; Viard and Fu, 2015; Zhang et al., 2017), "Cash for Clunker" program (Li et al., 2013), and low emission zone (Ellison et al., 2013). However, empirical studies on the impact of vehicle emission standards, an important instrument that many countries adopt to combat air pollution, are surprisingly limited. Environmental science simulation models suggest that large benefits from tightening emission standards could be achieved in the long run (Vijayaraghavan et al., 2012; Shindell et al., 2011), but in the short run, tightening standards might lead to delay of scrappage of old cars and thus offset part of the effect (Gruenspecht, 1982; Jacobsen and Van Benthem, 2015). Our study shows that the emission standards and the trade restriction policy do not deliver a significant reduction in local air pollution even in the short run.

Second, our work sheds light on the political economy behind the environmental policy choice. Political factors, such as political connections, informal institutions, evaluation cycles could influence workplace mortality (Fisman and Wang, 2015), economic report falsification (Jiang and Wallace, 2017) and selective enforcement of environmental regulation (Cao et al., 2019). Our study reveals that the importance of the auto sector in local tax revenue play a role in determining the adoption of environmental regulations.

Third, our study adds to the literature of "environmental protectionism", a disguised way to protect local industry using environmental regulations. Two recent examples are the differentiated CAFE standards favoring US auto makers (Levinson, 2017) and the fuel tax and emission standards in the EU favoring diesel vehicles largely produced by EU automakers (Miravete et al., 2018). Our analysis show that instead of reducing air pollution, the trade restriction policy on used vehicles protects local auto industry by increasing local brands' sales. This finding also speaks to the literature on local protectionism, manifested in decreasing regional specialization (Young, 2000; Bai et al., 2004), home bias in vehicle market (Barwick et al., 2018), subsidy in favor of local EV producers (Wan et al., 2015).

2 Background

2.1 Chinese automobile industry and vehicle market

From the first vehicle production in 1956, to a total production of 29 million in 2017, the last 60 years have witnessed tremendous changes in the Chinese automobile industry. The early-stage development was largely steered by the central government. Resources were integrated to a few big state-owned auto firms. Entry to the market was firmly controlled. Firm operations were subject to an administrative examination and approval system.

In 1980s, the auto manufacturing technology in China, especially in terms of production of passenger cars, was way behind the world's advanced level. A ground breaking strategy, "exchange-market-for-technology" or "Quid Pro Quo", was adopted in 1980s and then formally included in the "Automobile Industry Policies" issued by the State Council in 1994. Under the policy, joint ventures were formed and achieved great success. For example, the accumulated sales of one of the most popular models, Santana, which was produced by SAIC-Volkswagen, reached almost 4 millions.

The tax reform in 1994 established a tax-sharing system between the central government and local governments, and gave the local governments more discretion in the decision of auto plant construction. Since then, local governments started to play a more important role in attracting foreign investment and pushing the start of new plants. It was during this period that local protectionism began to emerge, in the form of starting many new plants or offering subsidies to local plants.

In 2004, the State Council issued a new version of the "Automobile Industry Policies" which required avoiding many starts of small scale plants and encouraged the formation of big automobile group company. Another important strategy was to urge the auto firms to increase their research and innovation ability and develop products with own intellectual property. Under the developing strategies, the automobile industry grew explosively for the past 15 years which makes China being the world's largest auto maker in a row of nine years since 2009 (MIIT, 2017).

Along with the fast growing auto industry is the booming of the vehicle market. new vehicle sales increased from 2.1 millions in 2000 to 28.9 millions in 2017, at an average annual growth rate of 16.7% (see Figure1). The number of cars has reached 209 millions and the number of motor vehicles 310 millions in 2017 (MEE, 2018), 14% more than the number of vehicles in U.S. at the same year.

The large amount of vehicle stock stimulates the development of the used vehicle market. used vehicle sales reaches 10.3 millions in 2017. The used-to-new ratio increases from 0.12 in 2000 to 0.36 in 2017, but still far below the used-to-new ratio in US, which fluctuates between 2.1-3.4 during the same period (Automotive News, 2019). Several factors hindered the formation of an active used vehicle market in China, including serious information asymmetry between buyers and sellers, and the trade restriction policy that prevents the free flow of used vehicles between cities. We will explain the trade restriction policy in more details in the following section.

2.2 Vehicle emission standards and trade restriction policy

An important tool to curb vehicle emissions is to establish tailpipe emission standards. Vehicle emission standards set limits of specific air pollutants that are allowed to be released into the air by vehicles. In 2001, China released the first emission standard level 1, which put caps on CO, HC+NOx and PM from vehicle exhaust. The emission standards were tightened along the time, from level 1 to level 6. The first four emission standards, i.e., level 1 to level 4, are as stringent as the corresponding EU standards, Euro 1 to Euro 4. The most recent one sets the limits on CO, HC, NO_x and PM at the level of 40-50% lower than the limits of Euro 6, and adds additional limits on N_2O and PN.

The vehicle emission standards were established and released by the Ministry of Environment Protection (MEP) and Standardization of Administration of China (SAC). A national implementation date was set in each version of the emission standards, but local governments can implement the standards earlier than the deadline based on their own discretion. Vehicle manufacturers have to upgrade their products and apply for certification of the emission standard for each model they produce. Once a local government tightens the emission standards, new vehicles sold and registered locally need to meet the new standards.

However, many cities use the emission standards to restrict the intercity trade of used vehicles. To be more specific, if a local government tightens its emission standards from level 3 to level 4, it also prohibited the registration of imported used vehicles from other cities that are below emission standard level 4. However, local transaction of used vehicles was not subject to this restriction. Used vehicles of whatever emission standards could be traded within the city and registered.

This policy was first introduced in Beijing in 2008, in a portfolio of measures to control the severe air pollution at that time, for the event of 2008 Beijing Olympic Games. It immediately led to large amount of used vehicles pouring into cities near Beijing in Hebei province. Those cities also suffered greatly from air pollution problem and therefore followed Beijing to implement similar restrictions. Then more and more cities, even those without a severe air pollution problem, followed suit and the restriction policy spread across the country.

This policy impeded free flow of used vehicles and limited the scale of the used vehicle market. In order to stimulate the development of the used vehicle market, the central government announced a directive *Several Opinions about Promoting Convenient Transactions of the used vehicles* on March 25^{th} 2016, requiring local governments, except for Beijing, Tianjing, Hebei, cities in Yangtz River Delta and 9 cities in Pearl River Delta, to remove the restriction policy before May 31^{st}, 2016.

However, by the deadline of May 31^{st}, 2016, only 3 cities complied. In December 29^{th} 2016, the Ministry of Environmental Protection and the Ministry of Commerce together made another announcement, clarifying that every used vehicle that was allowed to run on road locally should not be restricted from import. Another push was in March 2017 which required every city/province to report in details whether they had removed the restriction policy. The results would be reported to the State Council. Non-compliant cities could be subject to on-site inspection from the State Council. In March 2018, the Prime Minister Keqiang Li emphasized achieving overall removal of the trade restriction policy on used vehicles in his annual government's working report. After all these pushes, there are still about 40% of the cities that have not removed the restriction policy by June 2018.

3 Data

For this analysis, we compile a comprehensive city-level panel data on used vehicle trade, new vehicle sales, air pollution concentration and weather condition from various sources. In addition, we collect data on the timing of implementing the emission standards and trade restriction policy per city. This section describes each data source and shows some data patterns.

3.1 used vehicle and new vehicle registration

We have the universe of all used vehicle registration data in China from January 2013 to June 2018. There are 40.05 million observations in this data set. Each observation includes rich car attributes such as manufacturer, model, engine size, footprint, age, and the emission standard each car meets. It also includes quantity of cars for each transaction, transaction year and month, the original registration city and the destination registration city.

Figure 2 shows the intercity trade pattern of used vehicles in China. Similar to the international trade pattern of used vehicles, used vehicles in China flow from high income areas such as Beijing-Tianjin-Heibei, Yangtze river delta and Pearl river delta, to low income areas, such as northeast, northwest and southwest of China. The top exporters are Beijing, Shanghai, Shenzhen, Guangzhou, etc.

Figure 3 shows the volumes of local trade and intercity trade of used vehicles in China over time. The amount of local trade is about 3-4 times of that of the intercity trade. Trade peaks at the end of the year, which might be due to positive income shocks or seasonal promotions. The dotted line represents the time of June 2016, when the central government started to require the local governments to remove the restriction policy. Due to the gradual restriction removal, the amount of intercity trade of used vehicles grew at a faster rate, from a mean of 1354 cars/month before to a mean of 4706 cars/month after [3]. Intercity trade also accounted for a larger share of the total used vehicle trade after the restriction removal. The intercity-total-ratio was 18-20% before 2016 and quickly increased to 22.8% in 2017 and 24.9% in the first half of 2018.

We further zoom in and look at the trends of intercity trade of used vehicles by different emission standards. For simplicity, we divide used vehicles into two types: clean and dirty, according the emission standard level 4. Used vehicles that are below level 4 are characterized as dirty cars and they were restricted from importing into cities that imposed a trade restriction policy based on level 4, while used vehicles of emission standard level 4 or 5 are not restricted and defined as clean cars. As shown in Figure 4, the amount of intercity trade of dirty cars declined all the way down until June 2016 and started to increase thereafter. The change of the trends clearly indicates the influence of the restriction policy on the intercity trade of dirty cars. In contrast, the amount of intercity trade of clean cars kept rising since 2013.

We also have the universe of new vehicle registration data by city by trim by month from January 2013 to December 2018. Figure 5 describes the trend of total new vehicle sales in China. Again, there is obvious seasonality that peaks at December or January of each year. Albeit monthly fluctuations, there is an overall increasing trend from 2013 to 2017, but after 2017 the growth slowed down.

[3] These two numbers are calculated by fitting the intercity trade to a linear trend, before and after the policy change respectively.

3.2 Air pollution

Before 2012, China monitored PM_{10}, NO_2, SO_2, CO, NO_2 and released daily the Air Pollution Index (API) calculated based on the ambient concentration of PM_{10}, NO_2 and SO_2 for a limited number of cities (Chen et al., 2013). Since 2011, the US Embassy in Beijing tweeted their roof-top monitored $PM_{2.5}$ data and caused a dramatic increase in the public attention on $PM_{2.5}$. In 2012, the Ministry of Environmental Protection of China released a new national standard, *Ambient Air Quality Standards (GB3095-2012)*, adding $PM_{2.5}$ to the monitored pollutants. Since January 1^{st} 2013, 74 cities started to make public the hourly data of six pollutants, $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and NO_2. Up to now, more than 300 cities release the local air pollution data per hour. The number of air pollution monitoring stations have also expanded greatly, from 922 in year 2013 to 1605 in year 2018 (see Table 1).

In our analysis, we focus on four pollutants $PM_{2.5}$, PM_{10}, CO, NO_2, which are constrained by the Chinese vehicle emission standards. We obtain the hourly data of all monitoring stations in China from 2013 to 2018 from the Data Center of Ministry of Ecology and Environment (MEE), formerly the Ministry of Environmental Protection of China (MEP). The raw data set records the city that each monitoring station is located in. Therefore, we collapse the station-hourly data to city-daily level.

As we can see from Figure 6, the concentrations of the four air pollutants show obvious seasonality patterns. The peaks occur during winter time because of the weather condition and the central heating that uses coal burning in northern China. Also, there appears to have a long term decreasing trend for the pollution level.

3.3 Meteorology data

We retrieve the meteorological data from the National Meteorological Information Center of China. The Information Center has daily meteorological data for 699 basic weather stations across China. The data set includes a rich set of meteorological measures in terms of wind speed, temperature, atmospheric pressure, relative humidity, precipitation, wind direction, evaporation, ground temperature and sun light hours.

The data set also contains the longitude, latitude and altitude of each weather station. Using the longitude and latitude, we calculate the Vincenty distance between each station-city pair and match each city with the weather station that is closest in distance.

3.4 Policy Timing

We manually collect the data of timing of implementation and removal of the restriction policies in each of the prefecture-level cities in China. Most of the data are obtained from the official announcement of the policy on the local government's website. For those cities that do not publicize the policy on government's website, we try to find the data from news media or directly contacting the local DMV.

Table 2 summarizes the number of cities implemented and removed the restriction policy by year. Restriction 4 or 5 represents the policy that restricts the import of used vehicles below emission standard level 4 or 5, respectively. Based on our data, there were 212 cities implemented Restriction 4, mostly before 2016; 350 cities implemented Restriction 5, mostly during 2016-2017; and 192 cities removed the restriction policies, after June 2016.

Figure 7 shows the roll-out of Restriction 4 across prefecture-cities in China. There were 96 cities that implemented Restriction 4 before 2013, most of which in Beijing-Tianjing-Hebei area, Yangtz River Delta and Guangdong province. In 2013 and 2014, more cities in southwest, northwest and northeast areas adopted Restriction 4. Cities that did not implemented Restriction 4 are mostly in Xingjiang, Tibet, Inner Mongolia and provinces in the central part of China.

We focus our analysis on the policy Restriction 4. We set the sample window as January 2013 to December 2015 because most of the cities implemented Restriction 4 during this period while very few implemented Restriction 5 or removed the restrictions. Thus this window offers a clean time period for studying the impact of Restriction 4.

Table 3 reports the summary statistics of the data within our sample window, 2013-2015.

4 Empirical Framework

4.1 Impact on the used vehicle market

In order to estimate the policy impact on the trade flows of used vehicles, we estimate the following equation based on the structural gravity model. The identification follows a triple difference design.

$$log(trade_{ije,t}) = \pi_{i,t} + \chi_{j,t} + \mu_{ij} + \alpha_{et} + \beta Policy_{jt} \times Intercity_{ij} + \epsilon_{ije,t} \tag{1}$$

where i denotes the origin city; j denotes the destination cit; t denotes time (year-quarter) and e denotes vehicle emission standards. $trade_{ijet}$ is the trade volume of used vehicles. $Policy_{jt}$ represents the policy treatment that equals 1 for all periods after the destination city j implements the restriction policy. $Intercity_{ij}$ is an indicator that equals 1 for intercity trade $(i \neq j)$. π_{it} and χ_{jt} are origin by time fixed effects and destination by time fixed effects, which captures the theoretical construct of outward and inward multilateral resistances (Anderson and Van Wincoop, 2003). α_{et} are the emission standards by time fixed effects and capture different time trends for used vehicles of different emission standards. $\epsilon_{ije,t}$ denotes the idiosyncratic errors.

The interaction between the *Policy* dummy with the *Intercity* dummy captures the impact of the policy on intercity sales relative to local sales (i.e., triple difference). The policy variable itself is absorbed by destination by time fixed effects, implying that the net impact of the policy on local sales or aggregate sales is not identified. We follow Yotov et al. (2016) to address the challenge of estimating a unilateral trade policy by including intracity trade data. Because the policy is only effective on intercity trade, but not on intracity trade, we can estimate the policy effect on trade flows compared to the change of local sales.

To examine the potential endogeneity in policy adoption across cities, we apply a commonly-used diagnostic approach, event study, to look at whether the policy has any effect on the outcome before its implementation, i.e., "pre-trends".

$$log(trade_{ije,t}) = \pi_{i,t} + \chi_{j,t} + \mu_{ij} + \alpha_{et} + \sum_{\tau=-4}^{8} \beta_\tau D_{\tau,jt} \times Intercity_{ij} + \epsilon_{ije,t} \quad (2)$$

where $D_{\tau,jt}$ are separate indicators for each quarter τ relative to the implementation of the restriction policy. Since cities implemented the restriction policy at different time and mostly before 2014, we have more cities with short pre-periods and long post-periods. We choose the event window to be four quarters before and eight quarters after restriction to accommodate this pattern. During this event window, the composition of cities do not change much. Event time $\tau = -1$ is omitted as the baseline.

The key identification assumption behind the above gravity equation is that the policy is not correlated with demand shocks that affect intercity sales and local sales differently. While such shocks are hard to come up, we address this potential endogeneity concern with an IV strategy. We construct our IV as the share of auto sector in local government tax revenue in 2010, interacted with the post policy dummy, interact with the intercity dummy. The share of the auto sector in local tax revenue could be related to the implementation of the restriction policy because the more important the auto industry is for the local tax revenue, the more likely the local government will protect it by preventing the inflow of used vehicles that might drive down new vehicles sales. We use the share of auto sector in local tax revenue in 2010, three years before our sample period. The scale of the auto sector in the past might influence the scale of the auto sector in later years, but its direct impact on used vehicle trade could be absorbed by the destination×time fixed effects.

By interacting the auto tax share with the post policy dummy, we are making an assumption that the timing of policy implementation is exogenous, and we only try to correct for the potential endogeneity in policy adoption across cities. The timing choice of the restriction should not be a response to the month-to-month variation in used vehicle trade, conditional on destination by time fixed effects.

4.2 Impact on air quality

We use the staggered difference-in-differences strategy to identify the impact of policy on air pollution:

$$Pollution_{cd} = \beta Policy_{ct} + \mathbf{W_{cd}}'\gamma + \mathbf{X}'_{\mathbf{cy}}\alpha + \eta_{cq} + \delta_d + \mu_{prov,y} + \epsilon_{cd} \tag{3}$$

where c denotes a city and d denotes day. $Pollution_{cd}$ is the daily ambient pollution level of $PM_{2.5}$, PM_{10}, CO and NO_2 respectively in city c on day d. $Policy_{ct}$ is the policy indicator that takes the value of one for all periods after city c implements the restriction policy. $\mathbf{W_{cd}}$ is a vector of weather controls, including wind speed, wind directions, precipitation, atmospheric pressure, temperature, relative humidity and sun shine hours at city c at date d. $\mathbf{X_{cy}}$ is a vector of city controls including population, GDP, government expenditure and government revenue. η_{cq}, δ_d and $\mu_{prov,y}$ represent city$\times$quarter fixed effects, date of sample fixed effects and province $\times$ year fixed effects. ϵ_{cd} denotes the idiosyncratic errors not explained by the model.

Similarly, we use the event study framework to visualize the dynamics of the policy effects and to detect "pre-trends". We use the IV described before, the share of auto sector in local government tax revenue in 2010, interacted with the post dummy to instrument for the potentially endogeneity in policy adoption across cities.

4.3 Impact on new vehicle sales

The restriction policy could affect the market of new vehicles through the linkage between the used vehicle and new vehicle markets. The direction of impact is not clear a priori. When the trade of used vehicles is restricted, a vehicle ownership who is considering a new vehicle may have to hold onto the used vehicle longer if it cannot be sold, hence reducing demand for new vehicles. On the other hand, potential vehicle buyers who are on the market for a used vehicle now may need to buy a new vehicle due to limited choices in the used vehicle market, hence increasing demand for new vehicles.

We estimate the impact of the restriction policy on new vehicle sales using the following equation:

$$log(sales_{jct}) = \beta Policy_{ct} + \mathbf{X_{c,y}}'\gamma + \delta_{jc} + \eta_t + \epsilon_{jct} \tag{4}$$

where j denotes a vehicle model, c denotes a city and t denotes time (year-quarter). $Sales_{jct}$ is the new vehicle sales of model j in city c at year-quarter t. $\mathbf{X_{c,y}}$ is a vector of covariates including population, GDP per capita, government revenue and government expenditure. We control for model×city fixed effects and year-quarter fixed effects. ϵ_{ict} denotes the remaining idiosyncratic shocks.

We further examine the heterogeneous effects between locally produced brands vs. non-local brands:

$$log(sales_{jct}) = \beta_1 Policy_{ct} \times Local_{jc} + \beta_2 Policy_{ct} \times Nonlocal_{jc} + \mathbf{X_{c,y}}'\gamma + \delta_{jc} + \eta_t + \epsilon_{jct} \tag{5}$$

where $Local_{jc}$ is a dummy variable that equals one if model j's brand has a local plant in city c; $Nonlocal_{jc} = 1$ if otherwise. Other variables are defined in the same way as in the previous specification. We instrument two potentially endogenous variables, $Policy \times Local$ and $Policy \times Nonlocal$ by interacting the IVs with the local and nonlocal dummies.

5 Results and discussions

5.1 Used vehicle trade flows

Figure 8 shows the estimated coefficients of the policy impact on intercity trade flows of dirty cars and clean cars from event studies. There are two patterns shown in the figures. First, before the policy implementation, the coefficients are flat and not statistically different from zero, indicating no strong "pre-trends". Second, the coefficients for dirty cars decline gradually rather than sharply after the restriction is imposed, implying that the restriction policy does not take full effect immediately after its implementation.

Table 4 reports the OLS and IV regression results of the policy effect on intercity trade of dirty and clean used vehicles. OLS results show that compared to local trade of use cars, the intercity trade of dirty cars decreases by 40% while that of clean cars increases by 8.5% due to the implementation of the restriction policy. The IV estimates are similar, showing a decline of 44.7% in the intercity trade of dirty cars, but no significant change in the intercity trade of clean cars.

Table 5 shows the first stage results of the IV regressions. The coefficient for the IV is positive and significant at the 1% level, showing that the larger the auto share in local tax revenue, the more likely that the city implements the restriction policy. This result reveals some political economy behind the adoption decision of the restriction policy. The more important the auto industry is for local tax revenue, the more incentive a local government has to impose the restriction and protect the local auto industry.

5.2 Air pollution

Figure 9 shows the dynamic pattern of the policy impact on air pollution at different quarters before and after policy implementation. Most of the coefficients are not significantly different from zero, and no obvious shift in the level of coefficients before and after policy implementation.

The OLS and IV estimation of the policy effects on air pollution are presented in Table 6. Columns (1)-(4) are results for the monitoring pollutants, i.e., $PM_{2.5}$, PM_{10}, CO and NO_2. Both OLS and IV results are not significantly different from zero for all pollutants and the magnitudes are small, most of which less than 1%.

Notice that China expanded air pollution monitoring stations during 2012-2014 in three waves. Therefore, the sample is unbalanced in that air pollution data are available in 76, 160 and 336 cities respectively in year 2013, 2014 and 2015. In order to address this concern, we use the aerosol optical depth (AOD) data as an index for measuring air pollution with a balanced sample of 326 cities during 2013-2015. The regression results are reported in column (5). Again, both OLS and IV results are not significantly different from zero.

The results that the impacts on the air pollution are small in magnitude and not statistically significant do not give evidence of air quality improvement after the policy implementation. One possible reason is the small scale of the import of dirty used vehicles compared to local vehicle stock. During the sample period 2013-2015, the annual average import of dirty used vehicles accounts for only 0.3% of the local vehicle stock. Therefore, even if the policy barred the import of dirty used vehicles from other cities, it did not lead to a big change in local vehicle stock and the corresponding impact on local air pollution is thus limited.

5.3 New vehicle sales

Figure 10 illustrates the event study coefficients on new vehicle sales for 4 quarters before and 8 quarters after the policy implementation. Most coefficients are not statistically different from zero, but all the coefficients after the restriction implementation are positive.

Table 7 reports the average policy effect on new vehicle sales, experimenting fixed effects with different stringency. For OLS regression, when controlling for city FEs and year-quarter FEs and using variations across models within the same city before and after policy implementation, there is a significant 6% increase in new vehicle sales. However, if controlling for more stringent city by model FEs and year-quarter FEs, the leftover variations within city-model might be too small to identify a significant effect. The IV estimates are very close in magnitude as the OLS estimates, but none of them are significant due to the increase in standard errors.

Figure 11 shows the effects of new vehicle sales for locally produced brands and non-locally produced brands. Great heterogeneity is observed. For locally produced cars, there is an obvious shift up of the coefficients during post policy periods, implying a positive policy impact, while the coefficients for non locally produced cars are almost all zeros before and after the policy.

Table 8 summarizes the heterogeneity of the policy effects by brands. With the most stringent set of fixed effect in column (3), the OLS results show that the locally produced new vehicle sales increase significantly by 54.7% after policy implementation, but there is no significant increase in new vehicle sales of non-local brands. The IV regression gives a qualitatively similar results as OLS. The restriction policy leads to a significant increases of 36.6% in the sales of locally produced cars, but no significant increase in non-locally produced cars.

The dramatic increase in the sales of locally produced new cars could be driven by the fact that local brand cars are often subsidized by local governments for local consumers(Barwick et al., 2018). This may heavily distort consumers' purchase toward locally produced cars when their choice of used vehicles are restrained by the restriction policy.

5.4 Limitations and next step

We plan to develop a theoretical model of the decision of local governments in the spirit of Grossman and Helpman (1994) to understand the incentives of local government to engage in local protective practices. The restriction of free trade to help local industries may give rise to prisoner's dilemma.

One of the challenges to estimate the policy impact is the spatial spillover effect, i.e., the implementation of one city's restriction might have an impact on another city. For example, if one city imposes the restriction policy on the import of dirty used vehicles, then part of its previous import could be diverted to neighboring cities, therefore change the trade pattern of used vehicles, new vehicle sales and possibly air pollution in those cities.

For the impact on used vehicle trade, we may overcome this difficulty by estimating the general equilibrium (GE) effect with the structural gravity model (Yotov et al., 2016). For now we only estimate the partial equilibrium effect, but it still can tell an important part of the story because partial equilibrium effect is the first order effect which is larger than the second order GE effect. We plan to estimate the GE effect in the next step.

For estimating the policy effect on air pollution, we plan to deal with the spillover effect by controlling for the inverse-distance weighted average pollution in upwind cities. We can construct the weighted average pollution in upwind cities in the following way. First, calculate the bearings between any two city-pairs [4]. Then convert the bearings into 16 directions.These directions are N, NNE, NE, ENE, E, ESE, SE, SSE, S, SSW, SW, WSW, W, WNW, NW, NNW. The upwind cities for each city-day could be defined as the ones that lie in the same direction as the wind direction. Then calculate the average pollution levels in these upwind cities weighted by the inverse of distance between the upwind city and the local city.

For the impact on new vehicle sales, we tried to add additional controls of weighted number of cities that implemented the restriction policy, within different distance circles. Table 9 and Table 10 report the OLS results from including these additional controls. The results are very close to the previous estimates, which indicates that the spillover effect on new vehicle sales might be small.

6 Conclusion

Using detailed data on used and new vehicle registration and local air quality, we examine the impacts of the trade restriction policy on the used vehicle market, air pollution, and the new vehicle market. The trade restriction policy significantly reduced the intercity trade of used vehicles that do not meet the local emission standards. The reduced inflow of used vehicles however, did not lead to improvement of local air quality. Nevertheless,the policy dramatically increased new vehicle sales of local brands. This is consistent with the fact that cities that rely more on the local automobile sector for tax revenue are more likely to adopt

[4] Bearing is an geographical terminology that indicates the angle between the direction of two points on Earth and that of the true north.

tailpipe emission standards to restrict the flow of used vehicles.

Our study documents a concrete example where local governments engage in practices of local protectionism under the disguise of environmental protection. These type of policies not only hinder the development of the used vehicle market and limit the gain from trade but also distract attention from effective environmental regulations that are much needed to combat pressing environmental challenges. The recent mandate by the central government to remove trade restrictions on used vehicles should help the used vehicle market to grow and enhance social welfare.

References

Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: a solution to the border puzzle. *American economic review*, 93(1):170–192.

Auffhammer, M. and Kellogg, R. (2011). Clearing the air? the effects of gasoline content regulation on air quality. *American Economic Review*, 101(6):2687–2722.

Automotive News, 2019. Number of new and used light vehicle sales in the united states from 2000 to 2018.

Bai, C.-E., Du, Y., Tao, Z., and Tong, S. Y. (2004). Local protectionism and regional specialization: evidence from china's industries. *Journal of International Economics*, 63(2):397–417.

Barwick, P. J., Cao, S., and Li, S. (2018). Local protectionism, market structure, and social welfare: China's automobile market. Technical report, National Bureau of Economic Research.

Cao, X., Kostka, G., and Xu, X. (2019). Environmental political business cycles: the case of pm2. 5 air pollution in chinese prefectures. *Environmental Science & Policy*, 93:92–100.

Chen, Y., Jin, G. Z., Kumar, N., and Shi, G. (2013). The promise of beijing: Evaluating the impact of the 2008 olympic games on air quality. *Journal of Environmental Economics* *and Management*, 66(3):424–443.

Copeland, B. R. and Taylor, M. S. (2004). Trade, growth, and the environment. *Journal of Economic literature*, 42(1):7–71.

Davis, L. W. (2008). The effect of driving restrictions on air quality in mexico city. *Journal of Political Economy*, 116(1):38–81.

Ederington, J. (2001). International coordination of trade and domestic policies. *American Economic Review*, 91(5):1580–1593.

Ederington, J. and Minier, J. (2003). Is environmental policy a secondary trade barrier? an empirical analysis. *Canadian Journal of Economics*, 36(1):137–154.

Edwards, S. (1993). Openness, trade liberalization, and growth in developing countries. *Journal of Economic Literature*, 31(3):1358–1393.

Ellison, R. B., Greaves, S. P., and Hensher, D. A. (2013). Five years of london's low emission zone: Effects on vehicle fleet composition and air quality. *Transportation Research Part D: Transport and Environment*, 23:25–33.

Fisman, R. and Wang, Y. (2015). The mortality cost of political connections. *The Review of Economic Studies*, 82(4):1346–1382.

Grossman, G. M. and Helpman, E. (1994). Protection for sale. *The American Economic Review*, 84(4):833–850.

Gruenspecht, H. K. (1982). Differentiated regulation: The case of auto emissions standards. *American Economic Review*, 72(2):328–331.

Jacobsen, M. R. and Van Benthem, A. A. (2015). Vehicle scrappage and gasoline policy. *American Economic Review*, 105(3):1312–38.

Jiang, J. and Wallace, J. (2017). Informal institutions and authoritarian information systems: Theory and evidence from china.

Krueger, A. (1998). Why trade liberalisation is good for growth. *The Economic Journal*, 108(450):1513–1522.

Levinson, A. (2017). Environmental protectionism: The case of cafe. *Economics Letters*, 160:20–23.

Li, S., Hou, Y., Liu, Z., and Bo, C. (2004). The analysis on survey of local protection in china domestic market. *Economic Research Journal*, 11:78–84.

Li, S., Linn, J., and Spiller, E. (2013). Evaluating "cash-for-clunkers": Program effects on auto sales and the environment. *Journal of Environmental Economics and Management*, 65(2):175–193.

MEE (2018). China vehicle environmental management annual report. Technical report, Ministry of Ecology and Environment of People's Republic of China, Beijing.

MIIT (2017). *The mid-long term development plan for automotive industry*. Beijing.

Miravete, E. J., Moral, M. J., and Thurk, J. (2018). Fuel taxation, emissions policy, and competitive advantage in the diffusion of european diesel automobiles. *The RAND Journal of Economics*, 49(3):504–540.

Rivera-Batiz, L. A. and Romer, P. M. (1991). Economic integration and endogenous growth. *The Quarterly Journal of Economics*, 106(2):531–555.

Runge, C. F. (1990). Trade protectionism and environmental regulations: The new nontariff barriers. *Northwestern Journal of International Law & Business*, 11:47.

Shindell, D., Faluvegi, G., Walsh, M., Anenberg, S. C., Van Dingenen, R., Muller, N. Z., Austin, J., Koch, D., and Milly, G. (2011). Climate, health, agricultural and economic impacts of tighter vehicle-emission standards. *Nature Climate Change*, 1(1):59.

UN (2003). Dispute settlement, world trade organization 3.5 gatt 1994. Technical report, United Nations, New York and Geneva.

UN (2019). Key statistics and trends of trade policy 2018. Technical report, United Nations, Geneva.

Viard, V. B. and Fu, S. (2015). The effect of beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics*, 125:98–115.

Vijayaraghavan, K., Lindhjem, C., DenBleyker, A., Nopmongcol, U., Grant, J., Tai, E., and Yarwood, G. (2012). Effects of light duty gasoline vehicle emission standards in the united states on ozone and particulate matter. *Atmospheric Environment*, 60:109–120.

Wan, Z., Sperling, D., and Wang, Y. (2015). China's electric car frustrations. *Transportation Research Part D: Transport and Environment*, 34:116–121.

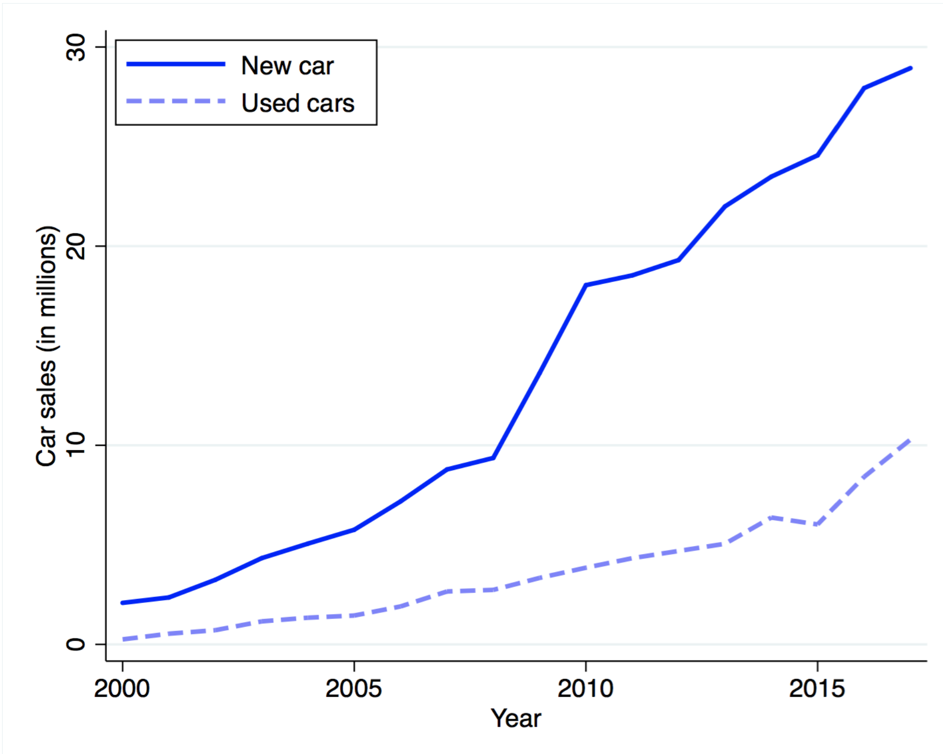
Yotov, Y. V., Piermartini, R., Monteiro, J.-A., and Larch, M. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. World Trade Organization Geneva.

Young, A. (2000). The razor's edge: Distortions and incremental reform in the people's republic of china. *The Quarterly Journal of Economics*, 115(4):1091–1135.

Zhang, W., Lawell, C.-Y. C. L., and Umanskaya, V. I. (2017). The effects of license plate-based driving restrictions on air quality: Theory and empirical evidence. *Journal of Environmental Economics and Management*, 82:181–220.

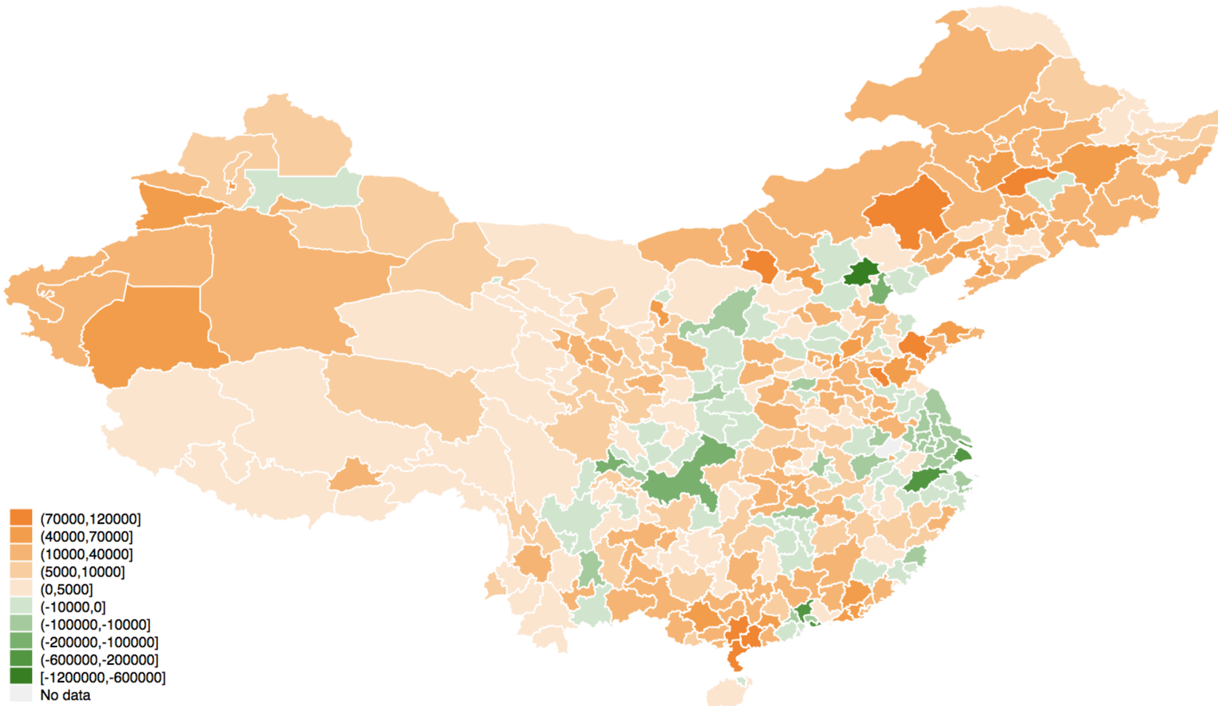
Figures

Figure 1: The Chinese vehicle market



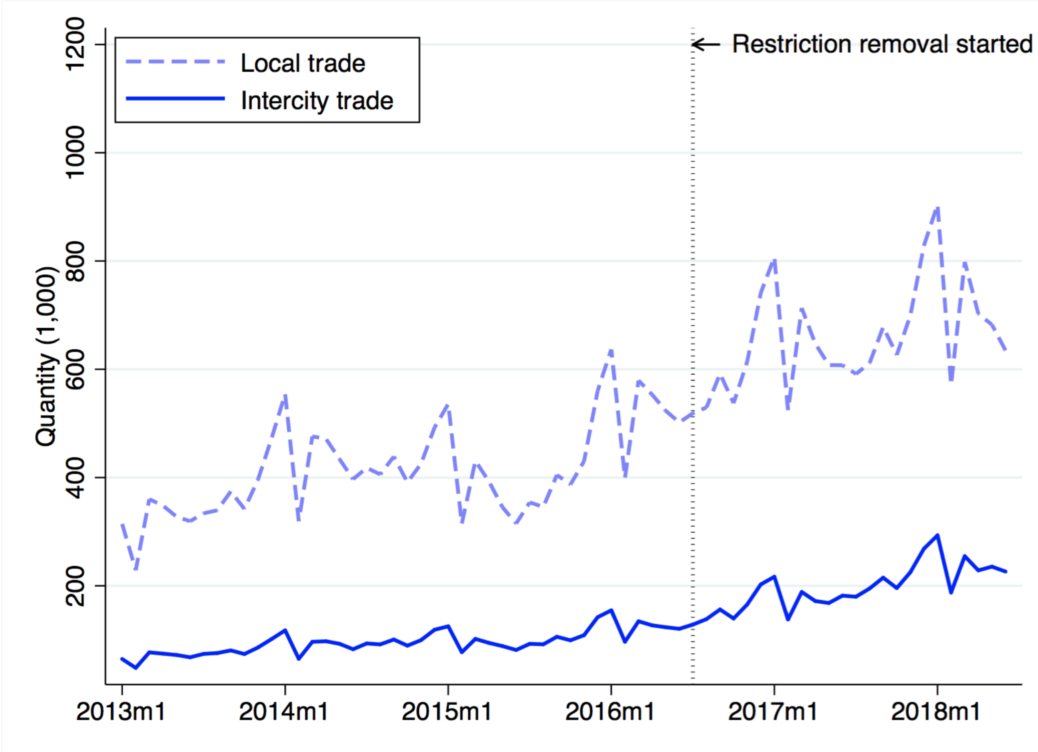
Notes: This graph shows the increasing trend of new vehicle sales and used vehicle sales. Data of new vehicle sales are from CEIC China Premium database. Used vehicle sales data in year 2000-2011 are from http://auto.163.com/special/observation50/, used vehicle sales data in year 2013-2017 are based on own calculation.

Figure 2: Intercity trade of used vehicles



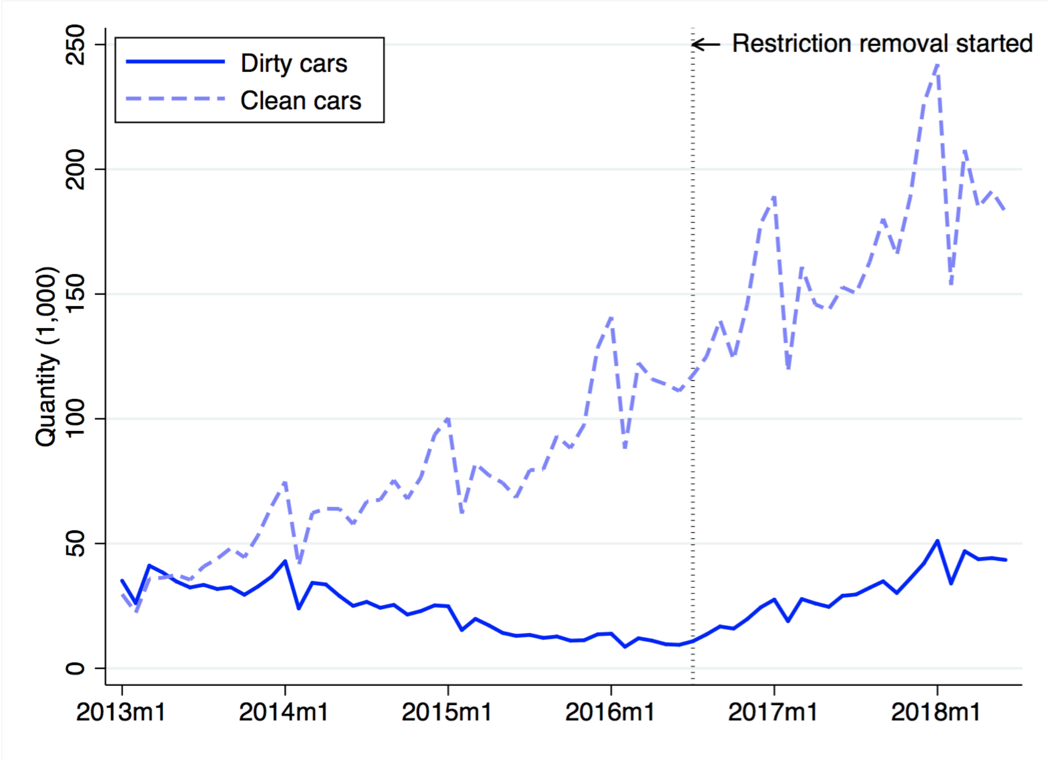
Notes: This map shows the net import of used vehicles per prefecture city during 2013.1-2018.6. Green areas are net exporters of used vehicles, while orange areas are net importers of used vehicles. The shades of the colors distinguish the magnitude of the trade amount.

Figure 3: Time series of used vehicle trade



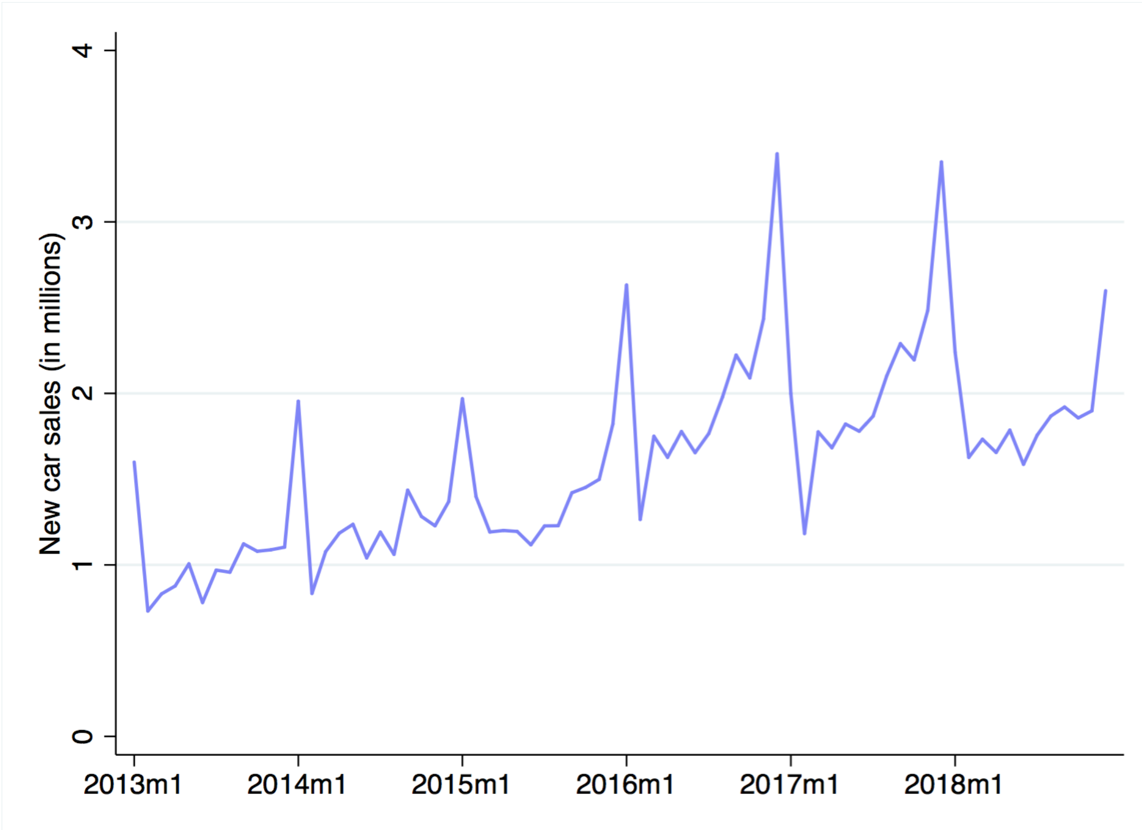
Notes: This graph shows the trends of local trade and intercity trade of used vehicles from 2013.1 to 2018.6. The vertical dotted line indicates June 2016, when local governments started to remove the restriction policy under the requirement of the central government.

Figure 4: Time series of intercity trade of used vehicles



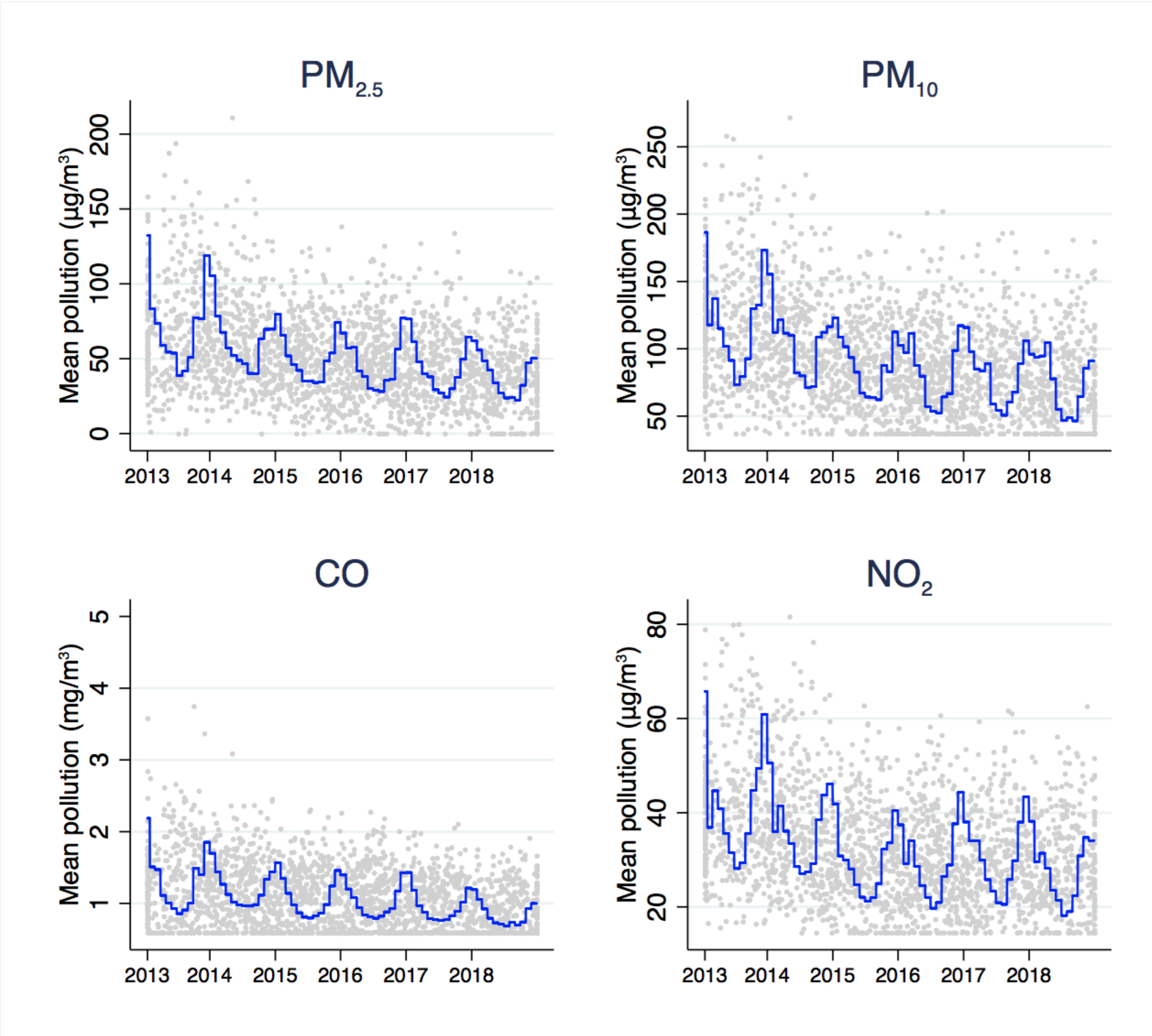
Notes: This graph shows the trends of intercity trade of used vehicles by emission standards. Dirty cars refer to the cars of emission standard below Chinese emissions standard level 4; clean cars otherwise. The vertical dotted line indicates June 2016, when local governments started to remove the restriction policy under the requirement of the central government.

Figure 5: Time series of new vehicle sales



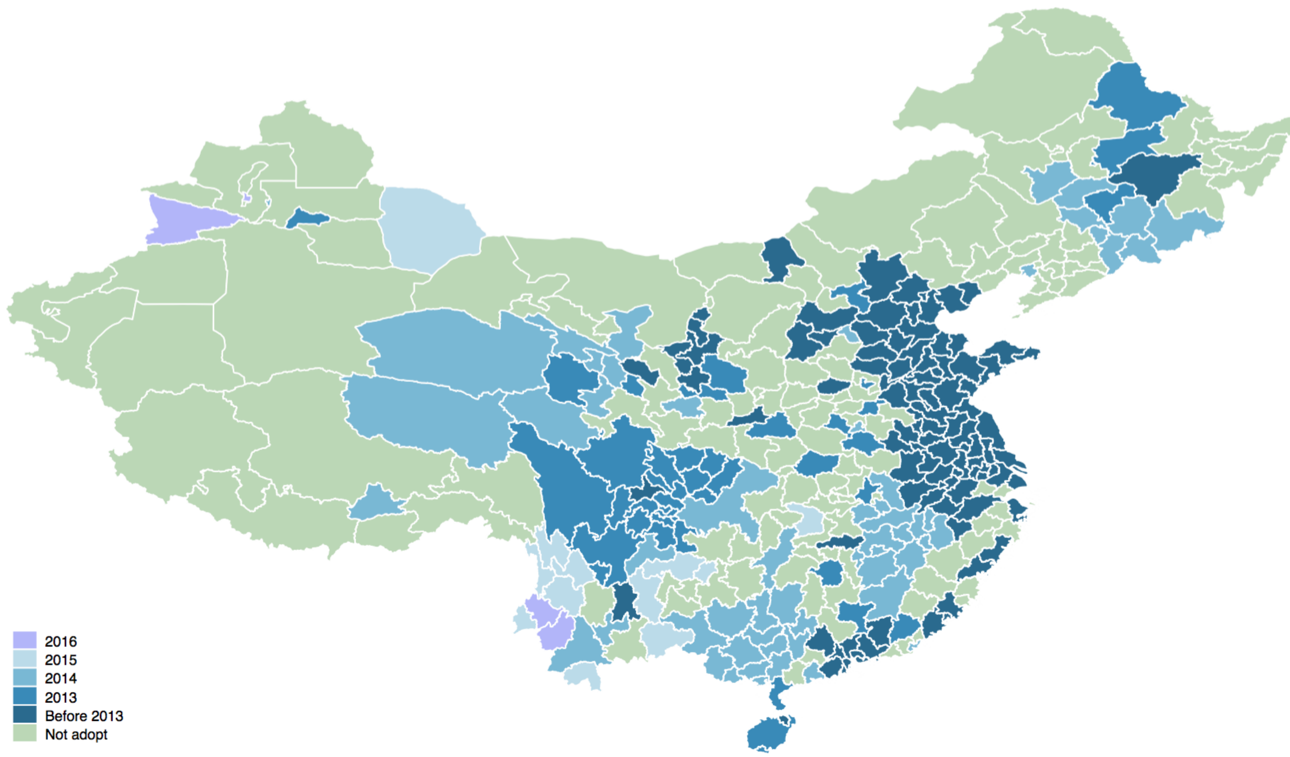
Notes: This graph shows the monthly new vehicle sales in China from Jan 2013 to Dec 2018.

Figure 6: Time series in air pollution



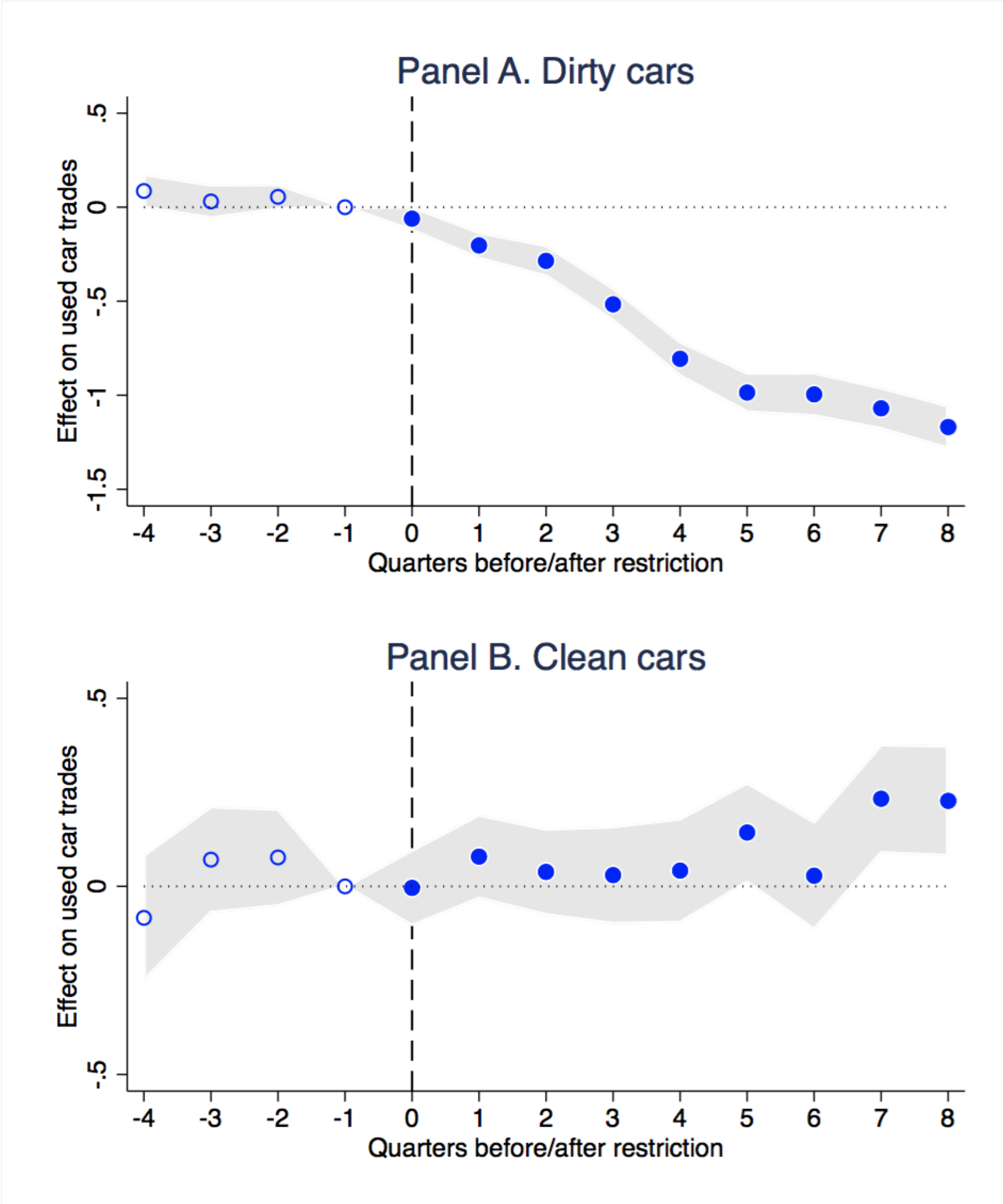
Notes: This graph shows the mean concentration of four air pollutants during 2013.1-2018.12. Each dot represents the daily average and the blue line shows the monthly average.

Figure 7: Roll-out of Restriction 4



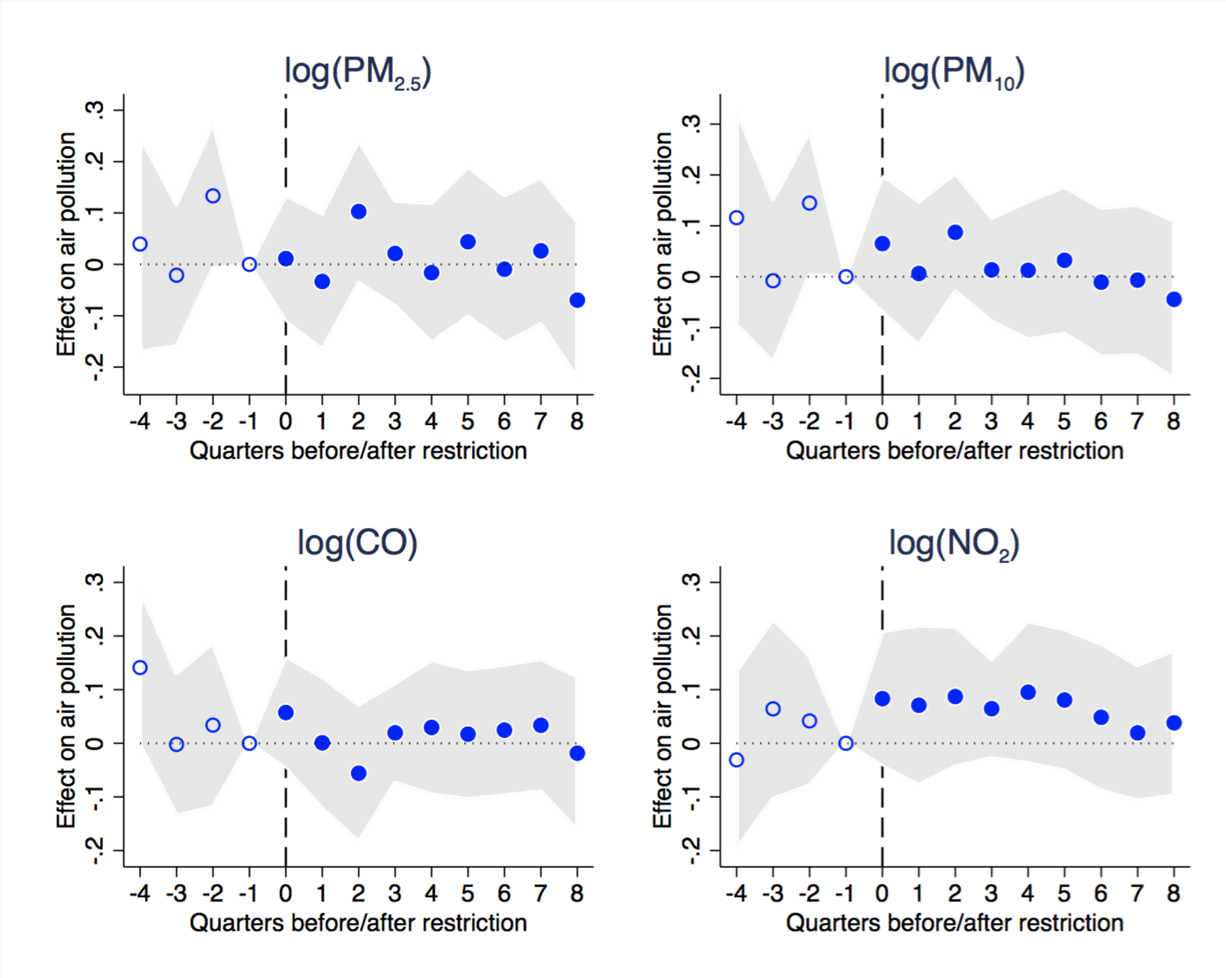
Notes: This map shows the roll-out of Restriction 4 across prefecture-level cities in China. Restriction 4 refers to the policy that restrict import of used vehicles below Chinese emissions standards level 4. Each color represents a different year in which the city implemented the restriction policy.

Figure 8: Changes in used vehicle intercity trade: dirty vs. clean cars



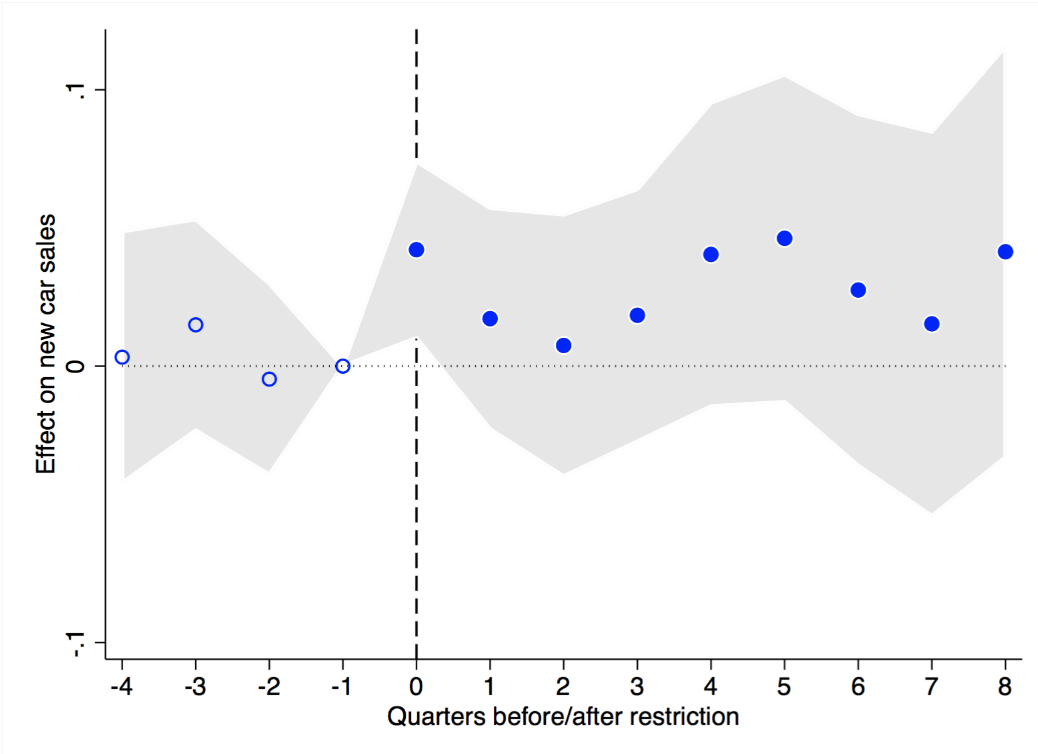
Notes: This graph shows the coefficients obtained from event studies that estimate the dynamic policy effects on trade flows for dirty cars and clean cars using OLS estimator. Trade data are at city-pair×year-quarter×vehicle emission standard level. The dependent variable is log(trade). Sample period is 2013.1-2015.12. Dirty cars refer to those below Chinese emissions standard level 4, clean cars otherwise. The regressions control for city-pair FEs, origin×year-quarter FEs, destination×year-quarter FEs and emission standard×year-quarter FEs. The vertical dashed line represents the time when the destination city adopted the restriction policy. Shaded area shows the 95% confidence interval. Standard errors are clustered at the city-pair level.

Figure 9: Changes in air pollution



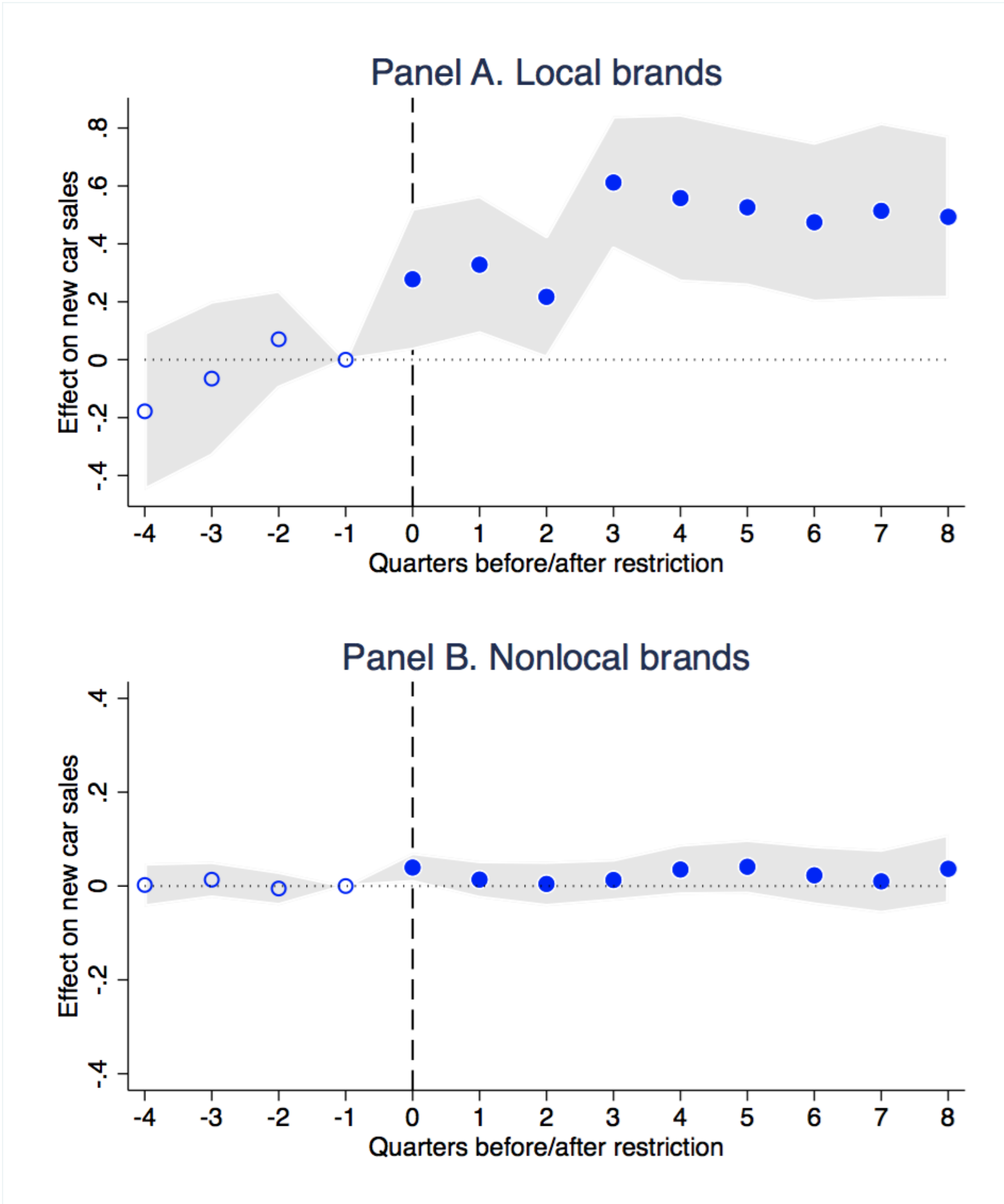
Notes: This graph shows the coefficients obtained from the event study regressions that estimate the policy effect on each pollutant in each quarter before and after policy implementation. The dependent variable is log of the pollutant concentration. The regressions control for weather conditions (wind speed, wind direction, precipitation, temperature, air pressure, relative humidity and sun shine hours), population, GDP, government expenditure and government revenue. The regressions include city×quarter FEs, date-of-sample FEs and province×year FEs. Shaded area shows the 95% confidence interval. Standard errors are clustered at the prefecture-city level.

Figure 10: Changes in new vehicle sales



Notes: This graph shows the coefficients obtained from the event study regression that estimates the policy effects on new vehicle sales at each quarter before and after policy implementation. New vehicle sales data are at city×year-quarter×model level. The dependent variable is log(Sales). Sample period is 2013.1-2015.12. The regression controls for population, GDP per capita, government expenditure, government revenue, city × model FEs and year-quarter FEs. The vertical dashed line represents the time when the city adopted the restriction policy. Shaded area shows the 95% confidence interval. Standard errors are clustered at city level.

Figure 11: Changes of new vehicle sales: local brands vs. nonlocal brands



Notes: This graph shows the coefficients obtained from the event study that estimates the heterogeneous effects of the restriction policy on new vehicle sales of local brands vs. nonlocal brands. new vehicle sales data are at city×year-quarter×model level. The dependent variable is log(Sales). Sample period is 2013.1-2015.12. The regression controls for population, GDP per capita, government expenditure and government revenue. The regression includes city × model FEs and year-quarter FEs. The vertical dashed line represents the time when the city adopted the restriction policy. Shaded area shows the 95% confidence interval. Standard errors are clustered at city level.

Tables

Table 1: Number of air pollution monitoring stations

Year	2013	2014	2015	2016	2017	2018
No. of monitoring stations	922	945	1497	1497	1563	1605
No. of cities with monitoring stations	159	188	364	364	364	364

Notes: This table reports the numbers of air pollution monitoring stations and the numbers of cities with monitoring stations over time. Source: Data Center of Ministry of Ecology and Environment (MEE).

Table 2: Number of cities that implemented/removed the restriction policy by year

Year	Restriction 4	Restriction 5	Restriction removal
Before 2013	95	0	0
2013	44	1	0
2014	58	1	0
2015	12	0	0
2016	3	104	52
2017	0	244	62
2018	0	0	78
Total	212	350	192

Notes: This table reports the number of cities that implemented/removed the trade restriction policy by year. Restriction 4 or 5 refers to the local policy that prevents the import of used vehicles from other cities, that are below Chinese emissions standard level 4 or 5.

Table 3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
used vehicle sales (city-pair$\times$quarter)					
Intercity trade of dirty cars	6.2	54.7	1	7,055	143,431
Intercity trade of clean cars	7.6	35.7	1	3,352	304,155
Intracity trade of dirty cars	1,424.7	2191	1	26,022	3,943
Intracity trade of clean cars	2,155.5	2992.1	1	25,922	3,953
new vehicle sales (city$\times$quarter)					
new vehicle sales	10,008.3	13,460	1	131,612	3943
Air pollution (city$\times$day)					
$PM_{2.5}$ ($\mu g/m^3$)	56.2	46	1	2074.2	227,250
PM_{10} ($\mu g/m^3$)	96.6	75	1	3456.1	227,061
CO (mg/m^3)	1.1	0.7	0	21.6	227,254
NO_2 ($\mu g/m^3$)	33.1	19.2	1	532.7	227,244
Weather (city$\times$day)					
Mean wind speed (m/s)	2.1	1.2	0	17.7	367,685
Mean temperature (°C)	14.3	11.1	-36.1	38.2	367,901
Mean daily precipitation (mm)	2.7	9.7	0	423.8	367,092
Mean air pressure (hPa)	952.3	87.3	573.8	1046.9	367,908
Mean relative humidity (%)	67.2	18.7	5	100	367,888
Mean sunlight hours (h)	5.6	4.2	0	14.5	367,802

Notes: This table reports the summary statistics of variables in used vehicle sales, new vehicle sales, air pollution and weather conditions within the sample period of Jan. 2013 to Dec. 2015. Dirty and clean used vehicles are classified based on whether below or above emissions standard level 4.

Table 4: Effect of restriction policy on used vehicle trade

Dep. var.	log(Trade)	
	Dirty cars	Clean cars
	(1)	(2)
Panel A: OLS		
Policy×Intercity	-0.512***	0.0813**
	(0.0465)	(0.0408)
N	181447	305213
R^2	0.860	0.850
Panel B: IV		
Policy×Intercity	-0.592***	0.0123
	(0.0845)	(0.0729)
K-P 1st stage F	39.86	32.84
N	181447	305213
R^2	0.002	0.000

Notes: This table reports the OLS and IV estimates of the heterogeneous effects on intercity trade of dirty cars and clean cars. Sample period is 2013.1-2015.12. Trade data are at city-pair×year-quarter×vehicle emission standard level. Dirty vehicles refer to those below emission standard level 4, clean vehicles if otherwise. $Policy = 1$ for all periods after a destination city has implemented the restriction policy. $Intercity = 1$ for intercity trade flows. For IV regressions, we use $Auto\ tax\ share \times Post \times Intercity$ to instrument for $Policy \times Intercity$. *Auto tax share* is the share of auto sector in local government tax revenue in 2010. *Post* is the dummy that equals 1 after policy implementation. The regressions control for city-pair FEs, origin×year-quarter FEs, destination×year-quarter FEs and vehicle emission standard×year-quarter FEs. Standard errors are clustered at the city-pair level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: First stage results

Dep. var.	Policy×Intercity	
	Dirty	Clean
	(1)	(2)
Auto tax share×Post×Intercity	0.306***	0.300***
	(0.0485)	(0.0523)
K-P 1st stage F	39.86	32.84
N	181447	305213
R^2	0.993	0.998

Notes: This table reports the first stage results of the IV regressions on used vehicle trade, controlling for city-pair FEs, origin×year-quarter FEs, destination×year-quarter FEs and vehicle emission standard×year-quarter FEs. *Auto tax share* is the share of auto sector in local government tax revenue in 2010. Robust standard errors clustered at city-pair level, in parentheses. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of restriction policy on air pollution

Dep. var.	$log(PM_{2.5})$	$log(PM_{10})$	log(CO)	$log(NO_2)$	AOD
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
Policy	0.000465	0.00693	-0.00793	0.0467	-0.00435
	(0.0328)	(0.0239)	(0.0317)	(0.0353)	(0.00675)
N	166900	166760	166898	166898	135867
R^2	0.627	0.649	0.662	0.736	0.545
Panel B: IV					
Policy	-0.0527	0.0146	-0.00228	-0.00406	-0.00516
	(0.0429)	(0.0221)	(0.0298)	(0.0367)	(0.0105)
K-P 1st stage F	42.30	42.31	42.30	42.30	19.55
N	166900	166760	166898	166898	135867
R^2	0.117	0.116	0.093	0.138	0.203

Notes: This table reports the OLS and IV regression results of the policy effects on air pollution. Pollution data are at the city×day level. We use *Auto tax share* × *Post* to instrument for *Policy*, in which *Auto tax share* is the share of auto sector in local government tax revenue in 2010 and *Post* is a dummy that turns on after policy implementation. The regressions control for daily weather conditions (wind speed, wind direction, precipitation, temperature, air pressure, relative humidity and sun shine hours), population, GDP, government expenditure and government revenue. Fixed effects controlled are city×quarter FEs, date of sample FEs and province×year FEs. Robust standard errors clustered at city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of restriction policy on new vehicle sales

Dependent variable	log(sales)		
	(1)	(2)	(3)
Panel A: OLS			
Policy	0.0608***	0.0539**	0.0197
	(0.0200)	(0.0213)	(0.0202)
N	553478	553476	551509
R^2	0.280	0.618	0.835
Panel B: IV			
Policy	0.0639	0.0557	0.0159
	(0.0442)	(0.0447)	(0.0444)
K-P 1st stage F	27.82	27.82	28.08
N	553478	553476	551509
R^2	0.001	0.001	0.004
City FEs	✓	✓	
Year-quarter FEs	✓	✓	✓
Model FEs		✓	
City×model FEs			✓

Notes: This ta ble reports the effect on new vehicle sales using OLS and IV regressions. In the IV regression, we use *Auto tax share* × *Post* as an IV to instrument for *Policy*. *Auto tax share* is the share of auto sector in local government tax revenue in 2010. The regression controls for population, GDP per capita, government expenditure and government revenue. Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Heterogeneous effects on new vehicle sales

Dependent variable	log(Sales)		
	(1)	(2)	(3)
Panel A: OLS			
Policy × Nonlocal brand	0.0544***	0.0484**	0.0163
	(0.0190)	(0.0204)	(0.0195)
Policy × Local brand	0.856***	0.738***	0.436***
	(0.112)	(0.115)	(0.104)
N	553478	553476	551509
R^2	0.282	0.619	0.835
Panel B: IV			
Policy × Nonlocal brand	0.0525	0.0461	0.0106
	(0.0453)	(0.0454)	(0.0431)
Policy × Local brand	0.709***	0.600***	0.312*
	(0.112)	(0.102)	(0.164)
K-P 1st stage F	13.95	13.94	14.15
N	553478	553476	551509
R^2	0.004	0.005	0.004
City FEs	✓	✓	
Year-quarter FEs	✓	✓	✓
Model FEs		✓	
City×model FEs			✓

Notes: This table reports the heterogeneous effects on new vehicle sales from OLS and IV estimation. Local brand = 1 if the brand (firm) has a local plant in the city; Nonlocal brand =1 if otherwise. Two IVs used are *Auto tax share* × *Post* × *Local* and *Auto tax share* × *Post* × *Nonlocal*. *Auto tax share* is the share of auto sector in local government tax revenue in 2010. The regression controls for population, GDP per capita, government expenditure and government revenue. Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table 9: The effect of the restriction policy on new vehicle sales

Dep. Var.	log(sales)		
	(1)	(2)	(3)
Policy	0.0222	0.0179	0.00145
	(0.0244)	(0.0259)	(0.0236)
Weighted number of adopted cities	0.000930	-0.00346	-0.0000126
(<=200km)	(0.0388)	(0.0420)	(0.0384)
Weighted number of adopted cities	0.0843*	0.0847	-0.00165
(200-500 km)	(0.0509)	(0.0549)	(0.0467)
Weighted number of adopted cities	0.339***	0.407***	0.318***
(500-1000 km)	(0.102)	(0.113)	(0.111)
Weighted number of adopted cities	-0.161	-0.115	-0.0690
(>1000 km)	(0.155)	(0.166)	(0.150)
City FEs	✓	✓	
Year-quarter FEs	✓	✓	✓
Model FEs		✓	
City×model FEs			✓
N	547038	547036	545104
R^2	0.282	0.619	0.835

Notes: This table reports the OLS estimates of policy impact on new vehicle sales. The regressions control for weighted number of cities that implemented the restriction within different distances, using city population as weights. It also controls for population, GDP per capita, government expenditure and government revenue. Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Heterogeneous effect of the restriction policy on new vehicle sales

Dep. Var.	log(sales)		
	(1)	(2)	(3)
Policy × Nonlocal brand	0.0144	0.0112	-0.00267
	(0.0236)	(0.0252)	(0.0231)
Policy × Local brand	0.817***	0.702***	0.430***
	(0.112)	(0.115)	(0.0927)
Weighted number of adopted cities (<=200 km)	0.00512	0.000142	0.00203
	(0.0383)	(0.0417)	(0.0382)
Weighted number of adopted cities (200-500 km)	0.0908*	0.0905*	0.00195
	(0.0501)	(0.0542)	(0.0462)
Weighted number of adopted cities (500-1000 km)	0.346***	0.413***	0.322***
	(0.103)	(0.113)	(0.111)
Weighted number of adopted cities (>1000 km)	-0.143	-0.0999	-0.0595
	(0.150)	(0.162)	(0.148)
City FEs	✓	✓	
Year-quarter FEs	✓	✓	✓
Model FEs		✓	
City×model FEs			✓
N	547038	547036	545104
R^2	0.282	0.619	0.835

Notes: This table reports the heterogeneous effects on new vehicle sales using OLS. The regressions control for weighted number of cities that implemented the restriction within different distances, using city population as weights. It also controls for population, GDP per capita, government expenditure and government revenue. Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.