ESSAYS ON ENVIRONMENTAL POLICIES IN THE TRANSPORTATION SECTOR

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This dissertation consists of three essays studying the effects of environmental regulations and policies in the transportation sector in China.

The first chapter studies the effectiveness, efficiency, and distributional effect of using trade restrictions on used vehicles to protect the local environment. Leveraging comprehensive data on the bilateral trade of vehicles across Chinese prefecture cities and the staggered rollout of import restrictions on used vehicles implemented by city governments from 2013 to 2015, this chapter shows empirical evidence that import restrictions reduce net imports of used vehicles, and cities' import restrictions are strategic complements. With a multi-sector multi-region structural trade model, this study shows that unilaterally restricting imports of used vehicles leads to welfare trade-offs between economic losses vs. environmental benefits. Restricting heavy-polluting vehicles makes some cities better off, especially lower-income cities. However, decentralized restrictions are socially inefficient due to strategic interactions, and the effectiveness and efficiency of using import restrictions as an environmental instrument are limited compared to emission taxes.

The second chapter, joint with Jie Bai, Danxia Xie, and Shanjun Li, explores the import restrictions on used vehicles in China from the perspective of local protectionism. Leveraging the universe of new and used vehicle registration/sales data and the staggered removal of the restriction across cities from 2016 to 2018, this analysis shows that the removal of restriction led to a sharp increase in the cross-city flow of used vehicles but had no significant impacts on local air quality in the short run. Interestingly, new vehicle market points to a prisoner's dilemma among city governments: a unilateral removal of the policy would reduce new vehicle sales in a city but increase new vehicle sales in

other cities. The effect is stronger in cities with a large automobile industry. The findings highlight alternative motives behind local environmental regulations and the need for coordinated efforts at the national level.

The third chapter, joint with Shanjun Li, Xianglei Zhu, Yiding Ma, and Fan Zhang, examines the effectiveness of various policy measures that underlie the rapid development of the EV market in China, based on detailed data on EV sales, local and central government incentive programs, and charging stations in 150 cities from 2015 to 2018. This research finds that consumer subsidies for vehicle purchases accounted for more than half of EV sales in China. Nevertheless, investments in charging infrastructure were much more cost-effective than consumer subsidies. An inexpensive policy that merely provided EVs with a distinctive, green license plate was strikingly effective. These findings demonstrate the varying efficacy of different policy instruments and highlight the critical role of the government in promoting clean technologies.

BIOGRAPHICAL SKETCH

Hui Zhou was born in Wuhan, Hubei. She got her bachelor's degree in Harbor and Coastal Engineering from Hohai University in 2001, and her Ph.D. degree in Engineering Economics and Management from Hohai University in 2006. She joined the School of Economics and Management at Nanjing University of Information Science and Technology (NUIST) in 2006. Her main research interests are environmental economics, energy economics, and climate change. She visited Cornell University as a visiting scholar from July 2016 to March 2017, hosted by Professor Shanjun Li. She loved the research environment so much and decided to pursue a Ph.D. in the U.S. She was very excited to be admitted to the Ph.D. program at the Dyson School of Applied Economics and Management in 2017. At Cornell, she worked on projects studying the effect and efficiency of environmental policies in the transportation sector in China. She will join the Department of Environmental and Natural Resource Economics at the University of Rhode Island as an Assistant Professor in the Fall of 2023.

Dedicated to my husband Wei, my daughter Cynthia, and my parents.

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CHAPTER 1

RESTRICTING TRADE FOR THE ENVIRONMENT? EVIDENCE FROM IMPORT RESTRICTIONS ON USED VEHICLES IN CHINA

1.1 Introduction

Fast-growing transboundary movements of dirty goods, such as used vehicles, hazardous waste and scrap[1] have created increasing environmental concerns (Davis and Kahn, 2010). To address these concerns, many countries or local jurisdictions have adopted policies to restrict imports of dirty goods (UNEP, 2020).[2] Restricting the trade of dirty goods for environmental purposes raises important questions about the effectiveness, efficiency, and distributional effect of such policies. Can restricting imports of dirty goods protect the local environment? Does it improve social welfare? Are decentralized policies socially efficient? Who gains and who loses?

Those questions have not yet been fully answered. Theoretically, trade policy can be used as a second-best environmental policy (Copeland and Taylor, 2004). However, studies on the trade of dirty goods, especially empirical evidence of the environmental effect and evaluations of the welfare effect, are limited. Regarding the efficiency question, the efficiency of decentralized policies could be impaired if local regulations generate spillovers to other jurisdictions (Shobe, 2020). This could be the case in the trade of dirty goods, as restricting imports by one government could change general equilibrium prices and flows of dirty goods through the trade network (Brooks et al., 2018), thus generat-

[1] From 2015 to 2018, the EU, Japan, and the USA exported a total of nearly 14 million used light-duty vehicles worldwide, mostly to developing countries (UNEP, 2020). From 2008 to 2012, international trade in waste and scrap exceeds 1 billion tons, and the growth rate between 1992 and 2012 is more than 500 percent (Kellenberg, 2015).

[2] For example, some U.S. states imposed higher taxes on hazardous waste imported from other states (Levinson, 1999a,b). The United Nations Environment Program (UNEP) surveys 146 countries and reports that 87 have adopted some regulation(s) to restrict used vehicle imports such as age limits, emission-based restrictions, taxes/subsidies, border inspections, etc. (UNEP, 2020).

ing economic and environmental spillovers into other locations and leading to strategic responses. However, these spillovers and strategic interactions in trade restrictions and their welfare consequences have not been well documented.

This paper examines the effectiveness, efficiency, and distributional effect of using trade restrictions for environmental purposes in the context of intercity import restrictions on used vehicles in China. To control vehicle pollution, many cities in China adopted trade barriers on used vehicles — cities restricted imports of used vehicles from other cities based on certain tailpipe emission standards they chose while allowing for free trade of used vehicles regardless of emission standards within the local market. This paper asks the following questions: Is restricting imports of used vehicles effective and what is the welfare effect? Are there interjurisdictional spillovers and strategic interactions in adopting the restrictions? How (in)efficient is the decentralized equilibrium? Which cities gain from the restriction and which lose?

This paper starts with a 2-country-2-good stylized model that extends the optimal tariff and retaliation model (Johnson, 1953; Mayer, 1981) to consider the trade of dirty goods. The model gives four predictions. A unilateral increase in the import barrier of one country may (1) reduce net imports of dirty goods and increase environmental benefits under certain conditions, (2) increase welfare when environmental benefits outweigh the losses from reduced trade, (3) generates spillovers on the other country, which leads to a strategic response in a "race-to-the-top" manner. (4) The decentralized equilibrium is inefficient.

To empirically test the first and third predictions, I compile comprehensive data on bilateral trade flows of used vehicles across cities in China from 2013 to 2015, and the timing and stringency of import restrictions on used vehicles adopted by city.

First, I use an event study framework to estimate the effect of adopting import restrictions on net imports of used vehicles. To address the "negative-weighting issue" in the standard two-way fixed effects estimator (Borusyak and Jaravel, 2017; Goodman-Bacon, 2021; Sun and Abraham, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021), I apply the doubly-robust DID estimator proposed by Callaway and Sant'Anna (2021). The result shows that the adoption of import restrictions reduces net imports of restricted used vehicles, consistent with the theoretical prediction.

Second, I test whether there are strategic interactions in the adoption of import restrictions across cities. Following Fredriksson and Millimet (2002b), I regress one city's restriction indicator on a lagged weighted average of other cities' restrictions,[3] controlling for city fixed effects, time fixed effects, and economic variables. The coefficients for the lagged index are positive and significant, implying that cities' import restrictions are strategic complements.

These empirical results provide supporting evidence on how import restrictions may generate environmental benefits through reduced net imports, and strategic interactions between cities. However, they are limited in making further statements about the welfare effect and the efficiency of decentralized policies. Therefore, I develop a multi-sector multi-region general equilibrium trade model à la Armington (1969) featuring the bilateral trade of vehicles across cities in China.

Then I estimate the key parameters of the model — aggregate demand elasticity,[4] aggregate supply elasticity, and elasticity of substitution between sectors, applying a "model-implied" instrumental variables approach (Allen et al., 2020) with a two-step procedure (Allen et al., 2020; Eaton and Kortum, 2002). The estimated parameters are

[3]The weights are the share of used vehicle trade between the adopting city and every other city, over the total trade of used vehicles of the adopting city in the first quarter of 2013. Higher weights are given to more important partners in the trade of used vehicles.

[4]The aggregate demand elasticity governs the relationship between bilateral trade flows and prices (including trade costs), which is often referred to as "trade elasticity" in literature. In the Armington model, this demand elasticity equals the elasticity of substitution between goods from different locations minus one.

consistent with estimates in the trade literature.

I consider four policy counterfactuals: (1) unilaterally optimal restrictions in which each city chooses an emission-based import restriction[5] to maximize its own welfare (gains from trade net of environmental costs); (2) non-cooperative Nash equilibrium in which all cities simultaneously choose their unilaterally optimal restriction, taking other cities' restrictions as given; (3) nationally optimal import restrictions in which a social planner decides which cities should restrict imports of used vehicles at what stringency to maximize the total social welfare; and (4) emission taxes on both imported and locally traded used vehicles based on lifetime emission damages. I use "exact hat algebra" (Dekle et al., 2008) to solve for changes in equilibrium outcomes under different counterfactuals and quantify welfare effects.

I find that unilaterally restricting imports of used vehicles could increase environmental benefits through two channels: reduced net imports and increased scrappage due to lower vehicle (real) prices; the scrap channel plays a bigger role. Restricting high-polluting vehicles makes cities better off, especially lower-income cities. However, these unilateral restrictions generate significant spillovers onto other cities and incentivize other cities to adopt or tighten restrictions in response. Due to spillovers and strategic interactions, the decentralized equilibrium is socially inefficient, achieving about 80 percent of welfare gains under the socially optimal restriction. Furthermore, the effectiveness and efficiency of using import restrictions as an environmental instrument are limited — the socially optimal restrictions can only achieve 14 percent of emission reductions and 12 percent of welfare gains attainable under emission taxes.

This paper contributes to existing research in several ways. Despite extensive studies quantifying gains from trade (Caliendo and Parro, 2015; Arkolakis et al., 2012; Grubel,

[5] An emission-based import restriction restricts the imports of used vehicles based on an emission standard. Vehicles that do not meet the standard are not allowed to be imported.

1980; Clerides, 2008), less is known about the welfare trade-offs between gains from trade and induced environmental costs. Shapiro (2016) is among the first to use a quantitative trade model to compare environmental costs from CO_2 emissions against benefits from international trade. Thakur (2022) evaluates the welfare effect of international trade in waste. This paper adds to this nascent literature by quantifying the welfare effect of (restricting) trade in used vehicles, which has important policy implications in regulating transboundary movements of environmental-damaging goods.

Second, this paper contributes to the literature on environmental federalism. Studies show that local jurisdictions could interact strategically in environmental regulations (Oates, 2001; Potoski, 2001; Fredriksson and Millimet, 2002a,b; Millimet, 2003; Brueckner, 2003), but little is known about the welfare consequence of such interactions. This paper adds empirical evidence of strategic interactions in decentralized import restrictions on used vehicles, and further evaluates the welfare effect from spillovers and strategic interactions, calling attention to the efficiency loss of using decentralized policies when interjurisdictional spillovers are present.

Last but not least, this paper contributes to the literature on environmental regulations of vehicle emissions. The existing literature has examined various vehicle regulations, such as vehicle exhaust standards (Jacobsen et al., 2021), fuel economy standards (Anderson and Sallee, 2011; Klier and Linn, 2012; Ito and Sallee, 2018; Bento et al., 2020; Reynaert, 2021), the "Cash-for-Clunkers" program (Li et al., 2013, 2022b), driving restrictions (Davis, 2008; Barahona et al., 2020), and gasoline taxes (Li et al., 2014; Jacobsen and Van Benthem, 2015). These studies provide important insights on how to regulate *local* vehicle emissions, while this paper adds a spatial and a trade policy dimension to the analysis. In addition, by comparing the trade channel and the scrap channel in which import restrictions affect the environment, this paper highlights the importance of speeding up the scrappage of dirty vehicles compared to limiting the inflow of dirty vehicles.

The rest of this paper is organized as follows. Section 1.2 presents a stylized model and makes several predictions. Section 1.3 introduces the institutional background and describes data sources. Section 1.4 empirically tests the effect of import restrictions on used vehicles in China on trade flows of used vehicles, and tests strategic interactions between cities. Section 1.5 develops a structural trade model. Section 1.6 estimates the key parameters of the trade model. Section 1.7 simulates welfare changes under different counterfactuals. Section 1.8 concludes.

1.2 A Stylized Model

This section extends the optimal tariff and retaliation model developed by Johnson (1953) and Mayer (1981) to a context of trade in dirty goods. I use this model to show how import restrictions on dirty goods can change trade flows and affect welfare, and generates spillovers that lead to strategic interactions, and whether decentralized restrictions are efficient.

Consider a two-country, two-good world. Label the two countries "home" and "foreign", and the two goods 1 and 2. Suppose that the home country has a comparative advantage in producing good 1, and the foreign country has a comparative advantage in producing good 2. The home country imports good 2, denoted by $M_2 > 0$, and the foreign country imports good 1, denoted by $M_1^* > 0$. Let $\tau \geq 1$ and $\tau^* \geq 1$ denote the iceberg trade costs of the home country and the foreign country to import, respectively. These iceberg trade costs include transportation costs and non-tariff barriers. Both goods are clean to produce, but dirty to consume. Marginal damage depends on where they are consumed. Assume that one unit of consumption leads to environmental damage of $\delta > 0$ in the home country, and $\delta^* > 0$ in the foreign country.

Let (p_1, p_2) and (p_1^*, p_2^*) be the prices of the two goods in the home country and the foreign country, respectively. Use good 1 as a numeraire. Then

$$p_1 = 1, p_2 = p_2^*\tau \quad \text{and} \quad p_1^* = \tau^*$$

Let $\pi = p_2^*/p_1$ be the price of good 2 relative to good 1, without iceberg trade costs. π measures the terms of trade for the foreign country. A decrease in π means an improvement in terms of trade for the home country but a worsening for the foreign country.

Write the indirect utility function of the home country from consumption as

$$V = V(p_2, Y) \tag{1.1}$$

where V is the maximum utility that could be achieved by the home country given the price p_2 and its income Y. V represents welfare from consumption, which is also denoted as "gains from trade".

$$p_2 = \pi\tau \tag{1.2}$$

$$Y = Q_1 \tag{1.3}$$

where Q_1 is the total quantity of good 1 produced in the home country, determined by its endowment.

Define the import demand functions for the two countries as follows:

$$M_2 = M_2(\pi, \tau) \tag{1.4}$$

$$M_1^* = M_1^*(\pi, \tau^*) \tag{1.5}$$

where M_2 is the quantity of good 2 imported into the home country from the foreign country, and M_1^* is the quantity of good 1 imported into the foreign country from the home country. $\partial M_2/\partial \pi < 0$, $\partial M_1^*/\partial \pi > 0$, and $\partial M_2/\partial \tau < 0$, $\partial M_1^*/\partial \tau^* < 0$.

Assume that trade is balanced:

$$\tau^* M_1^* = \pi \tau M_2 \tag{1.6}$$

Environmental damage in the home country is determined by the number of goods consumed and the marginal damage from consumption:

$$D = \delta(Q_1 + M_2 - M_1^*) \tag{1.7}$$

where δ is the marginal damage from one unit of consumption in the home country. $M_2 - M_1^*$ is the net imports into the home country.

Can restricting imports increase environmental benefits? I answer this question by analyzing how a unilateral increase in the import barrier in the home country affects trade flows. Intuitively, an increase in the import barrier will increase the total costs of importing goods and reduce imports. At the same time, the increase in import barriers will improve the terms of trade for the home country, making exports more expensive than before and thus reducing exports. The effect on net imports is ambiguous, depending on the relative magnitude of decreases in imports and exports. When the increase in import barriers reduces net imports of dirty goods, it can increase environmental benefits.

Proposition 1: *One country unilaterally increasing its import barrier reduces its imports and exports. The effect on net imports is ambiguous. Net imports decrease when the ex-ante imports-exports ratio is greater than $\frac{\epsilon-1}{\epsilon}$, where ϵ is the (negative) price elasticity of imports for the home country.*

Proof: See Appendix A.1.1.

Can restricting imports increase welfare? Denote the welfare of the home country as the sum of indirect utility from consumption minus environmental costs, which is a function of the trade frictions of the two countries (τ and τ^*).

$$W = V - D = W(\tau, \tau^*)$$

The marginal effect of increasing import barrier on the welfare of the home country depends on the marginal effects on gains from trade and on environmental costs:

$$\frac{\partial W}{\partial \tau} = \frac{\partial V}{\partial \tau} - \frac{\partial D}{\partial \tau} = \frac{\partial V}{\partial \tau} - \delta \frac{\partial (M_2 - M_1^*)}{\partial \tau} \tag{1.8}$$

I have shown that a unilateral increase in the import barrier can reduce net imports under certain conditions. However, gains from trade will always decrease due to higher import prices and reduced imports. The sign of the welfare effect hinges on the sign of the environmental effect and on δ: When environmental benefits from reduced imports outweigh the dead weight losses, welfare increases.

Proposition 2: *A unilateral increase in import barriers has two effects on its own welfare. It reduces gains from trade but may increase environmental benefits under certain conditions. Welfare may increase when the environmental benefits outweigh the losses.*

Proof: See Appendix A.1.2.

Are there spillovers? To examine the spillover effect, assume that the foreign country unilaterally increases its import barrier. The marginal effect on the welfare of the home country is as follows:

$$\frac{\partial W}{\partial \tau^*} = \frac{\partial V}{\partial \tau^*} - \frac{\partial D}{\partial \tau^*} = \frac{\partial V}{\partial \tau^*} - \delta \frac{\partial (M_2 - M_1^*)}{\partial \tau^*} \tag{1.9}$$

When the foreign country unilaterally increases its import barrier, it worsens the terms of trade for the home country and reduces its gains from trade. That is a negative spillover effect on gains from trade, $\frac{\partial V}{\partial \tau^*} < 0$. On the other hand, the sign of $\frac{\partial D}{\partial \tau^*}$ is ambiguous. When increasing τ^* reduces the foreign country's net imports ($\frac{\partial (M_1^* - M_2)}{\partial \tau^*} < 0$), it is equivalent to increasing the net imports of the home country, i.e., $\frac{\partial (M_2 - M_1^*)}{\partial \tau^*} > 0$, which implies a negative spillover on the environment of the home country. In this case, a unilateral increase in the import barrier could generate negative spillovers on the welfare of the other country. If $\frac{\partial (M_2 - M_1^*)}{\partial \tau^*} < 0$ and δ is large, then the total spillover effect could be positive.

Proposition 3: *A unilateral increase in the import barrier generates negative spillovers on the welfare of the other country under certain conditions.*

Proof: See Appendix A.1.3.

Do countries interact strategically? Next, I examine how one country's optimal import barrier depends on the other country's import barrier. Figure 1.1 plots the welfare contours of the home country in the (τ, τ^*) space. Each contour describes the combination of τ and τ^* for which the home country obtains the same level of welfare. The vertically lower curve corresponds to higher welfare. An expression for the slope of the contours is derived in Appendix A.1.4. For values of $\tau \geq 1$, their slopes are positive, zero, and negative. When the slope of the contour is zero, it indicates the best response of the home country τ to the foreign country's trade cost τ^*. Therefore, the locus of these points traces the best response function of the home country.

Proposition 4: *Under certain conditions, the best response function of the optimal import barrier is upward sloping, implying that one country may increase its import barrier in response to the other country's increase in the import barrier.*

Proof: See Appendix A.1.4.

Is the decentralized equilibrium efficient? The intersection of the best response functions for the two countries determines the non-cooperative Nash equilibrium of the game in which the home country and the foreign country set their import barriers strategically. Under the Nash equilibrium, both countries choose their optimal import barrier conditional on the other country's import barrier to maximize their own welfare without considering the spillovers on the other country. In contrast, in the problem of centralized policy-making, the social planner chooses import barriers for both countries to maximize the sum welfare of the two countries, internalizing the spillovers. Due to spillover effects, the first-order conditions for these two maximization problems are not identical; thus, the Nash equilibrium cannot achieve Pareto efficiency.

Proposition 5: *The non-cooperative Nash equilibrium of the static game in which the home country and the foreign country set their import barriers strategically is inefficient.*

Proof: See Appendix A.1.5.

These propositions make testable predictions on how restricting imports of dirty goods can change trade flows, and how governments may strategically interact with each other in adopting such restrictions. They also predict welfare gains for the country that adopts the restriction, the spillover effect on the other country, and the inefficiency of decentralized policies. The following sections use data on intercity import restrictions on used vehicles in China to empirically test predictions on trade flows and strategic interactions and to quantify welfare effects using simulations of a structural trade model.

1.3 Background and Data

1.3.1 Institutional Background

Many countries around the world restrict imports of used vehicles in different ways, such as completely banning, partially banning based on age or emission standard, using fiscal instruments like differential customs or registration tariffs, among others (UNEP, 2020). At the national level, China has imposed a complete ban on imports of used vehicles from other countries. In addition to that, there have been selective import restrictions at the subnational level, adopted by cities[6] based on tailpipe emission standards. China introduced the first set of tailpipe emission standards, *China 1*, in 2001, and has tightened the standards from *China 1* to *China 6* over time (see Figure 1.2).[7] The emission standards

[6] There are five levels of administrative divisions in China: provincial (province, autonomous region, municipality, and special administrative region), prefectural, county, township and village. Prefectural-level divisions include 293 prefecture-level cities, 7 prefectures, 30 autonomous prefectures, and 3 leagues. See https://en.wikipedia.org/wiki/Administrative_divisions_of_China#Prefectural_level_(2nd). In this paper, I use "cities" to refer to prefectural-level divisions and four municipalities.

[7] Tailpipe emission standards set the maximum amount of pollutants allowed in exhaust gases released from an internal combustion engine. Regulated pollutants include carbon monoxide (CO), hydrocarbons

were established by the Ministry of Ecology and Environment of China and applied to the manufacturing of new vehicles.[8] In 2008, Beijing began to use the emission standard to restrict imports of used vehicles from other cities. Consumers in Beijing were prohibited from buying used vehicles from other cities that were below an emission standard but were free to purchase used vehicles regardless of emission standards within the local market.[9] This policy, in essence, an emission-based import restriction, was quickly followed by many other cities. At the end of 2015, almost 95 percent of cities had adopted this policy, most of which used *China 4* as the minimum standard for imports.[10] Figure 1.3 shows the roll-out of import restrictions in cities over time.

Import restrictions on used vehicles provoked a public backlash and were considered "an abuse of administrative power to exclude or restrict competition" by the China National Development and Reform Commission. On 25 March 2016, the General Office of the State Council of China published a directive urging local governments, except for a few key areas, to remove the restriction before 31 May 2016.[11] However, cities were reluctant to comply. Some cities used a loophole in the definition of "clunkers" to try to bypass the directive.[12] The central government continued to push for the removal of the restriction, but the progress was slow. By June 2018, 40 percent of cities had not yet complied.

(HC), nitrogen oxides (NO_x), and particular matter (PM). The limits set in *China 1* to *China 5* are similar to those of the European tailpipe emission standards *Euro 1* to *Euro 5*.

[8]Vehicle (engine) makers are responsible for complying with tailpipe emission standards. Normally, before a vehicle (engine) is put on the market, it must pass an emission certification according to the emission standard in effect.

[9]This policy was enforced through vehicle registrations. Used vehicles purchased from other cities below the required standard were not able to be registered with the local Department of Motor Vehicles.

[10]Source: http://www.caam.org.cn/chn/8/cate_83/con_5192590.html

[11]The directive exempted cities in the designated *key areas of air pollution prevention and control* of compliance. Key areas of air pollution prevention and control include Beijing, Tianjin, Shanghai, Hebei province, Jiangsu province, Zhejiang province, Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, and Zhongshan. Source: http://www.gov.cn/zhengce/content/2016-03/25/content_5058006.htm

[12]In 2014, the Ministry of Environmental Protection of China issued a document to encourage the scrappage of "yellow labeled" vehicles and "clunkers". In this document, "yellow-labeled" vehicles are defined as those that do not meet the emission standard *China 1*, and "clunkers" as those that do not meet *China 4*. Source: https://www.mee.gov.cn/gkml/hbb/bwj/201409/W020140918616769509794.pdf

1.3.2 Intercity Trade of Used Vehicles

I compile a new data set on the intercity trade value of used vehicles in China during the period January 2013 to June 2018 from three components: (1) the volume trade flow of used vehicles, (2) the transaction price of each used vehicle (excluding transportation costs), and (3) the transportation costs to transport one vehicle unit from one city to another. This section explains each of these components in more detail.

Trade volume I compile the intercity trade flows of used vehicles in China from the universe of used vehicle registration data over the period of January 2013 to June 2018. The raw registration data record 40.05 million used vehicle transactions, with information on the number of vehicles in each transaction, transaction year and month, the origin registration city, the destination registration city, the emission standard each vehicle meets, and a rich set of vehicle attributes (manufacturer, model, engine size, footprint, age, etc.). The raw data are aggregated by origin×destination×emission intensity category×year-month. The origin and destination are cities in China. Used vehicles are classified into six emission intensity categories based on the emission standards they meet, that is, *China 1* to *China 5* for gasoline vehicles, plus electric vehicles.

Figure 1.4 illustrates the spatial pattern of intercity trade of used vehicles in China during 2013-2018. Each point represents a city included in our sample. The 45-degree line represents balanced imports and exports. The size of each point denotes the average GDP per capita for 2013-2018. Points above the 45-degree line are net importers of used vehicles, which are mostly from low-income cities. Points below the 45-degree line are net exporters which are mostly high-income cities. This pattern is consistent with the stylized fact of international trade that used vehicles mostly flow from high-income countries to low-income countries (Davis and Kahn, 2010; Clerides, 2008).

Transaction prices The used vehicle registration data contain only trade volumes, but not trade values. To impute transaction prices of used vehicles, I scrapped auction prices from one of the largest online auction platforms for used vehicles in China, Tiantian Paiche (`https://www.ttpai.cn/`). Data from 100,875 used vehicle auctions from November 2018 to February 2021 were scrapped, including auction price, vehicle brand, model, age, odometer, city of registration, vehicle type, and the number of previous ownership transfers. The Appendix Table A.1 summarizes the key statistics of the registration data and the auction data. The auction data cover a later period (November 2018 to February 2021) than the registration data (January 2013 to June 2018). Auction data include a similar number of vehicle brands and more models compared to registration data. However, the auctions were only listed in 54 cities out of a total of 350 cities. The age distributions of the used vehicles in the two data sets are very similar, as shown in Appendix Figure A.1.

I use the auction price data to estimate a price hedonic model based on vehicle age and model fixed effects:

$$p_{km} = \beta_0 + \theta_a + \alpha_m + \epsilon_{km}$$

where p_{km} is the auction price of vehicle k for vehicle brand-model m. θ_a is age fixed effects. α_m is brand-model fixed effects. ϵ_{km} is the idiosyncratic error term.

The estimates for the hedonic model are reported in Appendix Table A.2. The results show that the prices of used vehicles depreciate with age as expected. The coefficients remain robust when adding year-month fixed effects in column (2) and city fixed effects in column (3). The hedonic model could explain 94 percent of price variations. The predicted prices follow very closely the observed prices, as shown in the Appendix Figure A.2. Based on the high predictability of the hedonic model, I impute the prices of all vehicles in the registration data using the results of column (1).

Transportation costs I calculate the transportation costs of shipping one used vehicle unit from one city to another by multiplying the unit-distance cost parameter by the distance between the two cities. The unit-distance cost is made up of highway tolls and average fuel costs. I choose the value of ¥0.5 per km as the average toll rate on the highway, and ¥0.6 per km as the average fuel costs per unit distance.[13] The distance between two cities in China is calculated using Vincenty's formula based on the longitudes and latitudes of the city centers.[14]

With transaction prices and transportation costs, I construct the traded value of each used vehicle included in the registration data and collapse to the city-pair level to obtain the bilateral trade data in values.

1.3.3 Environmental Costs of Vehicle Emissions

This section describes the sources of various data sets needed to quantify the environmental costs of vehicle tailpipe emissions and how I construct them.

Marginal damage of pollution It is important to account for the spatial heterogeneity of environmental damage from emissions (Holland et al., 2016b). I follow three steps to calibrate the marginal damage of pollution by city by pollutant: (1) determine how emissions affect the exposure of the population to the pollution, (2) assess how exposure affects mortality risk, and (3) translate the change in mortality risk in monetary terms (Parry et al., 2014b). The heterogeneity comes from the first step only.

[13] Source: `https://en.wikipedia.org/wiki/Expressways_of_China`

[14] Vincenty's formulae calculates the distance between two points on the surface of a spheroid. This method is more accurate than other methods, such as the great-circle distance, by assuming that the Earth is an oblate spheroid rather than a spherical one. The distance within a city is assumed to be zero.

To circumvent the need to use a highly complex air quality model to determine the relationship between emissions and exposure concentrations (Muller and Mendelsohn, 2007, 2009), I use the intake fractions method, which has been widely adopted in the literature to estimate the damage from emissions (Parry et al., 2014b; Humbert et al., 2011; Apte et al., 2012). The intake fraction is defined as the ratio of the inhaled pollution by the exposed population to the total amount of pollution emitted from a specific source. The intake fraction depends on the size of the exposed population and the meteorological conditions. The steady-state intake fraction can be approximated by a simple equation.

$$iF_j = Q\frac{LPD_j}{DR_j} \tag{1.10}$$

where j denotes the location. iF is the intake fraction. Q is the average breathing rate ($m^3s^{-1}person^{-1}$). $LPD_j = P_j/\sqrt{A_j}$ is the linear population density (persons m^{-1}), in which P_j is the population and A_j the area of urbanized land. $DR_j = \overline{1/u_jH_j}^{-1}$ is the normalized dilution rate (m^2s^{-1}), also known as the "ventilation coefficient" (Singh and Pandya, 2013), which multiplies the wind speed (u_j) by the atmospheric mixing height (H_j).[15]

The next step is to determine how exposure to pollution affects the risk of mortality. The large health literature has shown that pollution will increase the mortality risk of pollution-related diseases and has established the dose-response relationship. Following Parry et al. (2014b), I choose the baseline annual mortality rate to be 4 persons per 1,000 population. Influential epidemiological studies find that a 10 $\mu g/m^3$ increase in PM concentrations increases total mortality by 4-10 percent (Künzli et al., 2000; Pope Ill et al., 2002; Burnett et al., 2014). I take the value of 10 percent in this paper, following Künzli et al. (2000). This indicates that an increase of 1 $\mu g/m^3$ in PM concentrations increases the

[15] I aggregate the wind speed data to the city level by taking an average of the 2-minute average wind speed data at the weather monitoring stations within a city. For the atmospheric mixing height, I refer to Zhu et al. (2018) and use a uniform value of 500 m for all cities, as comprehensive estimates of the mixing height for all cities in China are not available.

annual population mortality rate by 40 per 1 million.

The last step is to evaluate the change in mortality rate in monetary terms using the value of a statistical life (VSL). The value of VSL varies greatly. Using a hedonic wage model, Qin et al. (2013) estimate that the VSL in China is 1.81 million Chinese Yuan, approximately 0.22 million US dollars. This is similar to the estimate of 0.21 million US dollars obtained in Barwick et al. (2018), but significantly lower than the estimate of more than 1 million US dollars in Parry et al. (2014b). For the following analysis, I use 0.21 million 2015 US dollars for all exposed populations in China, not adjusted according to population age or per capita income of each city.

The marginal damage of a additional ton of pollution emission is then computed as

$$MD_{jk} = \frac{iF_j}{Q} m_k \text{VSL} \tag{1.11}$$

where iF_c is the intake fraction defined before. Q is the average breathing rate. $\frac{iF_c}{Q}$ is the exposure to pollution. m_k is the change in mortality rate due to one unit change of pollution concentration. VSL is the value of a statistical life.

The values of the city-specific marginal damage, intake fractions, and other intermediate variables are summarized in Table 1.1. From 2013 to 2015, the calculated values of the intake fraction vary from 4 ppm to 569 ppm, indicating significant heterogeneity between cities, driven by the density of the city population, the urbanized area, and the meteorological conditions. The nonweighted mean of the city intake fraction is 83.4 ppm, greater than the value obtained in Apte et al. (2012) for China (44 ppm). The marginal damage from an additional ton of $PM_{2.5}$ emission ranges from $\$5,611$ to $\$903,469$, and the mean is $\$132,302$. The mean of my calculation is consistent with the existing values obtained in China, $\$124,441$ from Parry et al. (2014b), and based on US data, $\$94,000$ from Goodkind et al. (2019), and $\$88,000$ – $\$130,000$ from Heo et al. (2016). The heat map of the marginal damage of $PM_{2.5}$ emissions in China by city is shown in Figure 1.5. I obtain the marginal damage of NO_x by scaling the marginal damage of $PM_{2.5}$ by a factor of 13000/94000, for which \$13,000 and \$94,000 are the estimates for the marginal damage of NO_x and $PM_{2.5}$ in Goodkind et al. (2019).

Emission factors An emission factor for vehicles is the representative amount of the pollutant emitted into the atmosphere per vehicle per unit distance traveled. Vehicle emission factors vary according to the emission standard that the vehicle meets and the age of the vehicle. Vehicles produced at different times were subjected to different tailpipe emission standards, which determine their baseline emission factors. I classify vehicles according to the emission standards they meet, namely *China 1* to *China 5*, and use the emission limits specified by each standard as baseline emission factors for vehicles in that category. Furthermore, for vehicles within the same emission standard category, emissions increase as they age (Jacobsen et al., 2021). Following Jacobsen et al. (2021), I choose the emission deterioration factor by emission standard based on the average age of used vehicles in that category. The final emission factor is the multiplication of the baseline emission factor and the deterioration factor. These values are reported in Table 1.2.

Lifetime vehicle kilometers traveled I draw the value of the mean annual vehicle kilometers traveled, 18000 km per year, from *Technical Guidelines for the Compilation of Air Pollutant Emission Inventory of Road Motor Vehicles*.[16]. However, the *Guidelines* does not report the annual VKT by vehicle age. Thus, I scaled the 2009 NHTS average annual vehicle miles of travel per vehicle by vehicle age and type[17] to obtain the annual VKT by

[16]The document was issued by the Ministry of Ecology and Environment to provide guidelines for building up motor vehicle emissions inventory at the local level. `https://www.mee.gov.cn/gkml/hbb/bgg/201501/W020150107594587831090.pdf`

[17]Source: `https://nhts.ornl.gov/tables09/fatcat/2009/best_VEHAGE_VEHTYPE.html`

age in China adjusted by their annual means. From the registration data of used vehicles, I calculate the mean ages of vehicles by emission standard (see Figure A.3 of the age distributions by emission standard). Assuming that a vehicle's life is 20 years, I compute the vehicle kilometers traveled for the remaining lifetime for vehicles in different emission standard categories.

Vehicle stock and scrappage rate I obtain the total number of vehicle stocks by city by year from the CEIC database and draw the composition of the national fleet by emission standard category from *China Vehicle Emission Control Annual Report* for the years 2013 to 2015. However, detailed information about the composition of the fleet per city is not available. Therefore, I use the national fleet composition to impute vehicle stock by emission standard for each city. Data on the scrappage rate per city in China are also not available. Therefore, I used data on vehicle exit rates by vehicle age in the U.S. from Davis and Kahn (2010), and scaled them to match the mean scrappage rate in China. The price elasticity of scrappage by vehicle age is obtained from Jacobsen and Van Benthem (2015).

1.3.4 Ambient Air Quality and Weather

Ambient air quality I obtain ambient air quality measures from the aerosol optical depth (AOD) using the Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm operated by NASA. MODIS records the degree of sunlight diffusion or adsorption in the entire atmospheric column corresponding to the section overpassed under cloudless conditions. Therefore, AOD captures the concentration of particles and is strongly correlated with $PM_{2.5}$, and could be used as a proxy for ambient particulate matter pollution (Barwick et al., 2019). I average the raw grid data to the city-quarter level from 2013 to 2015.

Meteorology I retrieve the meteorological data from 2013 to 2015 from the China National Meteorological Information Center. The Information Center has monthly meteorological data for 613 basic reference surface meteorological observation stations in China. The data include a rich set of meteorological measures in wind speed, temperature, atmospheric pressure, relative humidity, precipitation, and wind direction. Using the longitude and latitude of each meteorological station, I calculate the Vincenty distance between each station-city pair and match each city with the closest station. Then I average the city-monthly data to the city-quarter level.

The summary statistics of the data used in this paper are reported in Table 1.1.

1.4 Empirical Evidence

The theoretical model in Section 1.2 makes two predictions: (1) under certain conditions, increasing the import barrier can reduce net imports of restricted goods, and (2) one country can increase its import barrier in response to an increase in the import barrier of the other country. This section uses the roll-out of intercity import restrictions on used vehicles in China to empirically test these predictions. The sample is a panel of 312 cities by quarter between 2013 and 2015.[18]

1.4.1 The Effect of Import Restrictions on Used Vehicle Flows

A two-way fixed effects model seems a natural starting point to estimate the effect of import restrictions on used vehicle flows. I use the following specification:

[18] Cities whose annual used vehicle imports are less than 10 units, or with missing values for GDP per capita and population from 2013 to 2015 are dropped.

$$y_{it} = \beta_1 D_{it} + \beta_2 \sum_{j \neq i} w_{ij} D_{j,t-1} + \alpha_i + \delta_t + \gamma X_{i,yr-1} + \varepsilon_{it} \tag{1.12}$$

where the dependent variable y_{it} represents imports, exports, and net imports of restricted used vehicles in city i, year-quarter t. D_{it} is an indicator that equals 1 if city i has restricted imports of used vehicles based on emission standard *China 4* at time t. α_i and δ_t are city and time fixed effects. $X_{i,yr-1}$ is GDP per capita lagged one year.

In addition, one city's trade flows could also be affected if other cities impose import restrictions, that is, the spillover effect. To capture this effect, I construct an index of restriction exposure, $\sum_{j \neq i} w_{ij} D_{j,t-1}$, which is the weighted average of restriction indicators in cities other than i at time $t-1$ (Millimet and Roy, 2016). The weights are defined as $w_{ij} = \frac{trade_{ij}}{\sum_{j=1, j \neq i}^{N} trade_{ij}}$, which is the share of bilateral trade in used vehicles (imports plus exports) between city i and city j in the first quarter of 2013 (baseline), over the total trade in used vehicles (imports plus exports) of city i in the baseline. Thus, higher weights are given to larger trading partners of city i.

In the regression, the weighted average is lagged for one period. This is because including the contemporaneous term ($\sum_{j \neq i} w_{ji} D_{j,t}$) can lead to a "bad control" issue (Angrist and Pischke, 2008), if D_{it} and D_{jt} are interdependent. Including a lagged term will circumvent this issue under the assumption that strategic interactions (if any) occur with a time lag (Hayashi and Boadway, 2001), which I show below.

The results of the two-way fixed effects model are reported in columns (1) to (3) of Table 1.3. In columns (1) and (2), the coefficients for the restriction adoption dummy D_{it} are positive, and the coefficients for exposure to other restrictions $\sum_{j \neq i} w_{ij} D_{j,t}$ are negative. These signs are not expected with the theoretical prediction. In column (3), the coefficient for D_{it} is negative, and the coefficient for $\sum_{j \neq i} w_{ij} D_{j,t}$ is positive, both of which are consistent with the prediction that a unilateral import restriction could reduce net imports of the home city, and other cities' restrictions could increase net imports of the home city.

The inconsistency of the estimates in columns (1) and (2) could be driven by the "negative weighting issue" of the two-way fixed effects estimator with multiple treatment times when treatment effects are heterogeneous over time and (or) between groups, explored by a growing literature (Borusyak and Jaravel, 2017; Goodman-Bacon, 2021; Sun and Abraham, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021).[19] I apply the CSDID method proposed by (Callaway and Sant'Anna, 2021) to overcome this problem. This method is composed of two steps: the first step is to estimate the average treatment effect on the treated by treatment group and time,[20] only comparing treated units with never-treated units or later treated units; the second step then aggregates the average treatment effects between groups and time according to the study context.

In my sample, because most of the cities adopted the restriction at the end of the sample period, the size of the never-treated group is small. Therefore, in the first step estimation, I choose later-treated units as the comparison group and use the doubly robust DID estimand to recover the average treatment effect by treatment group and time.[21] The second step aggregates the average treatment effects estimated from the first step.[22]

To gain evidence to support the parallel trends assumption, I use this method to esti-

[19]The standard two-way fixed effects estimator compares treated units versus never-treated units, treated units versus not-yet-treated units, and later-treated units versus earlier-treated units. The third type of comparison is problematic when treatment effects are heterogeneous.

[20]Treatment groups are defined based on the time when they first get treated. Units treated at the same time are categorized into one treatment group.

[21]The doubly-robust estimand for the average treatment effect by treatment group and time is: $ATT_{g,t} = \mathrm{E}\left[\left(\frac{G_{i,g}}{\mathbb{E}[G_{i,g}]} - \frac{\frac{p_{i,g,t}(X)(1-D_{i,t})(1-G_{i,g})}{1-p_{i,g,t}(X)}}{\mathbb{E}[\frac{p_{i,g,t}(X)(1-D_{i,t})(1-G_{i,g})}{1-p_{i,g,t}(X)}]}\right)(Y_{i,t} - Y_{i,g-1} - m_{g,t}(X))\right]$, where $G_{i,g}$ is a dummy that equals one if unit i first gets treated at time g. $D_{i,t}$ is a dummy that equals one if unit i is treated in time t. $p_{i,g,t}(X) = Pr(G_{i,g} = 1|X, G_{i,g} + (1-D_{i,t})(1-G_{i,g}) = 1)$ is the probability of unit i being first treated at time g, conditional on covariates X and on either being a member of group g (that is, $G_{i,g} = 1$) or a member of not-yet-treated group by time t (that is, $(1-D_{i,t})(1-G_{i,g}) = 1$). $Y_{i,t}$ and $Y_{i,g-1}$ are the outcomes of unit i at time t and at time $g-1$ — one period before treated. $m_{g,t}(X) = \mathbb{E}[Y_{i,t} - Y_{i,g-1}|X, D_{i,t} = 0, G_{i,g} = 0]$ is the population outcome regressions for the "not-yet-treated" group by time t (Callaway and Sant'Anna, 2021).

[22]The aggregated treatment effect at event time e is: $\theta(e) = \sum_{g \in \mathcal{G}} \mathbb{1}(g + e \leq \mathcal{T}) Pr(G = g|G + e \leq \mathcal{T}) ATT_{g,g+e}$, where $\mathcal{T}$ is the last period of calendar time, $\mathcal{G}$ is the set of all treatment groups (Callaway and Sant'Anna, 2021).

mate the dynamic effects by event time. The coefficients are shown in Figure 1.6. For panels (a) to (c) the dependent variables are imports, exports, and net imports of restricted used vehicles (used vehicles that do not meet the standard *China 4*). All panels do not show significant pre-trends before restriction adoption, and imports, exports, and net imports decrease significantly after the restriction was adopted. The post-treatment coefficients are further aggregated to obtain an average treatment effect. The results are reported in columns (4) to (6) of Table 1.3. The coefficients for restriction adoption D_{it} are all negative and significant, which implies that imports, exports, and net imports decrease after restriction adoption, consistent with the theoretical prediction. These results provide empirical evidence that the import restriction could reduce net imports of restricted used vehicles and therefore could increase environmental benefits.[23]

1.4.2 The Effect of Import Restrictions on Ambient Air Quality

Does the adoption of import restrictions on used vehicles lead to an immediate improvement in local air quality? I use the aerosol optical depth (AOD) data with both the two-way fixed effects model and the CSDID method to explore this question. The specification for the two-way fixed effects model is similar to Equation (2.1), only adding two additional sets of controls. One set is meteorological variables; the other is the average air pollution in the upwind direction to account for the cross boundary transmission of pollution.

$$\ln(AOD)_{it} = \beta_1 D_{it} + \beta_2 \sum_{j \neq i} w_{ij} D_{j,t-1} + \mathbf{W}'_{it}\theta + \mathbf{U}'_{it}\xi + \alpha_i + \delta_t + \gamma X_{i,yr-1} + \varepsilon_{it} \tag{1.13}$$

[23] I don't interpret the values of these results as the causal effect because of the remaining endogeneity of restriction adoptions, after controlling for (lagged) restriction exposure, city- and time- fixed effects, and economic variables.

where the dependent variable is the log of AOD reading at city i at year-quarter t. $\mathbf{W}_{it}$ is a set of meteorological variables, including maximum wind speed, average temperature, average atmospheric pressure, average water vapor pressure, relative humidity, number of rainy days, and precipitation. $\mathbf{U}_{it}$ includes the inverse-distance-weighted average of air pollution (AOD) in the upwind direction.[24]

The results are reported in Table 1.4. Columns (1) to (3) are the estimates using the two-way fixed effects model, controlling for different sets of control variables. The coefficients for the restriction dummy are not significantly different from 0. Columns (4) and (6) are the estimates using the CSDID method. The estimated coefficients are negative, but not statistically significant. Figure A.4 shows the dynamic effects estimated with the full set of controls (weather and upwind pollution) using the CSDID method, which does not show significant pre-trends.

The null result suggests that the improvement in air quality induced by import restrictions on used vehicles could be limited in the short run. The import restriction affects air quality by changing the composition and size of the vehicle fleet. The vehicle fleet becomes cleaner as net imports of dirty used vehicles decrease and vehicle scrappage increases (which I will show in Section 1.5 below). However, this process takes time. On average, one city's net imports of restricted used vehicles decrease by 409 units in the next year, which is about 0.1 percent of the mean motor vehicle stock by city. In addition, the restriction on used vehicles may increase sales of new vehicles, which adds to the vehicle fleet and could partially offset the effect. Therefore, this paper focuses on the long-term cumulative environmental benefits generated from the reduction in lifetime vehicle emis-

[24] I use the following procedures to construct air pollution in the upwind direction. First, I calculate the bearings between any two city pairs (Bearing is a geographical terminology that indicates the angle between the direction of two points on Earth and that of the true north). Then convert the bearings into 16 directions, i.e., N, NNE, NE, ENE, E, ESE, SE, SSE, S, SSW, SW, WSW, W, WNW, NW, NNW. Upwind directions of city i at time t are the ones that lie in the same and two neighboring directions of the wind direction of city i at time t. Then calculate the average pollution levels of the cities in the upwind direction weighted by the inverse of the distance between the upwind city and the home city.

sions.

1.4.3 Strategic Interaction across Cities

The specification used to test strategic interactions between cities in the adoption of import restrictions draws on the literature on strategic interactions in environmental regulations, such as Fredriksson and Millimet (2002a,b). The specification is as follows:

$$D_{it} = \eta \sum_{j \neq i} w_{ij} D_{j,t-\tau} + \alpha_i + \delta_t + \gamma X_{i,yr-1} + \varepsilon_{it} \tag{1.14}$$

where D_{it} is an indicator that equals 1 if city i has adopted the import restriction in period t. $\sum_{j \neq i} w_{ij} D_{j,t-\tau}$ is defined in the same way described in section 1.4.1 , lagged for $\tau = 1, 2, 3, 4$ quarters. $X_{i,yr-1}$ is GDP per capita in city i lagged one year. α_i and δ_t are city and year-quarter fixed effects. ε_{it} is the error term.

The results are reported in Table 1.5. Columns (1) to (4) show estimated coefficients for the weighted average of other cities' restrictions lagged one to four quarters, respectively. The coefficients are positive and significant through all columns, showing that one city is more likely to restrict in response to other cities' (past) restrictions. The magnitude of the coefficients decreases with longer lags, implying that the more recent restrictions have a larger effect. Again, these results are consistent with the theoretical prediction that cities' import restrictions could be strategic complements.

1.5 A Structural Trade Model

Section 1.4 provides empirical evidence of how import restrictions on used vehicles affect net imports of used vehicles and how cities interact with each other when adopting the restrictions. However, empirical analysis is limited in dealing with spatial spillovers and cannot speak about the welfare effects of different policy counterfactuals. Therefore, in this section, I develop a quantitative trade model to fully incorporate the general equilibrium effect of the import restriction and to quantify the welfare effect under different counterfactuals. I choose the structural trade model as the workhorse for simulations, as trade models can nicely characterize trade flows across locations, which is the main feature of the data and the focus of the analysis.

The model is built around Armington (1969). There are N locations and S sectors. There are five used vehicle sectors differentiated by the emission standards they comply with (*China 1* to *China 5*), and a new vehicle sector that complies with *China 5*. Vehicles supplied by different locations within the same sector are regarded as differentiated. Vehicles are traded between locations subject to an iceberg trade cost $\tau_{ijs} \geq 1$ and an ad valorem tariff $\tilde{t}_{ijs} \geq 0$. Define $t_{ijs} \equiv 1 + \tilde{t}_{ijs}$.

1.5.1 Preferences

I assume that a representative consumer at location j has a nested CD-CES utility preference. At the top level, the representative consumer maximizes a Cobb-Douglas utility function by choosing the mix between (the composite) vehicle consumption and an outside good (numéraire):

$$\max_{C_{vj},C_{oj}} U_j = C_{vj}^{\alpha_j} C_{oj}^{(1-\alpha_j)} \tag{1.15}$$

subject to the budget constraint:

$$P_{vj}C_{vj} + C_{oj} = E_j \tag{1.16}$$

where α_j is the expenditure share that the representative consumer in location j spends on vehicles. C_{vj} is the aggregate consumption of vehicles in location j. C_{oj} is the consumption of the outside good. P_{vj} is the aggregate price of vehicles in location j, which I will elaborate below. The price for the outside good is normalized to be one. E_j is the total expenditure in location j.

The composite vehicle consumption C_{vj} that aggregates vehicle consumption across sectors is:

$$C_{vj} = \left(\sum_s \gamma_s^{\frac{1}{\varepsilon}} C_{js}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1.17}$$

where C_{vj} is the aggregate consumption of vehicles in region j. γ_s is the taste parameter for vehicles in sector s. ε is the elasticity of substitution between vehicle sectors. C_{js} is the aggregate consumption of vehicles purchased from different locations, defined as:

$$C_{js} = \left(\sum_{i=1}^{N} q_{ijs}{}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1.18}$$

where σ is the elasticity of substitution between locations (varieties).

By maximizing utility, the demand for vehicles in sector s from location i to location j can be written as:

$$E_{ijs} = \pi_{ijs} e_{js} \alpha_j E_j \tag{1.19}$$

where E_j is the total expenditure at location j. α_j is the share of vehicles out of total expenditure in location j. Out of the total vehicle expenditure in location j, a share of e_{js} is spent on vehicles of sector s. Within sector s, a share π_{ijs} is spent to import from location

i to location j.

The within-sector import share is defined as:

$$\pi_{ijs} = \left(\frac{p_{is}\tau_{ijs}t_{ijs}}{P_{js}}\right)^{1-\sigma} \tag{1.20}$$

where p_{is} is the price of vehicles of sector s at location i net of trade costs. P_{js} is the sectoral price index in j, which aggregates prices to import a vehicle unit in sector s from different origins to j:

$$P_{js} \equiv \left(\sum_{k=1}^{N}(p_{ks}\tau_{kjs}t_{kjs})^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{1.21}$$

The sector share is:

$$e_{js} = \left(\gamma_s \frac{P_{js}}{P_{vj}}\right)^{1-\varepsilon} \tag{1.22}$$

where P_{vj} is the price index of vehicles aggregating across sectors at location j:

$$P_{vj} = \left(\sum_{s} \gamma_s {P_{js}}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} \tag{1.23}$$

1.5.2 Supply

Assume that the supply of vehicles in each location and each sector can be characterized by a Cobb-Douglas production function, combining labor and an intermediate input.[25] Then the quantity supplied could be written as the following equation (Allen et al.,

[25]It is standard in the trade literature to describe the supply of (new) goods by a production function. For used vehicles, we can think of the supply as a "production" process in which vehicle dealers purchase used vehicles from individual owners across all locations as an intermediate input, refurbish them, and supply them to the market.

2020):[26]

$$Q_{is} = \bar{c}_{is} \left(\frac{p_{is}}{P_{is}} \right)^{\psi} \tag{1.24}$$

where $\bar{c}_{is}$ is a supply shifter determined by factor endowment and productivity in location i, $\frac{p_{is}}{P_{is}}$ is the real output price (output price scaled by the price index), and ψ is the aggregate supply elasticity. The supply elasticity is a function of the share of intermediate input in the Cobb-Douglas production function. If production only uses local inputs (such as labor whose supply is assumed to be perfectly inelastic), the supply elasticity ψ would be zero, and the quantity supplied in location i would be exogenously determined by the endowment of the input and the productivity in location i. If production uses an intermediate input, a composite that aggregates the goods produced at all locations (Caliendo and Parro, 2015), the supply elasticity would be greater than zero and the quantity supplied would increase with the real output price. I will estimate the supply elasticity below.

Hence, the revenue from vehicle sales of sector s in location i is:

$$R_{is} \equiv p_{is} Q_{is} = p_{is} \bar{c}_{is} \left(\frac{p_{is}}{P_{is}} \right)^{\psi} \tag{1.25}$$

1.5.3 Equilibrium

The model is closed by market clearing conditions and balanced trade conditions. Market clearing requires that the gross revenue of sector s in location i equals the total demand

[26] Allen et al. (2020) shows that this equation of quantity supplied is universal to many variants of trade models with different micro-foundations, such as the Armington model (Armington, 1969), the Recardian model (Eaton and Kortum, 2002), the Melitz model (Melitz, 2003), and to spatial models.

for sector s from all markets j net of tariffs:

$$R_{is} = \sum_{j=1}^{N} E_{ijs} \tag{1.26}$$

Assume that trade is balanced in each location, that is, total expenditure equals total income:[27]

$$E_j = R_j + T_j \tag{1.27}$$

where R_j is the total revenue in location j, which is the sum of vehicle revenue and revenue from the outside good sector, $R_j = \sum_s R_{js} + R_{jo}$. T_j is the tax revenue from import tariffs, $T_j = \sum_{i,s} \frac{t_{ijs}-1}{t_{ijs}} E_{ijs}$.

The general equilibrium system is composed of equations (1.19)-(1.27). For a given set of parameters, including the elasticity of substitution between locations (varieties) (σ), the elasticity of substitution between sectors (ε), the aggregate supply elasticity (ψ), bilateral trade frictions (τ_{ijs}), bilateral tariff rates ($\tilde{t}_{ijs}$), and supply shifters ($\bar{c}_{is}$), the general equilibrium real prices for used and new vehicles in each location (p_{is}/P_{is}) can be solved.[28] Once the general equilibrium prices are determined, other endogenous outcomes, such as the trade flows of used and new vehicles (E_{ijs}), expenditures on vehicles (E_{js}), and own expenditure shares (π_{jjs}) will also be determined.

[27] This assumption does allow vehicle trade to be unbalanced, but the deficit needs to be offset by the trade of the outside good.

[28] Note that the system of equations is homogeneous of degree 0 in $\{p_{is}, P_{is}\}$. Therefore, the levels of the output prices p_{is} and the aggregate price index P_{is} can not be pinned down separately (Allen et al., 2020).

1.5.4 Welfare

Define the welfare in location j as the sum of indirect utility from consumption (gains from trade) and disutility (environmental costs) from vehicles' local pollutant emissions:

$$W_j = V_j - D_j$$

The indirect utility from consumption is the total expenditure scaled by the price index:

$$V_j = \frac{E_j}{P_j} \tag{1.28}$$

where E_j is the total expenditure in location j. $P_j = P_{vj}^{\alpha_j}$ is the aggregate price index in location j.

Environmental costs from vehicle emissions are determined by the amount of pollution emissions and the marginal damage of the emission:

$$D_j = \sum_k MD_{kj} Z_{kj} \tag{1.29}$$

where subscript k represents the pollutant, j represents the location where the pollution is emitted. MD_{kj} is the marginal damage from emissions of pollutant k in location j. Z_{kj} is the amount of pollutant k emitted at location j.

1.5.5 Solving the Model under Shocks

I apply the "exact hat algebra" developed by Dekle et al. (2008) which cancels out time-invariant unobservables to solve for proportional changes in equilibrium outcomes under a shock.

Let $\hat{x} \equiv x'/x$ denote the proportional change in any variable x between the counterfactual and the initial equilibria. Let $\hat{\tau}_{ijs}$ represent a shock in trade costs, and $\hat{t}_{ijs}$ a shock in tariffs. The proportional change in vehicle prices is determined by the following system of equations:

$$\hat{P}_{is}^{1-\sigma} = \sum_{j=1}^{N} \hat{\tau}_{jis}^{1-\sigma} \hat{t}_{jis}^{1-\sigma} \hat{p}_{js}^{(1-\sigma)} \pi_{jis} \tag{1.30}$$

$$\hat{P}_{vi}^{1-\varepsilon} = \sum_{s} \hat{P}_{is}^{1-\varepsilon} e_{is} \tag{1.31}$$

$$\hat{\pi}_{ijs} = \left(\frac{\hat{p}_{is}\hat{\tau}_{ijs}\hat{t}_{ijs}}{\hat{P}_{js}}\right)^{1-\sigma} \tag{1.32}$$

$$\hat{e}_{js} = \left(\frac{\hat{P}_{js}}{\hat{P}_{vj}}\right)^{1-\varepsilon} \tag{1.33}$$

$$\hat{R}_{jv} = \sum_{s} \hat{p}_{js}^{1+\psi} \hat{P}_{js}^{-\psi} \frac{R_{js}}{R_{jv}} \tag{1.34}$$

$$\hat{p}_{is}^{1+\psi} \hat{P}_{is}^{-\psi} = \sum_{j=1}^{N} \hat{\pi}_{ijs} \pi_{ijs} \hat{e}_{js} e_{js} \hat{t}_{ijs} t_{ijs} \frac{\alpha_j (\hat{R}_{jv} R_{jv} + R_{jo})}{R_{is}} \frac{1}{1 - \sum_{k,m} \frac{\hat{t}_{kjm} t_{kjm} - 1}{\hat{t}_{kjm} t_{kjm}} \hat{\pi}_{kjm} \pi_{kjm} \hat{e}_{jm} e_{jm} \alpha_j} \tag{1.35}$$

Solving the Model For shocks $\hat{\tau}_{ijs}$ and $\hat{t}_{ijs}$, the system of equations could be solved in the following steps:

(1) Give an initial guess of price changes $\{\hat{p}_{is}^{0}\}$, calculate the change of sectoral price indices $\{\hat{P}_{is}\}$ and the vehicle price index $\{\hat{P}_{vi}\}$ using equations (1.30)-(1.31);

(2) Calculate the change of the import share $\{\hat{\pi}_{ijs}\}$, sector share $\{\hat{e}_{js}\}$, and the income change $\{\hat{R}_{jv}\}$ using equations (1.32)-(1.34);

(3) Substitutes $\{\hat{p}_{is}^{0}\}$, $\{\hat{P}_{vi}\}$, $\{\hat{\pi}_{ijs}\}$, $\{\hat{e}_{js}\}$, and $\{\hat{R}_{jv}\}$ into equation (1.35) to obtain an updated $\{\hat{p}_{is}^{1}\}$. Let $\{\hat{p}_{is}^{0}\} = \{\hat{p}_{is}^{1}\}$, and iterate steps (1)-(3) until $\{\hat{p}_{is}^{1}\}$ is extremely close to $\{\hat{p}_{is}^{0}\}$.

1.5.6 Welfare Effects

For policy shocks that change trade costs and (or) tariffs, equilibrium prices and trade flows would change, which affects welfare.

Effect on gains from trade The change in gains from trade in location j could be measured by the equivalent variation:

$$\Delta V_j = \frac{E_j}{P_j}(\frac{\hat{E}_j}{\hat{P}_j} - 1) \tag{1.36}$$

where $\hat{E}_j$ and $\hat{P}_j$ are the proportional changes of the total expenditure and price index in city j, which could be solved using the exact hat algebra described above.

Effect on the environment There are two channels through which policy shocks in trade costs and tariffs could affect vehicle emissions: (1) the trade channel — policy shocks change trade flows and thus net imports of vehicles;[29] (2) the scrap channel — policy shocks change prices of used vehicles, leading to changes in scrappage of the existing vehicle stock (Gruenspecht, 1982).

The change in environmental costs in location j can be written as:

$$\Delta D_j = \sum_k \sum_s MD_{kj}(\Delta N_{sj} - S_{sj}\Delta r_{sj}) \cdot EF_{sk} \cdot VKT_s \tag{1.37}$$

where ΔN_{sj} is the change in net imports of vehicles. S_{sj} is the vehicle stock of sector s at location j. Δr_{sj} is the change in the vehicle scrap rate of sector s at location j. Therefore, $\Delta N_{sj} - S_{sj}\Delta r_{sj}$ represents the change in the number of vehicles in sector s at location j,

[29]Net imports of new vehicles are just sales of new vehicles.

which can be obtained by solving the exact hat algebra. EF_{sk} represents emission factors for the vehicle sector s, pollutant k (g/km). VKT_s is the lifetime kilometers traveled for vehicles in sector s (km). MD_{kj} is the marginal damage caused by emissions of pollutant k at location j.

Gruenspecht (1982) shows that the scrappage rate is inversely related to the used vehicle price ratio (the used vehicle price divided by the maintenance and repair costs).[30] In this paper, I assume that the scrappage rate is a decreasing function of real prices of used vehicles:

$$r_{sj} = \kappa_j (\frac{p_{sj}}{P_{sj}})^{\xi_s} \quad (\xi_s < 0) \tag{1.38}$$

where κ_j is a scalar that calibrates baseline scrap rates. ξ_s is the price elasticity of scrappage for vehicles in sector s.

1.6 Estimation of the Parameters

The key parameters to quantify the welfare impact of trade are the elasticity of substitution between varieties (σ), the elasticity of substitution between sectors (ε), and the supply elasticity (ψ) (Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2014). For the following analysis, I denote $\phi = \sigma - 1$, and call ϕ and ψ the aggregate demand elasticity and supply elasticity, or gravity constants, following Allen et al. (2020). This section introduces how I estimate ϕ, ψ, and ε, using bilateral trade data of vehicles across cities in China. Since tariffs were not relevant in this context, I assume away tariffs ($t_{ijs} = 1$ for all i, j, s) throughout this section.

[30] Assume a vehicle is scrapped when its market value in operable condition, p, minus its scrap value, SV, is less than the cost of maintenance and repairs needed to keep it in operable condition, $PR \times R$, where PR and R are the repair price and repair quantity, respectively. If the repair quantity follows a distribution $f(R)$, then the scrappage rate r, is one minus the integral of the repair incidence distribution over the range where repair is rational: $r = 1 - \int_0^{(p-SV)/PR} f(R)\,dR$, in which r is inversely related to the used vehicle price ratio (the used vehicle price divided by the maintenance and repair costs) (Gruenspecht, 1982).

1.6.1 The Demand Elasticity and Supply Elasticity

Methodology The demand elasticity, which governs how bilateral trade flows change with prices and trade costs, is often referred to as trade elasticity in the literature. Trade elasticity plays a key role in understanding the welfare impact of trade. A large literature has estimated this parameter by exploiting variations in trade shares and variations that reflect (part of) trade costs, for example, the overall price indices (Feenstra, 1994), retail price differences of individual goods across countries (Eaton and Kortum, 2002; Simonovska and Waugh, 2014), tariffs (Caliendo and Parro, 2015), etc. On the other hand, there have not been many estimates for supply elasticity. Instead, most literature calibrates the parameter of labor share in production, which is related to the supply elasticity.

In this section, I use a two-step procedure to estimate ϕ and ψ simultaneously, following Allen et al. (2020) and Eaton and Kortum (2002).

Combining the gravity equation of E_{ij} and the gravity equation of the own expenditure E_{jj} yields:

$$\frac{E_{ij}}{E_{jj}} = \left(\frac{\tau_{ij}p_i}{\tau_{jj}p_j}\right)^{-\phi} \tag{1.39}$$

Take log of equation (1.39),

$$\ln\frac{E_{ij}}{E_{jj}} = -\phi\ln\frac{\tau_{ij}}{\tau_{jj}} - \phi\ln p_i + \phi\ln p_j \tag{1.40}$$

This equation shows that imports from i to j relative to expenditure on local goods in j decrease as the trade friction between i and j increases, or the goods in the origin i become more expensive, or the goods in the destination j become cheaper.

The revenue in location i is $R_i \equiv p_i Q_i$. Therefore,

$$p_i = \frac{R_i}{Q_i} = \frac{R_i}{\bar{c}_i (p_i/P_i)^{\psi}} \tag{1.41}$$

where $\bar{c}_i$ is the supply shifter.

Define $\pi_{ii} = \frac{E_{ii}}{E_i}$ to be the own expenditure share, i.e., the share of the expenditure on locally produced goods out of the total expenditure. From equation (1.20), we know that:

$$\pi_{ii} = [\tau_{ii}(p_i/P_i)]^{-\phi} \tag{1.42}$$

Combining equations (1.41) and (1.42) yields the following result:

$$p_i = \frac{R_i}{\bar{c}_i \pi_{ii}^{-\psi/\phi} \tau_{ii}^{-\psi}} \tag{1.43}$$

Substituting the output price (1.43) into Equation (1.40), the relative trade flow could be written as:

$$\ln \frac{E_{ij}}{E_{jj}} = -\phi \ln \frac{\tau_{ij}}{\tau_{jj}} - \ln \mu_i + \ln \mu_j \tag{1.44}$$

where $\ln \mu_i = \phi \ln R_i - \phi \ln \bar{c}_i + \psi \ln \pi_{ii} + \phi\psi \ln \tau_{ii}$. The fixed effects, $\ln \mu_i$ and $\ln \mu_j$, which are output prices to a scale, measure the "competitiveness" of products in city i and j, respectively (Eaton and Kortum, 2002).

The first step to estimate ϕ and ψ is to proxy the relative trade frictions scaled by the demand elasticity:

$$-\phi \ln \frac{\tau_{ij}}{\tau_{jj}} = \beta_{cd}^{l} + \epsilon_{ij} \tag{1.45}$$

where β_{cd}^{l} includes dummies of 10 distance deciles between i and j, and region-pair dummies.[31] ϵ_{ij} is the idiosyncratic shocks that affect trade frictions between i and j. Substituting equation (1.45) into (1.40) gives the following first-step regression equation:

$$\ln \frac{E_{ij}}{E_{jj}} = \beta^{l}_{cd} - \ln \mu_i + \ln \mu_j + \epsilon_{ij} \tag{1.46}$$

The second step then regresses the following equation:

$$\ln \hat{\mu}_i = \phi \ln R_i + \psi \ln \pi_{ii} + \nu_i \tag{1.47}$$

where $\ln \hat{\mu}_i$ is the origin fixed effects estimated from the first step. R_i is the revenue in city i. π_{ii} is the own expenditure share in city i. The error term $\nu_i = -\phi \ln \bar{c}_i + \phi\psi \ln \tau_{ii} + \hat{\nu}_i$ is composed of three elements — the supply shifter ($\bar{c}_i$), the within city trade costs (τ_{ii}) which are normalized to be one, and the estimation residual from the first step.

However, using OLS to estimate the second-step equation (1.47) will result in biased estimates of ϕ and ψ. As Equation (1.47) shows, the error term is correlated with the revenue and the own expenditure share through the supply shifter, as the revenue and the own expenditure share are endogenously determined in the general equilibrium system for any given supply shifters. The OLS estimates will be biased downward, since the supply shifter is positively correlated with revenue but negatively correlated with the output price, i.e., the estimated origin fixed effects.

I use a model-based instrumental variable strategy to overcome this identification challenge (Allen et al., 2020). The idea of this strategy is to construct instruments from the model using plausible exogenous shocks. For example, to estimate the impact of international trade on economic growth, Frankel and Romer (1999) construct an instrument

[31] China has seven geographic regions: North China, Northeast China, East China, South China, Central China, Southwest China, and Northwest China. See: https://www.chinacheckup.com/blog/regions-of-china.

by predicting trade flows from the gravity model based on geographic characteristics. In this paper, as shown in Section 1.5.3, equilibrium revenues and own expenditure shares are determined for any given set of elasticity parameters, bilateral trade costs, and supply shifters. Therefore, feeding the model with bilateral trade frictions and supply shifters that depend only on exogenous observables, I can predict hypothetical revenues and own expenditure shares, and use them as instruments for the observed revenues and own expenditure shares in equation (1.47).

In this hypothetical world, bilateral trade frictions are generated on the basis of the estimated coefficients of distance deciles and region-pair dummies obtained in the first-step estimation. I used two ways to construct the cost shifter. The first way is to use the average revenue as a cost shifter for each individual city. The second way is to allow the supply shifter to depend on the lagged motor vehicle stock in the city. Using these trade frictions and cost shifters, I solve two sets of hypothetical revenues and own expenditure shares. Then I estimate Equation (1.47) instrumenting for the observed revenues and own expenditure shares by the hypothetical revenues and expenditure shares while controlling for the observable (lagged motor vehicle stock).

Whether these model-based instruments are valid hinges on whether they are uncorrelated with the error term ν_i in equation (1.47). The identification variation of the instruments, i.e., hypothetical revenues and own expenditure shares, is generated through the general equilibrium structure of the model. Intuitively, differences in geography and lagged stock of motor vehicles in neighboring cities generate variations in the demand for vehicles from one city and variations in the price index it faces, conditional on its own lagged stock of motor vehicles. Therefore, the exclusion restriction is valid if the geography and lagged vehicle stock in neighboring cities do not correlate with the unobserved shock of the supply shifter in one city, after controlling for the observable of that city (lagged vehicle stock).

Estimation Results I use the aggregate intercity trade flows of used vehicles in China from 2013 to 2015 to estimate ϕ and ψ. The estimation results are reported in Table 1.6. Column (1) is the OLS estimates. The estimated (negative) demand elasticity (ϕ) and supply elasticity (ψ) are both negative. This is in line with the explanation in the previous section that the OLS estimates will be biased downward. Column (2) reports the results from using the first set of instruments, which are hypothetical revenues and home expenditure shares predicted from geographic trade frictions and the average revenue being the supply shifter. The demand elasticity becomes positive, but the supply elasticity is still negative. Column (3) reports the results for using the second set of instruments, which are constructed from geographic trade frictions and the supply shifter dependent on the lagged motor vehicle stock. The demand elasticity is estimated to be 2.468 and significant at the 1 percent level. The supply elasticity is estimated to be 1.830 but is not significant.

My estimate of the demand elasticity of used vehicles is slightly smaller but qualitatively consistent with the estimates of the trade elasticity of the transport equipment sector in recent studies. Shapiro (2016) estimates the trade elasticity with panel data on transportation costs and trade values for all US and Australian imports over 1991-2010, using fixed effects to address the issue of reverse causality or omitted variable bias, and instrumental variables to address measurement error. Their estimated trade elasticity for the Transport Equipment sector is 4.51 using the fixed-effects model and 6.87 using IV, which are larger than my estimates (2.343). Using interstate trade data in the US with a CES framework, Yilmazkuday (2012) estimates that the elasticity of substitution between varieties in the Transport Equipment sector is 2.98, which translates to a demand elasticity of 3.98. Head and Mayer (2014) reviews 32 papers that estimate the elasticity of the trade, and reports that the median estimates for all the papers included are 3.19, for papers that use a structural gravity model (as mine) is 3.78, for papers that control fixed effects of origin/destination are 3.5, and for papers that use ratio-type estimation is 4.82. However, some studies obtain much lower estimates. For example, Caliendo and Parro (2015) estimate the trade elasticity of the automobile sector to be 1.01, and not significantly different from zero. Boehm et al. (2020) estimate that the short-term elasticity in the year following a tariff shock is about 0.76, and it takes between 7 to 10 years to converge to the long-term value of 1.75-2.25.

My estimate of the supply elasticity of used vehicles is 1.830 but is not precise. Supply elasticity is not commonly estimated in the trade literature, but I can compare the implied labor share of my estimate with the existing literature. The supply elasticity of 1.830 implies that the labor share in the production functions is 0.35.[32] This is between the average labor share in the manufacturing industry used in Eaton and Kortum (2002) (0.21), and the labor share of the transportation and warehousing sector in the U.S. during the 2010s (0.56-0.58).[33]

1.6.2 The Elasticity of Substitution between Sectors

Methodology Taking log on both sides of the sector expenditure equation (1.22) yields the following:

$$\ln E_{js} = (1-\varepsilon)\ln P_{js} - (1-\varepsilon)\ln P_{vj} + \ln E_j + \ln \gamma_s \tag{1.48}$$

Thus, the elasticity of substitution between sectors can be estimated by regressing the expenditure on the price index, sector fixed effects, and city fixed effects as follows:

$$\ln E_{js} = (1-\varepsilon)\ln P_{js} + \delta_j + \gamma_s + \mu_{js} \tag{1.49}$$

where E_{js} is the expenditure in sector s in city j. P_{js} is the aggregated price index for sector

[32]From the supply elasticity $\psi = (1-\beta)/\beta$, labor share can be derived as $\beta = 1/(1+\psi)$.
[33]Source: https://www.bls.gov/opub/mlr/2017/article/estimating-the-us-labor-share.htm

s in city j.[34] δ_j is the city fixed effects. γ_s is the sector fixed effects. μ_{js} is the idiosyncratic shock of spending in sector s in city j.

Estimation Results The estimation results of the elasticity of substitution between sectors are reported in Table 1.7. The coefficient of $\ln P_{js}$ is the estimated value of $1-\varepsilon$. Column (1) includes city fixed effects which absorb the total expenditure on vehicles and the aggregated price index across sectors. Column (2) adds sector fixed effects, which control for consumers' taste preferences for vehicles of different sectors (new vehicles and five used vehicle sectors by emission standard). Column (3) adds year- fixed effects to control for common shocks on vehicle consumption for each year. Column (3) is my preferred specification. The estimated coefficient for $\ln P_{js}$ is -1.417, statistically significant at the 1 percent level. This estimate implies that the elasticity of substitution across vehicle sectors is 2.4, greater than the estimate from Yilmazkuday (2012), which is 1.09, using interstate trade data in the United States.

1.7 Counterfactual Analysis

In this section, I use the exact hat algebra (Dekle et al., 2008) to solve for changes in gains from trade and environmental costs under different counterfactuals. Based on the estimates from the previous section, I set $\phi = 2.5$, $\psi = 1.8$, and $\varepsilon = 2.4$ for the following simulations. The baseline of all simulations is the first year of my sample, 2013.

I consider two policies. The first is an emission-based import restriction that restricts imports of used vehicles according to an emission standard. Cities can choose between

[34] The aggregate price index for each vehicle sector is constructed in the following way: First, as I observe the quantity of bilateral trade q_{ijs}, I can calculate the aggregate consumption of varieties in sector s and city j (C_{js}) using equation (1.18) with the estimated elasticity of substitution between varieties ($\hat{\sigma}_s = \hat{\phi}_s + 1$) from the first step. After obtaining C_{js}, I calculate the aggregate sector price index by $P_{js} = E_{js}/C_{js}$ for all three sectors.

China 1 to *China 5* as the minimum standard for imports. Restricting used vehicles of *China 1* is the least stringent, and restricting all used vehicles from *China 1* to *China 5* is the most stringent. The second policy is an emission tax that charges an ad valorem tax at the rate of marginal damage of emissions over vehicle values.

I consider four counterfactuals. The first three counterfactuals consider implementing the import restriction policy unilaterally, strategically, or collaboratively while keeping the local trade in used vehicles unrestricted. The last counterfactual considers imposing an emission tax on used vehicles, regardless of whether they are imported or locally traded. The first scenario considers a unilaterally optimal import restriction, or myopic restriction, in which each city unilaterally chooses a level of import restriction to maximize its own welfare. The second scenario is the non-cooperative Nash equilibrium, which considers a static game where non-cooperative cities simultaneously choose their unilaterally optimal import restriction, taking other cities' restriction choices as given. This scenario allows strategic interactions between cities. The third scenario considers a nationally optimal import restriction, in which a social planner chooses the restriction level for each city to optimize the total social welfare of the country. The last counterfactual is an ad valorem emission tax levied on all used vehicles, locally traded and imported, at the rate of local (lifetime) emission damages over vehicle values.

1.7.1 Unilaterally Optimal Import Restriction

In this scenario, each city unilaterally chooses a level of import restriction to maximize its welfare, assuming that all other cities do not restrict. I run 5×312 simulations in total. For each city, there are five counterfactuals in which that city unilaterally restricts imports of used vehicles based on the emission standard from *China 1* to *China 5*.

The simulation results are shown in Figure 1.7. Panel (a) shows welfare changes for the city that adopts the restriction. From left to right, each panel corresponds to a restriction stringency that each city could unilaterally set, from the least stringent of restricting only *China 1*, to the most stringent of restricting all used vehicles from *China 1* to *China 5*. Each plot shows the distribution of the simulated changes in gains from trade, environmental benefits (negative environmental costs), and social welfare relative to the baseline under the corresponding scenario.

Several patterns are shown in panel (a) of Figure 1.7. First, regardless of the stringency of the restriction, restricting imports of used vehicles, in general, could lead to dead weight losses and environmental benefits. As the restriction becomes more stringent, both the dead weight losses and the environmental benefits increase. Second, less stringent policies that only restrict dirtier used vehicles such as *China 1* and *China 2* could improve the social welfare of more cities. However, adopting more stringent policies would decrease social welfare for many cities, as restricting comparatively cleaner vehicles has limited environmental gains but larger deadweight losses.

As the marginal damage of pollution and the pre-restriction imports/exports vary across cities, the optimal restriction stringency that maximizes the social welfare change differs across cities. Simulations predict that out of 312 cities in our sample, it is unilaterally optimal for 55 to choose not to restrict, 142 to choose to restrict only *China 1* used vehicles, 98 to choose to restrict used vehicles of *China 2* and below, and 17 to choose to restrict *China 3* and below.

Next, I examine the spillover effect of these unilateral restrictions. Under the same counterfactuals as in panel (a), panel (b) shows changes in aggregate welfare for cities that do not adopt the restriction. The plots show that, in general, one city's unilateral restriction reduces other cities' gains from trade. The more stringent the restriction, the larger the negative spillovers. The spillover effect on environmental benefits could be decomposed into two channels. One channel is through the trade in used vehicles. As shown before, a unilateral restriction could reduce its own net imports, i.e., reduce other cities' net exports, thus adding environmental costs to other cities. The other channel is through the change in the real output price. A unilateral import restriction reduces the demand for used vehicles in other cities, which drives down the real output price in other cities. This will increase scrappage and thus lead to a positive environmental spillover. The sign of environmental spillovers, therefore, depends on which channel is stronger. Overall, the more stringent the unilateral restriction is, the larger the negative spillover effect it could generate on the social welfare of other non-restricting cities.

Panel A of Table 1.8 reports the welfare effects if every city chooses its unilaterally optimal import restriction relative to the status quo as of 2013. Unilateral restrictions reduce gains from trade by 2,542 million RMB but lead to environmental benefits through the trade channel by 1,450 million RMB, and environmental benefits through the scrap channel by 4,479 million RMB. The total social welfare would increase by 3,387 million RMB.

1.7.2 Non-cooperative Nash Equilibrium

Next, I allow for strategic interactions between cities and consider the counterfactual of a non-cooperative Nash equilibrium. The non-cooperative Nash equilibrium is solved in sequential simulations. The first round of simulations finds the unilaterally optimal restriction for each city conditional on all other cities not adopting the restriction. In the next round, each city simultaneously updates its restriction choice conditional on other cities' choices in the first round. This process continues until all cities don't want to deviate from their restriction choices given other cities' choices, that is, converging to a Nash equilibrium.

Figure 1.8 compares the results for unilaterally optimal restriction and Nash equilibrium. Panel (a) summarizes the number of cities by their optimal restriction choices. In the unilaterally optimal scenario, 55 cities choose not to restrict, 142 cities choose to restrict *China 1*, 98 cities choose to restrict *China 2* and below, 17 choose to restrict *China 3* and below. However, in the Nash equilibrium, the number of cities that choose not to restrict decreases from 55 to 25, and the number of cities that choose to restrict *China 1* and *China 2* increases to 159 and 109, respectively. The results suggest that after strategically interacting with the decisions of other cities, 30 cities change from no restriction to restricting *China 1*, 13 cities increase their stringency from *China 1* to *China 2*, and two cities increase their stringency from *China 2* to *China 3*. This is consistent with the upward-sloping best-response curve that the theoretical model predicts and is consistent with the empirical evidence of strategic interactions in restriction adoption in China.

Panel (b) of Figure 1.8 shows the welfare effects on gains of trade, environmental benefits, and social welfare under unilaterally optimal restriction and Nash equilibrium. Environmental benefits are further decomposed into the trade channel and the scrap channel. Under both scenarios, the gains from trade decrease, the environmental benefits increase, and the social welfare increases. However, social welfare gains are smaller under the Nash equilibrium compared to gains under unilaterally optimal restriction, suggesting that strategic interactions between cities reduce welfare gains.

Panel B of Table 1.8 reports the welfare effects under the Nash equilibrium. Gains from trade decreased by 2,808 million RMB, but environmental benefits increased by 1,427 million RMB through the trade channel, and by 4,479 million RMB through the scrap channel. The total social welfare increased by 3,214 million RMB, which is 5 percent less than the welfare gains under the unilaterally optimal restriction scenario.

1.7.3 Nationally Optimal Import Restriction

This sector considers the counterfactual that a social planner decides the optimal restriction for each city to maximize the national social welfare. I use a greedy algorithm to search for the optimal restriction.[35]

Figure 1.9 contrasts the results between the Nash equilibrium and the nationally optimal restriction. Panel (a) shows the number of cities according to the restriction stringency they choose. Under the nationally optimal restriction, 112 cities do not restrict, 154, 38, and 8 cities restrict based on *China 1*, *China 2*, and *China 3*, respectively. Under the nationally optimal restriction, the number of non-restricting cities is much larger (112) than that under the Nash equilibrium (25), and much fewer cities choose to restrict China 2 and *China 3* compared to the Nash equilibrium scenario. This implies that cities over-restrict under the Nash equilibrium compared to the socially optimal level. This is not surprising, as cities do not internalize the negative spillovers they generate on society when choosing their unilaterally optimal restriction to maximize their individual social welfare.

Panel (b) of Figure 1.9 shows welfare effects in gains from trade, environmental benefits, and social welfare. Non-cooperative Nash equilibrium increases social welfare by about 3.2 billion RMB. However, this is only about 80 percent of the welfare gains attainable under the nationally optimal restriction. The result clearly suggests that the non-cooperative Nash equilibrium is inefficient.

Panel C of Table 1.8 reports the welfare effects under the nationally optimal import restriction scenario. Gains from trade decrease by 1,115 million RMB, but environmental benefits increase by 1,105 million RMB through the trade channel and by 4,075 million

[35]Greedy algorithm is a heuristic method to search for local optimal solutions by selecting the best choice at each step. At each step, I simulate and compare the additional welfare gain that each city unilaterally restricts can generate and choose the optimal restriction of the city that adds the largest welfare gain to the society. This process iterates until no additional gains could be obtained by adopting restrictions in more cities.

RMB through the scrap channel. The total social welfare increased by 4,065 million RMB. Compared to the welfare effects under the decentralized Nash equilibrium, centralized optimal restriction results in fewer dead weight losses (1,693 million RMB) and fewer environmental benefits (842 million RMB). Social welfare gains are 851 million RMB higher, which is a 26 percent increase.

Distributional effect In addition to the aggregate effect, it is also important to know how the effect varies between cities. The welfare changes are heterogeneous, as shown in Figure 1.10. I group cities into tertiles by GDP per capita and report the welfare effects by tertile in Table 1.8. There is a common pattern across three counterfactuals: the poorest third cities gain the most, the middle third gain modestly, and the richest third lose.

In general, import restrictions result in larger dead weight losses and larger environmental benefits to low-income cities. This is mainly driven by the pattern of used vehicle trade — most used vehicles flow from higher-income cities to lower-income cities. On one hand, import restrictions have a larger effect on the price index in lower-income cities which are more reliant on imports (lower home expenditure share), which leads to a larger decrease in gains from trade. On the other hand, import restrictions reduce the net inflow of used vehicles from higher-income cities to lower-income cities, thus generating environmental benefits to lower-income cities but environmental costs to higher-income cities through the trade channel. Import restrictions generate environmental benefits through the scrap channel for cities of all income levels, larger for lower-income cities because of the larger price effect.

1.7.4 Emission Tax

Instead of restricting imports of used vehicles, each city could alternatively allow free trade and implement an emission tax on all vehicles, both locally traded and imported. In this subsection, I consider a counterfactual in which every city levies an ad valorem tax set at the rate of the environmental damage of vehicle lifetime emissions over the vehicle value. This emission tax varies between cities and between vehicle sectors. The emission tax is higher for dirtier vehicles and in cities where the marginal damage of pollution is greater.

Panel D of Table 1.8 reports the welfare effects when all cities levy an emission tax on *China 1* vehicles. The tax leads to a decrease in gains from trade by 2,553 million RMB, and a small increase in environmental benefits through the trade channel (115 million RMB). However, the environmental benefits from the scrap channel are 37,716 million RMB, more than 10 times the dead weight loss. Social welfare increases by 35 billion RMB, which is almost nine times the welfare gains under the nationally optimal import restriction.

Columns (2) and (3) of Table 1.8 show that across alternative counterfactuals, the environmental benefits generated by increasing vehicle scrappage are greater than those generated by reducing vehicle trade. The prominence of the scrap channel implies that speeding up scrappage and making the fleet cleaner is the key to regulating vehicle emissions.

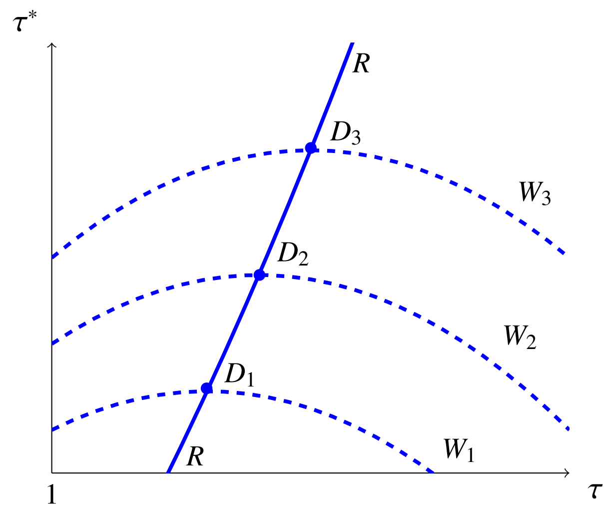
1.8 Conclusion

To address the ever-increasing environmental concerns created by the fast-growing trade of dirty goods, many countries and regions have adopted various restrictions on imports of dirty goods. This paper investigates the effectiveness, efficiency, and distributional effect of decentralized import restrictions, taking into account interjurisdictional spillovers and strategic interactions in the context of used vehicle trading in China. Using comprehensive data on the intercity trade of used vehicles, I find that the import restriction could reduce net imports of used vehicles, thus increasing environmental benefits. Then, I build a structural trade model to quantify welfare trade-offs between environmental benefits and losses from reduced trade. Simulation results show that unilaterally restricting imports of used vehicles could increase environmental benefits through two channels: reduced net imports and increased scrappage due to lower vehicle prices. The scrap channel plays a bigger role. Restricting high-polluting vehicles makes cities better off, especially lower-income cities. However, these unilateral restrictions generate significant spillovers into other cities and incentivize more cities to adopt or tighten existing restrictions. The decentralized decision leads to over-restrictions that are socially inefficient, achieving 80 percent of the welfare gains attainable under the nationally optimal import restriction. Lastly, to put import restrictions into perspective, I find that their effectiveness is modest compared to emission taxes. Nationally optimal import restrictions can achieve 14 percent of emission reductions and 12 percent of welfare gains attainable under emission taxes. These findings highlight the importance of coordination in using trade restrictions as the second-best policy to regulate transboundary pollution problems.

One limitation of this paper is the lack of empirical evidence on the effect of import restrictions on vehicle scrappage, due to data limitations. A related limitation is that I do not develop a full model to rationalize vehicle owners' choices between replacing, keeping, and scrapping their vehicles. Instead, I use the price elasticity of scrappage estimated from Jacobsen and Van Benthem (2015) to simulate changes in scrappage of used vehicles under counterfactuals. Future work could extend a discrete choice model that determines the general equilibrium prices of used and new vehicles, such as Gillingham et al. (2022), to a multi-market setting. Lastly, when calculating the marginal damage of pollution, I assume a linear relationship between pollutant emissions and environmental damage, not taking into account the baseline of air quality. Recent literature, Gong et al. (2023), for example, finds evidence of a concave dose-response function in the long-run effect of fine particulate matter ($PM_{2.5}$) pollution on mortality in China. Incorporating this concave dose-response function indicates higher marginal damage from pollution in low-income cities, where the baseline pollution is lower, thus reinforcing the distributional effect that low-income cities benefit more than high-income cities from the import restriction policy.

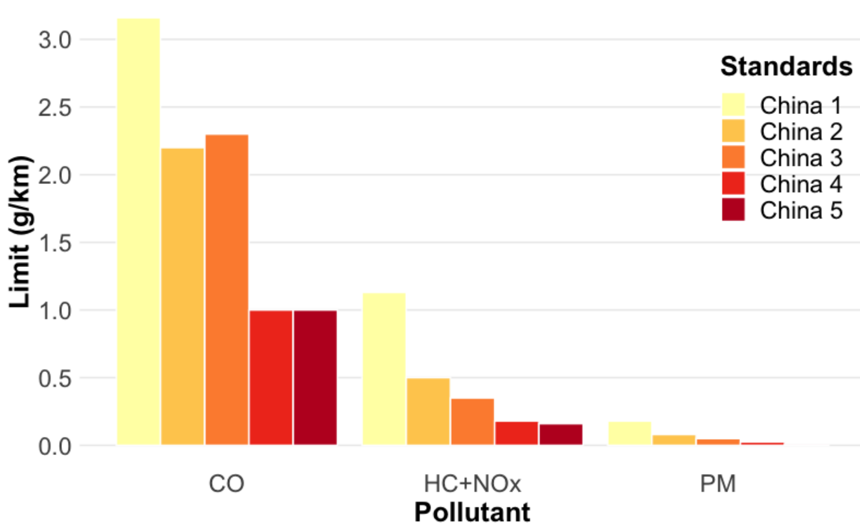
Figures and Tables

Figure 1.1. Welfare Contours and Best Response



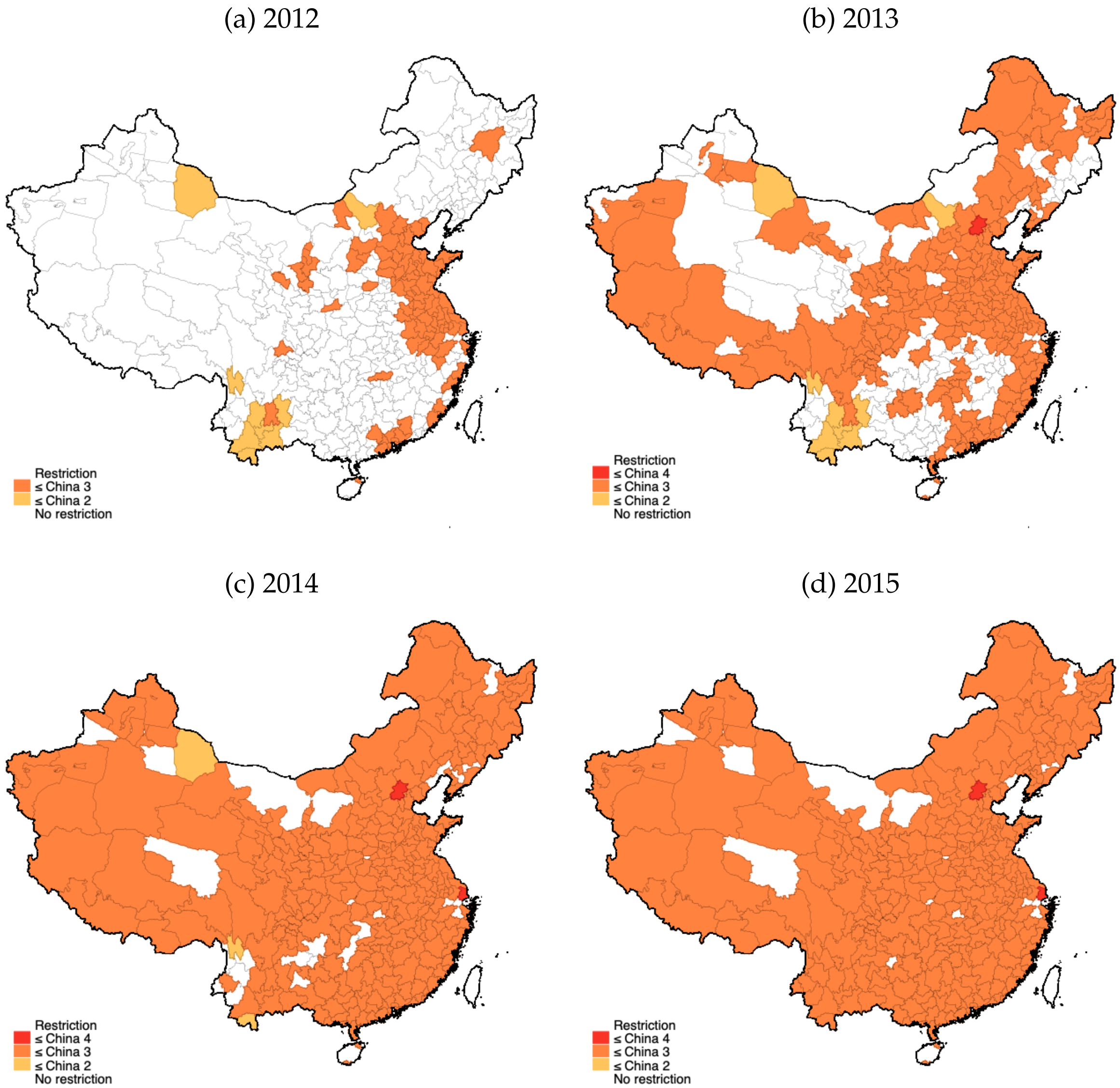
Notes: This figure illustrates three contours of the welfare of the home country. $W_1 > W_2 > W_3$. D_1, D_2, and D_3 are points where the slope of the contours is zero. RR is the locus of these maxima points that describes the optimal response of the home country.

Figure 1.2. China Tailpipe Emission Standards



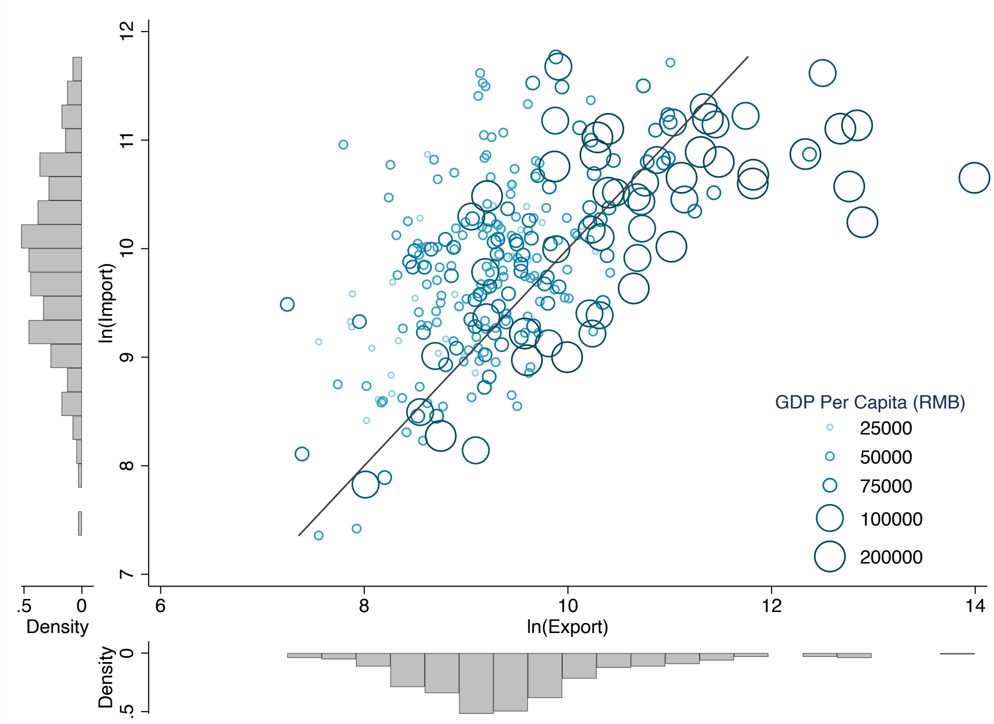
Notes: The figure shows the limits of tailpipe emissions for different pollutants set by emission standards from *China 1* to *China 5*.

Figure 1.3. Rollout of Used Vehicle Import Restrictions by City



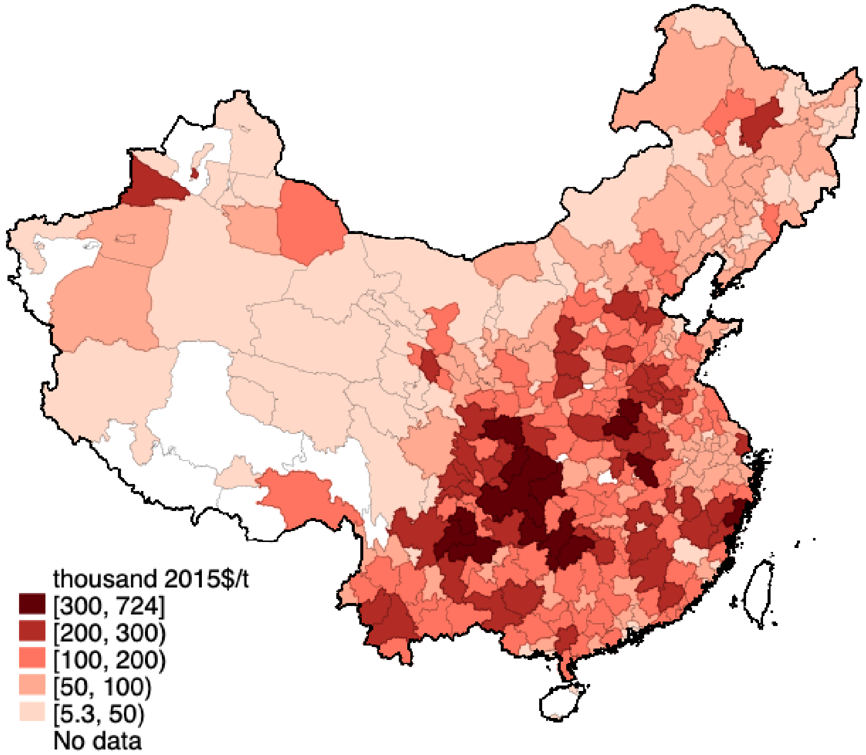
Notes: This figure shows the rollout of restricting cross-city imports of used vehicles in China from 2012 to 2015.

Figure 1.4. Imports and Exports of Used Vehicles, 2013.1-2018.6



Notes: This figure shows the total imports and exports of used vehicles from January 2013 to June 2018 by city. Each point represents a city included in our sample. The size of the point denotes the average GDP per capita over 2013-2018. The 45-degree line represents balanced import and export. Points above the 45-degree line are net importers of used vehicles while points below are net exporters.

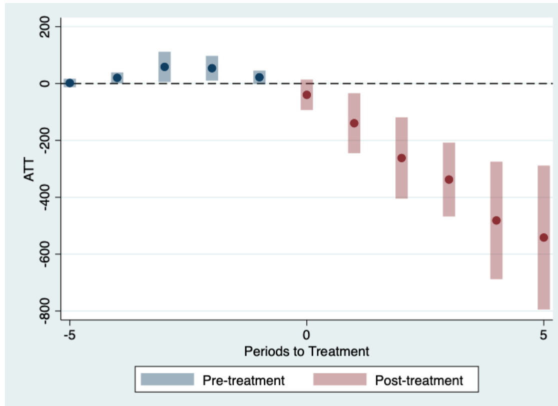
Figure 1.5. Marginal Damage of $PM_{2.5}$ Emissions



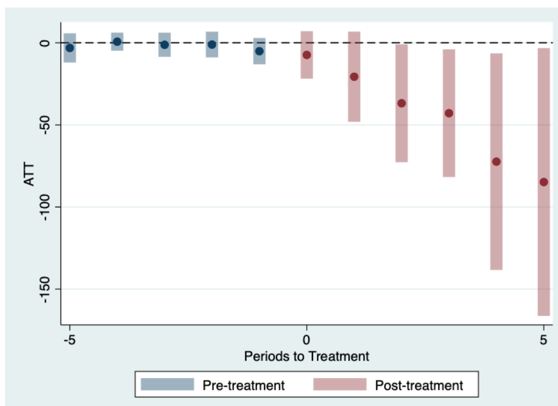
Notes: This figure shows the marginal damage of $PM_{2.5}$ emissions by prefecture city in China. The marginal damages are calculated using the intake fraction method following Parry et al. (2014b); Humbert et al. (2011); Apte et al. (2012).

Figure 1.6. Estimated Effects of Restrictions on Vehicle Flows

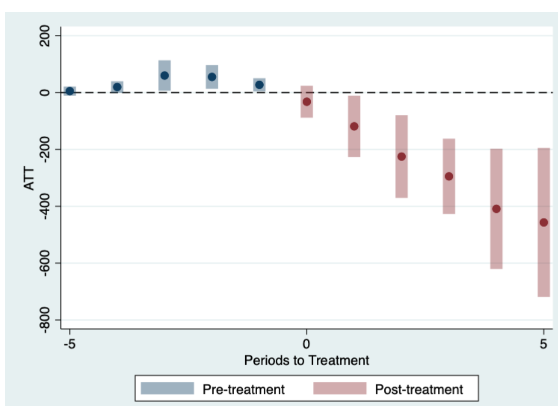
(a) Imports



(b) Exports



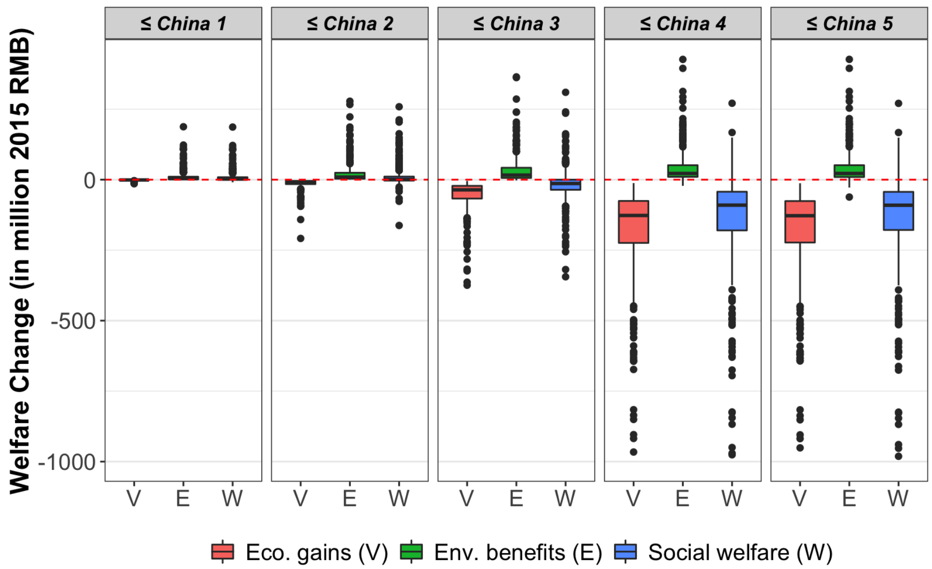
(c) Net imports



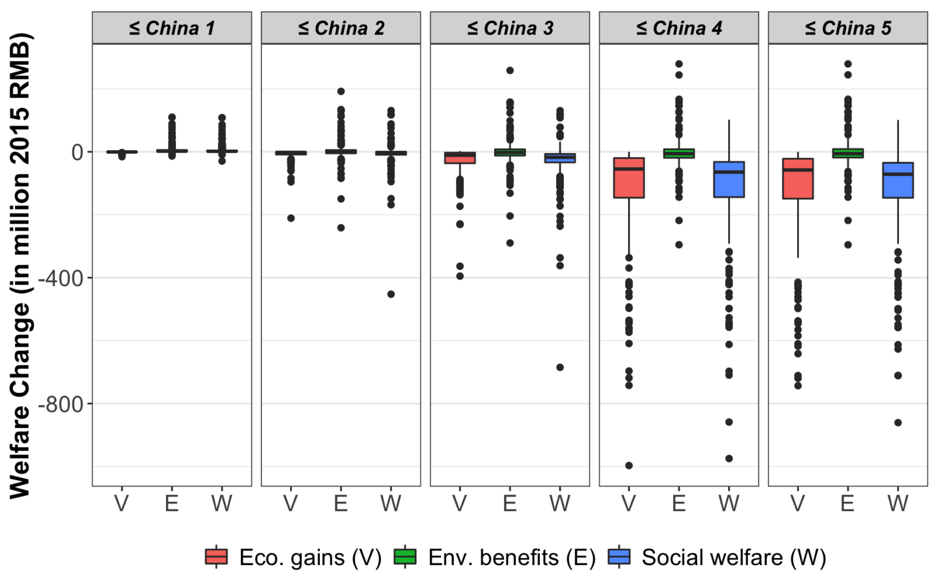
Notes: This figure shows the dynamic effects of restricting the (intercity) imports of used vehicles according to emission standard *China 4* on imports, exports, and net imports of restricted used vehicles. The average treatment effects are estimated using the CSDID method proposed by Callaway and Sant'Anna (2021). The data are at the city-year quarter level from 2013 to 2015.

Figure 1.7. Welfare Changes under Unilateral Restriction

(a) Own Effect



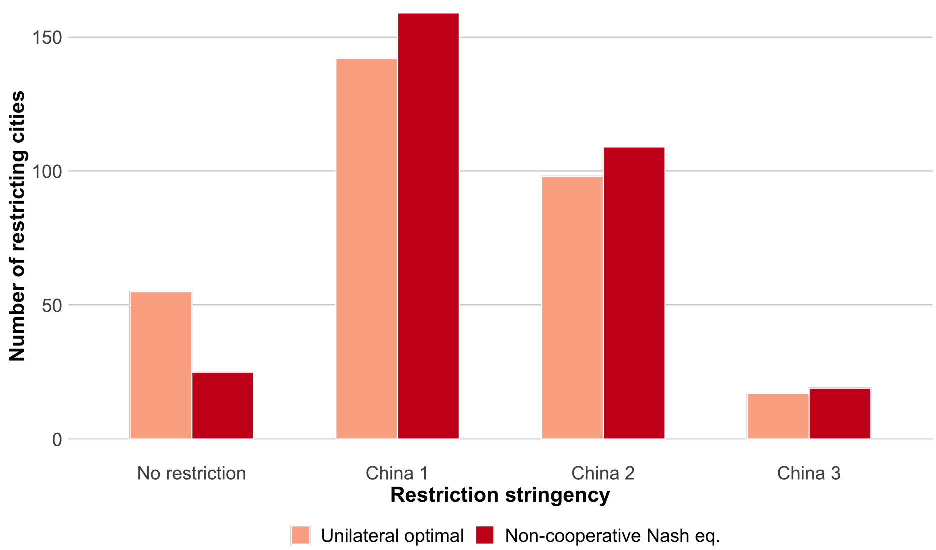
(b) Spillover Effect



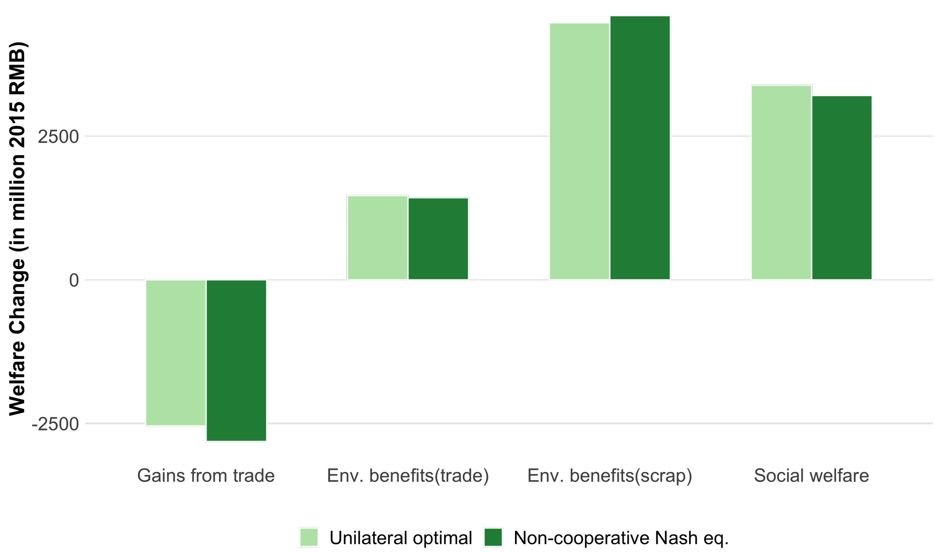
Notes: Panel (a) shows the distribution of own welfare effect by city in China when each one of them unilaterally restricts imports of used vehicles based on different emission standards. Panel (b) shows the distribution of the spillover effect of one city's restriction on all the other cities together. The subplots 1 to 5 represent different restriction stringency, from left to right, restricting used vehicles of only *China 1*, to restricting all used vehicles from *China 1* to *China 5*.

Figure 1.8. Optimal Choices and Welfare Effects under Decentralized Restrictions

(a) Optimal Choices by City



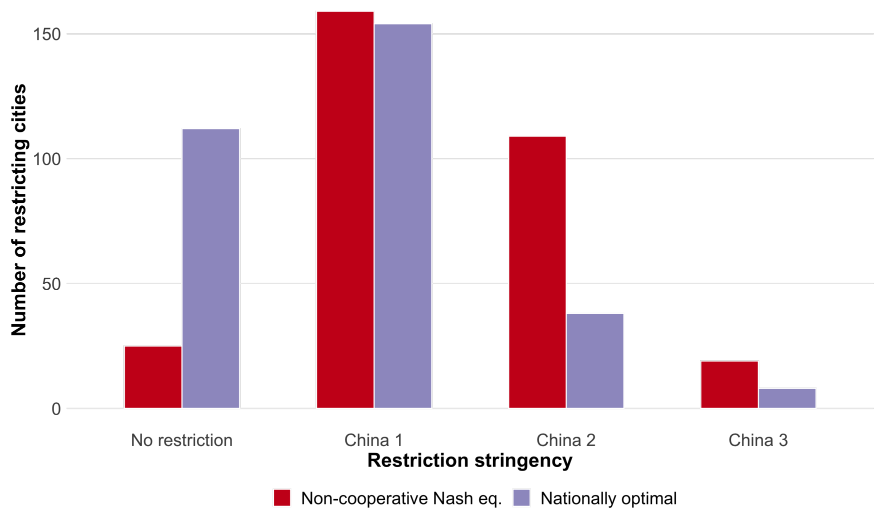
(b) Welfare Effect



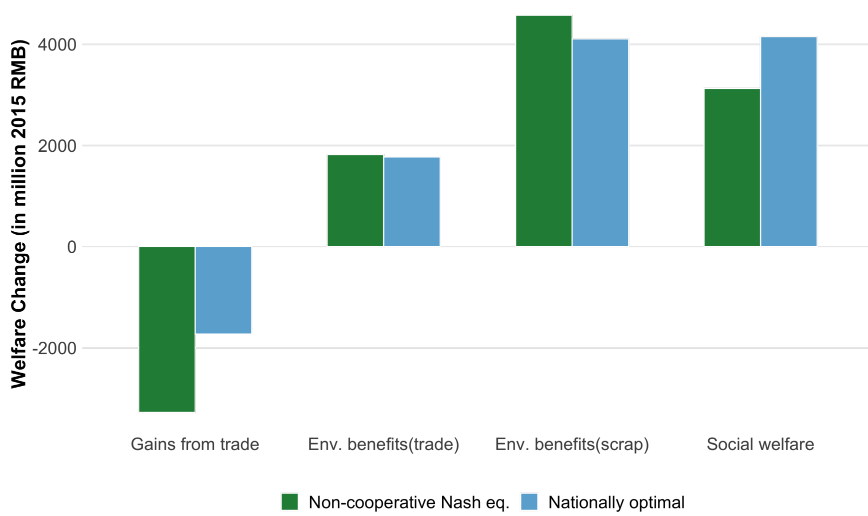
Notes: This figure compares optimal restriction choices of the unilaterally optimal restriction and the non-cooperative Nash equilibrium. Panel (a) shows the optimal restriction choices by city. Labels for the x-axis mean the stringency of restriction based on tailpipe emission standards. China 1 means restricting used vehicles of *China 1*, and *China 3* means restricting used vehicles from *China 1* to *China 3*. Panel (b) shows the effect of restriction on gains from trade, environmental benefits, and social welfare.

Figure 1.9. Optimal Choices and Welfare Effects: Decentralized vs. Centralized

(a) Optimal Choices

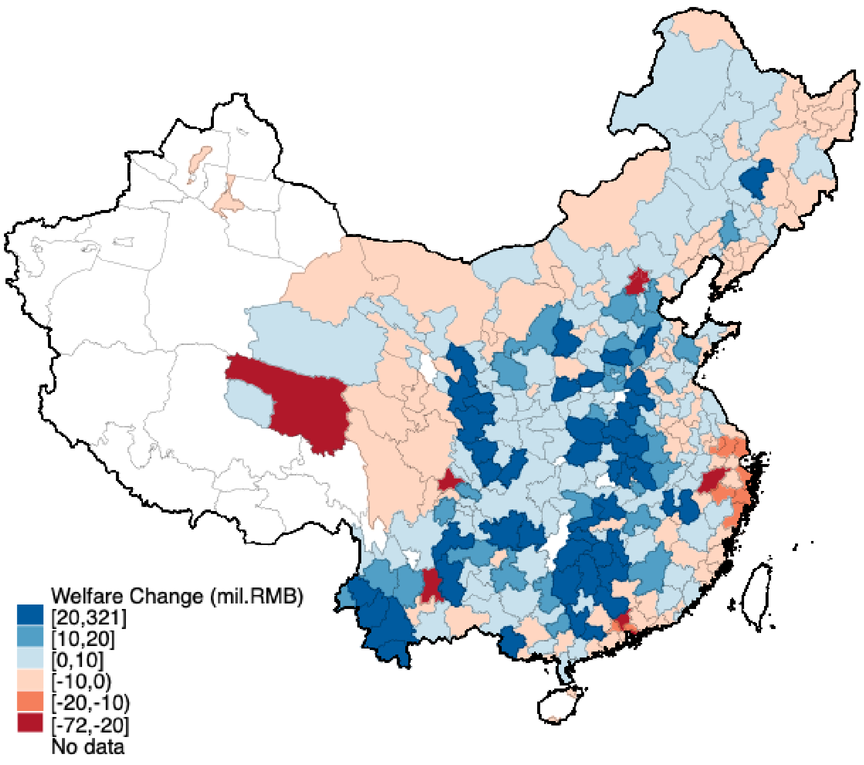


(b) Welfare Effect



Notes: Panel (a) compares optimal restriction choices by city between the non-cooperative Nash equilibrium with the optimal choices under the nationally optimal restriction. Panel (b) compares the welfare effects, including gains from trade, environmental benefits, and social welfare between the non-cooperative Nash equilibrium with nationally optimal restriction.

Figure 1.10. Welfare Changes Under Nationally Optimal Restriction



Notes: This figure shows the social welfare change under the nationally optimal restriction for 312 cities. All values are in million RMB.

Table 1.1. Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Used vehicle trade (city×year-quarter)					
Imports of used vehicles	809.7	829.6	24	8851	3744
Net imports of used vehicles	-43.4	2968.8	-55333	8254	3744
Local sales of used vehicle	3694.8	5135.2	9	45258	3744
New vehicle sales (city×year-quarter)					
New vehicle sales	8941.9	12193.9	9	103450	3744
Social economic status and vehicle stock (city×year)					
GDP per capita (RMB)	46162.3	28081.0	7134.5	207163.0	936
Population (1,000)	4248.0	3145.4	192.9	33752.0	922
Number of motor vehicles (1,000)	511.6	631.0	7.6	5350.0	936
Marginal damage of pollution					
Intake fraction (ppm)	83.4	65.9	4	569	936
Linear population density (persons m^{-1})	444.2	265.4	24	1664	936
Normalized dilution rate (m^2s^{-1})	1042.1	371.4	246	3321	936
Marginal damage of $PM_{2.5}$ (2015$/t)	132302.3	104618.6	5611	903469	936
Marginal damage of NO_x (2015$/t)	18297.1	14468.5	776	124948	936

Notes: This table reports the summary statistics of used vehicle trade, new vehicle sales, GDP per capita, motor vehicle stock, intake fraction, and marginal damage of $PM_{2.5}$ and NO_x emissions for 312 cities over 2013 to 2015. Intake fractions are calculated using equation (1.10). Linear population density is calculated by dividing city population over urbanized land area. Normalized dilution rate is the multiplication of wind speed and atmospheric mixing height. Marginal damage is calculated using equation (1.11).

Table 1.2. Emission Factors

Vehicle type	*China 1*	*China 2*	*China 3*	*China 4*	*China 5*	New
Emission Limit (g/km)						
CO	3.16	2.2	2.3	1.0	1.0	1.0
$HC+NO_x$	1.13	0.5	0.15	0.08	0.06	0.06
PM	0.18	0.08	0.05	0.025	0.0045	0.0045
Average age	13	10	7	4	2	0
Deterioration factor	2.0	1.6	1.3	1.0	1.0	1.0

Notes: Emission limits are set by tailpipe emission standards *China 1* to *China 5*. Assume that all new vehicles satisfy *China 5*. The average age of vehicles by emission standard are calculated from the used vehicle registration data. The emission deterioration factors are obtained from Jacobsen et al. (2021).

Table 1.3. Effect of Import Restrictions on Used Vehicle Trade

	TW fixed effects			CSDID		
Dependent variable	Imports	Exports	Net Imports	Imports	Exports	Net Imports
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	24.3	111.0**	-86.7	-258.7***	-40.5*	-218.2***
	(47.8)	(48.9)	(67.2)	(60.5)	(18.9)	(61.8)
$\sum_{j \neq i} w_{ji} D_{j,t-1}$	-52.0	-279.6***	227.6*			
	(108.1)	(86.1)	(135.1)			
City FE	Y	Y	Y	N	N	N
Year-quarter FE	Y	Y	Y	N	N	N
Observations	3432	3432	3432	1109	1109	1109

Notes: This table reports the impact of restricting imports of used vehicles below *China 4* on imports, exports, and net imports of restricted used vehicles. The unit of observation is city-by-year-quarter. The sample covers 312 cities from 2013 to 2015. Columns (1) to (3) report results from two-way fixed effects models, controlling for city fixed effects, year-quarter fixed effects, and GDP per capita lagged one year. Columns (4) to (6) report results using the CSDID method proposed by Callaway and Sant'Anna (2021), controlling for the index of restriction exposure and GDP per capita. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.4. Effect of Import Restrictions on Ambient Air Quality

Dependent variable	ln(AOD)					
	TW fixed effects			CSDID		
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	-0.002	-0.002	0.004	-0.024	-0.054	-0.052
	(0.022)	(0.022)	(0.021)	(0.041)	(0.041)	(0.044)
City FE	Y	Y	Y	N	N	N
Year-quarter FE	Y	Y	Y	N	N	N
Weather Controls	N	Y	Y	N	Y	Y
Upwind pollution	N	N	Y	N	N	Y
Observations	2982	2982	2982	806	675	675

Notes: This table reports the impact of restricting imports of used vehicles below *China 4* on local aerosol optical depth(AOD) reading. The unit of observation is city-by-year-quarter. The sample covers 312 cities from 2013 to 2015. Columns (1) to (3) report results from two-way fixed effects models, controlling for city fixed effects, year-quarter fixed effects, GDP per capita lagged one year, weather controls, and upwind pollution controls. Columns (4) to (6) report results using the CSDID method proposed by Callaway and Sant'Anna (2021), controlling for the index of restriction exposure, GDP per capita lagged one year, weather controls, and upwind pollution controls. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.5. Strategic Interaction over Restriction Policy across Cities

Dependent variable	Restriction dummy			
	(1)	(2)	(3)	(4)
Lagged Weighted Restriction	0.966***	0.754***	0.499***	0.244***
	(0.086)	(0.072)	(0.059)	(0.052)
Observations	3384	3080	2776	2472
Adjusted R^2	0.863	0.864	0.869	0.893
Lag length	1 quarter	2 quarters	3 quarters	4 quarters

Notes: This table reports strategic interactions between 312 cites in restriction adoptions. The dependent variable is a dummy variable indicating whether a city has restricted the imports of used vehicles below *China 4*. The dependent variables for columns (1) to (4) are the weighted average of the restriction dummy of all other cities weighted by bilateral trade of used vehicles between city pairs in the baseline, lagged one to four quarters, respectively. All regressions control for city FEs, year-quarter FEs, and GDP per capita lagged one year. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.6. Estimates of the Demand Elasticity and Supply Elasticity

	OLS	IV	IV
	(1)	(2)	(3)
Demand Elasticity (ϕ)	-0.229***	1.519***	2.468***
	(0.041)	(0.552)	(0.563)
Supply Elasticity (ψ)	-0.981***	-5.088	1.830
	(0.194)	(4.211)	(2.851)
Vehicle stock control	N	N	Y
Year FE	Y	Y	Y
First stage Sanderson-Windmeijer F-test			
Income		7.212	23.341
(p-value)		0.008	0.000
Own expenditure share		6.908	7.449
(p-value)		0.009	0.007
Observations	936	936	936
Elas. of sub. across locations (σ)			3.5

Notes: This table shows the regression results of equation (1.47) based on used vehicle trade of 2013-2015. The dependent variable is the estimated destination fixed effects obtained from regressing bilateral trade flows relative to the destination's own expenditure on a set of geographic dummies, origin and destination fixed effects. The independent variables is the destination revenue. Instruments are constructed by predicting hypothetical revenue from the general equilibrium model specified in section 1.5.3, for exogenous trade frictions and supply shifters. Trade frictions are generated only from geographic variables. IV regressions use lagged-three-year motor vehicle stock to predict the supply shifter per city. Standard errors clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.7. Estimates of the Elasticity of Substitution between Sectors

Dependent var.	$\ln E_{js}$		
	(1)	(2)	(3)
$\ln P_{js}$	-0.092**	-1.541***	-1.417***
	(0.043)	(0.066)	(0.065)
City FE	Y	Y	Y
Sector FE	N	Y	Y
Year FE	N	N	Y
Observations	5583	5583	5583
Elas. of sub. across sectors (ε)			2.4

Notes: This table shows the regression results of equation (1.49). The dependent variable is the log of expenditure, and the independent variable is the log of price index. The observations are at the city-sector-year level. The sample period is 2013-2015. Standard errors clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.8. Welfare Effects under Different Counterfactuals

(million RMB)	Economics gains	Environmental benefits		Social welfare
		(from trade)	(from scrap)	
	(1)	(2)	(3)	(4)
Panel A: Unilaterally optimal restriction				
Countrywide	-2,542	1,450	4,479	3,387
Poorest third	-1,119	1,393	2,613	2,888
Middle third	-1,272	1,090	1,416	1,234
Richest third	-152	-1,033	449	-735
Panel B: Non-cooperative Nash equilibrium				
Countrywide	-2,808	1,427	4,595	3,214
Poorest third	-1,246	1,450	2,649	2,853
Middle third	-1,386	1,115	1,453	1,183
Richest third	-176	-1,139	493	-823
Panel C: Nationally optimal restriction				
Countrywide	-1,115	1,105	4,075	4,065
Poorest third	-645	1,044	2,420	2,818
Middle third	-414	475	1,252	1,313
Richest third	-56	-414	403	-67
Panel D: Emission tax				
Countrywide	-2,552	115	37,716	35,280
Poorest third	-346	105	11,687	11,446
Middle third	-675	92	12,505	11,922
Richest third	-1,530	-82	13,525	11,912

Notes: This table reports the aggregate and heterogeneous welfare effects under four different counterfactuals. Panels A to C are scenarios of emission-based import restrictions on used vehicles. Panel D is the scenario in which each city levies a city- and vehicle sector-specific *ad valorem* emission tax on both locally traded and imported vehicles. The tax rate equals damages of vehicle life-cycle emissions divided by vehicle values. All values are 2015 RMB in millions.

CHAPTER 2

ENVIRONMENTAL PROTECTION OR LOCAL PROTECTIONISM? EVIDENCE FROM TAILPIPE EMISSION STANDARDS IN CHINA

A shorter version of this chapter was published in *AEA Papers and Proceedings* (Bai et al., 2021).

2.1 Introduction

Despite the promise of trade liberalization in promoting economic growth and increase social welfare (Rivera-Batiz and Romer, 1991; Edwards, 1993; Krueger, 1998), 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 interests 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 alleged non-tariff barriers are implemented under the stated goal of environmental protection.[1] To address this issue, 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 for the purpose of trade litigation.

The incentives to protect the local environment and local tax base could co-exist and interact with each other at the sub-national level, manifesting in environmental protec-

[1]See Runge (1990); Copeland and Taylor (2004); Ederington (2001); Ederington and Minier (2003) for examples.

tionism. This paper studies this issue in the context of used vehicle trading in China. Under the stated goal of protecting local air quality, many Chinese cities used tailpipe emission standards to restrict the import of used vehicles below local standards. In recent years, the central government speculated the restriction as a form of local protectionism and required the local governments to lift the restriction. The adoption and removal of the restriction provide a unique setting to study environmental protectionism for several reasons. First, China has a deep political root of within-country trade barriers. As pointed out by Montinola et al. (1995), "China lacks an adequate mechanism for policing the internal common market. This absence explains in part why many local governments have focused on trade barriers and aggressive anti-market policies within their jurisdiction." Second, the auto industry is regarded as a typical industry with practices of local protectionism due to its potentially large contribution to local GDP and employment (Wan et al., 2015; Barwick et al., 2021).[2] As a matter of fact, the auto industry was reported as the third most protected industry in China according to a survey administered by the Development Research Center of the State Council (Li et al., 2004). Third, trade liberalization of the used vehicle market could induce large potential gains (Grubel, 1980), but in reality, cities were very slow in removing the restriction. This further points to an important question of coordination in environmental regulation.

In this study, we first show a cross-sectional positive correlation between restriction adoption and the share of the auto industry in local tax revenue. Although not causal, it provides suggestive evidence that cities with a large automobile industry are more likely to impose the restriction, which is in line with the local protectionism speculation. We then focus on the removal of the restriction. We look at the direct impact on the imports, local sales, and total sales of dirty used vehicles. Then we examine the explicit goal of environmental protection to see whether removing the restriction had a negative impact

[2]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 enjoys tax benefits and various other government supports.

on air quality. Finally, we examine the implicit goal of protecting the local auto industry, by looking at how restriction removal impacts new vehicle sales.

We use the following identification strategies to address the concern that restriction removal could be endogenous. We first restrict our sample to cities that removed the restriction at the provincial level, thus mitigating the problem of self-selection. In addition to including city, time, and province-by-year fixed effects, we add a rich set of controls including economic status, political leader demographics, and flexible initial conditions interacted with linear time trends. To alleviate the potential over-fitting problem that may arise by adding many controls, we further use the post-double-selection (PDS) method (Belloni et al., 2012) to select the "right" set of controls in our specification.

We start by estimating the dynamic effects on the imports of dirty used vehicles using an event study framework. Dirty used vehicles are vehicles with emission standards below national standard *China 4* [3] and were subject to the import restriction in our study. It is shown that the import of dirty used vehicles increased sharply over time after the restriction was lifted. At the same time, local sales of dirty used vehicles decreased, suggesting that consumers shifted away from the local market when markets in other cities became accessible. Total sales of dirty used vehicles increased but were not statistically significant.

We then ask whether the increase in the import of dirty used vehicles led to the deterioration of local air quality. We did not find evidence that removing the restriction had any significant impact on ambient $PM_{2.5}$, CO, NO_2, but some minor effect on O_3. Thus the stated goal of continuing to enact the restriction is not strongly supported, at least in the short run.

[3]China established the first tailpipe emission standards, *China 1*, in 2001. Since then, the emission standards were tightened every several years from *China 1* to *China 6*. *China 4* was established and released by the Ministry of Environment Protection (MEP) and Standardization of Administration of China (SAC) in 2005 and was in effect from July 2011 to Dec 2016.

Our last set of analyses focuses on the new vehicle market. We find that a unilateral removal of the restriction would reduce new vehicle sales in the home city but increase new vehicle sales in other cities. The effect is stronger in cities with a large automobile industry. This represents a "prisoners' dilemma": cities were reluctant to lift the restriction on their own for it could hurt new vehicle sales and the local automobile industry, but if all cities cooperated and lifted the restriction together, new vehicle sales would increase. A failure of cooperation could make cities stuck in an inefficient equilibrium.

This study contributes to the literature in the following dimensions. First, while there is much literature studying the impact of environmental regulation on air quality (Davis, 2008; Auffhammer and Kellogg, 2011; Ellison et al., 2013; Wolff, 2014; Viard and Fu, 2015; Zhang et al., 2017; Salvo and Wang, 2017), little attention has been put on used vehicle trade. To the best of our knowledge, our paper is the first to evaluate the impact of used vehicle trade on air quality. A closely related study is Davis and Kahn (2010) which documents the change of emissions in the U.S. and Mexico due to increased bilateral trade of used vehicles after NAFTA. What's different is that we estimate the impact of the intra-national trade of used vehicles in China on the ambient pollution levels.

Second, although a lot of work has been done to understand the impact of environmental regulations on the vehicle market, especially how automakers and consumers respond to fuel economy standards (Anderson and Sallee, 2011; Klier and Linn, 2012; Bento et al., 2020; Reynaert, 2019; Klier and Linn, 2016; Dou and Linn, 2020), there are not many studies considering the interconnection between used vehicle market and new vehicle market. Existing studies show that the used vehicle market could respond to tightening standards in the new vehicle market by delaying the scrappage of used cars (Gruenspecht, 1982; Jacobsen and Van Benthem, 2015). Our study, on the contrary, documents that trade liberalization in the used car market could result in increased sales in the new vehicle market.

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 U.S. automakers (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 provides suggestive evidence that local governments with large auto industries are more likely to adopt the restriction, and show that the removal of restriction would hurt new vehicle sales, supporting the theory of protection for sales (Grossman and Helpman, 1994). This finding also speaks to the literature on local protectionism, manifested in forms of decreasing regional specialization (Young, 2000; Bai et al., 2004), home bias in vehicle market (Barwick et al., 2021), subsidy in favor of local EV producers (Wan et al., 2015), etc.

Lastly, our study relates to the literature on environmental federalism. Whether decentralized authority results in efficient outcomes is a big question that attracts many researchers. In theory, inter-jurisdictional competition could lead to Pareto-efficient outcomes only under a long list of assumptions that are hard to hold in practice (Levinson, 2003).[4] A commonplace in environmental regulation, "Conjoint federalism", where the central government sets a standard and the local governments then implement policies to meet, could be least efficient (Lin, 2010). A lot of studies try to look for evidence of "race to the bottom" or "race to the top" in environmental regulation (Oates, 2001; Potoski, 2001; Millimet, 2003) and whether local governments strategically interact with each other (Fredriksson and Millimet, 2002a; Brueckner, 2003), but less attention has been placed on the outcome of lack of coordination. We provide empirical evidence that unilateral behavior leads to an inefficient equilibrium, a prisoner's dilemma, while coordination would improve overall benefits.

[4]These assumptions include: "no cross-border externalities, many jurisdictions, all economic rents earned locally by the competing jurisdictions, welfare-maximizing local regulators, no constraints on available policy instruments and no redistributive policies (all taxes are benefits taxes)"

The rest of this paper is organized as follows: Section 2.2 reviews the institutional background and describes data sources. Section 2.3 describes the empirical framework. Section 2.4 presents the estimated impact of removing the restriction on the used vehicle market, air pollution, and new vehicle sales. Section 2.5 concludes.

2.2 Institutional Background and Data

2.2.1 Institutional Background

Growth of Chinese Vehicle Market China's vehicle market has experienced remarkable growth over the past twenty years. Annual sales of new vehicles increased from 2.1 million in 2000 to 28.9 million in 2017, at an average annual growth rate of 16.7 percent (see Figure 2.1). The total number of vehicles has reached 310 million in 2017 (MEE, 2018), which is 14 percent more than the total number of vehicles in the U.S. as of 2017.[5]

During the same period of time, the used vehicle market in China has also been growing, from a trading volume of 0.25 million in 2000 to 10.3 million in 2017. However, compared to the booming new vehicle market, the used vehicle market is much smaller and less active. Sales of used vehicles accounted for about 1/10 of new vehicle sales in 2000 and increased to about 1/3 in 2017. This used-to-new sales ratio is much smaller than that in countries like the U.S., where used vehicle sales are approximately 3 times new vehicle sales.[6]

The small size of the used vehicle market in China is partly due to its relatively young vehicle stock. Another important impediment is transaction costs (Gavazza et al., 2014).

[5]US total number of motor vehicles was 272.5 million in 2017. Data source: https://www.statista.com/statistics/183505/number-of-vehicles-in-the-united-states-since-1990/

[6]Source: https://www.statista.com/statistics/183713/value-of-us-passenger-cas-sales-and-le

In China, government intervention adds to the transaction costs by imposing an import restriction that prevents the free flow of used vehicles between cities. We will explain this restriction in more detail in the following section.

Adoption of Import Restriction on Used Vehicles Import restriction is a policy adopted by local governments that restricts the import of used vehicles from other cities that are below the local vehicle emission standards in effect. For example, many cities used *China 4* as the bar for imports, and used vehicles purchased from other cities that were below *China 4* were prevented from being registered in the local DMV. In essence, the import restriction on used vehicles is an example of using trade policy to address an environmental problem.

From the perspective of political economy, trade policies are shaped by politics to protect specific interests (Grossman and Helpman, 1994; Mitra, 1999). The equilibrium level of protection is determined by the demand for protection from interests group and supply from politicians maximizing self-interested objective (Trefler, 1993). In general, countries often provide more protection to industries that are at comparative disadvantage (Ray, 1981), in decline, politically important, or threatened by import competition (Lee and Swagel, 1997).

Import restriction on used vehicles has been pervasive in many countries and in different forms such as complete bans, banning imports of older vehicles, higher tariffs, and import licenses (Coffin et al., 2016). The key incentive is to protect domestic production and sales of new vehicles (Grubel, 1980). Data in Latin America shows that countries with the capacity to produce automobiles have much higher levels of import restrictions on used vehicles (Pelletiere and Reinart, 2002). Pelletiere and Reinert (2004) also finds strong evidence that automobile production, either domestic- or foreign-owned, contributes to more restrictions on imports of used vehicles. Other reasons, including environment, safety, and fraud concerns could also play a role (Pelletiere and Reinart, 2002).

Based on the theory and empirical evidence in the political economy of trade policy, we speculate that in addition to the stated goal of protecting the environment, there might be another incentive that drives local governments to adopt the import restriction, i.e., to protect the local automotive industry. We use the AOD concentration to measure air pollution and the share of the auto industry in local tax revenue as an index to capture the importance of the auto industry. We then regress the dummy of adopting restriction in 2013 on AOD, the tax share of the auto industry, and economic and political leader variables as of 2012.

Table B.1 shows the correlation between the adoption decision in 2013 and the variables we include in the regression. The restriction adoption is positively correlated with the AOD level as of 2012. This implies that cities with a more serious pollution problem are more likely to adopt an import restriction on used vehicles. This result supports the stated goal of the local government that the policy was intended to control the air pollution problem.

The result also shows that cities with a larger tax share of the auto industry as of 2012 are more likely to adopt the restriction. In cities with large auto industries, vehicles produced by local auto firms account for a large proportion of new vehicle sales (Barwick et al., 2021). Therefore, they have more incentive to impose the restriction to protect new vehicle sales and thus the local auto industry from import competition. This result supports our speculation that the local governments may want to use the trade barrier to protect local interests but under the disguise of environmental protection.

In a word, the adoption of import restriction could be viewed as a practice by local governments trying to use a trade intervention to achieve an explicit goal of environmental quality improvement and possibly an implicit goal of protecting the local auto industry and the new car market.

Removal of Import Restriction on Used Vehicles The import restriction of used vehicles was recognized as "abusing of administrative power to exclude or restrict competition" in a document *Guidelines of Anti Monopoly in Automotive Industry* drafted by the National Development and Reform Commission. On March 25, 2016, the General Office of the State Council made an announcement *Several Opinions about Promoting Convenient Transactions of the Used Vehicles*, urging local governments to lift the restriction before May 31, 2016, while excluding some key areas of air pollution prevention including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, and 9 cities in the Pearl River Delta.

However, by the deadline of May 31, 2016, only 3 cities lifted the restriction as required. On December 29, 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 the road locally should not be restricted from import. In March 2017, the Ministry of Commerce, the Ministry of Public Security, and the Ministry of Environmental Protection together issued another announcement requiring local governments to report whether they have lifted the import restriction on used vehicles. The reports would be submitted to the State Council and non-compliant cities could be subject to on-site inspection from the State Council. In March 2018, Prime Minister Li Keqiang emphasized the goal of national removal of the restriction in his annual government working report. However, after all these pushes, there is still about 40 percent of the cities that have not lifted the restriction by June 2018. Figure 2.2 panel (a) depicts the timeline for adopting and removing the import restriction.

For the following analysis, we focus on the removal of the import restriction rather than the adoption for two reasons. First, the import restriction and the emission standards were simultaneously adopted before the central government mandated the removal. Therefore, the effect of restriction adoption could be confounded by the effect of tightening emission standards. Second, we have highly unbalanced data on air pollution during the period of restriction adoption. As explained in more detail in the data section, China expanded the air pollution monitoring network in three waves during 2013-2014, thus the observations of air quality monitoring in 2013 are much fewer than the observations in 2014 and 2015.

As improving environmental quality and protecting the local auto industry could be two driving forces that make local governments adopt the import restriction, it is highly likely that local governments were reluctant to remove the restriction due to the same concerns. Based on this logic, we unfold our empirical analysis in the following line. We first look at the direct impact of restriction removal on the used vehicle market. Then we examine the explicit goal of environmental protection, to see whether removing the restriction would lead to a worsening of air quality. Finally, we examine the implicit goal of protecting the local auto industry, by looking at how restriction removal impacts new vehicle sales.

Tailpipe Emission Standards The fast growth of the vehicle population triggered great concerns about worsening air quality. Vehicle emissions could be an important source of air pollution in some cities. As estimated by Hao et al. (2000), vehicles contributed to 74 percent of CO concentration and 67 percent of NO_x concentration in Beijing, before substantial emission control policies were adopted. Therefore, China started to take various measures in the late 1990s to control vehicle emissions, including setting tailpipe emission standards, improving fuel quality, controlling traffic, promoting electric vehicles, etc. (Wu et al., 2017).

Being adopted in China, the U.S., European Union, Japan, etc., vehicle tailpipe emission standards set limits for specific air pollutants that are allowed to be released into the air by new vehicles. The standards push the manufacturers to adopt more advanced emission control technologies in their new vehicle productions (Reynaert, 2019). Once a new set of emission standards has been announced, vehicle manufacturers need to upgrade their vehicle models and apply for certification for the models that meet the new standard. When the new emission standard is adopted, new vehicles are not allowed to be sold and registered if they fail to meet the new standard. However, the trade of used vehicles is not subject to new standards.

In China, vehicle emission standards are established and released by the Ministry of Environment Protection (MEP) and the Standardization of Administration of China (SAC). In 2001, China released the first emission standard *China 1*, which put caps on CO, HC+NO_x, and PM from vehicle exhaust. Over time the standard has been tightened. The first five sets of emission standards, i.e., *China 1* to *China 5*, are as stringent as the corresponding EU standards, *Euro 1* to *Euro 5*. The most recent and the most stringent one, *China 6*, sets the limits on CO, HC, NO_x, and PM at the level of 40-50 percent lower than the limits of *Euro 6*, and adds additional limits on N_2O and PN. The emission standards vary for different categories of vehicles, including gasoline- and diesel-powered light-duty passenger vehicles and heavy-duty vehicles (commercial trucks and buses), etc. In our study, we focus on the emission standards for gasoline-powered light-duty vehicles.

It is the central government that establishes the emission standards. Once new and tighter emission standards have been released, local governments can choose when to adopt them using their own discretion. For example, *China 4* was released on July 1, 2007. Beijing was the first to adopt it on March 1, 2008. Adoption in other cities rolled out afterward until 2016.

Potential Confounding Policies We choose the period of 2016-2018 for our analysis, during which there was a staggered roll-out of restriction removal. As most cities adopted the restriction before 2016, this period is not confounded by the adoption decision.

However, during 2016-2017, there was a tightening of emission standards from *China 4* to *China 5*. Different from *China 4*, the timeline of adopting *China 5* was planned by the central government. In January 2016, the Ministry of Ecology and Environment (MEE) announced that the adoption of China 5 would be in two waves: in the first wave, 11 provinces in eastern China would adopt *China 5* on April 1, 2016; and on January 1, 2017, all the remaining provinces were required to adopt *China 5*.[7] Since the adoption of *China 5* were at the provincial level in two different years, in our specification, we add province-year fixed effects to absorb this confounding effect.

Two other policies have been effective during our sample period that could impact the new vehicle sales. One is a cut on vehicle acquisition tax. The tax rate for vehicles with displacement no larger than 1.6L was temporarily lowered from 10 percent to 5 percent from October 1, 2015, to December 31, 2016, and then adjusted to 7.5 percent from January 1, 2017, to December 31, 2017.[8] Since this policy applies to the entire country, its impact could be absorbed by the time fixed effects and thus not confound our estimates on new vehicle sales.

The other is the subsidy program for purchasing new energy vehicles (NEVs) during 2016-2020. Subsidies were offered both from the central and local governments.[9] Some cities implemented other policies that aimed at stimulating the sales of NEVs (Li et al., 2022a).[10] In order to alleviate the confounding effect, we exclude sales data of NEVs from

[7] Source: http://zfs.mee.gov.cn/hjjj/hjjjzcywxz/201606/20160623_355175.shtml

[8] Source: http://www.shanghai.gov.cn/nw2/nw2314/nw2315/nw17239/nw17243/u21aw1183289.html

[9] Source: http://fgk.mof.gov.cn/law/getOneLawInfoAction.do?law_id=83837

[10] For example, in Shanghai and Shenzhen, plug-in electric vehicles were exempted from new vehicle registration lotteries and fees (Sheldon and Dua, 2020).

our analysis of new vehicle sales.

2.2.2 Data

For this analysis, we compile comprehensive city-level panel data on the timing of policy roll-out, used and new vehicle sales, air pollution concentrations, and weather conditions from various sources. This section describes each data source and shows some data patterns. Table 2.1 reports summary statistics of the data within our sample window, 2016-2018.

Timing of Policy Roll-out We manually collect the timing of adoption and removal of the import restriction in each prefecture-level city in China.[11] 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 the government's website, we try to find the data from news media or directly contact the local DMV for information.

Our study focuses on the removal of the import restriction. Figure 2.2 panel (b) shows the staggered roll-out of restriction removal across cities. One thing worth noting is that there were 12 provincial jurisdictions (provinces and autonomous regions) that lifted the restriction at the provincial level.[12] For these provincial jurisdictions, it was the provincial government that made a decision and announced the removal of the restriction, rather than the city governments.

There is no official explanation why some provincial jurisdictions removed the restric-

[11]There are five levels of administrative divisions in China: the provincial (province, autonomous region, municipality, and special administrative region), prefecture-level cities, county, township and village. A prefecture-level city typically contains a central urban area and some surrounding counties and towns.

[12]Provincial jurisdictions that lifted the restriction at the provincial level are Yunnan, Inner Mongolia, Jilin, Sichuan, Ningxia, Anhui, Guangdong, Guangxi, Jiangsu, Jiangxi, Hainan, and Guizhou.

tion at the provincial level while others allowed the lower-level city governments to make the decision. However, we think it is very possible that the former has a more centralized administrative structure within its jurisdiction than the latter. Research on the determination of fiscal centralization, an extensively studied form of centralization and a predictor of governance structure, shows that fiscal centralization is negatively correlated with GDP per capita and population (Panizza, 1999; Bodman and Hodge, 2010). We see that out of the 12 provincial jurisdictions that removed the restriction at the provincial level, 9 have GDP per capita below the national mean, and 10 have population below the national mean. If those provinces tend to govern in a more centralized way, their decisions are less likely to respond to variations in a particular city within its jurisdiction.

Used Vehicle Registration Data 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 is a record of used car transactions including transaction quantity, transaction year and month, the original registration city, the destination registration city, and rich car attributes such as manufacturer, model, engine size, footprint, age, and emission standards each car meets. The data provide a complete picture of the intra-national trade of used cars, which is rarely observed in existing studies.

Figure 2.3 shows the pattern of used vehicle sales over time. Panel (a) are the aggregate imports and local sales of used vehicles across cities from January 2013 to June 2018. The dashed line represents May 2016 when local governments started to lift the restriction according to the central government's mandate. Imports of used vehicles started to rise faster after May 2016, from a mean of 1354 cars/month before to a mean of 4706 cars/month after.[13]

Next, we zoom in and look at the trends in the import of used vehicles by different

[13] These two numbers are calculated by fitting the import to a linear trend, before and after May 2016 respectively.

emission standards. For simplicity, we divide used vehicles into two types: clean and dirty, according to the emission standard *China 4*. Dirty vehicles do not meet standard *China 4* and are subject to the import restriction based on *China 4*, while clean vehicles that meet *China 4* or *China 5* are not restricted. As shown in panel (b) Figure 2.3, the import of dirty vehicles decreased sharply before May 2016, but the trend was reversed after May 2016 when cities started to lift the restriction. In contrast, the import of clean vehicles does not show a break in its increasing trend in May 2016.

New Vehicle Sales Data We obtain the universe of new vehicle sales data from China Automotive Technology and Research Center. The data report monthly sales of new vehicles by brand-model in 341 cities from 2015 to 2018. The sales include traditional gasoline vehicles and NEVs such as hybrid plug-in vehicles, electric vehicles, cell battery vehicles, etc. For our analysis, we drop the data on NEVs because they could be confounded by concurrent policies of NEV subsidies across cities. The total sales of NEVs account for 0.9 percent, 1.6 percent, 2.9 percent, and 5.3 percent in 2015-2018, respectively. New vehicle sales (gasoline vehicles only) increased from 21.1 million to 24.2 million from 2015 to 2016, but stagnated at 23.8 million in 2017 and declined to 21.3 million in 2018.

There is rich heterogeneity of new vehicle sales across cities. Mega-cities, such as Shanghai, Beijing, Chengdu, Chongqing, Zhengzhou, Guangzhou, etc., have much larger new vehicle sales than small and low-income cities. The top ten cities together account for 21 percent of the national sales over 2015-2018.

Air Pollution Data Before 2012, China monitored PM_{10}, NO_2, SO_2, CO, NO_2, and released daily 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 U.S. Embassy in Beijing tweeted their roof-top monitored $PM_{2.5}$ data and caused a dramatic increase of public attention on $PM_{2.5}$. In 2012, the Ministry of Environmental Protection (MEP) of China released a new national standard, *Ambient Air Quality Standards (GB3095-2012)*, adding $PM_{2.5}$ to the monitored pollutants. During 2013-2014, MEP rolled out a nationwide program expanding air pollution monitoring stations and disclosing real-time pollution information. On January 1, 2013, 74 cities started to make public the hourly data of six pollutants, $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, NO_2. 116 cities were added by October 31, 2013. By November 20, 2014, 367 cities have publicized real-time pollution data (Barwick et al., 2019). The number of air pollution monitoring stations has increased from 922 in 2013 to 1605 in 2018.

In our analysis, we focus on four pollutants $PM_{2.5}$, CO, NO_2, and O_3. We obtain the hourly data of all monitoring stations in China from 2013 to 2018 from the Data Center of the Ministry of Ecology and Environment (MEE), formerly MEP. For our analysis, we collapse the station-hourly data to the city-month level by simply averaging across stations and times within a city month.

Meteorology Data We retrieve the meteorological data from the National Meteorological Information Center of China. The Information Center has monthly meteorological data for 613 basic reference surface meteorological observation stations across China. The data includes a rich set of meteorological measures in wind speed, temperature, atmospheric pressure, relative humidity, precipitation, and wind direction. Using the longitude and latitude of each meteorological station, we calculate the Vincenty distance between each station-city pair and match each city with the closest station.

City Social Economic Variables We compile a panel of city social economic variables during 20015-2018 from the CEIC database. There are 286 prefecture-level cities included. The panel includes variables of GDP per capita, population, secondary industry share, tertiary industry share, government revenue, government expenditure, total import, total export, FDI, property price, unemployment, number of motor vehicles, and industry SO_2 emissions.

Mayors and Party Secretaries We obtain the data of political leaders in China at the city and provincial level from the China Research Data Service Platform (CNRDS). The data set contains demographic information, such as age, educational background, hometown, etc., and work experiences of all mayors(governors) and party secretaries for each city(province). We then construct a panel matching each city month by a mayor and a party secretary, including their age, education degree, and tenure length at the current position.

Firms' Tax Data We have the universe of firms' tax data during 2010-2015. The data set contains information on each firm's taxpayer id, industry id, administrative division codes of the firm's location, inputs, revenue, total output, value-added tax (VAT), consumption tax, income tax, etc. by year. We keep the data in the automotive industry and then collapse the data to the city-year level using the administrative division codes of the firms' locations. We merge the data set with the city's social economic data set. Lastly, we calculate the share of the auto industry in local tax revenue, by summing up 25 percent of the VAT and 40 percent of the income tax from the auto industries, divided by the total tax revenue of the city.[14] This ratio measures the share of local tax revenue contributed by the auto industry. The average share is 0.5 percent across all cities with the maximum share being 31.2 percent in Changchun, where China's first automotive manufacturer (FAW) is located (see Table 2.1). Other cities with a share of greater than 5 percent include Baoding, Shiyan, Guangzhou, Liuzhou, Wuhan, and Shenyang.

[14]Tax revenue of automotive industry are split between the central government and local governments, in a way that 25 percent of the value-added tax (VAT) and 40 percent of the income tax from the auto industry go to the local governments (Liu et al., 2016).

2.3 Empirical Strategy

In order to estimate the effects of restriction removal on used vehicle sales, air pollution, and new vehicle sales, a natural starting point is the Difference-in-Differences strategy

$$ln(y_{ct}) = \beta \cdot Lifted_{ct} + \alpha_c + \delta_t + \varepsilon_{ct} \tag{2.1}$$

where c denotes a city and t denotes time. y_{ct} are outcome variables including used vehicle imports, exports and total sales, ambient air pollution concentrations, and new vehicle sales. We collapse the used vehicle and new vehicle sales data to the city×year-quarter level and the pollution data to the city×year-month level. $Lifted_{ct}$ is the policy indicator that equals 1 if the restriction has been lifted in city c at time t. α_c is the city fixed effects that capture the difference in mean outcome across cities. δ_t is the time fixed effects that absorb common shocks to all cities in different time periods.

The key concern about identification is the endogenous timing of restriction removal due to omitted variable bias and (or) reverse causality. As mentioned in section 2.2.1, local governments did not follow the instruction of the central government to lift the restriction on May 31, 2016, but rather did it later at their own discretion. If the timing of restriction removal is correlated with some time-varying shocks that impact the outcome, say local governments removed the restriction at a time when they also strengthened the enforcement of environmental regulation, then the estimated effect on air pollution would be downward biased. Or if the local governments removed the restriction at a time when their new vehicle sales increase, then the estimated effect on new vehicle sales would also be downward biased.

We use several strategies to address this concern. First, we restrict our sample to a sub-sample of cities where the decision of restriction removal was made at the provincial level, rather than at the city level. As mentioned in Section 2.2.2, 12 provincial jurisdictions removed the restriction at the provincial level. For this subsample, the timing of restriction removal is less likely to be correlated to a time-varying unobservable in a specific city. We also add province×year fixed effects to control for other potential confounding policies at the provincial level.

The endogeneity issue is not fully addressed if the provincial decision still correlates with some city characteristics. Hence, we add a rich set of controls at the city level. We control for social economic variables of the city including a log of GDP per capita, second industry share and tertiary industry share, log of imports and exports, log of FDI, log of fixed asset investment, log of the property price, log of the number of motor vehicles, and log of industry SO_2 emissions. We also control for demographic information of the mayor and the party secretary of the city, including whether younger than 57,[15] whether having a master's degree, whether having a Ph.D. degree and their tenure length. In addition, we control for linear time trends interacted with initial conditions in 2015, where the initial conditions include the outcome variable, the share of the auto industry in local tax revenue, and the log of GDP per capita.

When the outcome variable is air pollution, we also control for meteorological variables including maximum wind speed, average temperature, average atmospheric pressure, average water pressure, average relative humidity, number of rainy days, and average precipitation.

Another potential confounder is air pollution in neighboring cities when pollution in neighboring cities spills over to the home city and correlates with the removal timing of the home city. Since pollutants travel to other cities by wind, we construct an inverse-distance-weighted average of air pollution by pollutant in upwind direction at

[15]If a mayor or a party secretary is older than 57, he or she would not be considered for further political promotion.

the city×year-month level.[16] We then control for the upwind average pollution in our specification.

However, as we put so many controls in the model, the issue of over-fitting arises. We face a trade-off between controlling not enough versus controlling too many. In order to find a balance, we use the "post-double-selection" (PDS) methodology proposed by Belloni et al. (2012) to select the "right" set of controls from what we include in our model.[17]

Therefore, the specification becomes:

$$ln(y_{ct}) = \beta \cdot Lifted_{ct} + X'_{ct}\gamma + \alpha_c + \delta_t + \eta_{prov,year} + \varepsilon_{ct} \tag{2.2}$$

where X_{ct} is the set of controls selected from the "post-double-selection" method.

Another challenge of the identification is the spillover effect — the outcome of one city is not only impacted by restriction removal in its own city, but also impacted by restriction removal in other cities.[18] In order to capture the spillover effect, we construct an index measuring the proportion of restriction removal in other cities:

[16]We use the following procedures to construct air pollution in the upwind direction. First, we calculate the bearings between any two city pairs (Bearing is a geographical terminology that indicates the angle between the direction of two points on Earth and that of the true north). Then convert the bearings into 16 directions, i.e., N, NNE, NE, ENE, E, ESE, SE, SSE, S, SSW, SW, WSW, W, WNW, NW, NNW. The upwind direction of city c at time t is the one that lies in the same and two neighboring directions of the wind direction of city c at time t (See Figure B.1 for an illustration). Then calculate the average pollution levels of the cities in the upwind direction weighted by the inverse of the distance between the upwind city and the home city.

[17]The PDS approach uses the lasso estimator in the process of selecting controls. There are two steps: first, the outcome variable is regressed on all the controls using a lasso regression; second, the policy indicator is regressed on the same set of full controls using a lasso regression. In both steps, some control variables are chosen with non-zero lasso coefficients. The final choice of the controls is the union of the variables selected in the first and second steps. Notice that we partial out time fixed effects and city fixed effects before post-double-selection to absorb the mean difference in the outcome variable across cities and common shocks at different times.

[18]For example, the import of used vehicles in one city could be diverted to other cities if other cities lifted the restriction, or new vehicle sales could increase when other cities lifted the restriction so that more used vehicle owners could trade in their old ones for new vehicles.

$$OtherLifted_{ct} = \sum_{i=1, i \neq c}^{N} w_{ic} Lifted_{i,t} \tag{2.3}$$

where $OtherLifted_{ct}$ is a weighted sum of the policy indicator in cities other than c at time t. The weights are defined as $w_{ic} = \frac{Y_{ic}}{\sum_{i=1, i \neq c}^{N} Y_{ic}}$, which is the share of used vehicle trade between city c and city i in the baseline year 2015, over the total trade of used vehicles of city c as of 2015. The index gives more weight to larger trading partners of city c in baseline used vehicle trade.

A potential issue arises when we add $OtherLifted_{ct}$ into the model. If there exist strategic interactions among governments, i.e., the policy decision of one city depends on the policy decision of its neighboring cities, then $OtherLifted_{ct}$ could be impacted by $HomeLifted_{ct}$, which makes $OtherLifted_{ct}$ an outcome of $HomeLifted_{ct}$ and thus a "bad control" (Angrist and Pischke, 2008). We circumvent this issue by including a lagged term of $OtherLifted_{c,t-1}$ in our model under the assumption that the policy interaction (if any) occurs with a time lag (Hayashi and Boadway, 2001).

Therefore, our preferred specification that accounts for the spillover effect is the following

$$ln(y_{ct}) = \beta \cdot HomeLifted_{ct} + \theta \cdot OtherLifted_{c,t-1} + X'_{ct}\gamma + OX'_{c,t-1}\mu + \alpha_c + \delta_t + \eta_{prov,year} + \varepsilon_{ct} \tag{2.4}$$

where $HomeLifted_{ct}$ is the policy indicator that is turned on if city c has removed the restriction at time t. $OtherLifted_{ct}$ is defined as in Equation (2.3). X_{ct} is a set of controls described in Equation (2.2). Following Millimet and Roy (2016), we add an additional set of controls, $OX_{c,t-1} = \sum_{i=1, i \neq c}^{N} w_{ic} X_{c,t-1}$, which is the weighted average of economic and political variables in other cities. We use the same weights as used in constructing $OtherLifted$.

The identification is based on two assumptions. The first assumption is parallel trends for the treated group and the untreated group. This means that for cities that have removed the restriction, their counterfactual outcomes had they not removed the restriction would be parallel with the outcome of the cities that have not yet removed the restriction.

We use an event study framework to test the parallel trends assumption. The event study specification is:

$$ln(y_{ct}) = \sum_{\tau=-4,\tau\neq-1}^{\tau=4} \beta_\tau \cdot D_{c\tau} + \theta \cdot OtherLifted_{c,t-1} + X'_{ct}\gamma + OX'_{c,t-1}\mu + \alpha_c + \delta_t + \eta_{prov,year} + \varepsilon_{ct} \quad (2.5)$$

where $D_{c\tau}$ are separate indicators for each quarter τ relative to the time of removal at city c. For cities that have never removed the restriction during our sample period, $D_{c\tau} = 0$.

The second assumption is that the timing of restriction removal in our subsample is as random conditional on city fixed effects, year-month (year-quarter) fixed effects, province×year fixed effects, and a set of control variables selected by the PDS method. This assumption should hold since the provincial decision is unlikely to correlate with shocks at the city level, conditional on the economic and political status of the city.

2.4 Results

We present our results in the following order. First, we look at the direct impact of removing restrictions on the used vehicle market. Then we look at the explicit goal of environmental protection, i.e., whether removal would lead to an increase in air pollution. Finally, we examine the implicit goal of protecting local interest by looking at the impact on new vehicle sales.

2.4.1 Used Vehicle Sales

We divide used vehicles into two types based on their emission standards: dirty and clean. Dirty vehicles refer to those whose emission standards are below *China 4* so that they are restricted from importing from other cities under the restriction. Clean vehicles, otherwise, refer to those whose emission standards are *China 4* or above, so that their imports are free of restriction.

Figure 2.4 shows the event study graphs for the import of used vehicles. The coefficients of -1 quarter are normalized to 0. The graph shows clearly that before restriction removal, the coefficients are not significantly different from 0, which implies no pre-trends. After the restriction was lifted, the import of dirty vehicles increases dramatically over time.

The event study graph in Figure 2.4 shows that the treatment effects increase over time. Recent literature in staggered DID and two-way fixed effects model find that the two-way fixed effects estimator are biased when treatment effects vary across time or units (Goodman-Bacon, 2021; Sun and Abraham, 2020; Imai and Kim, 2019; de Chaisemartin and d'Haultfoeuille, 2019). Therefore, we report separate coefficients for each quarter after restriction removal estimated from the event study model which is robust in estimating the dynamic treatment effects (Borusyak and Jaravel, 2017).

Table 2.2 reports the dynamic effects of lifting the restriction on different margins of dirty vehicle sales: imports, local sales, exports, and total sales of dirty used vehicles, using specification (2.5).

Column (1) shows the estimated effect on the import of dirty used vehicles after the restriction removal. The coefficients for one quarter, two quarters, and three quarters after the restriction removal are 1.075, 1.723, and 2.164, respectively, meaning a 193 percent, 460 percent, and 770 percent increase, respectively. On average, after three quarters of removing the restriction, the imports of dirty used vehicles increased by 360 percent. To put our estimates into context, if we take the total number of intranational trade of dirty used vehicles in 2016, 0.16 million, as the baseline, then lifting the restriction increased the dirty used vehicle trade by about 0.58 million in three quarters. This is the direct effect and exactly what we expect to see — the removal of the import restriction significantly boosted the import of dirty used vehicles. On the other hand, the coefficient for "Other Lifted", i.e., the weighted average of other cities' removal status, is not significant, which implies not much spillover in the import of dirty vehicles.

Column (2) reports the dynamic effects of the restriction removal for local sales of dirty vehicles. The estimated coefficients for one quarter, two quarters, and three quarters after the restriction removal are 0.004, -0.074, and -0.045. The estimates suggest that lifting the restriction led to a decrease of about 3 percent in local sales of dirty used vehicles on average. This effect could be mainly driven by the substitution between imported cars and local cars. When the import restriction was lifted, consumers had more opportunities to purchase a used vehicle from other cities for a lower price, thus their purchases from the local market declined. Further, the estimate for "Other Lifte" is -0.071 and significant, showing that other cities' restriction removal reduced local sales of dirty used vehicles by about 7 percent. As we see in column (3), when other cities opened their markets, the export of used vehicles increased dramatically, which left fewer vehicle owners willing to sell in the local market. Thus other cities' restriction removal had a negative effect on local sales of dirty vehicles.

Column (3) reports the effects of exports of dirty vehicles. The coefficient for "Other Lifted" is 0.904 and significant at the 1 percent level. This result is intuitive as more neighboring cities lifted their import restrictions, exports of dirty vehicles in the home city would increase. The magnitude is large, that exports of dirty used vehicles increased by 147 percent when all other cities lifted the restriction. Besides, the coefficients for "Home Lifted" are also positive and increased over time. Why did lifting the import restriction in the home city have a positive impact on its exports? As we see in column (2), the restriction removal reduced local sales of dirty used vehicles. Although we do not observe the data on used vehicle transaction prices, it is expected that the price for the local market also declined. The reduced price could make local vehicles more competitive in other markets and thus increase the exports of dirty vehicles from the home city.

Column (4) reports the effects on total sales of dirty vehicles, which is the sum of imports and local sales. We see that the imports of dirty vehicles increased after the restriction removal while the local sales decreased. These two effects are opposite in directions, making the effect on total sales undetermined ex-ante. The results show that for the first 2 quarters, the effect is negligible. In the third quarter after removal, the positive effect on the import over-weighs the negative effect on local sales which leads to an increase in the total sales of dirty vehicles, although not significant. The spillover effect from other cities is positive but also not significant.

2.4.2 Robustness Checks

Our main specification uses the subsample and PDS method to select the set of controls. For robustness checks, we try different specifications using different samples and models. Figure B.2 plots the estimated impact of removing restrictions on imports, local sales, exports, and total sales of dirty used vehicles for different combinations of full sample vs. subsample, and PDS vs. fixed effects model. The estimates across different specifications are similar in sign and magnitude, showing that the main results are robust.

In constructing the variable "OtherLifted", our baseline weights are bilateral trade of used vehicles as of 2015. We also try using baseline exports and imports of used vehicles as weights. The results are shown in Figure B.3. Most of the estimates using different weights are qualitatively similar, except that the coefficient for "OtherLifted" in imports and total sales is significantly positive when using exports as weights while not significant using the other two weights. This could be driven by the fact that we use the subsample of cities that lifted the restriction at the provincial level so that restriction removal within provinces is correlated with "HomeLifted". Then "OtherLifted" actually captures part of the effect that the province lifted the restriction.

We also examine the impacts of lifting restrictions on clean used vehicles. As shown in Table B.2, after the restriction was lifted in the home city, imports of clean used vehicles did not change significantly. Since imports of clean used vehicles were not banned by the restriction policy, this result can be seen as a falsification test. On the margin of local sales, there was a negative impact over time. This might be driven by the fact that consumers were shifted away from the local market when the import restriction was lifted. There is no significant spillover effect for all margins of clean used vehicle sales.

2.4.3 Pollution

Figure 2.5 shows event study graphs for coefficients before and after the restriction was lifted. For all four pollutants $PM_{2.5}$, CO, NO_2 and O_3, no significant pre-trends are detected.

Table 2.3 summarizes the effect of lifting the restriction on air pollution using specification (2.4). We find that the restriction removal in own city does not have a significant impact on $PM_{2.5}$, CO, and NO_2, but has led to a 3.7 percent increase in O_3.

On the other hand, restriction removal in other cities does not impact $PM_{2.5}$ and CO significantly but has a positive impact on NO_2 and a negative impact on O_3. As we show in the following section that restriction removal in other cities has led to a large increase in local new vehicle sales, this might contribute to the increase of NO_2. The decrease of O_3 could be attributed to the change of ambient NO_2. O_3 is a secondary pollutant produced from the chemical reaction of NO_2 and volatile organic compounds (VOC), in which the product can be divided into "VOC-saturated (NO_x-limited)" regime and "VOC-limited" regime. Under the "VOC-saturated" regime, NO_x reductions lead to a decrease of O_3, while under the "VOC-limited" regime, NO_x reductions induce more O_3 production (Salvo and Wang, 2017). Our result suggests a negative relationship between NO_2 and O_3, which is consistent with the impact of ethanol-blended gasoline policy in Sao Paulo (Salvo and Wang, 2017) and the COVID-19 lockdown in China (He et al., 2020).

The null effect could be driven by the small scale of the change in the import of dirty used vehicles compared to the local vehicle stock in the short run. Over our sample period from January 2016 to June 2018, the import of dirty used vehicles accounted for 0.66 percent of the local motor vehicle stock, on average. As shown in Figure B.4, the import share of dirty vehicles was less than 1 percent for the majority of cities, while only a handful exceed 5 percent. Thus, the increase in the import of dirty used vehicles induced by trade liberalization only added to a small fraction of the existing vehicle stock per city in the short run, rendering the null effect on air pollution.

2.4.4 New Vehicle Sales

Figure 2.6 shows the event study graph for new vehicle sales. We don't observe significant pre-trends before restriction removal. Table 2.4 reports the estimated results using specification (2.4). In line with what we see in the event study figures, there is no significant effect on new vehicle sales when the home city lifted its restriction. However, restriction removal in other cities has a large significant positive effect on new vehicle sales in the home city. If all the other cities lifted their import restriction altogether, new vehicle sales in the home city would increase by about 10 percent.

The large spillover effect could be driven by the connection between the used vehicle market and the new vehicle market. The used vehicle market provides an important service to low-valuation consumers and allows high-valuation consumers to trade in their used vehicle for a new one so as to maintain the level of quality they prefer (Porter and Sattler, 1999). As more cities opened their markets and allow imports of dirty used vehicles, the owners of dirty used vehicles get a better chance to trade in their used vehicles for a better price and then purchase a new vehicle. This is supported by the sharp increase in exports of dirty vehicles as other cities lifted their restrictions, shown in Table 2.2 column (3).

We further look at heterogeneous effects on new vehicle sales. We flag cities as large importers or large exporters if their import or export of used vehicles as of 2015 are in the top quartile. In column (2) of Table 2.4, it is shown that the positive effect of restriction removal in other cities is 9.8 percent larger for large exporters. This result is consistent with our hypothesis that used vehicle exports could be the channel that leads to the increase of new vehicle sales when other cities removed their restrictions.

Out of 100 cities in our subsample, there are 18 cities that have automotive manufacturing plant(s). Table 2.4 column (3) shows that new vehicle sales in cities without auto plants do not change significantly after restriction removal, but new vehicle sales in cities with auto plants decrease by about 7.8 percent. Also, other cities' restriction removal has a positive impact on new vehicle sales in the home city, and the impact is significantly larger for cities with auto plants.

The above results point to a prisoner's dilemma: cities have no incentive to lift the restriction unilaterally since it could hurt their new vehicle sales and the local auto industry, but if all cities coordinate and lift the restrictions altogether, every city would be better off. This finding highlights the importance of coordinated efforts to knock down trade barriers and build an integrated market.

2.4.5 Counterfactual on new vehicle sales

The results in the new vehicle market highlight a prisoner's dilemma that self-interest behavior leads to overall benefit loss. In this section, we present the gains in the new vehicle market under a counterfactual scenario if all cities lifted the restriction on May 31, 2016, as urged by the central government.

Based on our estimated coefficients, we calculate the predicted change of new vehicle sales under the counterfactual scenario.[19] The maps of counterfactual cumulative impact on new vehicle sales by city are shown in Figure 2.7. If all cities had lifted the restriction at the end of May 2016, then all cities would have had an increase in new vehicle sales from 1 percent-19 percent during 2016-2018, with large used vehicle exporters increasing more. This amounts to a cumulative total of 7.4 million more new vehicle sales for the whole country during 2016-2018.

[19] First, we calculate the counterfactual sales if all cities lifted the restriction in May 2016. Then we calculate the ratio between the counterfactual sales and the baseline sales (observed sales) using the formula $q_c/q_b = \exp\{(\beta_1 + \beta_2 \times \mathbb{1}(LargeImporter)) \times (AllLifted - HomeLifted) + (\beta_3 + \beta_4 \times \mathbb{1}(LargeExporter)) \times (AllLifted - OtherLifted)\}$, where q_c represents new vehicle sales under the counterfactual scenario, q_b represents the baseline sales (observed sales). $\beta_1, \beta_2, \beta_3, \beta_4$ are coefficients for HomeLifted, HomeLifted$\times\mathbb{1}$(LargeImporter), Other Lifted, and OtherLifted$\times\mathbb{1}$(LargeExporter) in column (2) of Table 2.4. Lastly, we calculate the percentage change and change in level as $\Delta\% = (\frac{q_c}{q_b} - 1) \times 100\%$ and $\Delta q = \Delta\% \times q_b$.

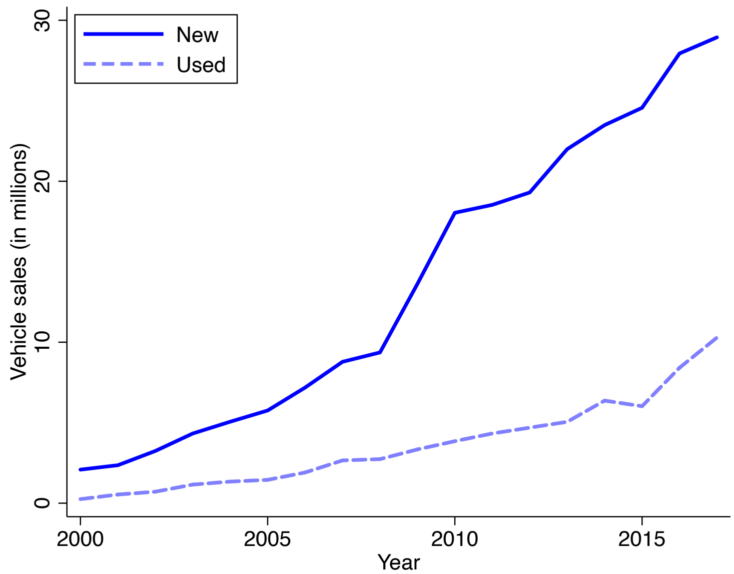
2.5 Conclusion

Using detailed data on used vehicle trade, local air pollution, and new vehicle sales, this paper examines the impacts of lifting the import restriction on the used vehicle market, air pollution, and new vehicle market. Restriction removal directly boosted imports of dirty used vehicles but did not lead to a significant impact on local air quality in the short run. What's more, restriction removal has a positive spillover effect on new vehicle sales in other markets. New vehicle sales would increase by 7.4 million if the restriction was removed nationally by May 2016 as the central government required. Our result in new vehicle sales reflects a prisoner's dilemma that unilateral removal of the restriction is not in the interest of cities, yet universal removal would benefit all.

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

Figures and Tables

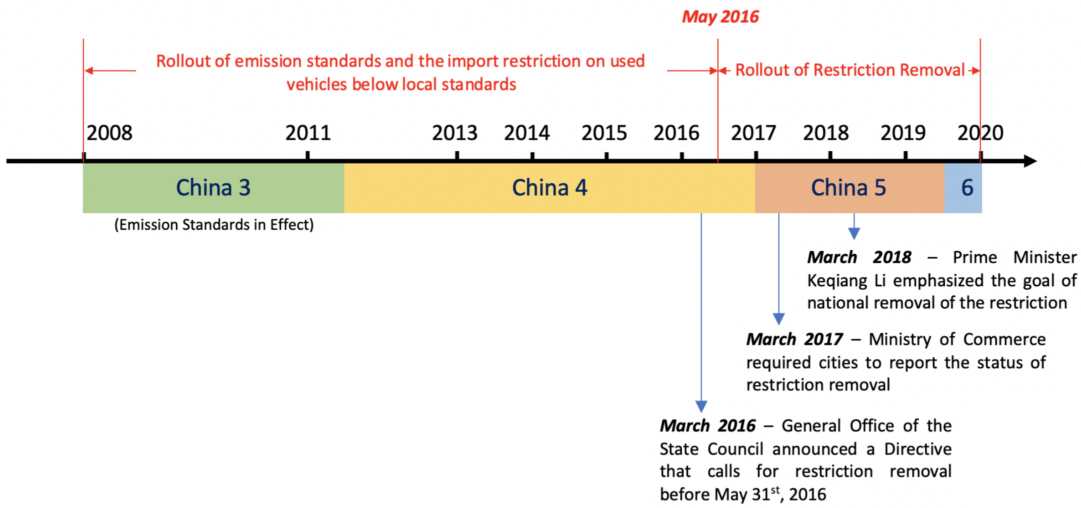
Figure 2.1. Total Sales of Vehicles in China, 2000-2017



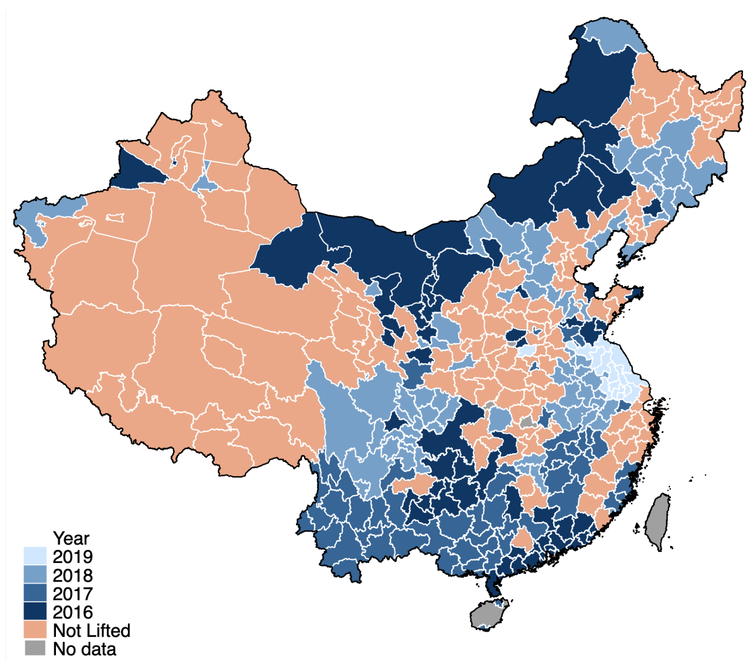
Notes: This figure shows the annual total sales of new vehicles and used vehicles in China during 2000-2017. Data on new vehicle sales are from the CEIC China Premium database. Used vehicle sales data in years 2000-2011 are from `http://auto.163.com/special/observation50/`, used vehicle sales data in 2013-2017 are based on own calculation.

Figure 2.2. Policy Timeline and Roll-Out of Restriction Removal

(a) Policy Timeline



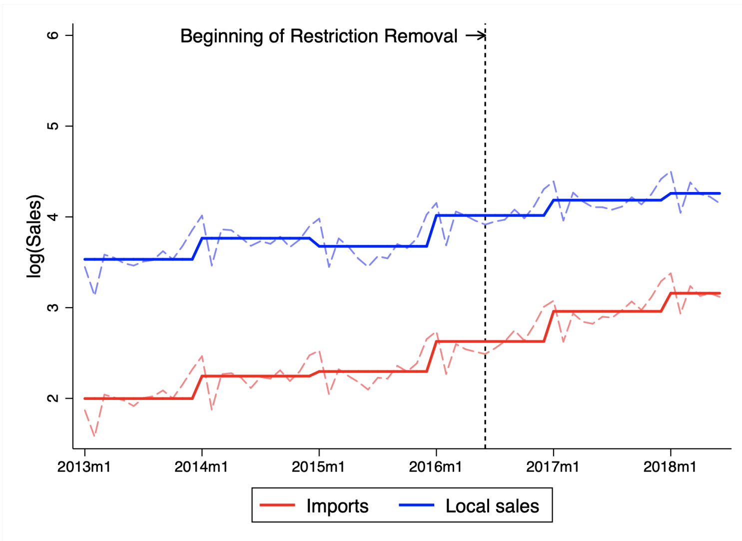
(b) Rollout of Restriction Removal



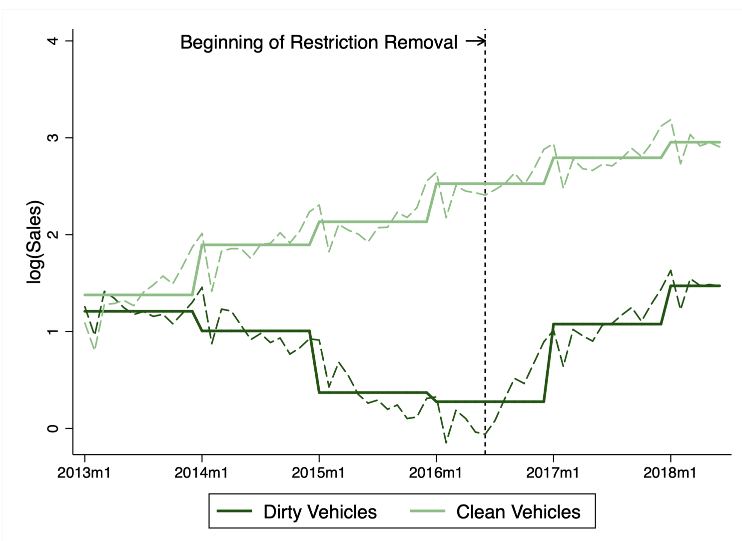
Notes: Panel (a) shows the timeline of adoption and removal of the import restriction on used vehicles below local emission standards. Panel (b) shows the year in which each city removed its import restriction on used vehicles.

Figure 2.3. Used Vehicle Sales, 2013.1-2018.6

(a) Total Sales

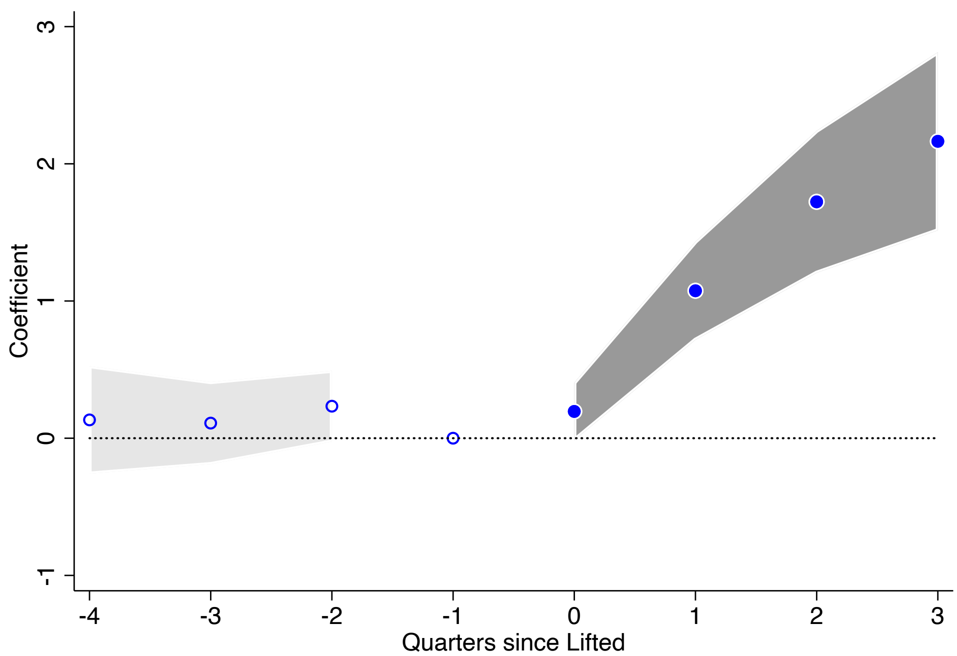


(b) Imports



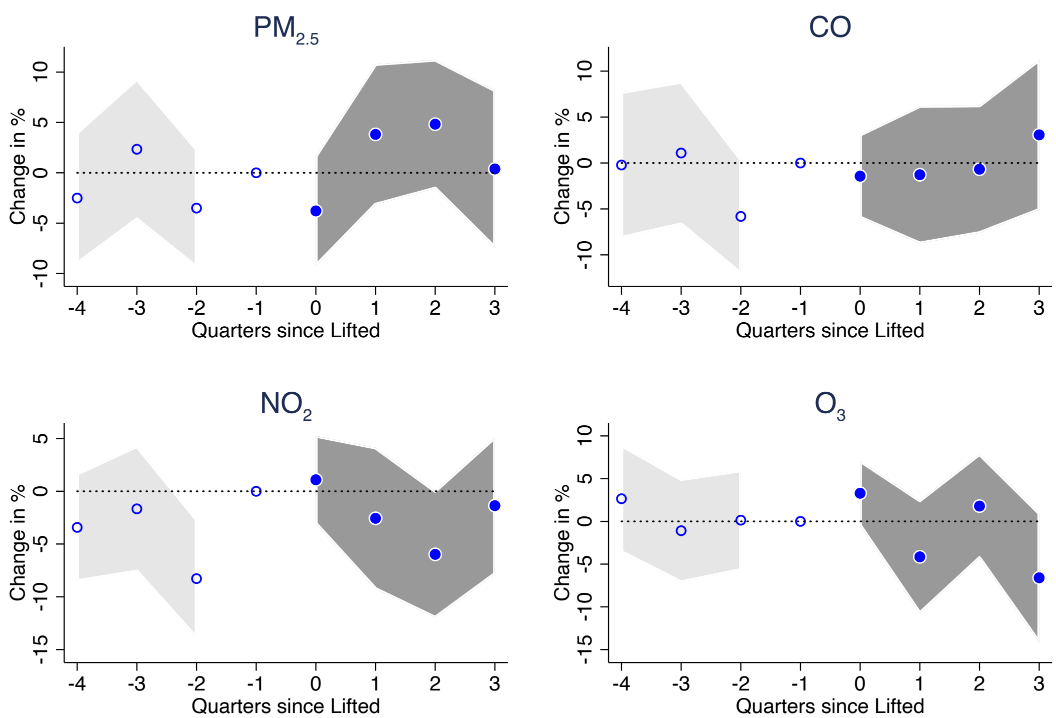
Notes: Panel (a) shows the imports and local sales of used vehicles. Panel (b) shows the import of dirty vs. clean used vehicles, where dirty vehicles are those below national emission standard 4, clean vehicles otherwise. Dashed lines are the monthly data and solid lines are yearly averages. Short dashed line indicates May 2016 when cities started to lift the import restriction on dirty used vehicles.

Figure 2.4. Event Study for Import of Dirty Used Vehicles



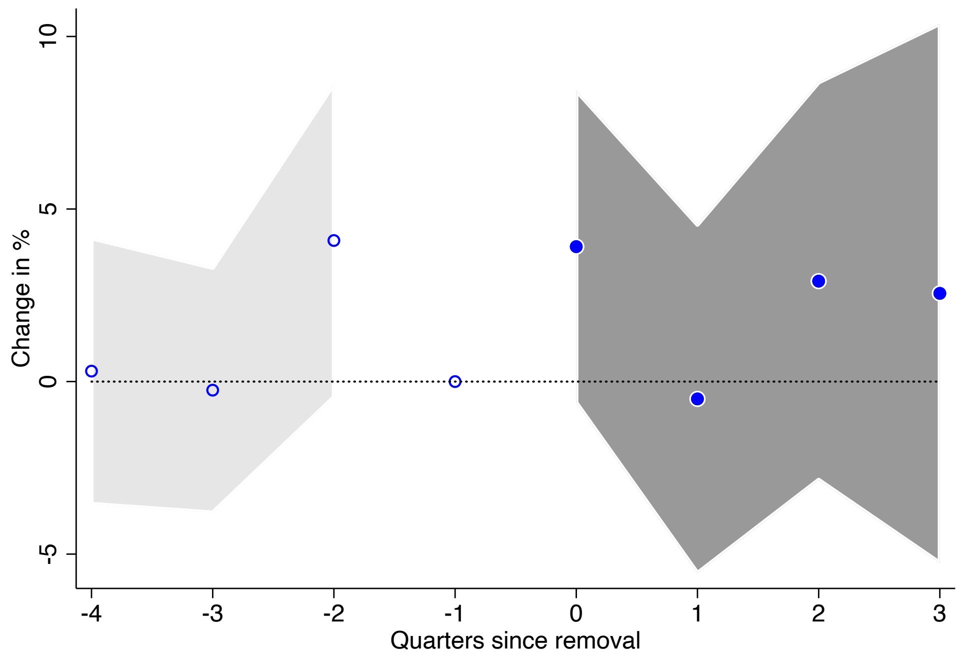
Notes: This graph shows the coefficients obtained from the event study regressions that estimate the effect on import of used vehicles in each quarter before and after policy removal. The dependent variable is log of the used vehicle import aggregated at the city×year-quarter level. Dirty vehicles refer to the vehicles whose emission standard is below Level 4. The regression controls for city FEs, year-month FEs, province×year FEs and uses PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). Shaded area shows the 95 percent confidence interval. Standard errors are clustered at the city level.

Figure 2.5. Event Study for Air Pollution



Notes: This graph shows the coefficients obtained from the event study regressions that estimate the effect on each pollutant in each quarter before and after policy removal. The dependent variable is log of the pollutant concentration. The regression controls for city FEs, year-month FEs, province×quarter FEs, weather conditions, upwind pollution, and uses PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). The shaded area shows the 95 percent confidence interval. Standard errors are clustered at the city level.

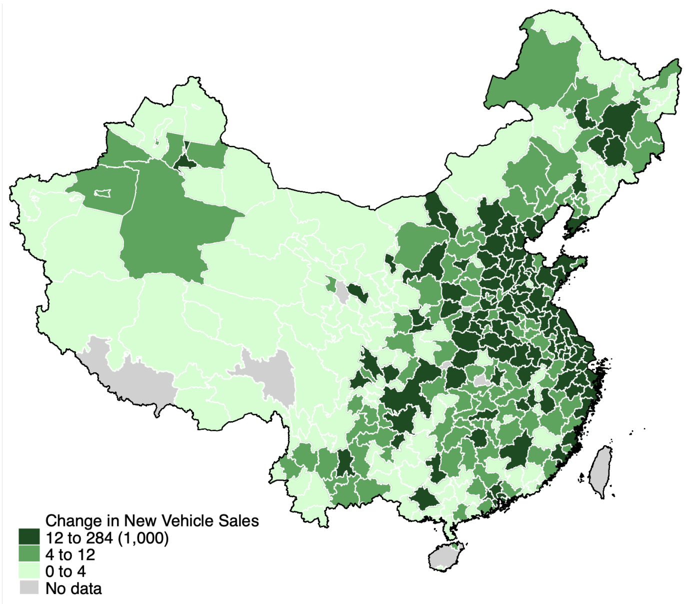
Figure 2.6. Event Study for New Vehicle Sales



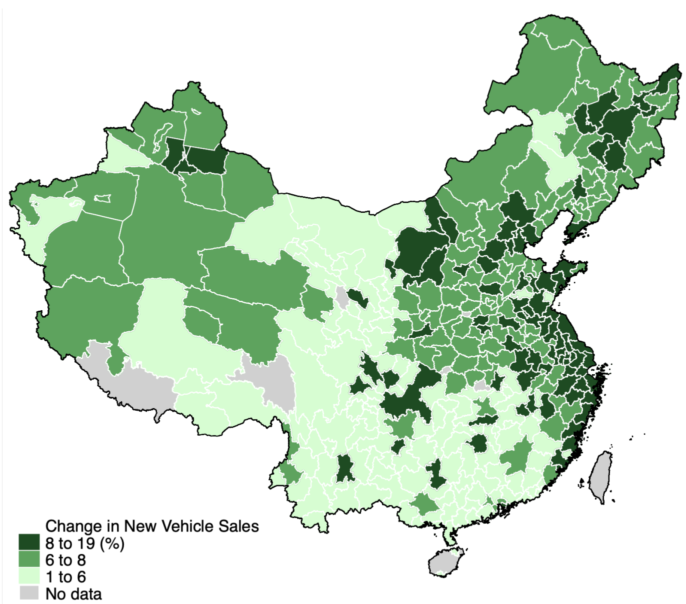
Notes: This graph shows the coefficients obtained from the event study regressions that estimate the effect on new car sales in each quarter before and after policy removal. The dependent variable is log of the new car sales. The regression controls for city FEs, year-month FEs, province×year FEs and use PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). The shaded area shows the 95 percent confidence interval. Standard errors are clustered at the city level.

Figure 2.7. Counterfactual Impact on New Vehicles Sales, 2016.1-2018.12

(a) Level Change



(b) Percentage Change



Notes: This map shows the counterfactual impact of the nationwide removal of the restriction on new vehicle sales by city from January 2016 to December 2018. Based on the estimated impacts of lifting restrictions on new vehicle sales (Table 2.4, column (2)), we calculate the counterfactual sales if all cities lifted the restriction in May 2016. Then we calculate the ratio between the counterfactual sales and the baseline sales (observed sales) [20]. The percentage change is this ratio minus 1. The level change is the percentage change multiplied by the baseline sales.

Table 2.1. Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Used vehicle sales (city×year-quarter)					
Import of dirty used cars	233.4	642.3	0	8650	3340
Local sales of dirty used cars	2346.9	2963.0	0	22875	3340
Import of clean used cars	1376.3	1419.7	0	11838	3340
Local sales of clean used cars	3305.0	4247.8	0	38695	3340
New vehicle sales (city×year-quarter)					
New car sales	17077.1	24378.3	2	230603	4044
Air pollution (city×year-month)					
$PM_{2.5}$ ($\mu g/m^3$)	42.9	25.8	4.5	510.5	12060
PM_{10} ($\mu g/m^3$)	79.0	50.3	7.6	1455.1	12060
CO (mg/m^3)	0.9	0.4	0.2	5.7	12060
NO_2($\mu g/m^3$)	28.9	13.5	3.1	100.4	12060
O_3($\mu g/m^3$)	62.2	23.8	3.9	174.4	12060
Weather (city×year-month)					
Max wind speed(m/s)	8.7	2.9	1.7	36.4	12131
Average temperature(°C)	14.4	10.8	-29.1	37.3	12120
Average air pressure(hPa)	951.7	88.0	582.0	1033.3	12120
Average water air pressure(hPa)	13.8	9.0	0.5	36.7	12120
Average relative humidity(%)	67.5	15.1	11.7	96.9	12120
Number of days with precipitation>=0.1mm	9.6	5.9	0.0	30.0	12128
Precipitation(mm)	84.3	99.1	0.0	817.2	12124
City Economy (city×year)					
GDP per capita (RMB)	57462.5	32997.4	11693.0	215488.0	858
Population(1,000)	4508.8	3216.7	205.3	34036.4	855
Government revenue (million RMB)	27374.7	61597.7	1404.5	710815.0	858
Number of motor vehicles (1,000)	715.9	823.9	42.0	6317.2	849
Share of auto industry in local tax revenue (%)	0.5	2.0	-0.1	31.2	1144

Notes: This table reports the summary statistics of variables in used vehicle sales, new vehicle sales, air pollution, weather conditions and city economic variables from January 2016 to December 2018 (the share of auto industry in local tax revenue is from 2012 to 2015). Dirty and clean used vehicles are classified based on whether below or above emissions standard level 4.

Table 2.2. Dynamic Effects on Used Vehicle Sales

Dep. var.	log(Imports)	log(Local Sales)	log(Exports)	log(Total)
	(1)	(2)	(3)	(4)
Home Lifted				
Event time=0	0.195*	-0.003	0.058	-0.025
	(0.107)	(0.016)	(0.071)	(0.020)
Event time=1	1.075***	0.004	0.132	-0.012
	(0.182)	(0.018)	(0.142)	(0.032)
Event time=2	1.723***	-0.074***	0.269	0.000
	(0.264)	(0.022)	(0.181)	(0.047)
Event time=3	2.164***	-0.045	0.509**	0.045
	(0.331)	(0.034)	(0.225)	(0.057)
Other Lifted	0.224	-0.071**	0.904***	0.030
	(0.325)	(0.032)	(0.340)	(0.067)
Year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y
Observations	928	929	929	929

Notes: This table reports the dynamic impacts of lifting restriction on dirty used vehicle sales from event study models with the sub sample and LASSO method. The event time refers to the time when restriction was lifted in the home city. "Event time=1" means 1 quarter after restriction lifted. Dirty vehicles refer to vehicles below emission standard China 4. The regression controls for city FEs, year-month FEs, province×year FEs and uses PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3. Effect on Air Pollution

Dependent variable	log($PM_{2.5}$)	log(CO)	log(NO_2)	log(O_3)
	(1)	(2)	(3)	(4)
Home Lifted	0.022	0.001	0.006	0.037**
	(0.020)	(0.022)	(0.019)	(0.017)
Other Lifted	-0.019	0.068	0.083**	-0.103**
	(0.049)	(0.062)	(0.039)	(0.052)
City FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
Province-Quarter FE	Y	Y	Y	Y
Observations	3149	3149	3149	3149

Notes: This table reports the effects of lifting the import restriction on air pollution. "Lifted" is the policy indicator that equals 1 if a city has lifted the restriction. "Other Lifted" is the lag of the weighted average of policy dummies in other cities. The regression controls for city FEs, year-month FEs, province×quarter FEs, weather conditions, upwind pollution, and uses PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.4. Effect on New Vehicle Sales

Dependent variable	log(Sales)		
	(1)	(2)	(3)
Home Lifted	0.006	0.013	0.014
	(0.020)	(0.021)	(0.022)
Other Lifted	0.103**	0.077*	0.081*
	(0.042)	(0.043)	(0.042)
Home Lifted $\times\mathbb{1}$(Large Importer)		-0.007	
		(0.032)	
Other Lifted $\times\mathbb{1}$(Large Exporter)		0.098*	
		(0.050)	
Home Lifted $\times\mathbb{1}$(Home w/ Auto Plant)			-0.078**
			(0.036)
Other Lifted $\times\mathbb{1}$(Home w/ Auto Plant)			0.184***
			(0.061)
City FE	Y	Y	Y
Year-quarter FE	Y	Y	Y
Province-Year FE	Y	Y	Y
Observations	1155	1155	1155

Notes: This table reports the effects of lifting the restriction on new vehicle sales. The sample period is 2016.1-2018.12. "Home Lifted" is the policy indicator that equals 1 if a city has lifted the restriction. "Other Lifted" is the lag of the weighted average of policy dummies in other cities. "$\mathbb{1}$(Home w/ Auto plant)" is a dummy that is turned on if the home city has auto plant(s). "$\mathbb{1}$(Large Importer)" is a dummy that equals 1 if the city's import of used vehicles as of 2015 is among the top 25 percentile. "$\mathbb{1}$(Large Exporter)" is a dummy that equals 1 if the city's export of used vehicles as of 2015 is among the top 25 percentile. The regression controls for city FEs, year-month FEs, province×year FEs, and uses PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

CHAPTER 3

THE ROLE OF GOVERNMENT IN THE MARKET FOR ELECTRIC VEHICLES: EVIDENCE FROM CHINA

3.1 Introduction

Many countries are seeking to reduce local emissions, greenhouse gas (GHGs) emissions, and fossil fuel use by transforming the transportation sector into an electrified system (Holland et al., 2020).[1] The pursuit of this pathway requires a shift away from vehicles powered by internal combustion engines (ICEVs) and toward vehicles powered by electricity. Plug-in electric vehicles (EVs) run on electricity generated from power plants and stored in rechargeable batteries. When operated in all-electric mode, EVs consume no gasoline and produce zero tailpipe emissions. The electricity that powers the vehicles may be generated from fossil fuels or from renewable sources. Fossil-fuel power plants produce air pollution, but they tend to have better fuel efficiency than the internal combustion engines in vehicles; moreover, renewable sources of electricity are becoming more prevalent, which would enhance the environmental benefit of EVs.

The transition from ICEVs to EVs faces challenging economic and technological barriers, including the high upfront EV purchase cost, limited driving range of EVs, the need for charging infrastructure, and the inherent and perceived uncertainty about the net ben-

[1] For example, Norway and Netherlands set the target of reaching full electric among new passenger vehicles by 2025 and 2030, respectively. Electric vehicles accounted for 74 percent and 25 percent of new passenger vehicle sales in these two countries in 2020. China aims to reach 20 percent by 2025 and 40 percent by 2030 in the share of EVs among new vehicle sales. Governor Newsom of California issued an executive order in 2020 requiring sales of all new passenger vehicles to be zero emission by 2035.

efit and quality of this new technology (Carley et al., 2013; Krutilla and Graham, 2012). Socially inefficient adoption of EVs could occur as the result of multiple market failures that may exist in the EV market. These market failures include consumer misperceptions or imperfect information on product attributes (e.g., quality or fuel-cost savings); inadequate pricing of externalities (local air pollution and greenhouse gases) from automobile gasoline usage; and spillovers, such as indirect network effects on the demand side, and technology spillovers among automakers.

To address the market failures, and to achieve the targets of EV penetration, central and local governments in major countries and regions have implemented various policies to promote the technology. What are the impacts of these various policy levers on EV adoption? What is the relative cost-effectiveness of these policies? Understanding the answers to these questions is critical in designing policies to promote wider uptake of the technology. This study provides a comprehensive analysis on various policy and market drivers of the rapid development of China's EV market. A study of these issues in the context of China is important for at least two reasons. First, China is by far the world's largest energy consumer and automobile market with sales of nearly 26 million vehicles in 2019, compared to 17 million vehicles sold in the United States the same year. Due to the unprecedented growth of vehicle ownership, China accounted for nearly 50 percent of the increase in the world's oil consumption that occurred over the past two decades. Therefore, China's transition from relying on ICEVs to EVs has important implications for the world's oil and energy markets, and for global greenhouse gas emissions. Second, all the major international automakers have production facilities in China. Joint ventures, and partnerships between domestic and foreign manufacturers, produce about two-thirds of the vehicles for the Chinese market, dominating the luxury segment; imports account for only about 5 percent of the market.[2] Thus, due to its sheer market size, China could

[2]The joint-venture requirement for foreign automakers is part of the long-term "technology-for-market" strategy by the Chinese government. Amid the recent trade war between China and the United States, the Chinese government has promised to end the joint-venture requirement for the auto industry in 2021. Tesla

prove to be a fertile trial ground for new technologies for automakers. The market growth in China could also help cultivate economies of scale in batteries, a key cost component that is critical to the technology transition — thus, potentially benefiting the electrification of the transportation system worldwide.

To quantify and compare the impacts and the cost-effectiveness of different policies addressing consumer demand for EVs, we have compiled what we believe to be the most comprehensive data on China's EV market. Our data include information regarding quarterly EV sales by vehicle trim (a unique combination of brand, model, fuel type, and driving range); vehicle attributes by trim; battery suppliers; public charging stations; consumer subsidies and other policies aimed at promoting consumer adoption of EVs from both central and local governments; and relevant social and economic variables at the city level. These data cover 150 cities in China over a period from 2015 to 2018. We use a linear regression framework to estimate EV demand among individual (i.e., non-institutional) buyers with a focus on price and subsidy response, non-financial policies, and charging infrastructure availability.[3]

To establish the causal effects of various policy and market drivers of EV demand, we face the following three empirical challenges: First, the vehicle-price variable could be endogenous due to unobserved product attributes, i.e., attributes that consumers value but are unobserved in the data (e.g., product quality and safety performance). Due to the likely positive correlation between prices and unobserved product attributes, the OLS estimates of the price coefficient would be biased toward zero, as has been well documented in the literature (Berry et al., 1995), leading to under-estimation of consumer response to prices. The second challenge is unobserved demand shocks that could be correlated with

received special permission to build its fully owned gigafactory, with a capacity of 250,000 units per year, in Shanghai. It began producing its Model 3 in December 2019.

[3]Individual buyers account for about 65 percent of total EV sales during our data period. Institutional buyers (e.g., government agencies, companies, and taxi fleets) are subject to different subsidy policies, and their decision-making process could be subject to different considerations.

government policies (subsidies and other policies) and, at the same time, could affect consumer EV demand. For example, if central and/or local governments design policies as a response to negative demand shocks, we would underestimate the effectiveness of the policies. The third challenge is due to the simultaneity between consumer EV demand and charging-station investment, which could render the charging infrastructure variable endogenous. The simultaneity arises because the EV market can be characterized as a two-sided market (requiring EVs and charging stations) with indirect network effects. The decision of consumer adoption depends to a degree on the availability and coverage of the charging infrastructure, while the decision to invest in charging stations hinges to a degree on the number of EVs that will use them.

We address these identification challenges by using two strategies: an instrumental variable (IV) method and a city-border-regression design. Our preferred specification implements both strategies in the same linear regression framework. First, we instrument for the vehicle-price variable using battery capacity (kWh) interacted with battery-supplier dummies. Battery capacity should affect vehicle prices, both because the battery is an important cost component, and because the cost of the battery largely depends on its capacity. Recognizing that battery capacity could also affect the vehicle's driving range and driving performance — characteristics that consumers are likely to care about — we control for driving range and driving performance (using a power-weight ratio) in our regressions. The identification assumption is that battery capacity is not correlated with unobserved product attributes; it recognizes that the choice of battery capacity is likely dictated by considerations about driving range and driving performance, rather than by unobserved product attributes. Our results are robust to using battery density as an alternative instrumental variable.

Second, we instrument for the charging-infrastructure variable by using the installed EV base by institutional buyers (lagged one period). The institutional EV stock likely affects investors' decision to build charging stations. The identification assumption is that the lagged institutional EV stock is unlikely to be correlated with concurrent demand shocks to individual buyers.

Lastly, we use a city-border-regression design to address potential endogeneity in policy variables due to unobserved local demand shocks. The design exploits the fact that local policies change sharply across city borders, but unobserved demand shocks such as changes in transportation costs, access to dealer stores, and consumer preferences are likely to be similar among neighboring cities. In practice, we group neighboring cities into clusters and then include cluster-time fixed effects to control for time-varying local unobservables common in the same cluster, as well as cluster-brand-year fixed effects to control for demand shocks that are specific to each brand in a cluster.

Based on the regression results, we conduct simulations to examine the effects of each policy and non-policy drivers, and we compare the cost-effectiveness of different policies. Our analysis provides the following three key findings that are robust across various specifications and sample cuts. First, generous consumer subsidies from central and local governments (about 26 percent of pre-subsidy vehicle prices) played a crucial role in the rapid growth of the market. We estimate that these subsidies explain over half of the EVs sold during our data period. The impact is similar in magnitude to that of the subsidy programs in the U.S. and Norway (Li et al., 2017; Springel, 2019). Second, there are significant, indirect network effects from charging infrastructure on EV demand. Investment in charging infrastructure is about four times as cost effective as consumer subsidies in promoting EV sales. The advantage of charging-infrastructure investment in cost-effectiveness is twice as strong in China as the levels found by Li et al. (2017) in the United States and by Springel (2019) in Norway. Third and perhaps most striking, a policy that merely grants EVs a distinctive-looking license plate in green is very effective, increasing EV sales by 37 percent. This large impact could be the result of "conspicuous conservation", whereby consumers seek status by signaling their environmental bona fides (Sexton and Sexton, 2014). It could also be due to the increased salience of EVs as consumer choices or perceived endorsement of product quality brought about this policy change (Chetty et al., 2009; Busse et al., 2015).

There is a large body of literature examining the efficacy of policy incentives on EV adoption. Existing studies have provided evidence that financial incentives such as consumer subsidies, tax credits, and rebates are positively related to EV adoption (Jenn et al., 2018; Li et al., 2017; Springel, 2019; Wee et al., 2018; Zambrano-Gutierrez et al., 2018). The literature has also shown EV adoption could be helped by non-financial privileges such as parking, access to bus lanes (Langbroek et al., 2016), driving or purchase restriction exemptions (Ma et al., 2019; Wang et al., 2017b). Studies have gone beyond examining individual policies, to compare the relative effectiveness of different incentive measures. The findings show that measures granting EV users special privileges (e.g., vehicle registration priority, road access, and charging facility access) could have a greater impact than financial incentives for the adoption of EVs (Li et al., 2019; Mersky et al., 2016; Sierzchula et al., 2014; Wang et al., 2017a).

While existing studies have revealed important relationship between governmental incentives and EV adoption, there are important gaps in the literature. Our study contributes to the literature by addressing these gaps. First, to inform policy design, there is a strong need to credibly establish the causal impacts of various policies by recognizing potential policy endogeneity. For example, local policies including subsidies for EV purchases or charging-station investment could be correlated with unobserved local demand shocks, leading to omitted variable bias. By carefully addressing the endogeneity of vehicle prices, charging infrastructure, and other EV policies using the instrumental variable method and the city-border design, our analysis identifies the causal effects of consumer subsidies and other policies on EV adoption.

Second, existing studies often use survey data that are based on hypothetical experiments or actual sales data that are coarse in frequency and confined to small geographic regions. Granular data based on revealed preferences could allow researchers to better leverage the spatial and temporal variation in policies and market conditions to identify their impacts. We leverage to our knowledge the most comprehensive and granular data sets on EV sales, subsidies, charging facilities, driving restriction exemptions, and green license plates to examine the effect of various policies targeted to promote EV adoption.

Third, although there have been estimates on the effect of different policy instruments, relatively less is known about the relative cost-effectiveness of different policies. To the best of our knowledge, no research attention has been placed on one of the unique instruments utilized in China — the green license plate policy. Our study compares the effects of a full sweep of policy options, including subsidies, charging facilities, and green license plates. Our results show that charging facilities are more cost-effective than subsidies, and that green plates are strikingly effective in stimulating EV adoption. These findings have important policy implications for not only China but also other countries to design effective policies to move the industry forward.

We organize the rest of the paper as follows: Section 3.2 discusses the industry background, policies, and data. Section 3.3 presents the empirical model and identification challenges. Section 3.4 discusses the estimation results and robustness checks. Section 3.5 presents the counterfactual simulations to evaluate the role of different drivers of consumer demand. Section 3.6 concludes.

3.2 Industry Background and Data Description

3.2.1 Industry Background

Electric vehicles are capable of running on electricity generated from outside sources. There are two types of EVs on the market: battery electric vehicles (BEVs) which run exclusively on high-capacity batteries (e.g., Nissan LEAF), and plug-in hybrid electric vehicles (PHEVs) which use batteries to power an electric motor, and use another fuel (gasoline) to power an internal combustion engine (e.g., Chevrolet Volt). EVs have the potential to reduce energy usage and emissions because of the efficiency gains from switching from ICEVs to large power plants. The estimated fuel efficiency (of converting the power source to usable energy) for internal combustion engines ranges from 12 percent to 30 percent. Such efficiency could reach levels exceeding 50 percent for coal power plants, or even 90 percent for hydro plants, which are associated with less emission than coal plants, according to the U.S. Department of Energy and Environmental Protection Agency.[4]

Since the introduction of Chevrolet Volt and Nissan Leaf as the first mass-market models into the U.S. in late 2010, worldwide EV sales have grown to about 4.2 percent (or 3.2 million units) of the new vehicle market in 2020. Figure 3.1 shows EV sales and the number of charging ports/outlets in China, the United States, and Europe. China is by far the largest EV market with the most charging ports. European countries collectively surpassed China in EV sales in 2020 due to the generous stimulus plans in the second half of the year. Figure 3.2 shows the number of EV automakers and EV models in China and the United States. There are 66 EV automakers and 195 models in 2019 in China, com-

[4]Sources: https://www.fueleconomy.gov/feg/evtech.shtml and https://www.eia.gov/totalenergy/data/annual/index.php. Apart from environmental impacts, the question of whether EV adoption could lead to unintended consequences on other externalities such as congestion and safety remains to be studied. Some evidence suggests that EV adoption could increase pedestrian traffic safety risk (Karaaslan et al., 2018).

pared to about 23 automakers and 45 models in the United States. As shown in Appendix Figure C.1, the U.S. EV market is quite concentrated; in 2018, the top five firms accounted for over 80 percent of the EV market, and with Tesla alone taking up half the market. In China, the top five firms accounted for less than 60 percent of the market in 2018; at that time, the largest EV producer in China, BYD, had a market share of about 20 percent, followed closely by the Beijing Automotive Group.

China's central government has developed ambitious short- and long-term goals to develop the EV industry, and to improve overall fleet fuel economy, as shown in Appendix Figure C.2. The explicit goal is to reach annual sales of 2 million EVs by 2020 (about 8 percent of new vehicle sales), 7 million (or 20 percent) by 2025, and 15 million (or 40 percent) by 2030. The fuel economy standards require automakers to reach 5 liter/100km (or 47 miles per gallon) among their new vehicle fleet by 2020, 4 liter/100 (or 59 miles per gallon) by 2025, and 3.2 liter/100km (or 74 miles per gallon) by 2030.[5] These ambitious fuel economy targets necessitate a dramatic increase of EVs in the vehicle fleet.

Figure C.3 depicts patterns of vehicle production across firms and cities in China from 2015 to 2018. Panel (a) shows that EV production in 2015 was highly concentrated among several large EV manufacturers, most of whom do not have a strong presence in the gasoline vehicle market. This pattern is consistent with the incumbent-entrant innovation gap in that the incumbents are less likely to make drastic innovations compared to new entrants (Christensen, 2013; Igami, 2017).[6] However, the pattern changed in 2018, as shown

[5]The the U.S. fuel economy standard was previously set to reach 55 miles per gallon under the rules promulgated under the Obama administration. As a major departure, the Trump administration rolled back the standard to a rule that would require automakers to achieve an average fuel economy of 40 miles per gallon by 2026. In April 2021, the Biden administration's EPA released that it is proposing a more stringent fuel efficiency rule, which is set to be announced in July 2021. This update will overturn the previous standard set by the Trump administration. Sources: https://www.cnet.com/roadshow/news/biden-administration-fuel-economy-emissions-epa-regulations/

[6]The literature has examined three competing forces that could determine the timing of innovation: cannibalization, preemption, and the cost difference. On one hand, incumbents may delay introducing a new technology because it may "cannibalize" their profit from current products. On the other hand, they have the incentive to accelerate innovation to preempt competition in the market. In addition, they may also have a cost advantage based on their accumulated R&D capital.

in Panel (b), when conventional automakers such as Geely, Chana, and GM-Shanghai-Wuling dramatically increased their EV production. Panels (c) and (d) show similar dynamics in the spatial pattern of EV production. While there was a weak spatial correlation between gasoline vehicle production and EV production in 2015, by 2018 the correlation becomes stronger, and the production becomes more diversified across cities.

3.2.2 Government Policies

The auto industry has long been considered as a strategic, pillar industry by central, provincial, and local governments. Governments at various levels have implemented many policies to promote the development of the industry (Barwick et al., forthcoming; Bai et al., 2020).

Policy Rationales

First, the environmental consequences from gasoline consumption by ICEVs such as greenhouse gas emissions are not adequately reflected in gasoline taxes (Parry and Small, 2005; Parry et al., 2014a). The adoption of EVs will help alleviate the environmental issues associated with gasoline vehicles, especially when renewable electricity generation becomes more prevalent. Second, there may not be efficient information provision for the cost of both production and consumption of new technologies, such as EVs. On the demand side, for example, consumers could misestimate the product quality and the operating costs associated with EVs (Allcott, 2013; Dumortier et al., 2015). Failure to reconcile the high up-front adoption costs and the future savings in operating costs could lead to suboptimal adoption of new technologies such as EVs (Jaffe and Stavins, 1999). On the supply side, firms may face under-provision of information in manufacturing activities; this could hinder the efficiency in production (Stigler, 1961; Hirshleifer, 1971). Third, demand- and supply-side spillover effects could lead to market failure and suboptimal EV adoption. From consumers' perspective, EV adoption decisions hinge on the availability of charging infrastructure, which in turn depends on EV stock. When the indirect network effect for such a two-sided market is overlooked by consumers and investors, inefficient welfare outcomes can result (Li et al., 2017; Zhou and Li, 2018; Springel, 2019; Liebowitz and Margolis, 1995).[7] From the producers' perspective, firms could benefit from early-stage technology diffusion (Stoneman and Diederen, 1994), and they could achieve better cost-savings through human capital spillovers and upstream suppliers (Kim and Marschke, 2005; Blalock and Gertler, 2008; Poole, 2013; Serafinelli, 2019). Therefore, firms may have less incentive to invest in private R&D — collectively leading to market-wide underinvestment.

Financial Incentives

Consumer subsidies are the most common policy to promote EV adoption across countries. As a comparison, Table 3.1 presents the level of subsidies and eligibility rules in the United States and China. In the United States, the policies are implemented at both federal and state levels, through tax credits, rebates, and exemptions and reductions of fees. In addition, federal, state, and local governments provide funding to support charging-station deployment (Li et al., 2017; Li, 2020).[8] Similarly, government policies in China at

[7]Given the nature of the market, each side of the market is unlikely to internalize the external effect on the other side through market transactions. If EVs are produced by one automaker, the automaker would have an incentive to offer a charging station network to increase EV adoption. Nissan and GM are the two early producers of EVs, but more and more automakers are entering the competition. Nissan is a large owner of charging stations, but GM is not. Tesla is building its own proprietary network for Tesla owners only. This suggests that they recognize the importance of charging stations in EV adoption. At the same time, proprietary stations would create duplicate systems.

[8]In 2010, the U.S. federal government began providing a federal income tax credit to new EV buyers based on each vehicle's battery capacity and the gross vehicle weight rating. The amount ranges from $2,500 to $7,500, with a phase-out target of 200,000 EVs sold. In addition, 46 out of 50 states had published incentives (both monetary and non-monetary) to promote the adoption of EVs as of 2017, according to the National Conference of State Legislatures (Source: https://www.ncsl.org/research/energy/

central and local levels have promoted EV adoption largely by using consumer subsidies tied to vehicle quality attributes. The central subsidy program expanded considerably, starting in 2009, with updates in every three to five years. The policy program followed a phase-out design over each effective policy period. Local subsidies are generally pegged to the central subsidy amount according to a certain ratio that depends on the respective government mandate at the provincial and city levels, some with additional restrictions contingent on various vehicle attributes other than those specified in the central subsidy policies. Panels (a) and (b) in Figure 3.3 show average consumer subsidies (including central- and local-government subsidies) per vehicle across the 150 cities in 2015 and 2018. In 2015, subsidies were available for only major cities and at a higher amount. In 2018, the coverage expanded as the central subsidy was made available for all cities; however, the amount decreased in general.

Central Policies In 2009, the Chinese government first initiated the federal-level EV policy through a pilot program named "Ten Cities, Thousand Vehicles" jointly announced by the Ministry of Finance (MoF), Ministry of Science and Technology (MoST), Ministry of Industry and Information Technology (MIIT), and the National Development and Reform Commission (NDRC). The program started in 13 pilot cities in 2010 and expanded to 88 cities by the end of 2013. The subsidy program was made nationwide starting in 2016.

Table 3.2 shows the subsidy structure from 2013 to 2018. The subsidy amount follows a step-wise structure with multiple tiers for BEVs and one tier for PHEVs. The minimum threshold for driving range for BEVs was raised from 80km to 100km in 2016 and further to 150km in 2018. At the same time, the subsidy amount for eligible vehicles was reduced. In 2018, the eligibility rules were revised to incorporate additional technical requirements including the minimum battery density of 105Wh/kg and minimum energy efficiency in

`state-electric-vehicle-incentives-state-chart.aspx`). These incentives include tax exemptions and rebates for EVs and non-financial incentives such as high-occupancy vehicle (HOV) lane access, toll reduction, and free parking.

kWh/100km (as a function of vehicle weight).[9] The policy was further revised in March 2019: the minimum threshold for the driving range was increased to 250km, and the subsidy amount was again reduced. The revision also required local governments to terminate subsidies by June 26, 2019.[10] After the reduction and cancellation of subsidies, EV sales experienced negative growth for six consecutive months in 2019. Due to the negative sales impact of the subsidy removal and the effects of the ongoing pandemic, the four ministries issued a policy in April 2020 to reinstate the subsidy policy with a gradual reduction of 10 percent in 2020, 20 percent in 2021, and 30 percent during 2022, relative to 2019 levels.[11]

Local Policies EV subsidies at the local level follow closely the central government's guidelines, with some variation (e.g., additional restrictions issued by local governments). The subsidy amount is generally pegged to the amount of the central subsidy, such as a 1:1 match. Hence, the phase-out timeline and eligibility conditions of the central subsidy also affect local subsidy programs. In general, cities issue subsidies following the catalog of eligible vehicle models provided by the MIIT, but there are exceptions. Some cities publish additional requirements, such as vehicle-quality attributes to further regulate the issuance of subsidies at local levels. For example, Beijing and Shanghai distribute local subsidies based on their own lists of eligible vehicles; Heifei set its minimum driving-range threshold for eligible BEVs at 150km in 2013 when the minimum threshold for the central-level subsidy was then 80km; and, in 2017, Hangzhou set subsidy parameters based on vehicle size.[12] Local financial incentives are generally funded by a combina-

[9] The four central ministries announced the revision in February 2018. Source: http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057585/n3057592/c6064667/content.html

[10] The policy was announced in March with a three-month transition period. Vehicles sold during the transition period that did not meet the 2019 revised standard were only eligible for 10 percent of the 2018-level central subsidy. Source: http://www.gov.cn/xinwen/2019-03/27/content_5377123.htm. The most recent policy announcement on April 23, 2020, postponed the termination of subsidies to 2022. Source: http://www.gov.cn/zhengce/zhengceku/2020-04/23/content_5505502.htm

[11] Source: http://www.gov.cn/zhengce/zhengceku/2020-04/23/content_5505502.htm

[12] Sources of the policies are as follows: Beijing, http://czj.beijing.gov.cn/zwxx/tztg/t20180130_883639.html; Shanghai, http://www.shanghai.gov.cn/shanghai/download/

tion of resources from both provincial and city governments. Cities in the same province can implement different local incentives. Major cities, such as provincial capitals and pilot cities that were enrolled in EV policy programs at earlier stages, tend to have more complicated policy designs with higher subsidy amounts; other cities tend to rely more heavily on central and provincial guidelines. The local-level measures often include other miscellaneous financial incentives, such as parking fee reductions, subsidies for the electricity bill, switching costs from ICEVs to EVs, and vehicle insurance.

Non-financial Incentives

Non-financial incentives play an important role in promoting electric-vehicle adoption. Many such types of incentives have been shown to be effective. For example, vehicle registration privileges have been granted to electric vehicles in cities (e.g., Shanghai, Beijing, Tianjin, Guangzhou, Hangzhou, and Shenzhen) that have quotas for vehicle purchases, and auctions or lotteries for issuing license plates. A growing number of cities have established provisions that give electric vehicles access to roads that are otherwise restricted to alleviate traffic congestion and pollution. The use of such driving-restriction exemptions grew from 7 cities in 2015 to 29 cities in 2018. More cities are also offering green license plates for electric vehicles that are distinguishable from the ICEV models — giving consumers a readily visible way to signal "conspicuous adoption" of an energy-efficient vehicle, and giving authorities an easy way to distinguish EVs' relevant driving and parking privileges. The green-plate policy, which began with five pilot cities in 2016, expanded to 20 cities in 2017, and, by the end of 2018, it had effectively reached the entire nation (all 147 cities in our sample), as shown in panels (c) and (d) in Figure 3.3.

In addition to these demand-side incentives, there are supply-side policies to directly

gongkai/hfbf1421.pdf; Hefei, http://www.caam.org.cn/chn/9/cate_104/con_5197593.html; and Hangzhou, http://www.hangzhou.gov.cn/art/2017/8/14/art_1302334_4131.html.

target fuel efficiency and EV penetration. In September 2017, the MIIT issued a mandate that established a dual credit-point system for both corporate average fuel consumption (CAFC) and new energy vehicles (NEVs) — measures that are essentially a modified version of California's Zero Emission Vehicle (ZEV) mandate.[13] The mandate aims at improving the fuel efficiency of the overall vehicle fleet and is considered to be an extension of consumer subsidy policies, with incentives instead injected through supply channels, and with fewer financial and administrative burdens for the government.

3.2.3 Data Description

Vehicle data We obtain data on EV sales from the China Automotive Technology and Research Center. The data are for the period from 2015 to 2018, and they are listed at the city-quarter-trim level. A vehicle trim is defined as a unique combination of the brand (e.g., Toyota), model (e.g., Camry), fuel type (e.g., BEV or PHEV), and driving range. Our sample of analysis consists of 150 cities — including the top 40 cities with the largest aggregate EV sales during our data period, and their neighboring cities, which are included so that we can conduct city-border analysis. In 2018, 0.82 million passenger EVs were sold in these cities; these sales represent 78 percent of the EV sales nationwide during the period.[14] Our analysis focuses on sales to individual buyers (rather than to institutions) because institutional purchases (e.g., by government agencies and rental companies) are subject to different subsidy policies, and institutions have different incentives than individual consumers. Individual sales accounted for about 65 percent of total EV sales in our 150 sample cities in 2018.

[13] The official document that provides a full description on the mandate issued by five central ministries available at: http://www.gov.cn/xinwen/2017-09/28/content_5228217.htm. A description of California's policy is available at: https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program.

[14] Among the EV sales, BEVs took up 76 percent. EV sales in the top 40 cities accounted for 69 percent of national EV sales; the other 110 cities in the sample accounted for only 9 percent.

We have detailed vehicle attributes at the vehicle trim level. After dropping very unpopular models with annual national sales of fewer than 400 vehicles, there are 27,577 observations with 190 unique trims from 44 firms in our data.[15] Panels (a) and (b) in Figure 3.4 present annual new EV sales (individual purchases) per million residents by city in 2015 and 2018. There are two salient features. First, sales increased dramatically from an average of 67 per million residents to 497 per million residents over this period. Second, figures from 2018 show large spatial heterogeneity, ranging from 5,587 sales per million residents in Shenzhen, Guangdong Province; to 7 sales per million residents in Hechi, Guangxi Autonomous Region.

To show how different levels of subsidies are associated with different levels of EV sales, we plot sales per million residents against the average EV subsidy for each city in each year, as shown in Appendix Figure C.5. The top 40 cities generally have higher subsidies and higher EV sales than their neighboring cities (non-top-40 cities). In addition, there seems to be a positive relationship between the level of subsidy and the level of EV sales, though the relationship appears to weaken over time, likely due to the increasing role of factors other than financial incentives.

To better control for other demand factors, we examine the within-cluster differences in sales and subsidies between the top-40 cities and their (average) non-top-40 neighboring cities in Figure 3.5. A point in the first (third) quadrant shows that the top-40 city has a higher (lower) level of subsidy and more (fewer) EV sales compared to neighboring non-top-40 cities in the same cluster, implying a positive correlation between subsidies and EV sales. Most of the clusters lie in the first and third quadrants, implying a positive relationship between subsidies and EV sales.

[15] We dropped the unpopular models for two reasons. One is that data on sales of unpopular models are more likely to contain measurement errors (Barwick et al., forthcoming). The other reason for dropping such models is to alleviate potential concerns about supply constraints. The results are robust to using a full sample with all vehicle models.

Charging Stations We obtain information on non-private charging stations from the China Electric Vehicle Charging Infrastructure Promotion Alliance, a member organization of charging operators. Our data on charging stations allow us to construct the number of charging ports/outlets (by AC or DC) on-site by city by quarter from 2015 to 2018. Public charging stations are open to all; dedicated charging stations are open to designated groups, such as residents in a community or company employees. The Alliance operates about 337,000 (public and dedicated) charging ports/outlets, which accounted for 69 percent of all operating charging ports in China at the end of 2019.[16] Panels (c) and (d) in Figure 3.4 show the number of charging ports per million residents for the 150 sample cities at the end of 2015 and 2018. The average number of charging stations per million residents across cities increased from 4.7 in December 2015 to 134 in December 2018. The overall temporal and spatial patterns are very similar to those of EV sales, shown in panels (a) and (b) in Figure 3.4. The correlation coefficient between EV sales and the number of charging ports per million residents for the 150 cities in our sample is 0.46 in 2015 and 0.79 in 2018.

Policies We are not aware of a centralized database on various EV policies in China. We collect the central and local policies from a variety of online sources including government websites, industry reports, and newspapers. Central subsidy programs are issued through official government documents that are generally published on the government official websites of the Ministry of Finance (MoF), Ministry of Science and Technology (MoST), Ministry of Industry and Information Technology (MIIT), and the National Development and Reform Commission (NDRC). Local subsidy policies are issued by provincial and city governments and can be retrieved from official documents released on government websites, and from unofficial online documentation sources such as news articles. The non-financial incentives, such as offering exemptions from driving restrictions

[16] 71 percent of the charging ports are open to the public, and the rest are exclusively for dedicated groups.

and offering green license plates, are mostly announced separately from the subsidy programs. The official policy documents and most news reports contain general information about the policy, the subsidy amount, eligibility conditions (e.g., vehicle attribute requirements), and the effective policy period. This information allows us to match a given policy directly to certain vehicle models over a defined period of time based on the eligibility conditions.

Summary Statistics Table 3.3 presents summary statistics of our full data, including vehicle sales, vehicle attributes, and policies. The average Manufacturer Suggested Retail Price (MSRP) is about ¥200,000 (or $30,000) with a range of ¥81,800 to ¥608,800. The 2018 Cadillac CT6, a PHEV, is the most expensive EV model in our data, followed by Audi A6, and the Volvo XC60, both of which are also PHEV.[17] While these high-end models are produced by joint ventures or are imported, the low-end models are mostly produced by China's domestic automakers such as Kangdi, Dongfeng Xiaokang, and ChangAn. In contrast to the high-end models, which are sold in various countries, these low-end models are not sold outside China. Due to the lack of transaction prices, we use MSRPs in our estimation. Dealer-level incentives are limited in China due to the practice of "minimum retail price maintenance" (RPM), whereby automakers either explicitly or implicitly prohibit dealers from selling below a preset price to reduce price competition among dealers (Barwick et al., forthcoming). To examine the correlation between MSRPs and transaction prices, we obtain data on dealer-level transaction prices in five cities (Beijing, Chengdu, Guangzhou, Hangzhou, and Shanghai) from 2011 to 2015. The data show that transaction prices and MSRPs are highly correlated (correlation coefficient 0.994). In addition, the instrumental variable for MSRPs could further address measurement errors in MSRPs.

The total subsidy includes vehicle purchase subsidies from the central, provincial, and

[17] The Cadillac CT6 PHEV is produced in the facility in Shanghai in a joint venture (JV) between GM and Shanghai Auto (SAIC). The popularity of the luxury Cadillac brand among Chinese consumers was a factor in the decision to base the production of this model in China.

local governments, and other miscellaneous subsidies, which together are worth more than ¥45,000 per vehicle on average in our sample period.[18] There is significant variation over time and across cities. In addition, because the subsidy amount depends on fuel type and driving range, there is important variation across vehicle models, even within a city. Our analysis of vehicle demand controls for a set of vehicle attributes such as vehicle size (the length by width), motor power, vehicle weight, and driving range. Battery capacity and the EV stock by institutional buyers are to be used as instruments in our analysis.

3.3 Empirical Model and Identification

In this section, we first present our empirical model and then discuss the identification strategy.

3.3.1 EV Demand

To describe the empirical model for EV demand, we define a vehicle model as a brand-model name combination (e.g., BYD Song) and a trim as a unique combination of model and driving range combination (e.g., BYD Song with a range of 80km). Let m index a model, k index an EV trim, c index a city, y index a year, and t index time (i.e., year-

[18]The miscellaneous subsidies are related to the services and facilities that are associated with EVs (e.g., parking fee reductions, charging subsidies, subsidies for replacing ICEV models with EV models, and so on). When we can identify these subsidies at the per-vehicle level, we record this information in our data.

quarter). We specify the following equation as the starting point of the analysis:[19]

$$ln(q_{ckt}) = \beta_1 MSRP_{ckt} + \beta_2 S_{ckt} + \beta_3 N_{ct} + \beta_4 DR_{ckt} + \beta_5 GP_{ct} + X'_{ckt}\alpha + \eta_{cm} + \delta_t + \xi_{cy} + \varepsilon_{ckt} \quad (3.1)$$

where q_{ckt} is the sales of EV trim k in city c and year-quarter t. $MSRP_{ckt}$ denotes the manufacturer's suggested retail price (MSRP). S_{ckt} denotes the total subsidies that consumers are eligible for. β_1 measures consumer demand response to MSRPs, and β_2 captures the effect of the subsidies. We separate MSRPs from consumer subsidies in the equation to allow for the possibility that consumers may respond to these two variables differently. N_{ct} denotes the total number of public charging ports/outlets that have been built in the city by the end of a given quarter.[20] The coefficient on N_{ct} captures the (indirect) network effect of charging infrastructure on consumer adoption of EVs. DR_{ckt} is an indicator variable being one for trim k if it is exempted from the driving-restriction policy. GP_{ct} is an indicator variable being one if city c implements a green-plate policy for EVs at time t. X_{ckt} is a vector of vehicle attributes including vehicle size, battery power over weight (a measure of acceleration), and driving range.

We also include a full set of city-model (e.g., BYD Song in Beijing) fixed effects and year-quarter (e.g., the first quarter of 2011) fixed effects in equation (3.1). City-model fixed effects control for time-invariant product attributes such as quality and brand loyalty that could affect vehicle demand, the time-invariant local preference for green products (Kahn, 2007; Kahn and Vaughn, 2009), and demand shocks for each model (e.g., a stronger preference or dealer presence for BYD Song in Beijing). Year-quarter fixed effects control for common demand shocks, such as the national changes in consumer awareness

[19]We include MSRPs and consumer subsidies (central + local) separately in our main specification. This is under the assumption of full pass-through of subsidies to consumers. Evidence from other existing studies of related programs suggests that full pass-through is a reasonable assumption for EV subsidies (Muehlegger and Rapson, 2018; Gulati et al., 2017; Sallee, 2011). The specification enables us to test whether consumers respond differently to the MSRPs and subsidies.

[20]We use the number of charging ports rather than the number of charging stations to represent the availability of charging infrastructure; regardless of which we use, the qualitative findings are the same.

of EV technology. In addition, we include city-year fixed effects to control for city-specific demand shocks that vary across years. These could be unobserved local incentives or changes in consumer preferences. Since the variation in charging ports is at the city-time (year-quarter) level, including city-time fixed effects would absorb N_{ct}. ε_{ckt} indicates, for each trim, the unobserved demand shocks that are time-varying and city-specific (for example, unobserved local incentives that vary across EV trims or city-specific promotions for a vehicle model that vary over time).

Our key parameters of interest are β's, which capture the effects of important policy and market drivers. However, each of the corresponding variables is subject to the concern of endogeneity even with the rich set of controls in (3.1). There are multiple sources of endogeneity. The first source is unobserved product attributes (e.g., quality or prestige) that could render MSRP endogenous. Previous literature on vehicle demand (e.g., Berry et al. (1995) and Petrin (2002)) has documented that failing to control for unobserved product attributes could lead to a downward bias in the price coefficient estimates. The city-model fixed effects included in (3.1) absorb model-level observed and unobserved vehicle attributes that do not vary over time. The remaining variation in MSRP and in observed attributes X_{ckt} comes from the variation across trims within the same model, and more importantly the variation over time for the same trim. Nevertheless, the variation in unobserved attributes across trims within the same model and over time could still be correlated with the vehicle price, rendering the MSRP-coefficient estimate inconsistent.

The second source of endogeneity is the simultaneous and intertwined nature of the relationship between consumer demand for EVs and investment decisions on charging stations. The availability of charging facilities could help promote consumer adoption by alleviating concerns consumers have about the limited driving range of EVs. The importance of charging infrastructure in the early stage of EV diffusion has been shown in Li et al. (2017), Zhou and Li (2018), Springel (2019), and Meunier and Ponssard (2020). At the same time, investors' decisions take into account current and future demand conditions. The simultaneity between consumer demand and charging infrastructure could result in N_{ct} being endogenous, as shown in Corts (2010) (in the context of the U.S. flex-fuel vehicle market) and Li et al. (2017) (in the EV market), respectively.

The third source of endogeneity is unobserved demand shocks or policies that could confound the policies of interest (subsidies, exemptions from driving restrictions, and the green license plate policy). National subsidies vary over time and across vehicle trims based on the driving range. Local subsidies vary over time, across cities and products. The driving restriction and the green license plate policies vary over time and across cities due to their staggered rollout. We include time fixed effects to control for common demand shocks at the national level and city-year fixed effects to control for city-specific demand shocks that vary across years but are constant within a given year. To the extent that these policies are a response of the government to time-varying and city-specific demand shocks, these policy variables could be endogenous. For example, if a city government observes or projects a negative demand shock to its local EV demand, it may start to implement a policy to counteract the negative demand shock. If this is true, the policy impact estimated from OLS would have a downward bias.

3.3.2 Identification Strategy

We address the first two sources of endogeneity — unobserved product attributes and simultaneity — using the instrumental variable method. For the third source of endogeneity, we use a city-border-regression design to address the selection of local policies. To incorporate these identification elements, we use an IV method paired with a city-border design.

To address price endogeneity due to unobserved product attributes, we construct a set of IVs based on battery capacity (kWh). We interact battery capacity with supplier dummies. We distinguish battery suppliers as CATL, BYD, and the rest. CATL is by far the largest EV-battery supplier in China with a market share of 41.3 percent in 2018 and 50.6 percent in 2019; while BYD is the second-largest battery supplier with a market share of 20 percent in 2018 and 17.3 percent in 2019.[21] Battery is a major cost component for EVs, accounting for anywhere between 20 to 60 percent of vehicle prices. The battery cost has decreased dramatically over time; technological improvements and scaling up of production have led the (volume-weighted) cost to fall from $1,100/kWh in 2010 to less than $160 in 2019.[22] Production scale and technology capabilities may give CATL and BYD batteries cost advantages. The identification assumption is that battery capacity is not correlated with unobserved product attributes. The choice of battery capacity is likely to be dictated by the decisions on vehicle driving range, power, and weight — matters for which we control in our regressions.[23]

To address the endogeneity of the availability of charging infrastructure (i.e., the number of charging ports) due to simultaneity, we use as an IV the lagged stock (i.e., cumulative sales) of EVs purchased by institutions (e.g., government agencies or taxi fleets) during all previous quarters. Our demand analysis focuses on individual purchases, which account for about 65 percent of total EV sales in the sample cities during our data period.

[21] BYD started as a rechargeable battery manufacturer in 1995, and the company entered the automobile business in 2003. Now the largest EV producer by volume in China, it supplies batteries to all BYD models. CATL was founded in 2011, and it specializes in the manufacturing of lithium-ion batteries for electric vehicles and energy storage systems. It grew quickly to become the largest battery supplier for EVs in China.

[22] Source: bloom.bg/2LiZSu5

[23] We argue that, in our setting, battery capacity should satisfy the exclusion restriction. Consumers are most likely to care about driving range and driving performance, like handling and road feel. These characteristics correlate with battery capacity, but they are distinct from battery capacity per se. Therefore, we control for a set of vehicle attributes including driving range, vehicle size, and motor power over weight (a measure of acceleration) in our model. In doing so, we assume that battery capacity affects consumer demand through these controlled attributes, rather than by providing utility directly by itself. The relationship between battery capacity and driving range/performance in consumer demand for EVs is similar to the relationship between fuel economy and specific fuel-saving technologies (such as gasoline direct injection, and valve timing and lift technologies) in consumer demand for gasoline vehicles. These fuel-saving technologies would likely affect consumer demand, but only through their desire to assess overall fuel efficiency.

The size of the EV stock by institutions could affect investment decisions on charging stations. A similar strategy is used in Corts (2010) to study the investment decision of flex-fuel charging stations. The identification assumption is that the lagged institutional EV stock is unlikely to be correlated with concurrent demand shocks to individual buyers. Our results hold when we use the second lag of the institutional EV stock.

To address potential policy endogeneity due to unobserved local demand shocks, we use a city-border-regression design, similar in spirit to studies such as those by Holmes (1998), Dube et al. (2010), Kahn and Mansur (2013), Hagedorn et al. (2015), and Barwick et al. (forthcoming). The city-border-regression design is essentially a difference-in-differences (DID) estimator with a more deliberate choice of the control group. To examine the impact of a policy, a standard DID compares the outcome of the treatment group and that of the control group before and after the policy implementation. In our case, the treatment group would consist of cities with the policy, and the control group would be cities without the policy. A key challenge with this framework is that changes in EV sales over time between treatment cities and control cities could be systematically different due to local unobservables (demand shocks or other policies), confounding the estimated impact of the policy of interest. In our city-border regression, we compare EV sales for cities with a certain policy (e.g., a driving restriction exemption or green license plates) before and after the policy was implemented. The design exploits the fact that local policies change sharply across city borders, but other demand factors such as transportation costs, access to dealer outlets, and consumer preferences are likely to be similar among neighboring cities.[24] To identify the policy impacts, the city-border regression deliberately compares cities nearby (e.g., neighboring cities) and leverages the contemporaneous policy variation across cities within a cluster.

In practice, we group adjacent cities into a cluster of multiple cities. Among the 150

[24]Subsidies are tied to the city of residence.

cities, we create 34 clusters with each cluster having 4.4 cities on average. Each cluster includes at least one city that is among the top 40 EV cities (e.g., a major city). To control for time-varying local unobservables common in each cluster, we include cluster-time fixed effects and cluster-brand-year fixed effects. Cluster-brand-year fixed effects to control for demand shocks that are specific to each brand in a cluster — such as, for example, as the result of the change in dealer presence, or changes in consumer preferences for a brand among cities in a cluster. In a robustness check, we restrict the clusters to include only bordering cities with average household incomes that are within 20 percent of the household incomes of the major city in the cluster. This leaves 31 clusters with 106 cities. The results using this grouping are very similar to results using all 150 cities.

3.4 Estimation Results

We first present estimation results for the main specifications, and we then present the results from robustness checks.

3.4.1 Parameter Estimates

Table 3.4 reports the estimation results of the demand model in Equation (3.1) from seven specifications. All the regressions include MSRPs, consumer subsidies, the total number of charging ports, the dummy variable for exemptions from driving restrictions, the dummy variable for the green license-plate policy, and three key vehicle attributes: vehicle size (length by width), power over weight, and driving range. The first five columns show the OLS results and the last two columns show the results from the IV specification. The last column is our preferred specification, which we use to derive the results of our policy analysis.

From columns (1) to (5), we add more and more controls to examine the effects of potential confounding factors on our key parameters of interest. Column (1) includes city-model fixed effects to control for city-specific but time-invariant consumer preferences or demand shocks for each model. All the coefficient estimates have intuitive signs and are statistically significant. Bearing in mind that these estimates may not be consistent, the results suggest the following: (1) an increase of ¥10,000 in the MSRP leads to a decrease of EV sales by 2.7 percent.; (2) a subsidy of ¥10,000 increases EV sales by 11.6 percent, a much larger impact than the impact from an equivalent price change; (3) an increase of 1,000 charging ports increase EV sales by 4.7 percent; (4) an exemption from driving restrictions increases EV sales by more than 50 percent, and (5) the green license-plate policy increases EV sales by more than 30 percent.[25] Column (2) adds time (year-quarter) fixed effects to control for national time-varying demand shocks. Including time fixed effects meaningfully changes the coefficient estimates for the number of charging ports, green license-plate policy, and driving range, suggesting that time-varying unobservables are important confounders for these three variables of interest.

Column (3) adds city-year fixed effects to control for city-specific demand shocks that vary from year to year. This addition results in two significant changes in the coefficient estimates. First, the estimate of the number of charging ports becomes statistically significant and the magnitude stays roughly the same in all the remaining specifications. The key variation for identifying the effect of charging infrastructure in column (3) is within-city, quarter-to-quarter variation in the number of charging stations within a year. Second, the coefficient estimate decreases for the policy that provides an exemption from driving restrictions, the estimate becomes statistically insignificant for the remaining specifications. By removing the year-to-year variation in the policy, the identification relies solely on the within-city, within-year changes in the policy status. That is, the identification

[25] The percentage impact of a policy dummy on EV sales can be consistently estimated by 100*[$exp(\hat{\beta} - \widehat{var}(\hat{\beta})/2) - 1$].

is based on the limited cases in which a city adopted the policy in mid-year. There is limited quarter-to-quarter variation within a year in policy adoption, as suggested by Appendix Figure C.4. The result suggests that the policy that provides EVs with exemptions from road access restrictions does not significantly incentivize consumers to switch from gasoline vehicles to EVs. This could be due to the weak enforcement of the policy, or to consumers' adaptive behavior in their travel decisions. The driving restrictions that are in place at present only apply to peak hours and for roads that are within the city center. Thus, consumers could adjust their travel times, or use other modes of transportation (e.g., using public transit) without having to resort to buying EVs.

As discussed in Section 3.3.1, one of the key identification challenges is the time-varying and city-specific demand shocks. To examine the effect of charging infrastructure on EV demand, it is not practical to include city-time fixed effects. Instead, we use a border-regression design in columns (4) to (7) in which bordering cities are classified into clusters. Column (4) adds cluster-time fixed effects and relies on cross-city but within-cluster variation as the key source of variation in identifying the effects of charging infrastructure and policy variables. Intuitively, if a city has a larger increase in the number of charging ports relative to the change in other cities within the same cluster during a given quarter, and if it also observes a larger increase in EV sales during the same period, these commensurate changes would suggest a positive impact of access to charging infrastructure on EV demand. The identification assumption is that the larger increase in the number of charging ports in the city is exogenous to concurrent city-specific demand shocks for EVs. Similarly, the effect of the green license-plate policy is identified from contemporaneous policy variation within the same cluster. The coefficient estimate on the charging port increases slightly, but the effect size of the green license-plate policy increases by one-half. Column (5) further adds cluster-brand-year fixed effects to control for brand-specific demand shocks that are common in each cluster but vary by year — such as the change in dealer presence of a brand, or advertising efforts of a brand in a region. These fixed effects also control for year-to-year changes in consumer preferences or product quality by brand. The coefficient estimate on vehicle size becomes negative and imprecise.

When relying on the border-regression design and the rich set of fixed effects, one might still worry about potential endogeneity in consumer price due to unobserved product attributes, and in the number of charging ports due to simultaneity and unobservables. We address these issues in columns (6) and (7) using IVs. Column (6) instruments MSRPs using battery capacity interacting with supplier dummies (CATL, BYD, and others). In column (7), we instrument both MSRPs and the number of charging ports by adding one more IV, the stock of institutional EVs as of the previous quarter. The first-stage results for column (7) are reported in Appendix Table C.1; the results are consistent with our intuition. Column (1) shows that battery capacity is positively correlated with MSRPs. Column (2) indicates that the lagged EV stock owned by institutions is positively correlated with the number of charging ports.

The IVs in columns (6) and (7) produce strong first-stage results, and they pass the weak identification test in all specifications. The key difference between column (5) and columns (6) to (7) is that the coefficient estimate on MSRPs more than quadrupled in magnitude in columns (6) and (7). This is consistent with the finding in the literature that unobserved product attributes tend to bias consumer price sensitivity to zero. The comparison highlights that OLS results would dramatically underestimate the impact of MSRPs on EV diffusion. Nevertheless, the estimation results across columns (6) to (7) are very close in magnitude. This suggests that the number of charging ports could be reasonably taken as exogenous to current demand shocks after controlling for time fixed effects, and city-year fixed effects, likely due to its nature of being a stock variable.

Taking the estimates from the last column as the preferred results, the estimates suggest the following: (1) an increase of ¥10,000 in the MSRP decreases EV sales by 18.1

percent; (2) a subsidy of ¥10,000 increases EV sales by 16 percent, implying that consumers respond to MSRPs and subsidies in similar magnitudes; (3) an increase of 1,000 charging ports increases EV sales by 20 percent; (4) the policy that exempts EVs from driving restrictions does not seem to impact EV sales; and (5) the green license-plate policy increases EV sales by nearly 37 percent. The results are qualitatively similar to those of Zambrano-Gutierrez et al. (2018), who find that both tax credits for individuals and grants for charging infrastructure have a positive effect on plug-in electric vehicle registrations. The coefficient estimate on the MSRP variable implies an own-price elasticity of -3.7 for a vehicle at the average price of ¥203,000. The implied price elasticity is in line with the estimates from recent studies on EVs in other countries. For the United States, for example, Li et al. (2017) estimate a price elasticity of -1.3, using estimates based on the initial stage of EV sales (from 2011-2013) and a similar empirical framework; Xing et al. (2019) provide an elasticity estimate of -2.7 using a rich random-coefficient, discrete-choice model with the second-choice data from U.S. consumer surveys; and Muehlegger and Rapson (2019) report a price elasticity estimate from -3.1 to -3.9 among California households with an annual income of less than $100,000. For Norway, Springel (2019) estimates the price elasticities for EVs to be between -1 to -1.5 in that EV market. In the policy analysis (Section 5), we further discuss the implications of our parameter estimates, and we compare our findings with those in the literature.

3.4.2 Alternative Specifications

We estimate several alternative model specifications to examine the robustness of our findings. We include our benchmark result from Table 3.4 column (7) in Table 3.5 column (1), and report the results from other specifications in columns (2)-(7) of Table 3.5.

In Tables 3.4, the dependent variable is log(sales) as specified in Equation (3.1). There is 13 percent of observations with zero sales. The observations concentrate on less-popular models and in small cities. These observations could contain useful information about consumer demand. For example, if zero sales are more likely to occur in cities with less generous policy incentives, it would help us identify the effects of the policies. Thus, we added 0.5 to the sales for these observations in order to keep them in the sample instead of dropping them. To examine the robustness of our results to the ad hoc method of using 0.5 to replace zero, we replace the dependent variable in Equation (3.1) with the inverse hyperbolic sine function, which has a value of zero at zero but a similar shape with the logarithm function at positive support. The results are reported in Tables 3.5 column (2). The coefficient estimates are similar in magnitude to those in column (1), our benchmark results.

On the other hand, one might worry that zero sales do not represent true zero demands but are instead driven by supply constraints. To examine the robustness of our results, we dropped those observations with zero sales. The results are reported in column (3) of Table 3.5. These estimates are qualitatively similar to those in column (1), suggesting that our findings are robust regarding whether or not there are supply constraints.

The demand equation (3.1) takes a convenient form for the purpose of estimation and interpretation rather than being derived from an underlying utility maximization framework. However, with a slight modification of the dependent variable, equation (3.1) could be consistent with a stylized utility maximization framework. In particular, the dependent variable would be $ln(s_{kct}) - ln(s_{0ct})$ where s_{kct} is the market share of trim/choice k in market c and time t, and s_{0ct} is the share of consumers who do not purchase an EV (i.e., they choose an outside option instead). This (linear) logit demand function is an aggregation of choices made by individuals with homogeneous consumer preferences (Berry, 1994). Column (4) of Table 3.5 provides the estimates of the logit model. The implied price elasticity can be derived based on the price-coefficient estimate in column (4) as $\hat{\beta}_1 * p_k * (1 - s_k)$. The implied price elasticities are very similar between the two columns since s_j is close to zero. The coefficient estimates on other variables are nearly identical as well.

It is important to note that with only EV models in our data, our analysis treats all other non-EV models to be in one category (i.e., the outside good). Limiting the choice set and the substitution pattern across choices could potentially impact the estimate of the price elasticity and policy simulations. EV models represent a technology that is dramatically different from conventional gasoline vehicles. Therefore, consumers making purchase decisions are likely to consider them as a separate category. Traditional hybrid vehicles are nearly nonexistent in the Chinese market, limiting the possibility of substitution between PHEV and traditional hybrid vehicles. (This is different from the situation in the U.S. market, which features hybrid vehicles.) EVs represented only about 4.4 percent of new vehicle sales in China in 2018. Including gasoline models in our regressions does not meaningfully change the estimates of the key variables of interest. Nevertheless, identifying the nuanced substitution pattern is important in understanding the environmental benefit of the policies, as shown in Xing et al. (2019); as demonstrated in that United States-based study, the micro-level data with the second-choice information are much better suited to assess the substitution pattern between EVs and non-EVs than the aggregate data that we use in our study. We leave this issue for future research.

As discussed above, the border-regression design relies on the identification assumption that unobserved confounding factors are common across cities within a cluster due to the fact that cities in the same cluster tend to be similar. Nevertheless, some neighboring cities could have large differences in household income, which is likely the most important demographic variable in affecting EV demand. If large differences in household income translate to large differences in unobserved demand shocks across cities, including these cities could invalidate our key identification assumption. In alternative specifications, we remove the neighboring cities whose average household income levels differ by more than 20 percent from the household income levels in the major city in the cluster (the city with the largest EV sales). This subsample includes 106 out of the 150 cities. The regression results based on the subsample are presented in column (5) of Tables 3.5. The results based on the subsample are very similar to those in column (1), providing support for the key identification assumption behind the border-regression design.

In our main specification, we dropped the unpopular vehicle models with annual national sales of fewer than 400. Column (6) reports the results based on the full sample with all vehicle models. Again, the results are similar to our baseline in column (1).

Our last robustness check is to use an alternative set of IVs. To further address the concern that battery capacity may provide additional (or stand-alone) value to consumers than its impact through the driving range, we use battery density as an alternative IV. Battery density is the ratio of battery capacity and battery weight — a metric that consumers are likely to be even less familiar with than battery capacity, but one that affects EV prices through the cost of batteries. The IV results are shown in column (7) in Table 3.5, where we instrument MSRPs using battery density interacting with battery-supplier dummies. The estimate on MSRPs in column (7) is smaller in magnitude than that in column (1), but other coefficients remain very close across the two columns.

Heterogeneity analysis and Policy Interactions Appendix Table C.2 presents regressions with additional interaction terms to examine heterogeneity and policy interactions. We first interact the total subsidy with the number of charging ports to examine whether there is complementarity between financial subsidies and the investment of charging ports. The IV estimate in column (7), our preferred specification, is positive and significant. The result is in line with the intuition that when more charging ports are available, subsidies could have a larger impact on stimulating EV adoption. Next, we interact the exemption from driving restrictions with the green license-plate policy to examine the presence of policy interactions. The coefficient estimate from the preferred specification in column (7) is positive but not statistically significant. Therefore, there is no strong evidence to suggest policy interactions between the policy offering green license plates and exemptions from driving restrictions.

One might be interested in the impacts of electricity and gasoline prices on EV demand. Higher electricity prices could deter EV purchases. However, electricity prices (on average ¥0.5 per kwh) may be low enough that they may not be a significant cost factor in vehicle-purchase decisions. In practice, there is very limited within-year variation in average electricity prices in a city, preventing us from precisely identifying the coefficient estimate. The coefficient estimate on gasoline prices has a counter-intuitive sign but is not statistically significant. We also interact vehicle size and income to capture consumer preferences heterogeneity based on income. Intuitively, high-income households may have a stronger demand for larger vehicles for safety and comfort. The coefficient for the interaction term is positive and statistically significant in columns (2)-(4), and positive but not precise in our preferred specification in column (7). We add to this set of regressions a final interaction, between the driving range and the number of charging ports. The availability of charging ports should alleviate consumers' driving-range anxiety, and, hence, wider charging availability should disproportionately benefit vehicle models with a lower range. Again, the coefficient estimate on the interaction term is intuitively signed but not precise.

To examine the heterogeneity of the subsidy effect by time, we separate our study period (2015-2018) into two sub-periods, 2015-2016, and 2017-2018, and examine the difference in the impact during these two sub-periods. We generate an indicator variable "1(Post-2016)" that equals one for the end of the study period (2017-2018), and we interact it with consumer subsidies and the number of charging ports. The regression results are reported in Appendix Table C.3. We find that the coefficient estimates for the interaction term between consumer subsidies and the post-2016 dummy are positive and significant, suggesting that consumer subsidies played a bigger role in stimulating EV sales during the 2017-2018 period than they did in the 2015-2016 period. This finding is likely driven by two factors. First, many more EV models were available in the latter period (35 models in 2015 and 2016, relative to 104 models in 2017 and 2018). Second, early EV adopters are likely less sensitive to prices/subsidies because for them other factors (such as environmental awareness, and conspicuous consumption) may play a bigger role in their purchase decisions.

We also examine the heterogeneity of the subsidy effect by vehicle price. We divide EV models into two groups: low-priced models with MSRPs below the mean and high-priced models with MSRPs above the mean.[26] Appendix Table C.4 shows that the coefficient estimates for the interaction term between consumer subsidies and the dummy for low-priced models are negative and significant across different columns. Based on column (7), the sales effect of subsidies on low-priced EVs is more than twice as large as that on high-priced EVs; a ¥10,000 subsidy leads to a 16.7 percent increase in sales of low-priced models, compared to a 7.2 percent increase in high-priced models. This result could be driven by the fact that buyers of low-priced models tend to have a lower income and are more price sensitive (Barwick et al., forthcoming).

Nonlinear analysis Appendix Table C.5 shows the results with a quadratic term of the number of charging ports used to check whether there is a nonlinear effect. The intuition is that as more charging ports become available, the impact from an additional charging-port unit of the charging port could be decreasing. The estimates of the square term

[26]The average MSRPs is ¥150,000 for the low-priced models, and ¥265,000 for the high-priced models. The average subsidies for the two groups are ¥47,800 for the low-priced models and ¥42,900 for the high-priced models.

agree with this pattern. In all columns except for column (3), the sign of the coefficient is negative, but none of the estimates are significant. There might be a threshold effect whereby the size of the charging infrastructure needs to reach a critical point to sustain EV demand in the long run. Zhou and Li (2018) study the critical mass issue in the EV market in the United States, and find that in many cities in the US, the EV market exhibits multiple equilibria. This implies that the number of charging stations needs to pass a critical threshold; otherwise, EV adoption will converge to zero in the long run. We leave this question for future research.

Mediating Analysis To examine whether charging-station availability (e.g., due to charging station incentives) affects the estimated sales impact of consumer subsidies, we check the four necessary conditions for the mediating effect to occur, following the approach used by Zambrano-Gutierrez et al. (2018).[27] The results are reported in Appendix Table C.6. Column (1) shows that lower EV prices (MSRPs) or higher consumer EV subsidies increase the availability of charging stations, likely due to the indirect network effect as documented in the literature (e.g., more EVs leading to more charging stations). This suggests that the second condition for the mediating effect holds. Columns (2) and (3) show that the coefficient estimates on consumer subsidies are very close (0.162 compared to 0.160), whether excluding or including the number of charging ports. This comparison suggests that the fourth condition for the mediating effect to occur does not hold. Therefore, our results suggest that consumer subsidies have a direct impact on EV sales rather than having an effect that takes place through the channel of charging stations. While our data do not include subsidies on charging stations, it is likely that this type of subsidy would affect EV sales through the channel of charging stations, as shown in Zambrano-Gutierrez et al. (2018) in the U.S. context.

[27] The four necessary conditions for the mediating effect to occur are as follows: (1) The number of charging stations influences registrations. (2) Policies influence the number of charging stations. (3) Policies influence registrations in the absence of control for charging stations. (4) The impact of policies on registrations changes when the model includes the mediator.

3.5 Policy Analysis

In this section, we conduct simulations to examine the role of the underlying driving factors behind the dramatic growth of China's EV market. Based on the model estimates, we simulate the counterfactual number of EV sales that would occur in the absence of certain policies.

3.5.1 Consumer Subsidies

The average subsidy from the central government is ¥34,600 with a range of ¥0 to ¥55,000 during our sample period. The average local subsidy is ¥9,800 with a range of ¥0 to ¥60,000. Together, the total subsidy amounts to ¥44,400 (or about $7,000) per EV, or nearly 26 percent of MSRP, on average, and reaching levels as high as 73 percent of MSRP in some cases. The total subsidy from the central and local governments is nearly ¥55 billion during our sample period for the 150 cities.[28]

To examine the impact of consumer subsidies on EV sales, we simulate the EV sales without the subsidies based on the coefficient estimates of column (7) in Table 3.4. The simulated sales and the 95 percent confidence interval are depicted in Figure 3.6. The results suggest that the subsidies played an important role in promoting EV sales. The subsidies explained nearly 55 percent of the EV sales during the data period. Appendix Figure C.6 presents simulation results based on the coefficient estimates using the subsample of 106 cities as shown in column (5) of Table 3.5. The effect size is similar to the baseline estimate. The significance of consumer subsidies in the diffusion of alternative fuel vehicles (hybrid vehicles and EVs) has been documented in previous studies in

[28] The total consumer subsidies from both central and local governments from 2011 to 2019 were nearly ¥300 billion (or nearly $50 billion) including subsidies to commercial vehicles. Source: http://www.21cnev.com/html/201912/783429_1.html.

other countries. Li et al. (2017) estimates that the federal tax credit of $2,500 to $7,500 per EV contributed to about 40 percent of EV sales from 2011 to 2013 in the United States. Springel (2019) finds that the subsidies for consumer purchases and charging stations explained about 37 percent of EV sales from 2011 to 2015 in Norway.[29] Jenn et al. (2018) find that every $1000 rebate or tax credit increases EV sales by 2.6 percent in the United States. Wee et al. (2018) find that a $1,000 increase in the subsidy for an EV model increases the registration of that model by 5 percent to 11 percent in the United States. Comparing these estimates shows that the effect of consumer subsidies is stronger in China as a result of greater price sensitivity among Chinese consumers.

3.5.2 Green License Plates

Under the green license-plate policy, EVs receive special license plates that are green in color, making them distinct from the license plates for gasoline vehicles. The policy rolled out in three waves: 1) beginning in five cities in December 2016, 2) adding another 12 cities in November 2017, and 3) covering the rest of the country in 2018.

Our regressions suggest a robust and large effect of this policy on EV sales. The preferred specification in Table 3.4 suggests that the green license-plate policy has an EV-sales effect that is equivalent to about ¥20,000 in subsidies. Based on the parameter estimates, Panel (b) in Figure 3.6 depicts the number of sales that would have occurred in a counterfactual scenario in which the green-license plate policy had not been implemented. It shows that the policy contributed to nearly 17 percent of EV sales during our sample period. A similar effect is shown in Panel (b) in Appendix Figure C.6 using the subsample

[29] Norway has the highest EV penetration in the world. Sales of such vehicles accounted for nearly 56 percent of new vehicle sales in 2019 — an increase from 2015, when they accounted for 25 percent of sales. In Norway, EVs are exempt from the value-added tax of 25 percent levied on all other new vehicle purchases. For an EV with an average price of $33,000 (the average price during the 2011-2015 period), this tax exemption was equivalent to roughly $8,250.

of 106 cities. The efficacy of the policy is substantial, in fact, it may be difficult to believe that this accurately reflects its influence, given that the measure's cost was likely to have been minimal. However, the coefficient estimates on the green license-plate-policy variable across all specifications are economically large and statistically significant. This finding highlights the large value that the green license plate brings to consumers potentially through multiple channels.

One might worry that the green license-plate policy may capture the effect of other (unobserved) policies or the policy interactions whereby the green license-plate policy is enhanced by its links with other incentivizing policies (such as the parking privileges and exemptions from certain driving restrictions). In terms of unobserved EV policies, city-year fixed effects control for city-level unobserved policies/shocks that vary from year to year. Cluster-time (i.e., year-quarter) fixed effects control for within-year variation in policies/shocks that are constant across cities in a cluster. For the estimated impact of the green license-plate policy to capture the impact of other unobserved policies, those policies have to be rolled out in the same fashion as the green license-plate policy in both temporal and spatial dimensions. We are not aware of such coordination of policies. To examine the possibility of policy interaction, we include in our specification for heterogeneity analysis and policy interactions the interaction term of the policies on green license plates and offering exemptions from certain driving restrictions (see Appendix Table C.2). The coefficient estimate is positive but imprecise.

Recent literature has found that consumers demonstrate their environmental preferences through buying green products (Kahn, 2007; Kahn and Vaughn, 2009) to seek status. Sexton and Sexton (2014) define "conspicuous conservation" as a phenomenon in which individuals seek status conferred upon demonstration of actions and purchases that minimize the environmental impact of consumption. The authors find that consumers are willing to pay an additional $430 to $4,200 for the distinctively designed Toyota Prius.

Our finding is also consistent with the findings from the eco-labeling literature, which shows that such labeling can help guide consumer purchasing decisions, and encourage a behavioral change of consumers and producers towards sustainability (Teisl et al., 2002; Bjørner et al., 2004; Mason, 2013).

3.5.3 Charging Infrastructure

As in many new technology markets, the EV market is characterized by indirect network effects. That is, the demand for EVs depends on the availability of publicly accessible charging stations, and, in turn, the supply of charging infrastructure depends on the installed base of EVs to use the stations. An inherent challenge in the development of this type of market is the coordination problem whereby one group of market participants tends to wait for the other group to act.[30] Policies that strengthen one side of the market could help the development of the other side of the market. The government can choose to subsidize EV purchases (demand) or investment in charging stations (supply) — or to do some of both. The question of whether the policies on either side of the market are equally effective or not in promoting EV sales (i.e., the symmetry/neutrality of the policies) is an empirical question that has important implications for effective policy design.

The preferred specification in Table 3.4 shows that adding 1,000 charging ports has an effect on EV sales that is equivalent of offering a ¥12,500 consumer subsidy. To examine the issue of neutrality, we examine the average cost of per induced EV sales from charging station investment, and from consumer subsidies separately during our data period. The total consumer subsidies during our data period amount to ¥55 billion, and the total sales

[30] More broadly, the consumer's benefit from adopting the primary good (i.e., EVs) depends on the availability of complementary goods (i.e., charging stations); by contrast, an investor's benefit from supplying the complementary goods depends on the installed base of the primary good. The interdependence is referred to as an indirect network effect. Examples of this type of market include computer hardware and software, CD players and CDs, video game consoles and games, and e-readers and ebooks.

induced by these subsidies were 561,904 vehicles (or 55 percent of all EVs sold). These numbers imply an average government cost of ¥97,825 to induce consumers to buy one extra EV through consumer subsidies.

To calculate the total investment cost of charging ports, we assume that, during our data period, the average cost of an AC charging port was ¥10,000, while that of a DC charging port was ¥100,000.[31] A total of 132,207 AC charging ports and 65,902 DC charging ports were constructed during our data period. The total cost would have been ¥7.92 billion. Since our data only capture 60 percent of all public charging stations, this implies the total cost of ¥13.2 billion for all public charging stations in the sample cities. During our data period, the total induced sales by the availability of the charging infrastructure are estimated to be 482,967 vehicles, as based on results in Table 3.4. These results imply an average government cost of ¥27,331 to induce consumers to buy one extra EV through subsidizing or investing in charging stations. This cost estimate is an underestimation of the effectiveness of the charging infrastructure because these charging stations will continue to contribute to future EV sales that are not included in our calculations.

These estimates above suggest that investing in charging stations is nearly four times as effective as subsidizing consumer purchases in promoting EV sales from the perspective of government expenditure. This finding on the superior cost-effectiveness of spending on charging infrastructure to promote EVs is consistent with findings in other countries. Both Li et al. (2017) and Springel (2019) show that subsidizing charging stations is more than twice as effective as subsidizing consumer purchases on a per-dollar basis in the United States and Norway, respectively. Both studies also find that the effect of subsidies on charging stations tapers off as the charging network grows larger. (Li et al. (2017) reach their findings using aggregate sales data by city from 2011 to 2013; Springel (2019) uses individual registration records from 2011 to 2015.) Our finding of the rela-

[31] Source: https://zhuanlan.zhihu.com/p/20800474. The cost has been reduced by about 20-30 percent by 2020. https://www.shangyexinzhi.com/article/547872.html.

tive cost-effectiveness of charging-station investments is even more striking given that our data are from a relatively later time period (2015 to 2018) than those used in other countries, and given that Chinese consumers appear to be more price sensitive than consumers in the United States and Norway. The greater cost-effectiveness of subsidizing charging stations in China could be driven by certain prevalent features of housing and urban structures in China. The vast majority of city residents in China live in apartment complexes, where they lack space to build private charging stations. Also, cities in China are denser, a feature that allows public charging stations to serve more drivers.

3.6 Conclusion

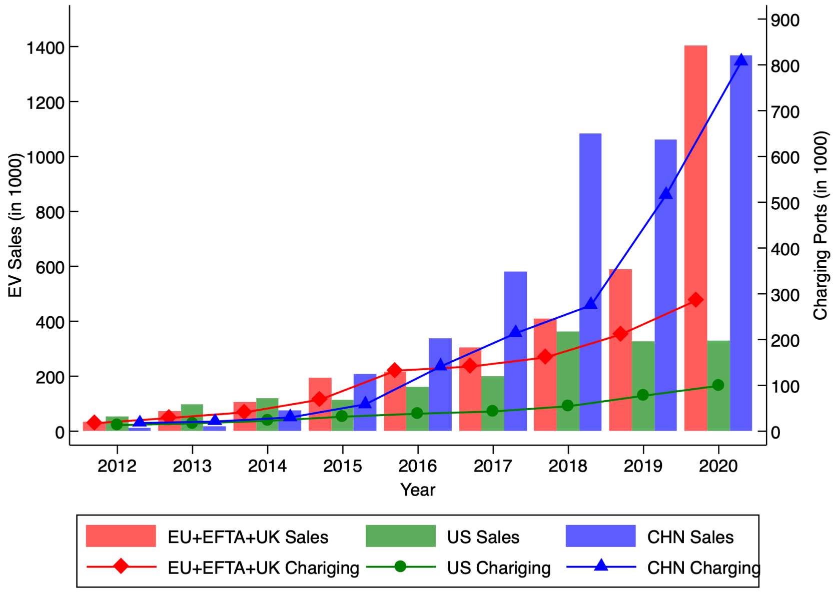
This study provides a comprehensive analysis of the factors that underlie the rapid growth of the world's largest electric vehicle (EV) market: China. Using detailed data on EV sales, charging infrastructure, and policy measures implemented from 2015 to 2018, our analysis offers the following three key findings: First, generous consumer subsidies from both central and local governments played a crucial role, explaining at least half of the EV sales purchased during the period. Second, a program that offered signature, green license plates for EVs worked surprisingly well; the low-cost policy had substantial impacts, highlighting the important psychological and social dimensions that can play a part in hastening the diffusion of environmentally friendly technologies. Third, the availability of charging infrastructure had a large effect on the diffusion of EVs. The strength of the indirect network effects that charging infrastructure has on EV demand means that, at the current diffusion stage, subsidizing the deployment of charging stations is much more cost-effective than subsidizing the purchases of electric vehicles.

While this study focuses on China, the lessons gleaned from this study could offer important guidance on designing future EV policies in other countries. Offering consumers generous subsidies is the most commonly used policy strategy for governments seeking to support the EV market; however, our study reveals that this strategy does not appear to be the most cost-effective option in the early stage of EV diffusion. Governments could help promote wider EV adoption through relatively inexpensive, non-financial policies — such as providing information on the potential environmental benefits of EVs and offering license plates or exterior designs that give consumers a way to visually signal that they have made such environmentally friendly purchases. The early stage of the EV market can be reasonably characterized by a signature line from the 1989 movie, "Field of Dreams": "If you build it, they will come." Building charging infrastructure is a cost-effective strategy for governments to leverage the indirect network effects in the EV market.

These findings point to several important directions for future research. First, understanding the pass-through of consumer subsidies could further shed light on the cost-effectiveness of policies. Given the relatively low price sensitivity of EV buyers as well as other policies such as vehicle purchase restrictions that favor EVs in several major cities, it is not clear *a priori* how much consumers would have captured the subsidies. Second, although our empirical framework allows us to examine the aggregate impacts of policies and charging infrastructure on EV adoption, it does not capture the substitution pattern, especially between EVs and gasoline models, a crucial element in evaluating the environmental impacts and welfare consequences of the new technology. Future research should rely on richer demand models and consumer-level data to better capture consumer choices among different EV and gasoline models to evaluate the environmental impacts of EV adoption (Holland et al., 2016a; Xing et al., 2019). To gain these important policy insights, additional information is needed on the sources of fuel used to generate electricity by location, and on the generation sources that will be used at the times when EV charging is most likely to take place. Third, our analysis focuses on demand-side policies that directly affect consumer EV adoption; these same policies could have had important impacts on the supply side, too — affecting product choices of automakers and their parts (e.g., battery) suppliers. Similarly, supply-side policies such as R&D subsidies and production subsidies could also affect EV adoption. For example, R&D subsidies could influence consumer EV adoption choices by improving quality and reducing costs. A better understanding of the impacts of supply-side policies would further aid effective policy designs.

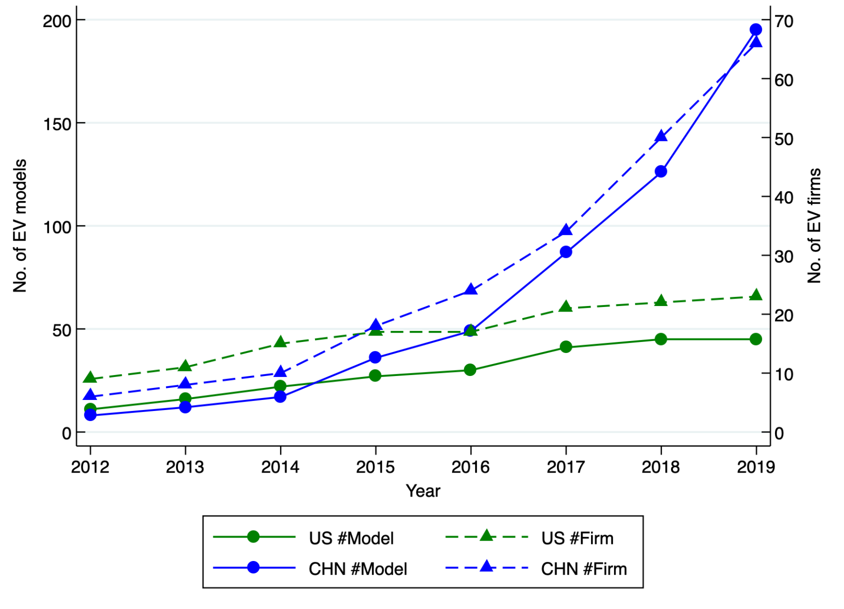
Figures and Tables

Figure 3.1. EV Sales and Charging Station by Country and Region



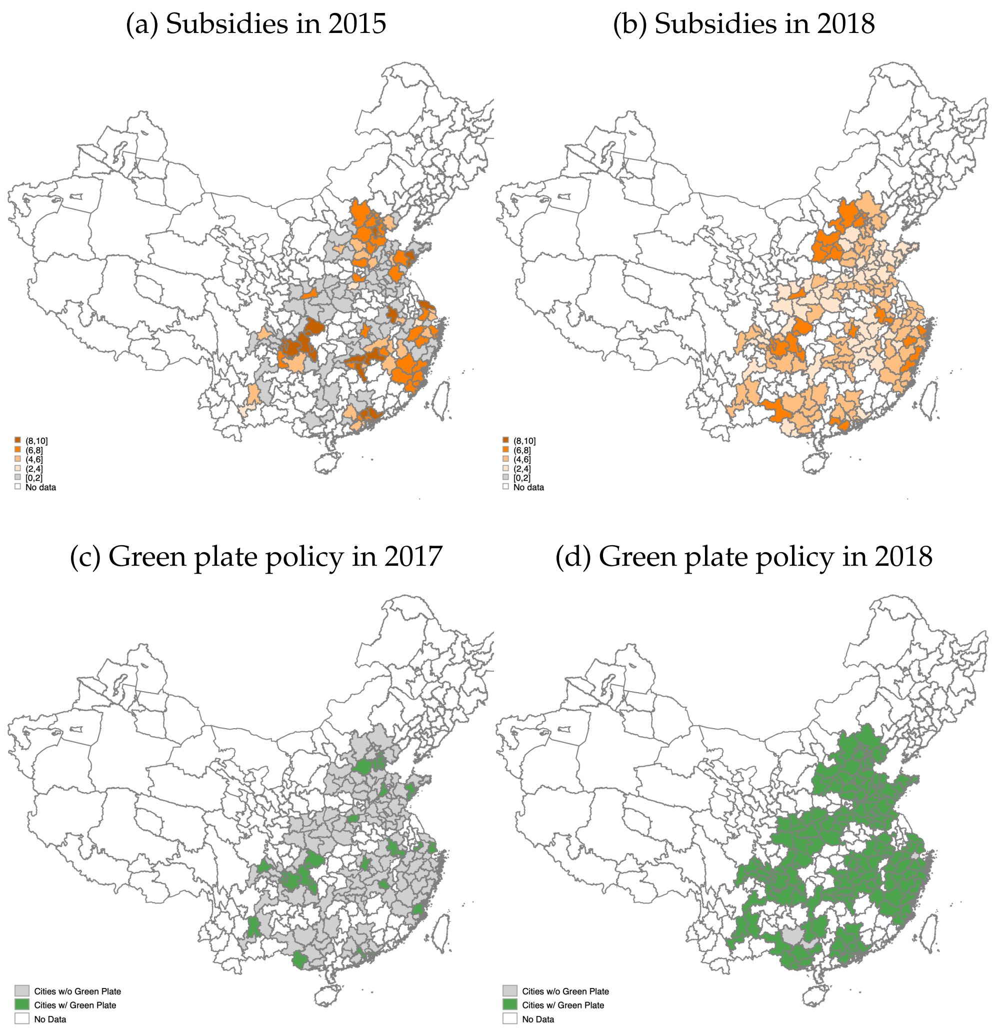
Notes: The figure plots passenger EV sales (bars) and charging outlets/ports (lines) separately for China, US, and EU, EFTA (Iceland, Liechtenstein, Norway, and Switzerland) and UK combined. EVs include both battery EVs (BEVs) and plug-in hybrid EVs (PHEVs). Source: International Energy Agency, and marklines.com

Figure 3.2. Number of EV Firms and Models



Notes: This figure shows the number of EV firms and models (BEVs and PHEVs) in China and US. Data for China is up to May 2019.

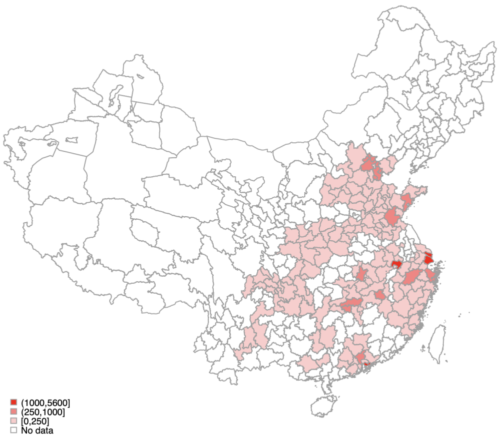
Figure 3.3. Consumer Subsidies and Green Plate Policy by City



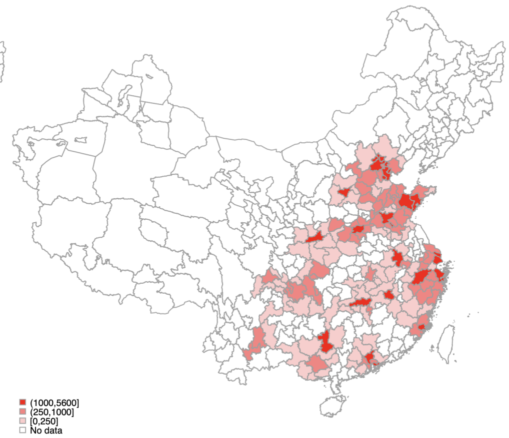
Notes: Panels (a) and (b) depict average consumer subsidies from central and local governments in ¥10,000 per EV in 2015 and 2018. Panels (c) and (d) show the rollout of the green plate policy for EVs in 2017 and 2018. The policy started in 2016 with five cities: Shanghai, Nanjing, Wuxi, Jinan, and Shenzhen.

Figure 3.4. EV Sales and Charging Ports (per million Residents) by City

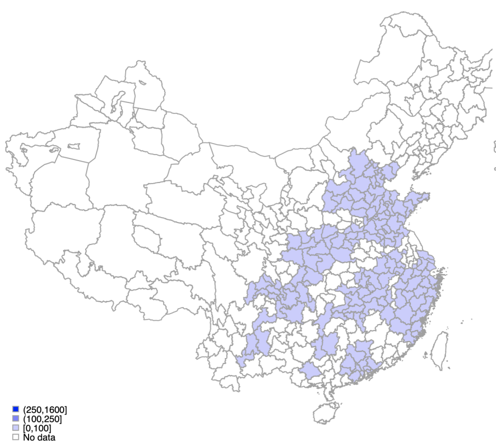
(a) EV sales in 2015



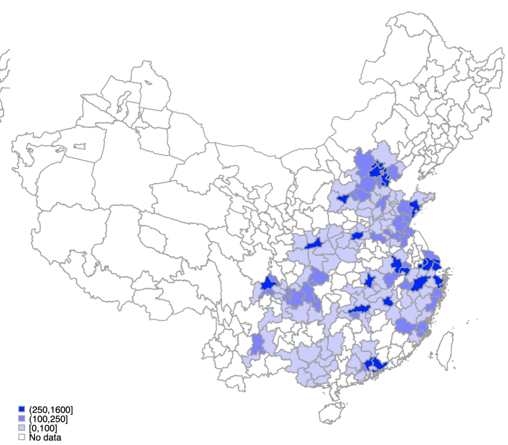
(b) EV sales in 2018



(c) Charging ports in 2015

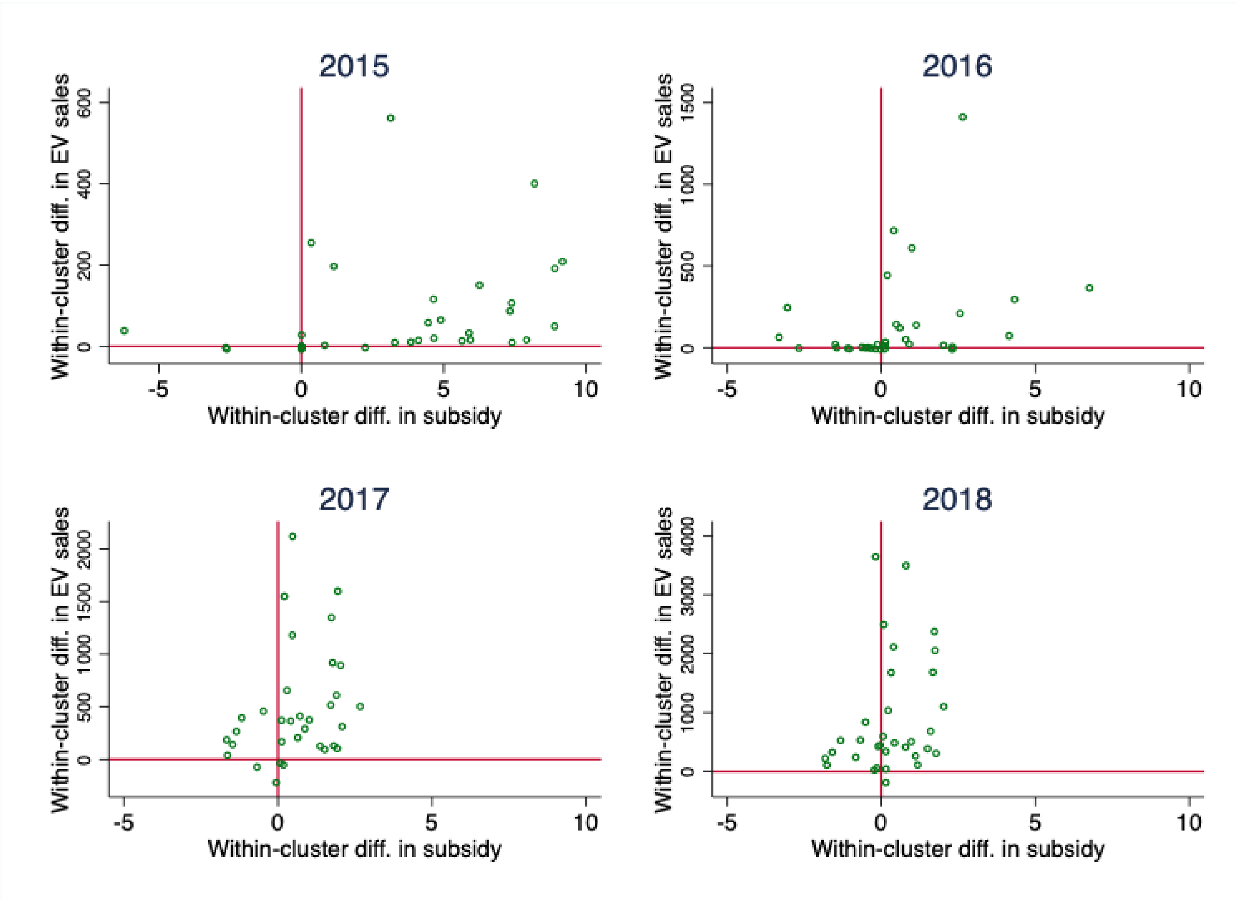


(d) Charging ports in 2018



Notes: Panels (a) and (b) depict annual EV sales (in units) per million residents by city for 150 sample cities in 2015 and 2018. Panel (c) and (d) show the number of charging ports per million residents by city for 150 sample cities by the end of 2015 and 2018.

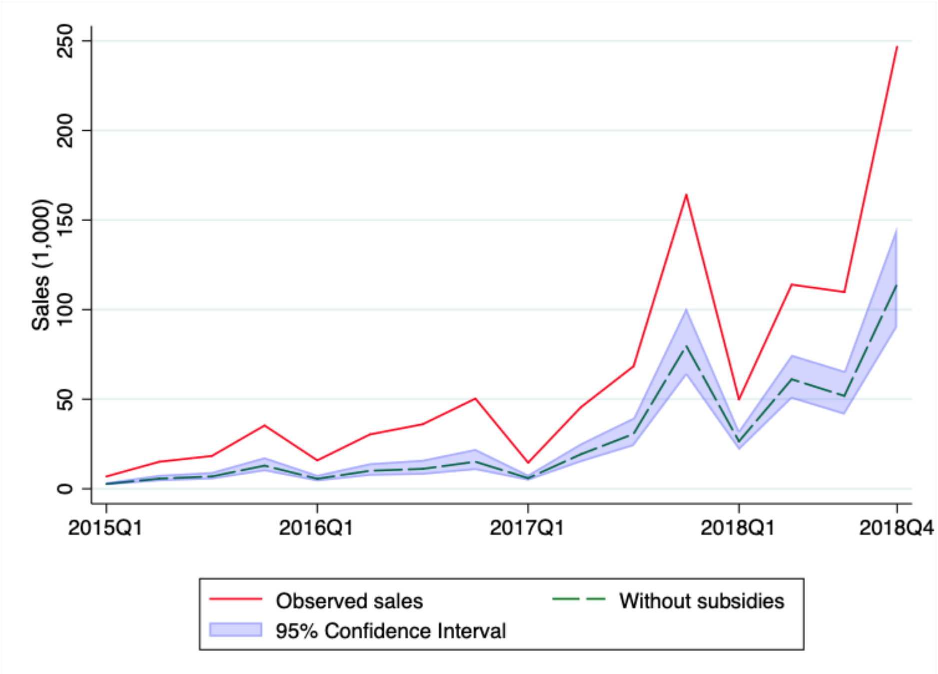
Figure 3.5. Within-Cluster Variation in Subsidy and EV Sales



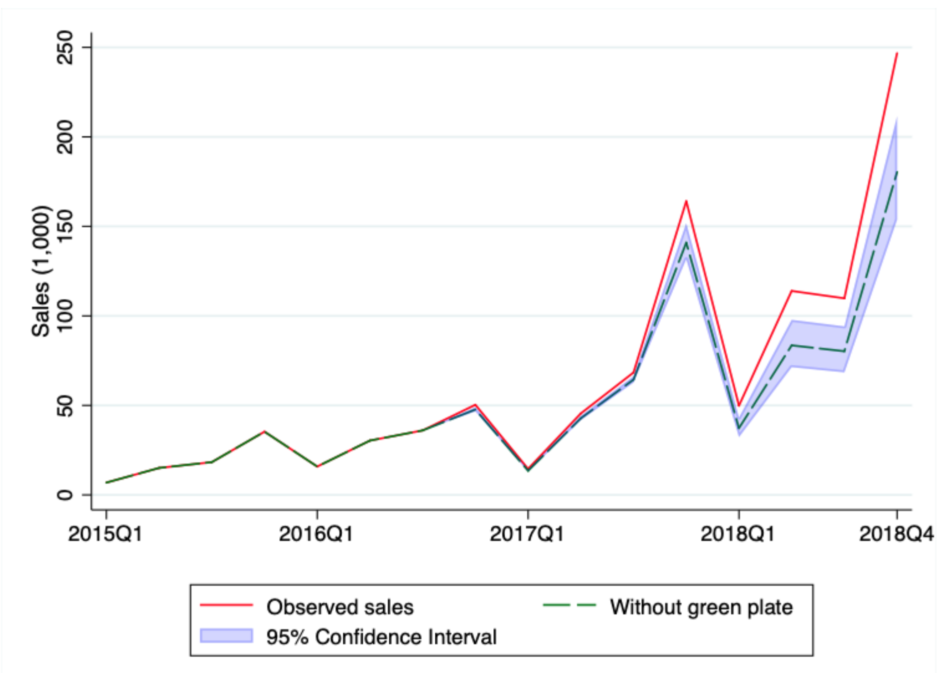
Notes: The figure plots the within-cluster (min and max) difference of EV sales per million residents versus the difference of average subsidy per vehicle (including both central and local subsidies), between top-40 cities and non-top-40 cities. Each circle represents a cluster with at least one city from the top-40 city list.

Figure 3.6. Simulation Results

(a) Removing subsidies



(b) Removing green plate



Notes: The figures plot the counterfactual sales and the 95% confidence interval based on the estimation results from column (7) of Table 3.4. Panel (a) removes central and local subsidies while Panel (b) removes the green plate policy. The counterfactual sales would have been 45 percent and 83 percent of what have been observed in the data during the sample period, respectively.

Table 3.1. Consumer Subsidies in China and US

	Federal	Local
China	**Subsidy based on driving range** 2010: 13 pilot cities 2013: 88 pilot cities 2016: nationwide subsidy	Matched with central subsidy by 1:1 to 1:0.5 ratio Shared by provincial and city governments Total subsidy no more than 50% to 70% of MSRPs
US	**Subsidy based on battery capacity** From 2010: $2500 for 4kWh battery, with an additional $417 per kWh to $7500 200k qualifying vehicles per automaker	Rebates: CA, IL, MA, NY, PA, TX Tax credit: CO, GA, LA, MD, SC, UT, WV Sales tax exemption or reduction: CO, NJ, WA Fee exemptions or reduced fee: AZ, IL

Table 3.2. Central Subsidies from 2013 to 2019

Type	Range	2013	2014	2015	2016	2017	2018	2019
BEV	≥ 80km	¥35,000	¥33,250	¥31,500	-	-	-	-
	≥ 100km				¥25,000	¥20,000	-	-
	≥ 150km	¥50,000	¥47,500	¥45,000	¥45,000	¥36,000	¥15,000	-
	≥ 200km						¥24,000	-
	≥ 250km	¥60,000	¥57,000	¥54,000	¥55,000	¥44,000	¥34,000	¥18,000
	≥ 300km						¥45,000	
	≥ 400km						¥50,000	¥25,000
PHEV	≥ 50km	¥35,000	¥33,250	¥31,500	¥30,000	¥24,000	¥22,000	¥10,000

Notes: This table shows the subsidies from the central government. The amount of subsidies is based on driving range. Starting from 2018, the subsidies are adjusted based on two additional requirements for EVs to be eligible: minimum energy efficiency (kWh/100km) as a function of vehicle weight, and battery energy density ≥ 105 Wh/kg. For comparison, the amount of EV subsidies in the US is only based on battery capacity.

Table 3.3. Summary Statistics

	Mean	S.D.	Min	Max
Sales	37.02	209.21	0.00	7834
MSRP (in ¥10,000)	20.01	8.25	8.18	60.88
Total subsidy (in ¥10,000)	4.53	2.27	0.00	14.17
Central subsidy (in ¥10,000)	3.51	1.42	0.00	5.71
No. of charging ports (1,000)	1.62	3.99	0.00	36.65
No. of charging stations	177	446	0.00	3666
EV exempt from driving restrictions	0.21	0.41	0.00	1.00
Green plate for EVs	0.54	0.50	0.00	1.00
Vehicle size (m^2)	7.21	1.58	3.75	9.85
Motor power (100kW)	0.87	0.71	0.09	4.80
Weight (ton)	1.23	0.45	0.51	2.19
Driving range (100km)	1.85	1.07	0.50	4.20
Battery capacity (kWh)	26.66	14.74	8.00	82.00
EV stock by institutions	5.86	12.68	0.00	81.44
Population (in mil.)	7.52	5.15	0.74	31.02
Income (in ¥10,000)	3.90	1.07	2.02	6.80

Notes: The unit of observation is city-quarter by vehicle trim. The number of observations is 27,577. The data are from 2015 to 2018 for 150 cities. MSRP is the manufacturer suggested retail price.

Table 3.4. Regression Results of EV Demand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSRPs (in ¥10,000)	-0.027**	-0.035***	-0.044***	-0.046***	-0.038***	-0.174***	-0.181***
	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)	(0.030)	(0.031)
Consumer subsidies per vehicle (in ¥10,000)	0.116***	0.106***	0.162***	0.159***	0.154***	0.160***	0.160***
	(0.015)	(0.015)	(0.026)	(0.028)	(0.029)	(0.027)	(0.027)
No. of charging ports (1,000)	0.047*	0.010	0.168***	0.189***	0.191***	0.192***	0.200***
	(0.024)	(0.016)	(0.032)	(0.034)	(0.034)	(0.034)	(0.038)
EV exempt from driving restrictions	0.456***	0.478***	0.121	-0.008	0.036	0.029	-0.028
	(0.116)	(0.131)	(0.176)	(0.139)	(0.149)	(0.150)	(0.156)
Green plate for EVs	0.338***	0.144**	0.197***	0.316***	0.325***	0.312***	0.314***
	(0.056)	(0.067)	(0.064)	(0.077)	(0.080)	(0.079)	(0.081)
Vehicle size (m^2)	0.525***	0.376**	0.281	0.305	-0.214	-0.088	-0.143
	(0.187)	(0.178)	(0.182)	(0.186)	(0.184)	(0.166)	(0.171)
Power/Weight (kW/kg)	9.937***	12.383***	13.231***	13.025***	10.894***	6.372***	6.180***
	(2.087)	(2.034)	(2.088)	(2.092)	(2.062)	(2.010)	(2.007)
Driving range (100km)	0.075*	-0.101**	-0.141***	-0.129***	-0.007	0.111**	0.118**
	(0.041)	(0.040)	(0.042)	(0.043)	(0.053)	(0.055)	(0.054)
City-Model FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y
Observations	25003	25003	24995	24994	24828	24828	24493
Adjusted R^2	0.495	0.554	0.564	0.567	0.564	-0.108	-0.110
Joint-F on excluded IVs						105.456	85.959
Underidentification stat						89.758	88.137
Weak Identification stat						105.456	85.959
Overidentification stat						22.094	21.691

Notes: The regressions are based on 150 cities. The dependent variable is ln(sales). Column (6) instruments for MSRPs using battery capacity interacted with battery-supplier dummies. Column (7) instruments for MSRPs and the number of charging ports using battery capacity interacted with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5. Robustness Checks

	Baseline (1)	Asinh (2)	Drop Zero (3)	Logit (4)	Subsample (5)	All Models (6)	Alternative IV (7)
MSRPs (in ¥10,000)	-0.181***	-0.173***	-0.161***	-0.181***	-0.194***	-0.150***	-0.224***
	(0.031)	(0.030)	(0.028)	(0.031)	(0.035)	(0.055)	(0.069)
Consumer subsidies per vehicle (in ¥10,000)	0.160***	0.155***	0.193***	0.160***	0.167***	0.161***	0.162***
	(0.027)	(0.027)	(0.023)	(0.027)	(0.031)	(0.032)	(0.027)
No. of charging ports (1,000)	0.200***	0.200***	0.140***	0.223***	0.157***	0.185***	0.202***
	(0.038)	(0.037)	(0.036)	(0.040)	(0.038)	(0.038)	(0.039)
EV exempt from driving restrictions	-0.028	-0.021	-0.010	-0.033	-0.047	-0.002	-0.031
	(0.156)	(0.154)	(0.129)	(0.155)	(0.154)	(0.165)	(0.156)
Green plate for EVs	0.314***	0.310***	0.321***	0.331***	0.405***	0.298***	0.310***
	(0.081)	(0.080)	(0.079)	(0.089)	(0.095)	(0.086)	(0.083)
Vehicle size (m^2)	-0.143	-0.134	-0.025	-0.143	-0.239	0.501***	-0.108
	(0.171)	(0.169)	(0.172)	(0.171)	(0.201)	(0.146)	(0.199)
Power/Weight (kW/kg)	6.180***	5.969***	9.448***	6.121***	6.839***	10.786***	4.761
	(2.007)	(1.959)	(2.004)	(2.010)	(2.180)	(2.466)	(3.626)
Driving range (100km)	0.118**	0.118**	-0.119**	0.117**	0.135**	0.149**	0.155**
	(0.054)	(0.053)	(0.058)	(0.055)	(0.061)	(0.069)	(0.074)
No. of cities	150	150	150	150	106	150	150
Observations	24493	24493	20447	24493	20143	26586	24493
Adjusted R^2	-0.110	-0.108	-0.132	-0.108	-0.124	-0.102	-0.121
Joint-F on excluded IVs	85.959	85.959	106.718	85.959	76.396	87.123	31.889
Underidentification stat	88.137	88.137	84.291	88.137	70.194	79.704	62.870
Weak Identification stat	85.959	85.959	106.718	85.959	76.396	87.123	31.889
Overidentification stat	21.691	21.767	31.616	21.618	23.519	26.952	17.142

Notes: All columns include the same set of fixed effects as in Column (7) of Table 3.4: city-model FEs, city-year FEs, city cluster-time (i.e., year-quarter) FEs, and city cluster-brand-year FEs. Column (1) is our benchmark specification where the dependent variable is ln(sales). The dependent variable is the inverse hyperbolic sine of sales in column (2). Column (3) drops all observations with zero EV sales but otherwise is the same as column (1). Column (4) is the logit demand with the dependent variable being $ln(s_{kct}) - ln(s_{0ct})$ where s_{kct} is the market share of trim k in city c and time t and s_{0ct} is the share of consumers who are not purchasing an EV. Column (5) is based on 106 cities in clusters that contain cities with similar average household income. Column (6) is based on the full sample of all vehicle models including models with small sales. Columns (1)-(6) instrument for MSRPs and the number of charging ports using battery capacity interacting with battery-supplier dummies, and the lagged institutional EV stock. Column (7) instruments for MSRPs and the number of charging ports using battery density interacting with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX A

APPENDIX OF CHAPTER 1

A.1 Proofs

A.1.1 Proof of Proposition 1

Differentiating (1.4)-(1.6), we can solve for:

$$d\pi = \frac{\pi}{\Delta}\left[-\frac{\epsilon-1}{\tau}d\tau + \frac{\epsilon^*-1}{\tau^*}d\tau^*\right] \tag{A.1}$$

$$dM_1^* = -\frac{M_1^*\epsilon^*}{\Delta}\left[\frac{\epsilon-1}{\tau}d\tau + \frac{\epsilon}{\tau^*}d\tau^*\right] \tag{A.2}$$

$$dM_2 = -\frac{M_2\epsilon}{\Delta}\left[\frac{\epsilon^*}{\tau}d\tau + \frac{\epsilon^*-1}{\tau^*}d\tau^*\right] \tag{A.3}$$

where $\epsilon = -\frac{\pi}{M_2}\frac{\partial M_2}{\partial \pi} = -\frac{\tau}{M_2}\frac{\partial M_2}{\partial \tau} > 0$, $\epsilon^* = \frac{\pi}{M_1^*}\frac{\partial M_1^*}{\partial \pi} = -\frac{\tau^*}{M_1^*}\frac{\partial M_1^*}{\partial \tau^*} > 0$ are the elasticities of import demand for the home and foreign countries, respectively. Assume that the Marshall-Lerner conditions are satisfied $\Delta = \epsilon + \epsilon^* - 1 > 0$.

By equations (A.2)-(A.3), the marginal effects of unilaterally increasing import barrier on imports and exports of the home country are:

$$\frac{\partial M_2}{\partial \tau} = -\frac{M_2\epsilon}{\Delta}\frac{\epsilon^*}{\tau} \tag{A.4}$$

$$\frac{\partial M_1^*}{\partial \tau} = -\frac{M_1^*\epsilon^*}{\Delta}\frac{\epsilon-1}{\tau} \tag{A.5}$$

$$\frac{\partial(M_2 - M_1^*)}{\partial \tau} = \frac{\epsilon^*}{\Delta\tau}[-M_2\epsilon + M_1^*(\epsilon-1)] \tag{A.6}$$

Equation (A.4) implies that $\frac{\partial M_2}{\partial \tau} < 0$. Equation (A.5) implies that $\frac{\partial M_1^*}{\partial \tau} < 0$ if $\epsilon > 1$.

Equation (A.6) shows that $\frac{\partial(M_2 - M_1^*)}{\partial\tau} > 0$ if and only if $\frac{M_2}{M_1^*} > \frac{\epsilon-1}{\epsilon}$. Therefore, if the home country increases its import barrier, both its imports and exports will decrease. Net imports decrease if and only if $\frac{M_2}{M_1^*} > \frac{\epsilon-1}{\epsilon}$.

A.1.2 Proof of Proposition 2

Total differentiating (1.1)-(1.3) yields:

$$dV = V_p\,dp_2 + V_Y\,dY = V_p(\pi\,d\tau + \tau\,d\pi) \tag{A.7}$$

where $V_p < 0$. The second equality holds because $dY = 0$.

Substituting $d\pi$ in (A.8) yields:

$$dV = \frac{V_p\pi}{\Delta}\left[\epsilon^*\,d\tau + \frac{\tau}{\tau^*}(\epsilon^* - 1)\,d\tau^*\right] \tag{A.8}$$

Assume that the home country unilaterally increases τ while the foreign country keeps τ^* fixed. $\frac{\partial V}{\partial\tau} = \frac{V_p\pi}{\Delta}\epsilon^* < 0$ as $V_p < 0$, implying that unilaterally restricting imports would reduce the gains from trade.

Differentiating (1.7) and substituting dM_1^* and dM_2 yields the following results:

$$dD = \frac{\delta}{\Delta}\left\{\frac{\epsilon^*}{\tau}[-M_2\epsilon + M_1^*(\epsilon - 1)]\,d\tau + \frac{\epsilon}{\tau^*}[-M_2(\epsilon^* - 1) + M_1^*\epsilon^*]\,d\tau^*\right\} \tag{A.9}$$

Substituting dV and dD yields the following:

$$dW = dV - dD \tag{A.10}$$

$$= \frac{1}{\Delta}\left\{V_p \pi \epsilon^* + \delta\frac{\epsilon^*}{\tau}[M_2\epsilon - M_1^*(\epsilon - 1)]\right\} d\tau + \frac{1}{\Delta}\left\{V_p \pi \frac{\tau}{\tau^*}(\epsilon^* - 1) + \delta\frac{\epsilon}{\tau^*}[M_2(\epsilon^* - 1) - M_1^*\epsilon^*]\right\} d\tau^* \tag{A.11}$$

Therefore,

$$\frac{\partial W}{\partial \tau} = \frac{1}{\Delta}\left\{V_p \pi \epsilon^* + \delta\frac{\epsilon^*}{\tau}[M_2\epsilon - M_1^*(\epsilon - 1)]\right\} \tag{A.12}$$

The first term is negative; the second term is positive when $\epsilon > 1$ and $\frac{M_2}{M_1^*} > \frac{\epsilon-1}{\epsilon}$. When δ is large enough, the environmental benefits of unilaterally restricting imports could outweigh the deadweight losses from reduced trade, leading to an increase of the social welfare, i.e., $\frac{\partial W}{\partial \tau} > 0$.

A.1.3 Proof of Proposition 3

If the foreign country unilaterally increases τ^*, from Equation (A.11), we have:

$$\frac{\partial W}{\partial \tau^*} = \frac{1}{\Delta}\left\{V_p \pi \frac{\tau}{\tau^*}(\epsilon^* - 1) + \delta\frac{\epsilon}{\tau^*}[M_2(\epsilon^* - 1) - M_1^*\epsilon^*]\right\} d\tau^* \tag{A.13}$$

The first term captures the spillover effect on the gains from trade. It is negative when $\epsilon^* > 1$. The second term captures the spillover effect on the environment. The sign is ambiguous. It is negative when $\epsilon^* > 1$ and $\frac{M_1^*}{M_2} > \frac{\epsilon^*-1}{\epsilon^*}$, indicating that increasing the import barrier in the foreign country could generate negative spillovers on the environment of the home country. In this case, the total spillover effect on the welfare is negative. If the second term is positive and δ is large, it is possible that total spillover effect becomes positive.

A.1.4 Proof of Proposition 4

The slope of the home country's welfare contours is obtained from setting $dW = 0$ and solving for:

$$\frac{d\tau^*}{d\tau}|_{home,welfare} = -\frac{V_p \pi \epsilon^* + \delta \frac{\epsilon^*}{\tau}[M_2 \epsilon - M_1^*(\epsilon - 1)]}{V_p \pi \frac{\tau}{\tau^*}(\epsilon^* - 1) + \delta \frac{\epsilon}{\tau^*}[M_2(\epsilon^* - 1) - M_1^* \epsilon^*]} \tag{A.14}$$

Assume further that $\epsilon > 1$ and $\epsilon^* > 1$. Since $V_p < 0$, the first term of the numerator is negative. The sign of the second term depends on $M_2\epsilon - M_1^*(\epsilon - 1)$, which can be rewritten as $M_1^*\epsilon(\frac{M_2}{M_1^*} - \frac{\epsilon-1}{\epsilon}) = M_1^*\epsilon(\frac{\tau^*}{\tau\pi} - \frac{\epsilon-1}{\epsilon})$. Assume that when $\tau = \tau^* = 1$, we have $\frac{1}{\pi} > \frac{\epsilon-1}{\epsilon}$. Then $M_2\epsilon - M_1^*(\epsilon - 1) > 0$. If δ is large enough, the numerator would be positive.

For the denominator, the first term is negative. As $M_2(\epsilon^* - 1) - M_1^*\epsilon^* = M_1^*(\epsilon^* - 1)(\frac{M_2}{M_1^*} - \frac{\epsilon^*}{\epsilon^*-1}) = M_1^*(\epsilon^* - 1)(\frac{\tau^*}{\tau\pi} - \frac{\epsilon^*}{\epsilon^*-1})$. If $\frac{1}{\pi} < \frac{\epsilon^*}{\epsilon^*-1}$, then the second term is negative. Then the denominator would be negative.

Therefore, if $\epsilon > 1$, $\epsilon^* > 1$, $\frac{\epsilon-1}{\epsilon} < \frac{1}{\pi} < \frac{\epsilon^*}{\epsilon^*-1}$, then $\frac{d\tau^*}{d\tau}|_{home,\tau=\tau^*=1} > 0$. As τ increases, $\tau\pi$ would increase as $d(\tau\pi) = \frac{\pi}{\Delta}\left[\epsilon^*\, d\tau + \frac{\tau}{\tau^*}(\epsilon^* - 1)\, d\tau^*\right] > 0$. Therefore, $M_1^*\epsilon(\frac{\tau^*}{\tau\pi} - \frac{\epsilon-1}{\epsilon})$ decreases. At some point of τ, the numerator would be zero. After that point, the numerator would become negative. The denominator is always negative. Therefore, as τ increases, the sign of $\frac{d\tau^*}{d\tau}|_{home}$ will be positive first and then negative, suggesting that the home country's welfare contour is first increasing and then decreasing with τ.

Setting $\frac{d\tau^*}{d\tau}|_{home,welfare} = 0$ defines the (implicit) best response function of the home country:

$$V_p p_2 + \delta[M_2\epsilon - M_1^*(\epsilon - 1)] = 0 \tag{A.15}$$

By the implicit function theorem, the slope of the best response function of the home country is:

$$\frac{d\tau^*}{d\tau}|_{home,br} = -\frac{(p_2V_{pp} + V_p)\epsilon^*\pi + \delta\frac{\epsilon^2\epsilon^*M_1^*}{\tau}\left[-\frac{\tau^*}{\tau\pi} + (\frac{\epsilon-1}{\epsilon})^2\right]}{(p_2V_{pp} + V_p)\frac{\tau}{\tau^*}(\epsilon^* - 1) + \delta\frac{\epsilon^2(\epsilon^*-1)M_1^*}{\tau}\left[-\frac{\tau^*}{\tau\pi} + \frac{\epsilon-1}{\epsilon}\frac{\epsilon^*}{\epsilon^*-1}\right]} \tag{A.16}$$

Assume $V_p < 0, V_{pp} > 0, p_2V_{pp} + V_p > 0$. When $(\frac{\epsilon-1}{\epsilon})^2 < \frac{\tau^*}{\tau\pi} < \frac{\epsilon-1}{\epsilon}\frac{\epsilon^*}{\epsilon^*-1}$, $-\frac{\tau^*}{\tau\pi} + (\frac{\epsilon-1}{\epsilon})^2 < 0$ and $-\frac{\tau^*}{\tau\pi} + \frac{\epsilon-1}{\epsilon}\frac{\epsilon^*}{\epsilon^*-1} > 0$. When δ is large enough, the numerator is negative and the denominator is positive, thus the slope of the best response function could be positive.

A.1.5 Proof of Proposition 5

The non-cooperative Nash equilibrium are determined when both the home country and foreign country maximizes their own social welfare, conditional on the other country's import barrier decision:

$$\max_{\tau} W(\tau, \tau^*) \quad \text{and} \quad \max_{\tau^*} W^*(\tau, \tau^*) \tag{A.17}$$

The FOCs are:

$$\frac{\partial W}{\partial \tau} = 0 \quad \text{and} \quad \frac{\partial W^*}{\partial \tau^*} = 0 \tag{A.18}$$

On the other hand, the Pareto optimum could be solved through maximizing the home country's welfare subject to the constraint that the foreign country is guaranteed with a minimum amount of welfare:

$$\max_{\tau,\tau^*} W(\tau,\tau^*) \quad \text{s.t} \quad W^*(\tau,\tau^*) \geq \bar{w}_0 \tag{A.19}$$

Let λ be the Lagrange multiplier on the constraint, then the FOCs of the Pareto optimality are:

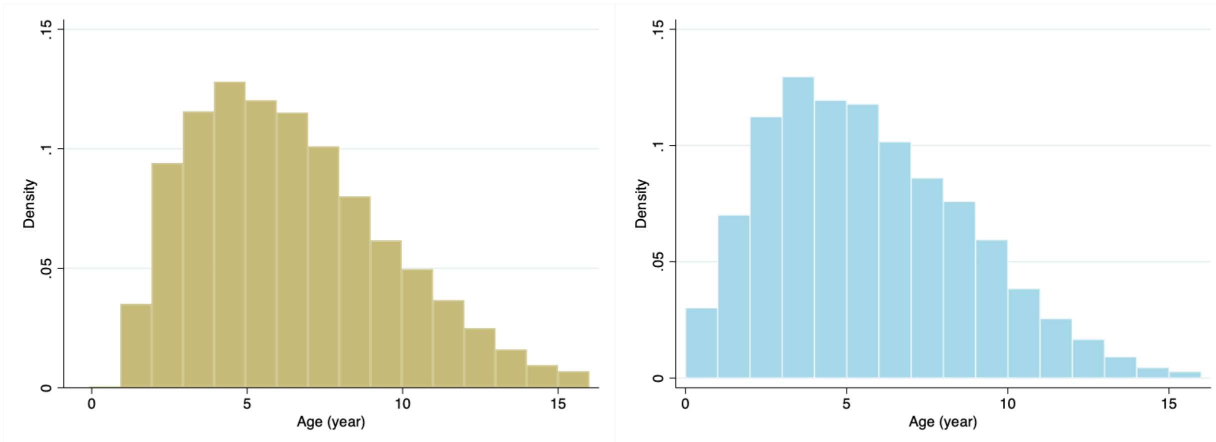
$$\frac{\partial W}{\partial \tau} + \lambda \frac{\partial W^*}{\partial \tau} = 0 \quad \text{and} \quad \frac{\partial W}{\partial \tau^*} + \lambda \frac{\partial W^*}{\partial \tau^*} = 0 \tag{A.20}$$

From (A.11) we know that $\frac{\partial W^*}{\partial \tau} \neq 0$ and $\frac{\partial W}{\partial \tau^*} \neq 0$. Therefore, (A.18) and (A.20) are not equivalent, which implies that the Nash equilibrium is inefficient.

A.2 Figures and Tables

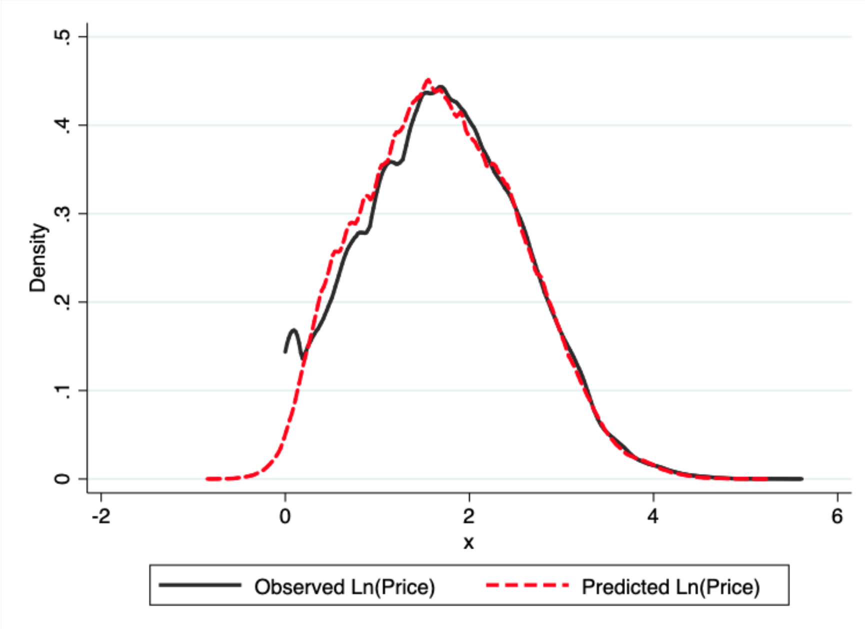
Figure A.1. Age Distribution of Used Vehicles

(a) Registration Data (b) Auction Data



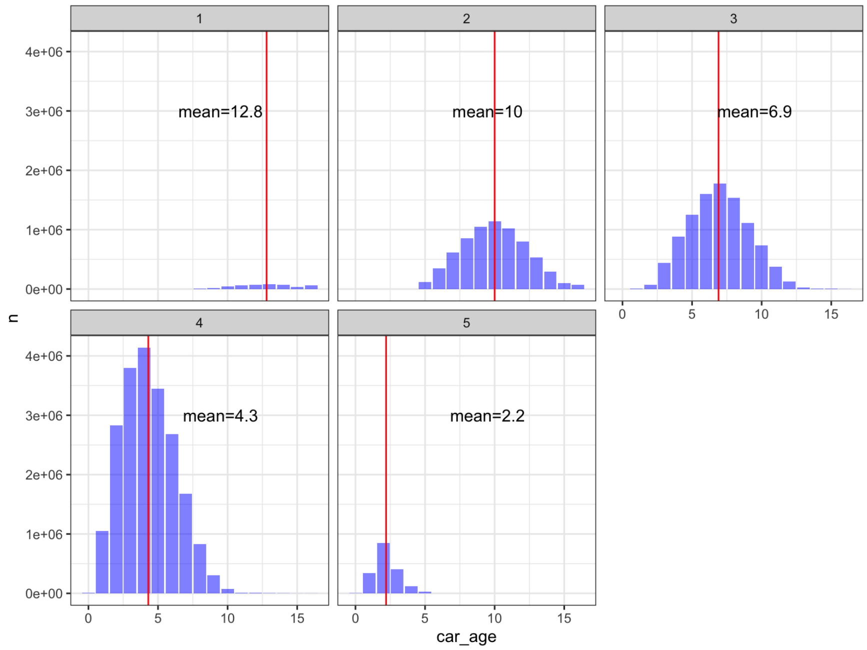
Notes: This figure plots the age distributions of used vehicles in the registration data and the auction data, respectively. The registration dataset contains 40,053,363 observations of used vehicles transactions from January 2013 to June 2018. The auction dataset contains 100,875 observations scraped from a Chinese online used vehicle auction platform, Tiantian Paiche, from November 2018 to Februray 2021.

Figure A.2. Observed and Predicted Prices



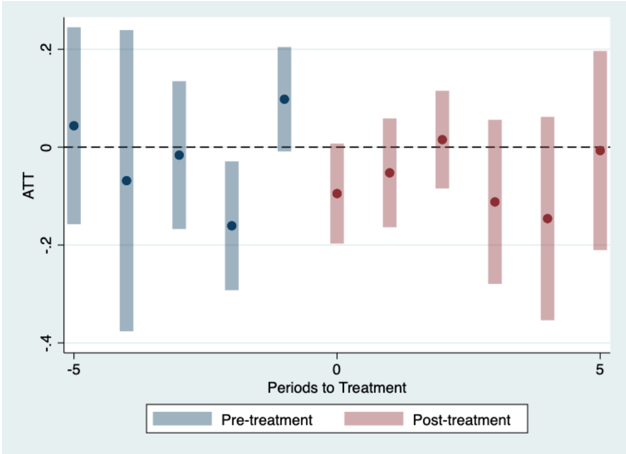
Notes: This figure plots the density of observed used vehicle auction prices and the density of predicted prices based on a hedonic model regressing prices on vehicle age dummies and brand-model dummies.

Figure A.3. Age Distribution by Emission Intensity



Notes: This figure plots the age distributions of used vehicles in the registration data by vehicle emission standard. The labels 1 to 5 represents used vehicles that meet emission standards *China 1* to *China 5*, respectively. The registration dataset contains 40,053,363 observations of used vehicles transactions from January 2013 to June 2018.

Figure A.4. Estimated Effects of Restrictions on AOD



Notes: This figure shows the dynamic effects of restricting the (intercity) imports of used vehicles according to emission standard *China 4* on city AOD readings. The average treatment effects are estimated using CSDID method proposed by Callaway and Sant'Anna (2021). The data are at the city-year quarter level from 2013 to 2015.

Table A.1. Summary Statistics of Registration Data and Auction Data

	Registration Data	Auction Data
Observations	40,053,363	100,875
Sample Period	2013.1-2018.6	2018.11-2021.2
Number of vehicle brands	185	180
Number of vehicle models	1,566	1,849
Number of cities	350	54
Price (10,000 RMB)	-	Mean = 8.01
		Min = 1, Max = 273

Table A.2. A Hedonic Model for Used Vehicle Prices

Dependent variable	ln(Price)		
	(1)	(2)	(3)
Constant	2.377***	2.389***	2.389***
	(0.012)	(0.013)	(0.013)
Age=1	-0.109***	-0.112***	-0.113***
	(0.006)	(0.006)	(0.006)
Age=2	-0.227***	-0.234***	-0.234***
	(0.008)	(0.008)	(0.008)
Age=3	-0.346***	-0.355***	-0.354***
	(0.010)	(0.011)	(0.011)
Age=4	-0.470***	-0.482***	-0.481***
	(0.012)	(0.013)	(0.013)
Age=5	-0.603***	-0.615***	-0.615***
	(0.014)	(0.014)	(0.014)
Age=6	-0.746***	-0.761***	-0.760***
	(0.015)	(0.015)	(0.015)
Age=7	-0.912***	-0.928***	-0.927***
	(0.016)	(0.017)	(0.017)
Age=8	-1.073***	-1.089***	-1.088***
	(0.018)	(0.018)	(0.018)
Age=9	-1.235***	-1.253***	-1.252***
	(0.021)	(0.022)	(0.022)
Age=10	-1.413***	-1.435***	-1.434***
	(0.026)	(0.027)	(0.027)
Age=11	-1.623***	-1.643***	-1.642***
	(0.035)	(0.036)	(0.035)
Age=12	-1.829***	-1.851***	-1.849***
	(0.041)	(0.042)	(0.041)
Age=13	-2.039***	-2.064***	-2.061***
	(0.044)	(0.045)	(0.045)
Age=14	-2.253***	-2.280***	-2.277***
	(0.065)	(0.065)	(0.065)
Age=15	-2.500***	-2.527***	-2.525***
	(0.070)	(0.070)	(0.070)
Age=16 and above	-2.654***	-2.680***	-2.680***
	(0.082)	(0.082)	(0.082)
Brand-model FE	Y	Y	Y
Year-month FE		Y	Y
City FE			Y
Observations	100432	100429	100429
R^2	0.94	0.95	0.95

Notes: This table reports the estimates of a hedonic model regressing used vehicle auction prices on vehicle age dummies and different fixed effects. The auction price data are scrapped from one of the largest online used vehicle auction platform, Tiantian Paiche (https://www.ttpai.cn/). Robust standard errors are clustered at the model level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX B

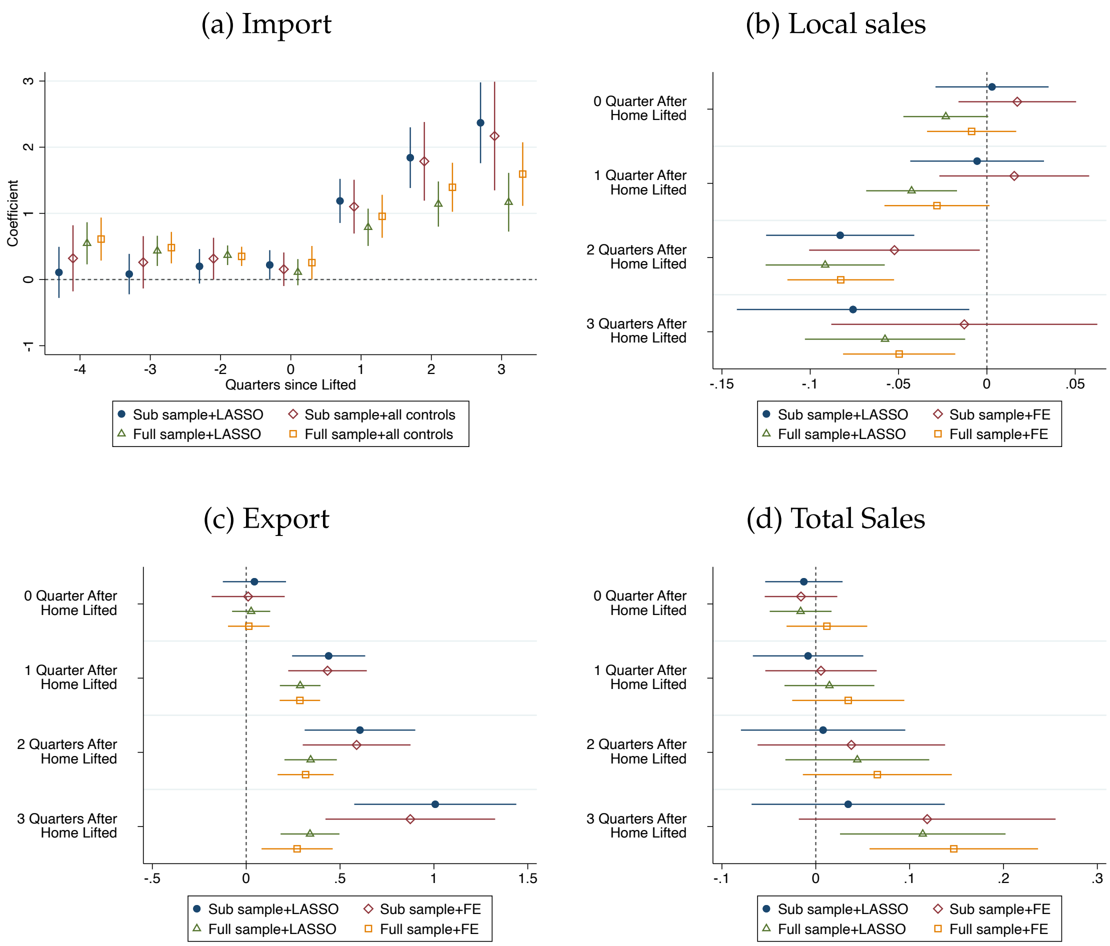
APPENDIX OF CHAPTER 2

B.1 Figures and Tables

Figure B.1. Upwind Direction

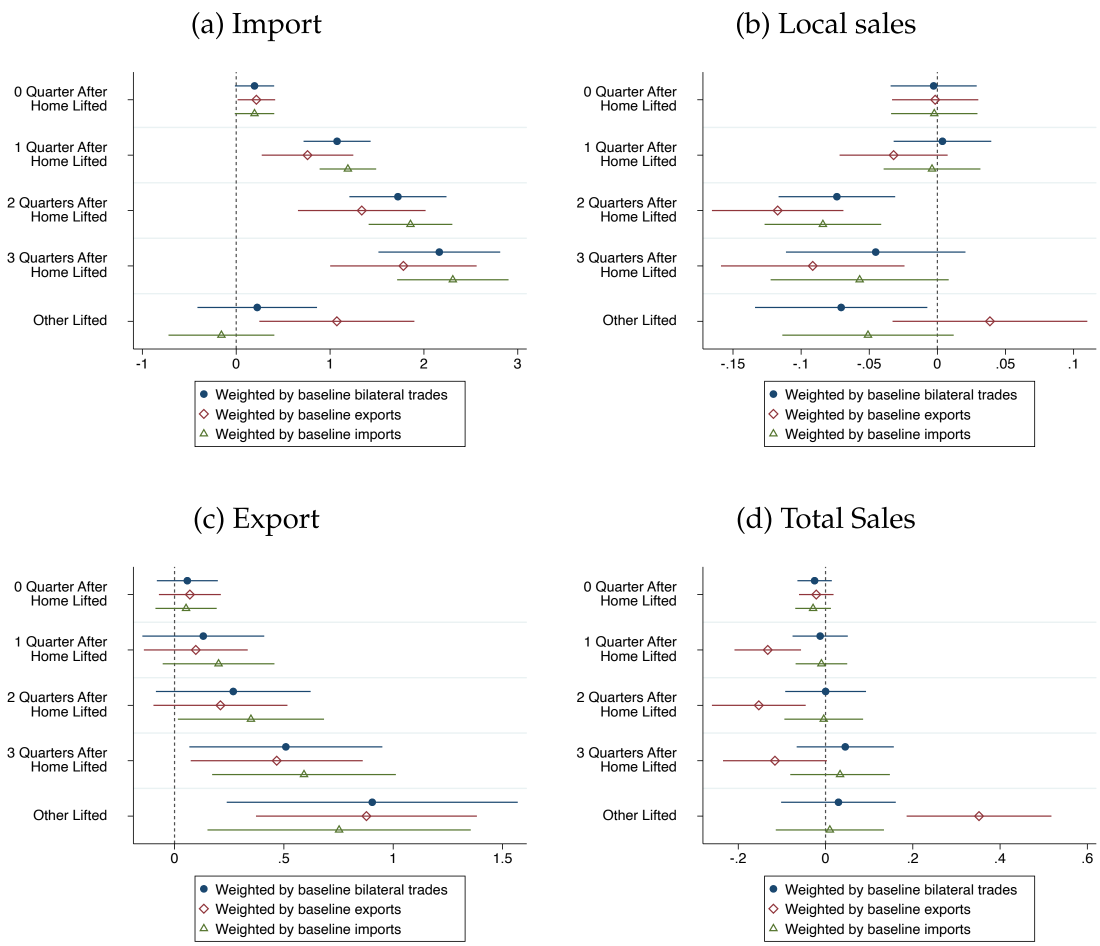
Notes: This figure illustrates how we define the upwind direction in calculating upwind pollution. The upper right figure shows a 16-wind compass. The upwind direction for Beijing in a month when the wind direction is NE includes three adjacent directions of NE, i.e., NE, NNE, and ENE.

Figure B.2. Robustness Checks of Different Samples and Models



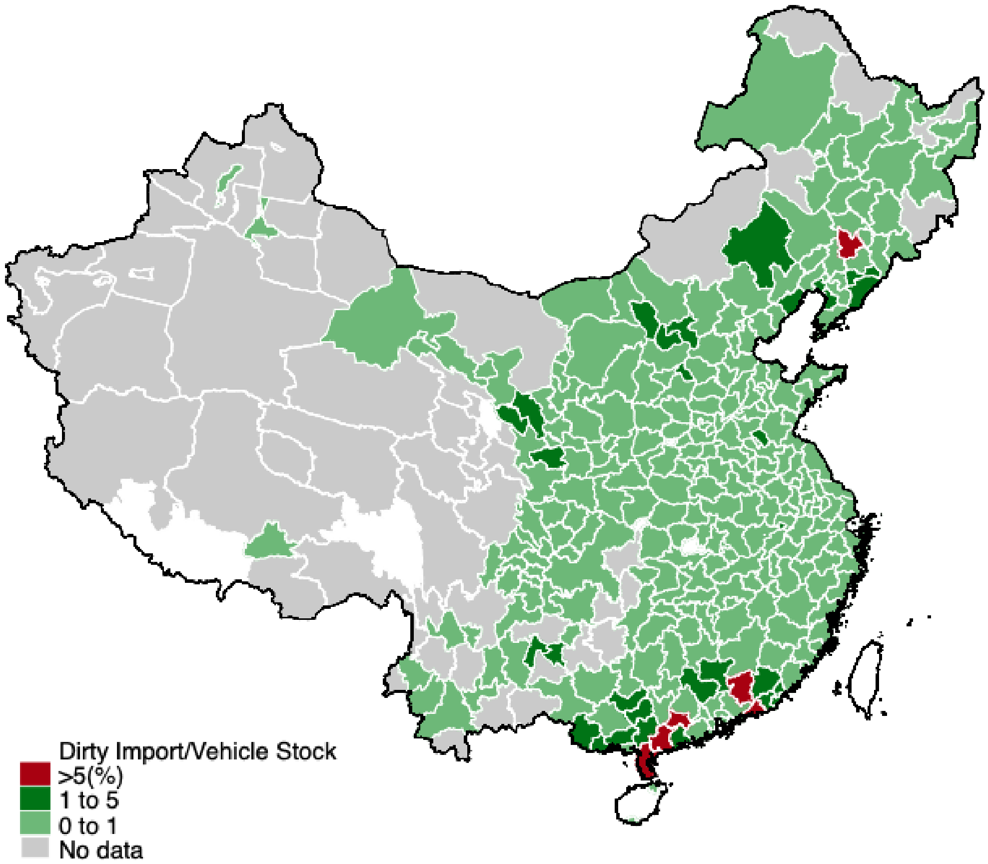
Notes: This figure shows the estimated impact of removing the restriction on import, local sales, export and total sales of dirty used vehicles, using different samples and models. Filled blue circles represent point estimates for our main specification with subsample and LASSO method. Hollow diamonds, triangles and squares represents the other three specifications. Bars represent 95 percent confidence intervals constructed with standard errors clustered at the city level.

Figure B.3. Robustness Checks of Different Weights



Notes: This figure shows the estimated impact of removing the restriction on import, local sales, export and total sales of dirty used vehicles, using different weights. Filled blue circles represent point estimates for our main specification using bilateral trades of used vehicles as of 2015 as weights to construct the "Other Lifted" variable. Hollow diamonds and triangles represents using baseline exports and imports of used vehicles as weights. Bars represent 95 percent confidence intervals constructed with standard errors clustered at the city level.

Figure B.4. Map of Import Share of Dirty Vehicles to Vehicle Stock: 2016.1-2018.6



Notes: This figure shows the import share of dirty used vehicles to motor vehicle stock by city from January 2016 to June 2018. Dirty used vehicles are those below emission standard China 4.

Table B.1. Restriction Adoption and City Characteristics

Dependent var.	𝟙(Adopted in 2013)	𝟙(Adopted during 2013-2015)
	(1)	(2)
AOD	0.354***	0.276*
	(0.133)	(0.158)
Tax Share of Auto Industry	2.393**	1.604
	(1.109)	(1.376)
ln(GDP Per Capita)	-0.091	-0.264***
	(0.066)	(0.093)
ln(Number of Motor Vehicles)	-0.139***	-0.216***
	(0.048)	(0.071)
ln(Government Revenue)	0.027	0.138
	(0.061)	(0.092)
ln(Number of Unemployed)	0.054	0.021
	(0.050)	(0.086)
Mayor Tenure Length	-0.007	0.057**
	(0.021)	(0.026)
𝟙(Mayor Age < 57)	-0.504*	-0.093
	(0.259)	(0.258)
𝟙(Mayor Has Master Degree)	-0.151**	-0.100
	(0.070)	(0.088)
𝟙(Mayor Has PhD Degree)	0.073	0.071
	(0.073)	(0.097)
Party Secretary Tenure Length	0.018	0.041*
	(0.021)	(0.024)
𝟙(Party Secretary Age < 57)	0.323*	-0.414
	(0.190)	(0.310)
𝟙(Party Secretary Has Master Degree)	0.042	-0.028
	(0.057)	(0.090)
𝟙(Party Secretary Has PhD Degree)	0.059	0.137
	(0.081)	(0.091)
Adjusted R^2	0.143	0.129
Observations	182	182

Notes: This table reports the cross-sectional correlation between restriction adoption and city pollution, economy and politics factors. The dependent variable in column (1) is the policy indicator that equals 1 if the city adopted the restriction in 2013, while the dependent variable in column (2) equals 1 if the city adopted the restriction during 2013-2015. The regressors are pollution, economic and politics variables as of 2012. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2. Dynamic Effects on Clean Used Vehicle Sales

Dep. var.	log(Imports)	log(Local Sales)	log(Exports)	log(Total)
	(1)	(2)	(3)	(4)
Home Lifted				
Event time=0	0.012	-0.016	-0.005	-0.025
	(0.049)	(0.014)	(0.021)	(0.017)
Event time=1	-0.069	-0.038**	-0.037	-0.061**
	(0.073)	(0.017)	(0.050)	(0.025)
Event time=2	-0.118	-0.086***	-0.088	-0.105***
	(0.116)	(0.022)	(0.074)	(0.037)
Event time=3	0.016	-0.091**	-0.057	-0.112***
	(0.141)	(0.037)	(0.098)	(0.042)
Other Lifted	0.185	-0.008	0.017	0.034
	(0.130)	(0.033)	(0.112)	(0.067)
Year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y
Observations	929	929	929	929

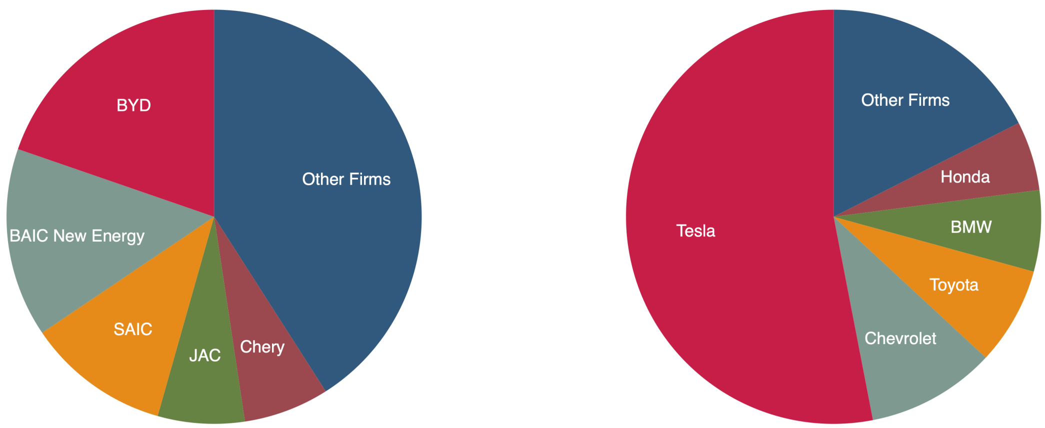
Notes: This table reports the dynamic impacts of lifting restriction on clean used vehicle sales from event study models with the sub sample and LASSO method. The event time refers to the time when restriction was lifted in the home city. "Event time=1" means 1 quarter after restriction lifted. Dirty vehicles refer to vehicles below emission standard China 4. The regression controls for city FEs, year-month FEs, province×year FEs and uses PDS (Post Double Selection) method to select controls from a rich set of variables described in the main text (Belloni et al., 2012). Robust standard errors are clustered at the city level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX C

APPENDIX OF CHAPTER 3

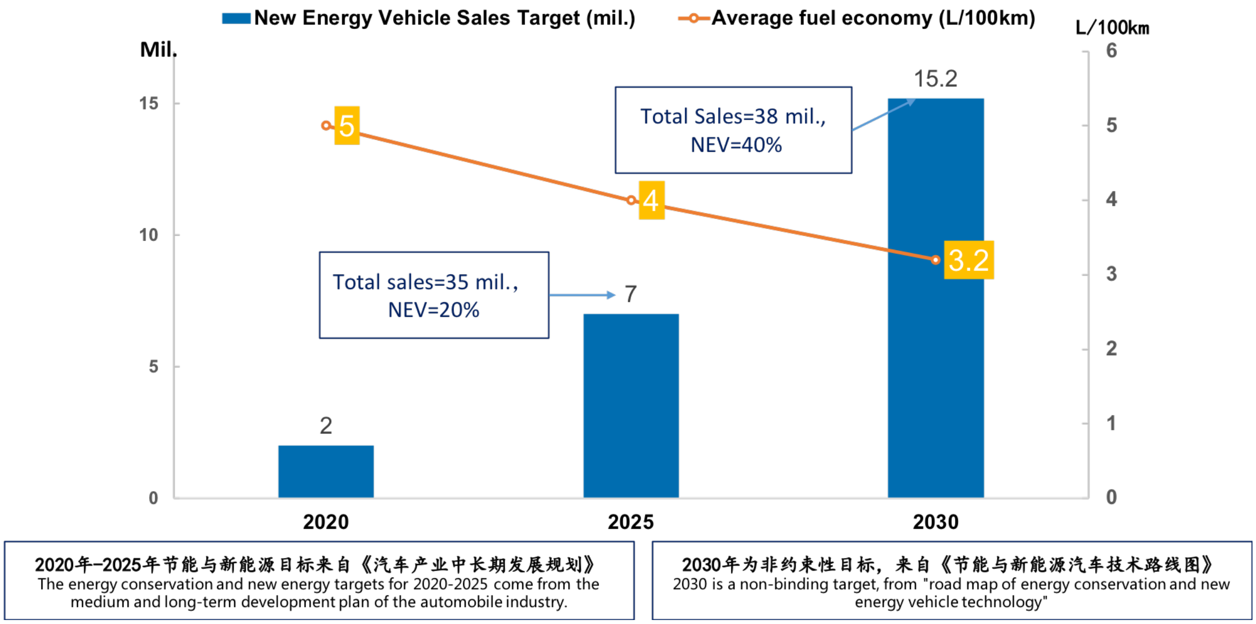
C.1 Figures and Tables

Figure C.1. Top 5 EV Firms in China and US



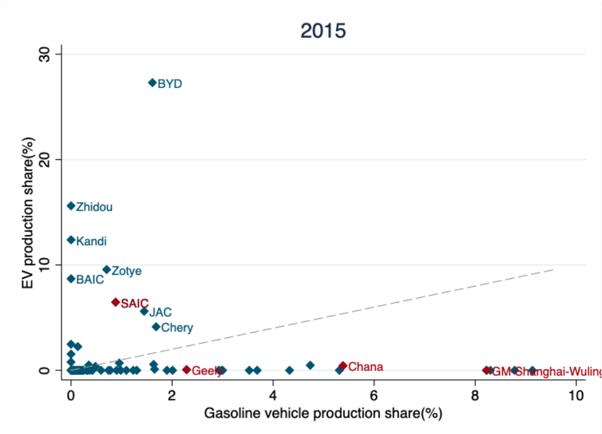
Notes: This figure shows the top five automakers by EV sales and their market shares in China and US in 2018.

Figure C.2. China's EV and Fuel Economy Targets

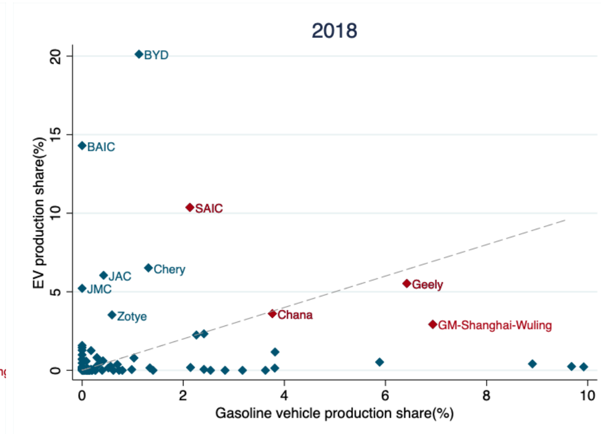


Notes: China's long-term national goals on EV sales, and fleet average fuel economy standards.

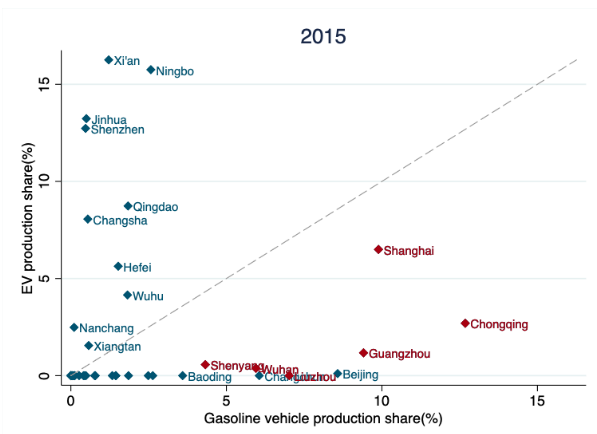
Figure C.3. Patterns of EV Production across Firms and Cities



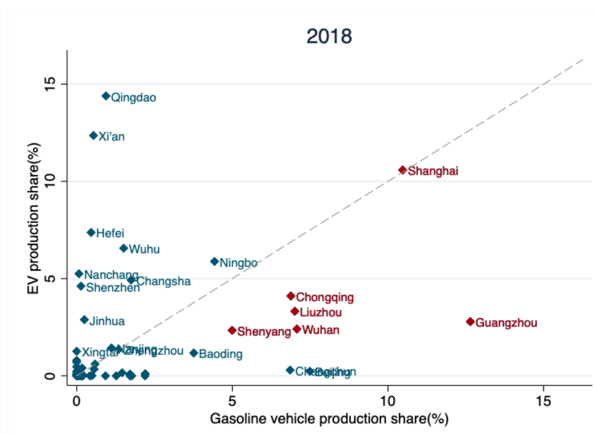
(a) Production across firms in 2015



(b) Production across firms in 2018



(c) Production across cities in 2015



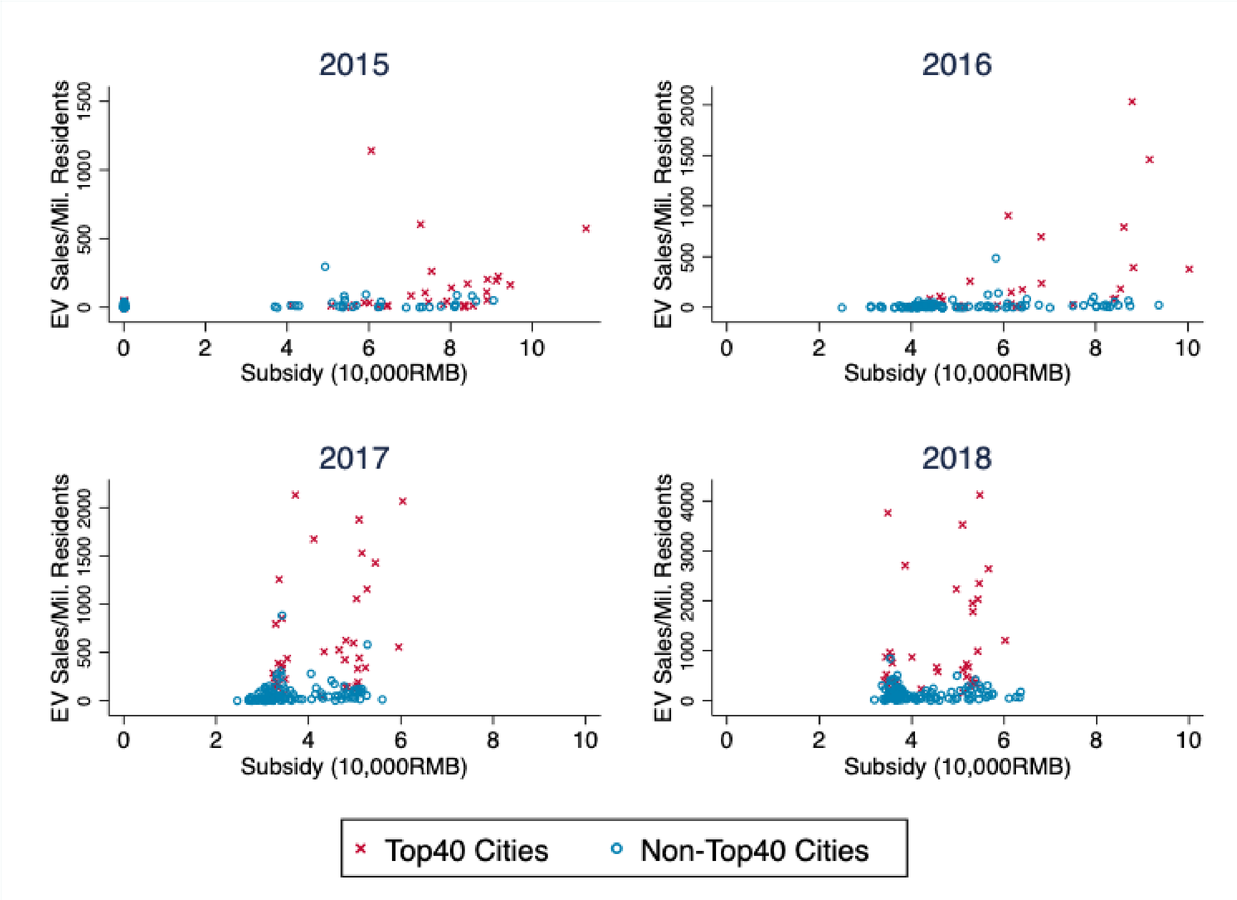
(d) Production across cities in 2018

Notes: Panels (a) and (b) plot the shares of EV production against the shares of gasoline vehicle production by firm in 2015 and 2018. The EV (gasoline vehicle) production share is the firm's EV (gasoline vehicle) production divided by the total EV (gasoline vehicle) production. Each point represents an automaker. Panels (c) and (d) plot the shares of gasoline vehicle production against the shares of EV production by city in 2015 and 2018. Each dot represents a city that has automobile manufacturing.

Figure C.4. Policy Rollout over Time

Notes: The figure plots the number of cities with driving restriction exemption and green plate by quarter from 2015 to 2018.

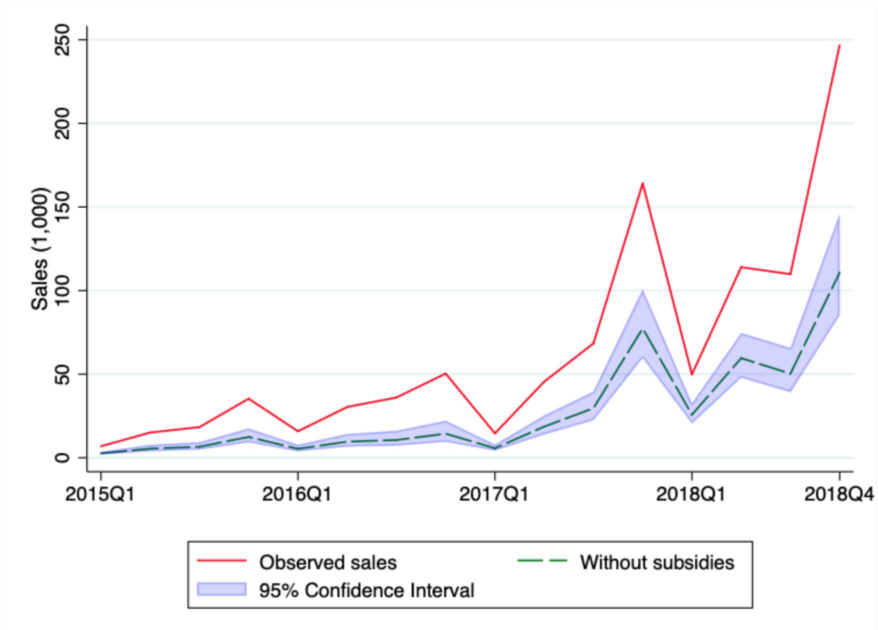
Figure C.5. Subsidy and EV Sales



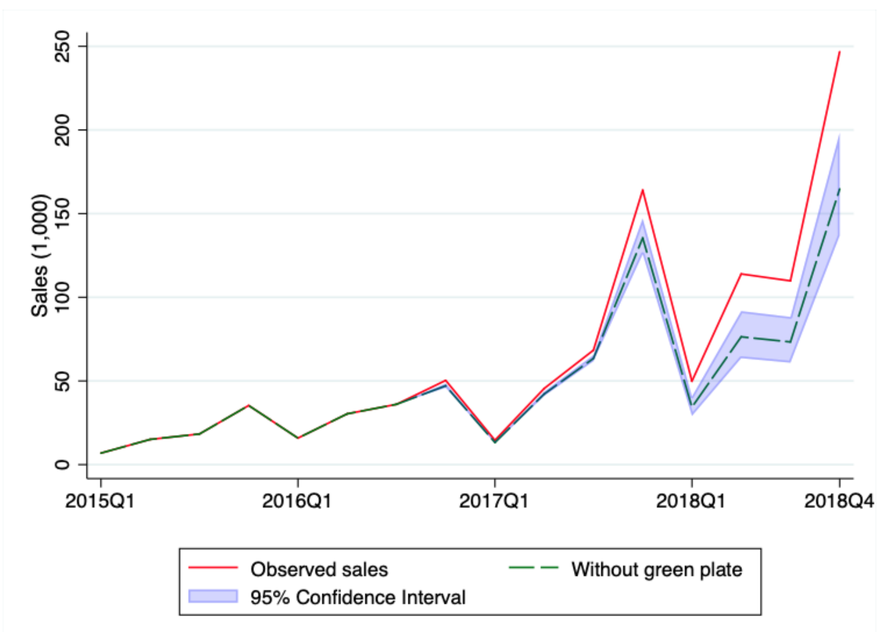
Notes: The figure shows the scatter plots of the EV sales per million residents against average subsidy per vehicle (including both central and local subsidies) for each city at each year from 2015 to 2018. The top-40 cities with the largest aggregate EV sales are distinguished from their neighboring cities (non-top-40 cities).

Figure C.6. Simulation Results

(a) Removing subsidies



(b) Removing green plate



Notes: The figures plot the counterfactual sales and the 95 percent confidence interval based on estimation using 106 cities. Panel (a) removes central and local subsidies while Panel (b) removes the green plate policy. The sales would have been 44 percent and 79 percent of what have been observed in the data on average during the sample period, respectively.

Table C.1. First-stage results

Dependent variable	MSRPs	No. of Charging Ports
	(1)	(2)
1(Battery supplier=CATL) × Battery capacity (kwh)	0.027	-0.001
	(0.019)	(0.002)
1(Battery supplier=BYD) × Battery capacity (kwh)	0.432***	-0.005***
	(0.039)	(0.001)
1(Battery supplier=Other) × Battery capacity (kwh)	0.042**	-0.001
	(0.019)	(0.002)
Lagged EV stock by institutions	0.005	0.317***
	(0.004)	(0.068)
Consumer subsidies per vehicle (in ¥10,000)	0.074***	0.002
	(0.021)	(0.005)
EV exempt from driving restrictions	-0.069	-0.094*
	(0.080)	(0.054)
Green plate for EVs	-0.091***	0.050
	(0.035)	(0.075)
Vehicle size (m^2)	0.269*	0.006
	(0.149)	(0.026)
Power/Weight (kW/kg)	-29.717***	-0.542
	(4.976)	(0.334)
Driving range (100km)	0.374**	0.026
	(0.179)	(0.020)
Observations	24493	24493

Notes: This table reports the first-stage regression results for Column (7) of Table 3.4. The dependent variable is MSRPs in Column (1) and the number of charging ports in Column (2). Both columns include the same set of fixed effects as in Column (7) of Table 3.4: city-model FEs, city-year FEs, city cluster-time (i.e., year-quarter) FEs, and city cluster-brand-year FEs. 1(Battery supplier=CATL) is a dummy indicating the supplier is CATL, 1(Battery supplier=BYD) is a dummy indicating the supplier is BYD, and 1(Battery supplier=Other) is a dummy indicating other (smaller) suppliers. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2. Heterogeneous Effects and Policy Interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSRPs (in ¥10,000)	-0.046***	-0.031***	-0.040***	-0.041***	-0.037***	-0.172***	-0.179***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.031)	(0.031)
Consumer subsidies per vehicle (in ¥10,000)	0.083***	0.092***	0.140***	0.133***	0.139***	0.147***	0.109***
	(0.012)	(0.013)	(0.026)	(0.026)	(0.028)	(0.027)	(0.034)
No. of charging ports (1,000)	0.027	-0.074**	0.118*	0.141***	0.155***	0.160***	0.116**
	(0.020)	(0.031)	(0.060)	(0.050)	(0.056)	(0.054)	(0.054)
Subsidies * No. of charging ports	0.021***	0.022***	0.009*	0.010**	0.007	0.006	0.026*
	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.006)	(0.016)
EV exempt from driving restrictions	0.579***	0.575***	0.139	-0.129	-0.080	-0.107	-0.228
	(0.148)	(0.130)	(0.213)	(0.162)	(0.180)	(0.178)	(0.239)
Green plate for EVs	0.484***	0.174***	0.196***	0.273***	0.285***	0.268***	0.238***
	(0.062)	(0.062)	(0.069)	(0.072)	(0.072)	(0.072)	(0.072)
Driving restriction Exemption * Green plate	-0.199	-0.169	-0.015	0.144	0.133	0.156	0.222
	(0.150)	(0.113)	(0.148)	(0.153)	(0.178)	(0.176)	(0.216)
Gasoline price (RMB/liter)	0.081	0.055	-0.052	-0.085	-0.127	-0.117	-0.098
	(0.067)	(0.083)	(0.081)	(0.095)	(0.098)	(0.102)	(0.102)
Vehicle size (m^2)	1.273***	-0.085	-0.526**	-0.534**	-0.471	-0.240	-0.245
	(0.211)	(0.228)	(0.255)	(0.269)	(0.489)	(0.469)	(0.483)
Vehicle size * Income(¥10,000)	-0.103***	0.079***	0.139***	0.145***	0.053	0.030	0.020
	(0.024)	(0.030)	(0.035)	(0.037)	(0.104)	(0.100)	(0.104)
Power/Weight (kW/kg)	10.942***	12.567***	13.260***	13.105***	10.901***	6.535***	6.523***
	(2.156)	(2.052)	(2.098)	(2.099)	(2.173)	(2.104)	(2.109)
Driving range (100km)	0.120***	-0.122***	-0.141***	-0.116**	-0.022	0.095*	0.163**
	(0.042)	(0.041)	(0.047)	(0.046)	(0.056)	(0.057)	(0.065)
Driving range * No. of charging ports (1,000)	-0.024**	-0.020**	-0.001	-0.006	-0.002	-0.001	-0.034
	(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.022)
City-Model FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y
Observations	25003	25003	24995	24994	24828	24828	24493
Adjusted R^2	0.500	0.557	0.565	0.568	0.564	-0.107	-0.111
Joint-F on excluded IVs						103.595	67.546
Underidentification stat						89.559	87.995
Weak Identification stat						103.595	67.546
Overidentification stat						21.823	20.743

Notes: The regressions are the full sample from 150 cities. The dependent variable is ln(sales). Column (6) instruments for MSRPs using battery capacity interacted with battery-supplier dummies. Column (7) instruments for MSRPs and the number of charging ports using battery capacity interacted with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3. Heterogeneous Effects Before- and Post-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSRPs (in ¥10,000)	-0.029***	-0.036***	-0.044***	-0.045***	-0.039***	-0.168***	-0.175***
	(0.010)	(0.009)	(0.008)	(0.008)	(0.010)	(0.030)	(0.030)
Consumer subsidies per vehicle (in ¥10,000)	0.106***	0.084***	0.087***	0.073**	0.106***	0.107***	0.104***
	(0.015)	(0.014)	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)
Subsidies * $\mathbb{1}$(Post-2016)	-0.001	0.147***	0.158***	0.172***	0.092**	0.101**	0.104**
	(0.014)	(0.028)	(0.026)	(0.028)	(0.043)	(0.043)	(0.043)
No. of charging ports (1,000)	0.189***	0.137***	0.110*	0.037	0.056	0.060	0.061
	(0.059)	(0.041)	(0.065)	(0.110)	(0.115)	(0.117)	(0.089)
No. of charging ports * 1(Post-2016)	-0.133***	-0.130***	0.065	0.176*	0.157	0.154	0.163
	(0.036)	(0.028)	(0.065)	(0.105)	(0.110)	(0.111)	(0.110)
EV exempt from driving restrictions	0.421***	0.457***	0.138	0.006	0.047	0.040	-0.019
	(0.111)	(0.119)	(0.173)	(0.136)	(0.148)	(0.148)	(0.153)
Green plate for EVs	0.332***	0.130*	0.210***	0.341***	0.347***	0.335***	0.338***
	(0.057)	(0.070)	(0.062)	(0.085)	(0.088)	(0.087)	(0.089)
Vehicle size (m^2)	0.526***	0.448**	0.400**	0.437**	-0.208	-0.087	-0.143
	(0.185)	(0.175)	(0.176)	(0.180)	(0.184)	(0.166)	(0.171)
Power/Weight (kW/kg)	10.042***	11.564***	12.127***	11.846***	10.795***	6.459***	6.274***
	(2.106)	(2.099)	(2.089)	(2.101)	(2.067)	(2.012)	(2.011)
Driving range (100km)	0.094**	-0.277***	-0.267***	-0.263***	-0.072	0.035	0.040
	(0.045)	(0.053)	(0.052)	(0.053)	(0.067)	(0.069)	(0.069)
City-Model FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y
Observations	25003	25003	24995	24994	24828	24828	24493
Adjusted R^2	0.497	0.557	0.566	0.569	0.565	-0.106	-0.107
Joint-F on excluded IVs						107.375	70.197
Underidentification stat						89.854	88.224
Weak Identification stat						107.375	70.197
Overidentification stat						22.809	22.402

Notes: The regressions are based on the full sample from 150 cities. The dependent variable is ln(sales). $\mathbb{1}$(Post-2016) is a dummy that equals one for years 2017-2018. Column (6) instruments for MSRPs using battery capacity interacted with battery-supplier dummies. Column (7) instruments for MSRPs and the number of charging ports using battery capacity interacted with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4. Heterogeneous Effects by Vehicle Price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSRPs (in ¥10,000)	-0.009	-0.017*	-0.025***	-0.026***	-0.011	-0.151***	-0.160***
	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)	(0.030)	(0.030)
Consumer subsidies per vehicle (in ¥10,000)	0.050**	0.036**	0.063**	0.055*	0.026	0.076*	0.072*
	(0.021)	(0.017)	(0.028)	(0.030)	(0.041)	(0.041)	(0.041)
Consumer subsidies*$\mathbb{1}$(Low MSRP)	0.097***	0.101***	0.110***	0.114***	0.139***	0.091***	0.095***
	(0.014)	(0.013)	(0.012)	(0.012)	(0.019)	(0.022)	(0.022)
No. of charging ports (1,000)	0.040*	0.005	0.170***	0.191***	0.194***	0.194***	0.204***
	(0.022)	(0.015)	(0.032)	(0.034)	(0.034)	(0.034)	(0.039)
EV exempt from driving restrictions	0.448***	0.479***	0.135	0.007	0.053	0.040	-0.017
	(0.117)	(0.130)	(0.179)	(0.136)	(0.147)	(0.148)	(0.155)
Green plate for EVs	0.344***	0.138**	0.194***	0.311***	0.317***	0.308***	0.310***
	(0.056)	(0.067)	(0.064)	(0.077)	(0.080)	(0.080)	(0.082)
Vehicle size (m^2)	0.551***	0.411**	0.335*	0.362**	0.116	0.122	0.077
	(0.183)	(0.174)	(0.178)	(0.181)	(0.173)	(0.173)	(0.177)
Power/Weight (kW/kg)	10.116***	12.573***	13.444***	13.239***	11.453***	6.921***	6.660***
	(2.047)	(1.987)	(2.021)	(2.019)	(2.040)	(1.972)	(1.963)
Driving range (100km)	0.082**	-0.098**	-0.107**	-0.092**	0.004	0.114**	0.122**
	(0.041)	(0.040)	(0.044)	(0.044)	(0.055)	(0.055)	(0.055)
City-Model FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y
Observations	25003	25003	24995	24994	24828	24828	24493
Adjusted R^2	0.498	0.556	0.567	0.569	0.567	-0.100	-0.101
Joint-F on excluded IVs						120.864	97.375
Underidentification stat						89.862	88.537
Weak Identification stat						120.864	97.375
Overidentification stat						18.185	18.126

Notes: The regressions are based on the full sample from 150 cities. The dependent variable is ln(sales). $\mathbb{1}$(Low MSRP) equals one if the vehicle MSRP is below the mean (¥200,000); otherwise it equals zero. Column (6) instruments for MSRPs using battery capacity interacted with battery-supplier dummies. Column (7) instruments for MSRPs and the number of charging ports using battery capacity interacted with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5. Nonlinear Effects of Charging Station Availability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSRPs (in ¥10,000)	-0.027**	-0.035***	-0.044***	-0.046***	-0.038***	-0.174***	-0.181***
	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)	(0.030)	(0.031)
Consumer subsidies per vehicle (in ¥10,000)	0.118***	0.107***	0.162***	0.159***	0.154***	0.160***	0.160***
	(0.017)	(0.016)	(0.026)	(0.028)	(0.029)	(0.027)	(0.027)
No. of charging ports (1,000)	0.064	0.020	0.161**	0.221***	0.226***	0.226***	0.201***
	(0.071)	(0.053)	(0.062)	(0.064)	(0.066)	(0.066)	(0.070)
No. of charging ports squared (mil.)	-0.611	-0.345	0.201	-0.874	-0.950	-0.933	-0.020
	(1.961)	(1.573)	(1.323)	(1.210)	(1.269)	(1.266)	(1.657)
EV exempt from driving restrictions	0.450***	0.478***	0.122	-0.007	0.038	0.030	-0.028
	(0.116)	(0.130)	(0.177)	(0.138)	(0.148)	(0.148)	(0.156)
Green plate for EVs	0.330***	0.138**	0.197***	0.315***	0.324***	0.312***	0.314***
	(0.054)	(0.057)	(0.062)	(0.076)	(0.079)	(0.079)	(0.082)
Vehicle size (m^2)	0.523***	0.376**	0.281	0.307	-0.212	-0.086	-0.143
	(0.187)	(0.178)	(0.183)	(0.186)	(0.185)	(0.166)	(0.171)
Power/Weight (kW/kg)	9.949***	12.404***	13.227***	13.036***	10.911***	6.393***	6.184***
	(2.083)	(2.025)	(2.084)	(2.087)	(2.060)	(2.010)	(2.007)
Driving range (100km)	0.072	-0.104***	-0.142***	-0.130***	-0.007	0.111**	0.118**
	(0.046)	(0.038)	(0.043)	(0.043)	(0.053)	(0.054)	(0.054)
City-Model FE	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y
Observations	25003	25003	24995	24994	24828	24828	24493
Adjusted R^2	0.495	0.554	0.564	0.567	0.564	-0.108	-0.110
Joint-F on excluded IVs						105.451	68.566
Underidentification stat						89.762	88.143
Weak Identification stat						105.451	68.566
Overidentification stat						22.384	21.925

Notes: The regressions are based on 150 cities. The dependent variable is ln(sales). Column (6) instruments for MSRPs using battery capacity interacted with battery-supplier dummies. Column (7) instruments for MSRPs and the number of charging ports using battery capacity interacted with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6. Mediating Analysis: Charging Station Availability and Subsidy Effectiveness

	(1)	(2)	(3)
Dependent variable	No. of Charging Ports	Ln(Sales)	Ln(Sales)
	IV	IV	IV
MSRPs (in ¥10,000)	-0.013***	-0.176***	-0.181***
	(0.004)	(0.030)	(0.031)
Consumer subsidies per vehicle (in ¥10,000)	0.013**	0.162***	0.160***
	(0.006)	(0.027)	(0.027)
EV exempt from driving restrictions	-0.071	0.015	-0.028
	(0.096)	(0.160)	(0.156)
Green plate for EVs	-0.082	0.297***	0.314***
	(0.100)	(0.081)	(0.081)
Vehicle size (m^2)	-0.023	-0.092	-0.143
	(0.032)	(0.166)	(0.171)
Power/Weight (kW/kg)	-2.856***	5.822***	6.180***
	(0.772)	(2.008)	(2.007)
Driving range (100km)	-0.008	0.110**	0.118**
	(0.015)	(0.055)	(0.054)
No. of charging ports (1,000)			0.200***
			(0.038)
City-Model FE	Y	Y	Y
Time FE	Y	Y	Y
City-Year FE	Y	Y	Y
Cluster-Time FE	Y	Y	Y
Cluster-Brand-Year FE	Y	Y	Y
Observations	24828	24828	24493
Adjusted R^2	-0.114	-0.117	-0.110
Joint-F on excluded IVs	105.433	105.433	85.959
Underidentification stat	89.752	89.752	88.137
Weak Identification stat	105.433	105.433	85.959
Overidentification stat	0.541	21.721	21.691

Notes: The regressions investigate the potential mediating effect of subsidies through charging stations availability following Zambrano-Gutierrez et al. (2018). The dependent variable is the number of charging ports in Column (1) and ln(sales) in Columns (2) and (3). Columns (1) and (2) instrument for MSRPs using battery capacity interacted with battery-supplier dummies. Column (3) instruments for MSRPs and the number of charging ports using battery capacity interacted with battery-supplier dummies, and the lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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