ABSTRACT

Title of Dissertation: ESSAYS ON TRANSPORTATION AND ENVIRONMENT IN CHINA

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My dissertation focuses on environmental issues associated with the transportation sector in China. Automobile industry in China has grown exponentially in the past 20 years. The rapid growth poses enormous challenges for the reduction of CO_2 emissions and pollution. My dissertation utilizes a variety of data sources and explores what policies and market incentives can effectively promote greener transportation and reduce GHG emissions and pollution.

In my first chapter, I investigate how Chinese consumers value fuel economy. Understanding this is central to determining what is the optimal policy for reducing vehicle emissions under current policy environments. I find that the new vehicle market displays full valuation, ranging from 85-105% under different specifications and assumptions. Consumer accessibility to reliable fuel economy information has a positive impact on the valuation ratio. The high valuation of fuel economy suggests that a gasoline tax or carbon tax could be an efficient tool in reducing greenhouse gas emissions for China. In my second chapter, which I co-authored with Professor Joshua

Linn, I look at how rapidly rising income contributes to exploding vehicle demand in China, and how we can use this knowledge to better forecast future GHG emissions. We estimate an elasticity of new car sales to income of about 2.6. This estimate indicates that recent projections of vehicle sales in China have understated actual sales by 40 percent. In my third chapter, instead of looking at GHG I look at pollution from high-emission trucks. I evaluate how a ban on these trucks improves local NO2 levels in Beijing. The result suggests that the policy helped reduce NO_2 by 1.26 $\mu g/m^3$, or approximately 2.6% of the NO_2 level. Additionally, it was found that stations located in areas with a high density of major roads, fewer natural surroundings, and more buildings saw a more significant policy effect than their counterparts.

ESSAYS ON TRANSPORTATION AND ENVIRONMENT IN CHINA

by

Chang Shen

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Foreword

The Dissertation Committee has agreed that Chang Shen made substantial contributions to the jointly authored work (Chapter 2) included in this dissertation.

A letter certifying the approval of the inclusion of the work from Chang Shen's examining committee, dissertation advisor, and the Graduate Director is included with the submission of this dissertation.

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1.1 Introduction

The transportation sector has become one of the major contributors to greenhouse gas emissions. The IEA estimates that the sector accounts for about 22% of global energy consumption and 26% of greenhouse gas emissions in 2018 and that the sector's energy consumption will continue to increase by approximately 30% between 2020 to 2050, from 112.28 QBtu to 145.77 QBtu (IEA 2017).

Given the high vehicle ownership in developed countries, the driving force of the transportation greenhouse gas emission will come from developing countries. For example, China has one of the fastest-growing automobile industries in the world. In 2005, there were fewer than 3 million vehicles sold. Only 12 years later, the annual vehicle sales in China increased nearly ten-fold to 25 million. This exponential growth has placed China as the largest vehicle market in the world since 2009.

The rapid growth of the transportation sector poses enormous challenges for the reduction of energy consumption and CO_2 emissions (Li et al., 2019). In particular, Zeng et al. (2016) warn that it creates a significant obstacle for China to keep its 2014 promise in the "U.S.-China Joint Announcement on Climate Change" to peak carbon emissions by 2030.

Without proper policy intervention, future transportation energy consumption and CO_2 emissions will continue to rapidly increase (Yin et al., 2015; Gan et al., 2020). To address this problem, the Chinese government has been actively pushing a variety of policies to reduce vehicle usage of fossil fuel. Figure 1.1 shows a stylized timeline for vehicle-related policies in recent years aiming to reduce energy consumption and emissions. The Chinese government is experimenting with various market-based policy instruments. These policies include both “energy tax” type of policies, such as gasoline sales taxes, and “product tax” type of policies, such as tax cuts for small-engine cars and subsidies for new energy vehicles.

There is increasing debate among scholars and policymakers over which policy is the most efficient in China. For example, Yang and Tang (2019) investigate the effectiveness of major “product tax” type policies in China, including vehicle and vessel tax, fuel-efficient vehicle subsidy program (FEV-subsidy program), and a NEV purchase subsidy pilot program (NEV-subsidy program). They find these policies promote the diffusion of fuel-efficient vehicles but increase CO_2 emissions, as the programs have stimulated vehicle purchases. Xiao and Ju (2014) compare fuel tax with vehicle excise tax and conclude fuel tax is more effective in decreasing fuel consumption.

Investigating consumer myopia lies at the center of the policy debate between energy tax and product tax (Grigolon et al., 2018; Allcott and Greenstone 2012). Both taxes are designed to decrease the final use of energy. While energy taxes such as gasoline tax target energy usage directly, product taxes increase taxes to penalize energy-inefficient products or implement tax cuts or subsidies to encourage the purchase of energy-efficient ones. Since gasoline tax targets driving behavior itself, it is supposed to be more efficient. However, one crucial assumption for a gasoline tax to work is that consumers are fully responsive to fuel costs. If the gasoline price increases by 20% but consumers cannot fully recognize or correctly calculate the extra 20% burden in total fuel expense, a gasoline tax could be inefficient compared to subsidy policies for fuel-efficient vehicles.

This paper mainly contributes to providing further evidence on the energy tax VS product tax debate by investigating whether Chinese consumers are myopic. If Chinese consumers can fully capitalize the value of fuel economy, they are willing to pay 100 more RMB now for an increase in fuel-efficiency in exchange for a 100 RMB decrease in future fuel expenses. On the other hand, if they are only willing to pay 90 RMB now in exchange for 100 RMB fuel expense savings, the valuation or capitalization rate is 90%, which means they are only able to perceive 90% of the true savings. If this is the case, then an energy tax type of policy will not be efficient since consumers cannot fully recognize the fuel expense. Therefore, estimating the capitalization rate of Chinese consumers could help to identify the most suitable policy for reducing vehicle emissions.

This paper adds to the existing literature on estimating the value of fuel economy where there is a wide range of results in terms of rate of capitalization. On the one hand, many studies find that there is moderate undervaluation by consumers (Allcott and Wozny, 2014; Alberini et al., 2019); others find correct valuation (Busse et al., 2013; Chugh et al., 2011); and yet others find considerable undervaluation (e.g., Gillingham et al., forthcoming)). Researchers have proposed various possible reasons for undervaluation. Some observers argue that people might not pay as much attention to fuel economy compared to other vehicle attributes (Sallee el al., 2016), or that the notion of fuel economy is difficult to conceptualize for some consumers (Allcott and Knittel, 2019). Other possible reasons include over-discounting – people are myopic and put insufficient weight on future states (Busse et al., 2013).

Almost all studies in this area have been devoted to mature automobile markets such as the US and European countries, while less attention has been paid to emerging automobile markets and their consumers. However, emerging markets might exhibit different purchasing behavior compared with developed countries. For instance, the Chinese are more inclined to “save for uncertainty” due to both cultural and economic reasons. The saving rate in China is much higher than in the US (47% versus 16%), suggesting that Chinese consumers might behave differently than American buyers. My paper contributes to this area by shedding some light on consumers’ behavior in emerging automobile markets and understanding the mechanisms that affect the valuation of fuel economy from a broader perspective.

This paper differs from other similar studies on fuel economy by constructing a unique panel from two sources using both official data and user comments. The first data is Chinese new vehicle registration data. It contains information on monthly, province-level, new vehicle registration records between 2010 to 2017, by car model. However, this dataset only provides quantity information for vehicle models;

it does not contain transaction price, which is essential for this study. To get this price information, I download all available users' comments from the website Autohome (https://www.autohome.com.cn) and extract consumers' self-reported transaction prices from their posts. Autohome is the most popular Chinese online vehicle forum with a very active community. After cleaning the data, I have 380,000 valid comments with transaction price information. In addition to this, I obtain a rich set of car attributes for all vehicle models from Autohome's comprehensive automobile library.

I follow an approach similar to Busse et al. (2013) and Leard et al. (2017) to estimate the valuation of fuel economy. I first evaluate the impact of unit fuel cost (price per kilometer driven) on market equilibrium price and quantity of vehicle sales separately. To identify the impact of fuel cost, I exploit the variation in fuel economy across different sub-models within the same model and variation in gasoline price across time and region, controlling for a rich set of car attributes, model-year fixed effects, regional fixed effects, and a time trend.

Next, I recover the willingness to pay and valuation ratio by adding together the price and quantity response associated with improvement in fuel economy (reduction in total fuel cost), under various assumptions on vehicle demand elasticity and annual vehicle kilometer traveled. I find that the Chinese new vehicle market displays almost full valuation. Assuming price elasticity of demand equal to -3, Chinese consumers appear to value fuel economy at 85-105% capitalization rate under different specifications, and assumptions on annual vehicle kilometer traveled. I also find that the release of fuel economy data to the public in 2010 has a positive effect on consumers' awareness of fuel economy and the responsiveness to fuel cost. The rising popularity of the vehicle rating website Autohome provides a new information source and leads consumers to focus on real-world fuel consumption data.

A gasoline tax or an energy tax may well be the most efficient tool given the high valuation of fuel economy in the Chinese automobile market. Take the 2017 new vehicle sales for example: For compositional effect alone, if the gasoline tax were to increase by 50%, CO_2 emission could be reduced by 0.6% to 309.1 million tons per year. If a 100% gasoline tax were implemented, then CO_2 emission could be reduced by 1.3% to 307.1 million tons per year.

The remainder of this paper is organized as follows: Section 2 describes the data; Section 3 explains the empirical strategy; Section 4 shows the results; Section 5 discusses potential implications; and Section 6 provides conclusions.

1.2 Data

My main dataset is compiled from several sources. First, I use new vehicle registration data to approximate sales of vehicles at the model-province-month level. Second, I use comments from Autohome to extract user-reported information on the transaction price for each model. Third, I gather information on car attributes for all existing vehicles from the Autohome car library.

The registration data is collected from the Chinese Department of National Security. This dataset documents the registration information for each car model produced domestically in China from 2010 to 2017. It is aggregated to province-month level, and accounts for ~92% of total new vehicle registrations in China in that timeframe. In addition to the model, location of registration, and month of registration, it also contains information on the purpose of usage (private or business), vehicle type, and fuel type. I exclude trucks, vans and commercial vehicles and focus on privately-owned passenger vehicles (sedan, SUV, MPV, crossover) since they account for the majority of vehicle sales (approximately 95%). Further, I only keep vehicles that use gasoline. Unlike Europe, where diesel cars account for a large market share (around 50%), China does not have many diesel cars. The market share for diesel cars has fluctuated between 1% and 5% over the past two decades.

I use the registration data as a proxy of new car sales data since the time difference between purchase and registration is generally small. Most first-time car buyers choose to pay an additional service fee and apply for registration through car dealers immediately after they finish their purchase. The application process usually takes 2-7 days, and driving without registration is illegal and can lead to major penalties. Overall, the new registration data represents around 70% of the total vehicle sales in China (see Figure 1.2).

The registration data, however, does not include a transaction price for each model. Previous research on China's automobile market often uses Manufacturer Suggested Retail Prices (MSRP) due to the unavailability of more detailed, individual-transaction data (e.g., Li et al. 2015; Li, 2018; Tan et al., 2019). However, Yang and Tang (2019) argue transaction price should be preferred over MSRP since transaction price captures price negotiation or unobserved incentives, and they observe substantial differences between the MSRP and transaction price in practice.

I supplement the registration data with self-reported transaction prices from a Chinese vehicle online forum Autohome (https://www.autohome.com.cn). This website is the most popular online platform for car buyers to search for professionally produced car information, compare different cars, and share information. It has a very active community, and the company is listed in the New York Stock Exchange (under the ticker ATHM). I web-scraped all available users' comments from the website. After cleaning out comments with incomplete content, I have 386,472 comments within the study period. To make my two sources of data comparable, I only focus on domestically-produced gasoline passenger cars. Each comment contains information on the user-reported transaction price, time and location of the purchase, and the vehicle model. I assume the difference between the user-reported transaction price and the real transaction price is uncorrelated with the fuel economy of the vehicle.

In addition, I collect a rich set of vehicle attributes from Autohome's automobile library. The library contains detailed characteristics for all models released since 2005. For each model, the library provides performance-related attributes such as fuel economy, horsepower, gross weight, and the size of the car. Since there is substantial heterogeneity within each model on non-performance related attributes such as Bluetooth speakers or leather seats which could affect the model price and popularity, I also collect a rich set of such non-performance related attributes.

Fuel economy information on Autohome comes from a database from the Ministry of Industry and Information Technology of China (MIITC). Since 2010, MIITC has dictated that all light-duty passenger vehicles must be tested for fuel economy at a designated MIITC test center, and the test results be reported to MIITC. I measure each car model's fuel economy with MIITC's "Combined Fuel Consumption," which is a weighted average of highway and city test results. The test results are expressed as fuel consumption rate in liters per 100 kilometers driven. In China, the fuel consumption rate is the common metric to measure fuel efficiency, whereas in the U.S., fuel economy is more commonly used, which is reciprocal of the fuel consumption rate. The higher the fuel consumption rate is, the lower the fuel economy. As is shown in Figure 1.3, the fuel consumption rate has been decreasing, possibly due to a combination of technology improvement, rising gasoline price, and stricter fuel economy standards over this time period.

Finally, I link the registration data to the online comment data by detailed model, province, and month, and use total registrations as a weight to adjust the representativeness for each vehicle model in the comment data. Models that appeared in Autohome comments account for 70-80% of the new registrations each year. The registration weighted summary statistics of key variables are shown in Table 1.1. The mean transaction price is ~125,000 RMB – 9% lower than the MSRP, which is ~138,000 RMB on average. The transaction price is lower than MSRP in every quartile, which indicates cars are usually sold at prices below the MSRP. The matched dataset has 79 unique makes (e.g., "Audi"), 413 nameplate models (e.g., "Audi A3"), and 5,298 unique sub-models (e.g., "Audi A3 Limousine 35 TFSI Sports").

The monthly-province level gasoline prices come from CEIC's China premium dataset. CEIC is a commercial data vendor founded in Hong Kong. Gasoline prices in China are less volatile than in the United States since they are controlled by the government. The government adjusts the price according to the international oil price and stabilizes the price as needed. More information about the gasoline price adjustment mechanism can be found in Section 1.5.2. As shown in Figure 1.4, there is considerable intertemporal variation during the study period.

One concern with using the comment data is that users self-select in reporting their transactions. If such self-reporting behavior is correlated with fuel economy through unobserved variables, then such self-selection would confound the coefficient of fuel economy and generate biased estimates. To address this concern, I calculate the percentage discount off the MSRP received by the car buyer for each vehicle and plot the discount ratio against the fuel consumption rate of the vehicle. As shown in Figure 1.5, the magnitude of the discount is not correlated with fuel consumption. Furthermore, as shown in Figure 1.6, transaction prices fluctuate around the MSRP for all price ranges of vehicles. Thus, I assume that the Autohome comment data do not have selection bias and can be used to represent the universe of cars sold in the Chinese new car market.

1.3 Empirical Strategy

1.3.1 The implication of WTP and valuation ratio

In this section, I explain how to recover WTP from the price and quantity response, which is presented in Figure 1.7. Assume in the new vehicle market, the demand meets the supply and the market has reached an equilibrium. Then a fuel efficiency improvement occurs, which reduces future fuel cost and shift the demand curve upward, forming a new equilibrium.

The willingness to pay is the distance of this vertical upward shift, which is denoted by the red line segment. However, this distance is not equal to the change in equilibrium price. Actually, the change in price is only the "observed" part of the willingness to pay, which is denoted as P_o. When the slope of the supply curve is upward, the shift in equilibrium price underestimates the true willingness to pay because part of the effect is absorbed into quantity change.

$$WTP\ change = Observed\ price\ change\ \ + unobserved\ price\ change \tag{1.1}$$

The WTP consists of two parts. The first part is price change that can be observed directly from price response. The second part, though, is unobservable. It is the indirect price change caused by an equilibrium quantity shift. However, if we assume a demand elasticity, we can recover the real demand shift. I denote observed price change as ΔP_o and unobserved price change as ΔP_u, and we have the following:

$$\epsilon = \frac{\frac{\Delta Q}{Q}}{\frac{\Delta P_u}{P}} \qquad \Delta P_u = P * \frac{\frac{\Delta Q}{Q}}{\epsilon} \tag{1.2}$$

$$\Delta \mathrm{WTP} = \Delta P_u + \Delta P_o = P * \frac{\frac{\Delta Q}{Q}}{\epsilon} + P * \frac{\Delta P_o}{P} \tag{1.3}$$

$$\Delta\overline{WTP} = \bar{P} * (\frac{\frac{\Delta Q}{Q}}{\epsilon} + \frac{\Delta P_o}{P}) \tag{1.4}$$

As shown in Equation (1.4, the average change in the willingness to pay is a function of average percentage change in equilibrium price and quantity, as well as demand elasticity. The first part in the parenthesis recovers the “observed” price change associated with an increase in fuel efficiency and a reduction in future fuel cost. This effect can be estimated using a reduced-form model where vehicle price is a function of total fuel expenses. The second part recovers the “unobserved” price change associated with reduced total fuel cost, and can be estimated using a similar model but with quantity as the dependent variable. Finally, I can recover the WTP by adding these two parts together, with a realistic assumption of demand elasticity.

There have been several attempts to estimate the elasticity of demand for vehicles. Goldberg (1995) estimates demand elasticities in the -2 to -4 range. Berry et al. (1995) estimate the elasticities ranging from -3 to -6. Both Busse et al. (2013) and Leard et al. (2017), two papers using a similar empirical strategy to this study, assume the elasticities to be in the range of -2 to -5. I take the most common range from previous literature and assume the elasticities to be in the range of -3 to -5. Finally, I assume the demand has a constant elasticity functional form.

A measurement of how consumers value fuel economy is the valuation ratio (capitalization ratio), which is simply the ratio of WTP for better fuel economy to total fuel savings from the better fuel economy in the lifespan of the vehicle.

$$Valuation\ ratio\ =\ WTP\ /\ Lifetime\ fuel\ expense\ savings \qquad (1.5)$$

For instance, if consumers are willing to pay 100 RMB for an improvement in fuel efficiency now in exchange for 100 RMB of fuel expense savings in the future, the valuation ratio is 1. This means that consumers capitalize 100% of the value of fuel economy. If the valuation ratio is less than 1, then the consumers underestimate the value of fuel economy. In other words, consumers are myopic. This is the metric I focus on since it has important policy implications. If the valuation rate is almost equal to one, then the energy tax is efficient for reducing energy usage. In this study's context, this means fuel tax or carbon tax is the optimal policy[1] for reducing greenhouse gas emissions. However, if the valuation rate is much lower than one, then policymakers should consider options such as a product tax. In this context, that means subsidies and tax rebates for purchasing fuel-efficient vehicles.

[1] Since the study is evaluating the valuation of fuel efficiency under the prevailing environment during the study period, including pre-existing policies, consumer sentiments, etc., the "optimal" should be interpreted as optimal under prevailing conditions at the time.

1.3.2 The effect of future fuel cost on price

To estimate the willingness to pay (WTP) for fuel economy, first, I estimate the effect of future fuel cost on equilibrium vehicle price. More specifically, I estimate how much Chinese consumers are willing to pay for a 1% decrease in unit fuel cost (price in RMB/km). I use a reduced-form model and assume a log-log relationship between the transaction price and the unit fuel cost. Similar to Alberini et al. (2019) and Rosen (1974), I apply a hedonic model and estimate the following:

$$lnP_{ijrt} = \gamma \ ln \ Fuel \ Cost_{ijrt} + \alpha_{m \cdot yr} + \theta_{rt} + \boldsymbol{X}_i \boldsymbol{\beta} + \epsilon_{ijrt} \qquad (1.6)$$

Where P_{ijrt} denotes the transaction price for consumer *i* for vehicle *j* in region r in month *t*. $Fuel \ Cost_{ijrt}$ is the fuel cost per kilometer for this vehicle, expressed in RMB/km. It is calculated by using the fuel economy of the particular vehicle and the gasoline price at the time and location of purchase. Thus, it varies across vehicles, as well as across regions and time. $\alpha_{m \cdot yr}$ is model by year fixed effect, which controls for demand and supply shocks for a particular model. θ_{rt} includes province-by-month fixed effects to account for possible macro-economic divergence, vehicle demand shocks, and locale-specific seasonality. $\boldsymbol{X}_i$ further includes a rich set of vehicle attributes from the Autohome car database.

The most difficult challenge in estimating the marginal value of the fuel economy is that the fuel economy is correlated with other attributes of the vehicle, especially the gross weight (Franzese and Davidson, 2011). High-end vehicles also tend to have higher fuel consumption to power all the premium functions these vehicles provide. If these vehicle attributes cannot be controlled for, fuel economy could correlate with these unobserved variables which have an impact on the vehicle price. If this happens, the coefficient for the fuel economy estimation will be biased. One common practice to tackle this issue is to control for the sub-model fixed effects, which capture all observed and unobserved time-invariant vehicle attributes, including the fuel economy of a vehicle. This approach then relies completely on the changes in gasoline prices across regions and time as a source of external variation for future fuel costs. This practice has gained popularity in recent literature and is used for a variety of studies (e.g., Busse et al., 2013; Allcott and Wozny, 2014; Sallee et al., 2016; Grigolon et al., 2018; Gillingham et al.,forthcoming). However, such a method could have two potential issues. First, it cannot control for consumer perceptions that change over time. Second, Leard et al. (2017) argue that consumers respond directly to fuel economy and not necessarily to fuel prices. As such, the sub-model fixed effects method identifies the valuation of fuel economy only through fuel price variation rather than fuel economy variation, which might not capture the main channel of influence.

Considering the potential issues aforementioned, I control for model-year fixed effects. This allows for two sources of variation in fuel costs in my specification. The variation comes from different fuel economies across sub-models within each model, as well as from temporal and geographic variation of gasoline prices. To control for the car attributes that might correlate both with fuel economy and price, I take advantage of the rich set of vehicle characteristics from the Autohome car library. The first set of attributes is performance-related, including engine size, gross weight, horsepower, vehicle dimensions, transmission type, number of doors, seats, number of cylinders, number of valves per cylinder, and whether the vehicle engine is turbocharged or naturally aspirated. The second set of attributes are variables indicating the non-performance-related quality of the vehicle, showing whether a vehicle has a high-end design and many add-on functions. For example, it includes whether the sub-model has leather-trimmed seating, touchscreen display, bird's eye view 360-degree camera, etc. (see Table A.1).

1.3.3 The effect of future fuel cost on quantity

This section shows the empirical strategy to identify the effect of future fuel costs on the quantity of new vehicle sales. In other words, I want to estimate how a 1% decrease in unit fuel cost (price per kilometer) would affect the sales of the vehicle. This part is vital to the final calculation of the WTP for fuel economy because a shift in car demand induced by a change in fuel economy can both affect equilibrium price and quantity. I use the following model to identify the effect of future fuel costs on new car sales.

$$lnQ_{jrt} = \alpha\ ln\,Fuel\ Cost_{jrt} + \alpha_{m\cdot yr} + \theta_{rt} + \boldsymbol{X}_i\boldsymbol{\beta} + \epsilon_{jrt} \tag{1.7}$$

The quantity regression has the same independent variables as the price regression. The only difference is that the dependent variable is the number of new registrations instead of the price. Q_{rjt} is the quantity of monthly aggregated new registrations for vehicle j at time t in province r. The rest of the notation is the same as the price specification. The price and quantity regressions use the same identification strategy and exploit the same variation in fuel cost to make results compatible. The coefficients of the fuel cost in price and quantity regressions can be interpreted as average effects on equilibrium price and quantity.

1.4 Estimation Results

1.4.1 Main Results

The main results are presented in Table 1.2. Panel A shows results from price regression in Equation (1.6; Panel B presents estimations for quantity regression in(1.7. Panel C calculates the implied WTP using the results from corresponding price and quantity estimations, and finally, Panel D converts the WTP to the valuation ratio for better comparison.

Column 1 shows the estimates of the baseline specification. In both the price and quantity models, the regressions include model-year fixed effects (e.g., “Audi A3 2010”) and province-by-month fixed effects to control for regional-level shocks and seasonality, as well as model-specific demand and supply shocks. The baseline regressions also include a rich set of car attributes, as discussed in the previous section. The attributes include both performance-related attributes such as horsepower, gross weight, and engine size, and non-performance-related attributes such as leather seats and Bluetooth speakers. Additionally, users’ ratings on their experience are included to control for consumers’ preferences over time. The detailed car attributes information to the greatest extent controls for sub-model specific vehicle characteristics that might be correlated with both fuel economy and price or sale. Observations are weighted by new registrations in all price regressions, but not weighted in any quantity regressions. The standard errors are clustered by model-province.

Column 2 further includes a policy fixed effect, which is the interaction of a "small engine" vehicle dummy and time trend. Over the study period, there were overlapping vehicle policies designed to promote "small engine" vehicles, which is defined as vehicles with engine sizes smaller than 1600 ml (see Figure 1.1). These policies, either a tax cut or a subsidy, might have a great impact on the demand and supply for the vehicles targeted by the policy. Controlling for this variable would avoid possible confounding between policy effects and fuel cost effects.

Column 3 controls for all variables mentioned above. In addition, it also includes vehicle class-by-year fixed effects. In recent years SUVs and MPVs have gained massive popularity among Chinese households. The spacious design of these vehicle classes satisfies the travel need for large families of five or six, which is typical for Chinese households where grandparents tend to live with young parents to take care of grandchildren. Including vehicle class-by-year fixed effects controls for different trends in popularity among vehicle classes.

Finally, column 4 takes into account vehicle purchase restrictions. China is one of the few countries that implement this type of policy on a large scale.[2] The policy controls the supply of vehicle licenses to tackle the rising urban traffic congestion and

[2] Singapore also put a limit on the number of cars on its roads in 2018.

air pollution (Ma et al., 2017). In particular, it targets traffic-heavy cities/municipalities, and began with Shanghai in 1994. Beijing was the second municipality to implement this policy in 2010. Currently, there are a total of seven cities/municipalities with this policy in effect, each with different starting times. I construct a dummy that indicates whether the province contains cities/municipalities that have the vehicle purchase restrictions in effect.

For both price regressions and quantity regressions (Panel A and Panel B), the fuel cost coefficients are stable across different specifications (column 1 to column 4). In the price regressions (Panel A), the coefficients on fuel cost in all specifications are negative and statistically significant at the 1% level, changing from -0.089 in baseline specification in column 1 to -0.094 in column 4, which has the most comprehensive controls. For quantity regressions (Panel B), all coefficients of fuel cost are negative and significant at the one percent level, ranging from - 0.751 in baseline specification in column 1 to -0.779 in column 4. The result for column 2 is in between that of column 1 and column 4 in both price regression and quantity regression. Estimates for column 3 are basically the same as for column 4, most likely because the two major municipalities that are most impacted by the vehicle purchase policy, Beijing and Shanghai, already had this policy implemented before the start of the study period.

Because both dependent variables (transaction price and new registration) and unit fuel cost are in log form, the coefficient of unit fuel cost (price per kilometer) should be interpreted as elasticity. Taking the specification with the most comprehensive controls (column 4) as an example, I find that a 1% improvement in fuel economy (thereby reducing unit fuel cost by 1%) will increase the transaction price by 0.094% and promote sale growth by 0.779% at equilibrium.

Thus, I find much larger quantity responses than price responses. Busse et al. (2013) also find quantity responses much greater than price responses, whereas Leard et al. (2017) find price and quantity responses have similar magnitude. One potential explanation for my result is that in China, transaction prices are adjusted infrequently. Compared with the promotion-heavy US market (Langer and Miller, 2013), Chinese automobile manufacturers and dealers have much fewer promotion events (F. Wu et al., 2019). This could be due to the fact that many Chinese car manufacturers are partially funded by the government, and they are less responsive to the market in terms of pricing strategy. Therefore, sales could respond faster and more drastically than transaction prices since consumers can vote with their feet and choose vehicles with better fuel-saving potentials.

Panel C translates the price and quantity responses in equilibrium to willingness to pay associated with a 1% improvement in fuel economy (thus reducing unit fuel cost by 1%) using Equation (1.4. Under demand elasticity assumptions ranging from -3 to -5, the average WTP ranges from 300.1 RMB to 425.7 RMB for my baseline estimation in column 1 and ranges from 313.4 RMB to 443.7 RMB for the most comprehensive model in column 4.

To better understand whether Chinese consumers value fuel economy, I further convert the willingness to pay in Panel C to the valuation ratio in Panel D using Equation (1.5. Since I already have the estimates for WTP associated with a 1%

improvement in fuel economy, the only piece of the puzzle remaining to calculate the valuation ratio is to determine what is the lifetime fuel expense savings associated with this amount of increase in fuel efficiency. I assume the lifetime total fuel expense is the present value of the stream of future fuel expenses.

$$Total\ Fuel\ Cost_{jrt} = \mathrm{AVKT} * Fuel\ Consumption_{jrt} * Gas\ Price_{rt} * \frac{1-e^{-\delta T}}{\delta} \qquad (1.8)$$

Here I use the number from Sallee et al. (2016) and assume a 5% discount rate, since the short-term mortgage rate (3-5 years) from the Bank of China during the study period ranges from 4.75% to 6%. I also assume the average vehicle kilometers driven per year (AVKT) is 12,377 kilometers, and the average lifespan for an average vehicle is ten years. This number comes from the survey by Ou et al. (2019) on the daily driving pattern of Chinese drivers. The monthly gasoline price is from the CEIC China Premium dataset.

After evaluating at these numbers, the average lifetime total fuel expense for a Chinese vehicle is found to be 42,198 RMB. A 1% improvement in fuel economy will result in a 1% saving of this lifetime total cost, which is averaged as 421.98 RMB. After applying Equation (1.5, I get the valuation ratio shown in Panel D. On average, Chinese consumers almost fully capitalize the future fuel cost in the present value of the vehicle under the demand elasticity of -3, with the valuation ratio ranging from 101% to 105%, depending on specifications. Under other demand elasticity assumptions, the valuation ratio ranges from 71% to 86%.

1.4.2 Alternative assumptions on AVKT

The average vehicle kilometer traveled (AVKT) is an essential part of estimating lifetime total fuel expense and thus would affect the final calculation of the valuation ratio. In the previous estimation, I use a simple annual average that is constant for each year for a vehicle's lifespan. In this section, I test whether the result is robust when compared with a more complex method, using the following equation:

$$Total\ Fuel\ Cost_{jrt} = \sum_{1}^{T} \frac{P_t * AVKT_{jrt}}{(1+\delta)^t} * Fuel\ Consumption_{jrt} * Gas\ Price_{rt} \tag{1.9}$$

Here I assume $AVKT_t$ is no longer constant but instead declining with vehicle age. P_t is the survival probability of the vehicle at year *t*. A surviving vehicle is a vehicle that is not retired and still in service. The rest of the notation is the same as Equation (1.8.

A standard methodology for understanding how annual driving distance is affected by vehicle age and other basic vehicle characteristics is to conduct a large-scale driving pattern survey. A well-cited research article that studies vehicle miles traveled (VMT) in the United States is Lu (2006), which analyzes the annual vehicle miles traveled (VMT) as a function of vehicle age for passenger cars up to 25-years-old based on a 2001 National Household Travel Survey (NHTS). The study also estimates a passenger car survival rate schedule by vehicle age based on Polk's New Registration Data (NVPP) from 1977 to 2003. There have been a number of studies that base their VMT estimations on this model, sometimes using more updated data (Anderson et al., 2013; Jenn et al., 2015; Daziano et al., 2017; D. Greene et al., 2018).

I follow the model built by Ou et al. (2019), which is based on a survey they conducted in 2018 on 169,292 privately-owned passenger vehicles. The paper tries to estimate annual vehicle kilometers traveled (AVKT) for Chinese drivers by vehicle class, price range, and geographic region. The study was jointly conducted by Oak Ridge National Laboratory (ORNL), China Automotive Technology and Research Center (CATARC), and the Aramco Service, and to my knowledge is the best of its kind. Some Chinese cities have conducted their own surveys on local vehicle usage, but China does not have a national survey that is comparable to NHTS in the United States. I use the parameters estimated in Ou et al. (2019) (see Table A.2) and calculate the AVKT for the fleet in my vehicle dataset. Table A.3 lists the average AVKT by vehicle age. However, this study does not give information on survival probability. I rely on the survival rate estimates from Busse et al. (2013) and Leard et al. (2017) as an approximation for the Chinese vehicle fleet (see Table A.4).

I also estimate the lifetime fuel cost under three assumptions of vehicle lifespan for 15, 20, and 25 years. Leard et al. (2017) assume a maximum lifetime of 35 years for cars, and Busse et al. (2013) assume this number to be 25 years. These assumptions seem too high for Chinese vehicles. China used to mandate that vehicles be retired after 15 years until the government canceled this regulation in 2013. Even after the rule was revoked, however, vehicles over 15 years are required to go through inspection at the local DMV every half year. Not only is the process time-consuming, but it's also difficult for these old vehicles to pass the inspection and meet the latest emission standards[3].

The results using different assumptions mentioned above are presented in Table 1.3. I use the WTP from the most comprehensive specification (column 4) and use alternative lifetime fuel cost saving based on the abovementioned assumptions. Under demand elasticity of -3, the valuation ratio ranges from 85% to 101 %. Realistically, estimates from 20- and 25-year-lifespans should serve as a lower bound since Chinese vehicles tend to be retired earlier than the 20-year-lifespan. Therefore, Chinese consumers can almost fully capitalize the future fuel cost.

1.5 Discussion

1.5.1 The role of reliable sources on the valuation of fuel economy

Information plays a significant role in the consumer's decision-making. If consumers don't have a reliable source for fuel economy information, they might not bother to go through all the steps to estimate future fuel costs and compare vehicles to purchase. For an emerging market like China, the availability of reliable information could also be an essential factor for how consumers behave. In mature car markets like the EU or the United States, the government for decades has been collecting and compiling information on vehicles with established standards and releasing the data to

[3] Chinese emission standards for gasoline passenger vehicles went up from China III (similar to Euro III) in 2007 to China V (similar to Euro V) in 2017.

the general public. By contrast, consumers in emerging markets without a reliable information source might simply rely on reputation or recommendations from friends, and could be heavily influenced by marketing campaigns. For example, among Chinese consumers, there has been a widespread belief that Japanese cars are “fuel saving,” and American cars are “fuel guzzling.” Many consumers therefore rule out American cars without even looking at manufacturer brochures.[4]

This misconception has been decreasing since the Ministry of Industry and Information Technology of China (MIITC) started to release fuel economy data to the public at the start of 2010 as a result of the light-duty vehicle fuel consumption label law. The law dictates that all light-duty passenger vehicles be tested for fuel economy from designated MIITC test centers. The official test results are then printed on a sticker that needs to be affixed on the vehicle’s windshield at the time of sale in the dealership. These test results are also collected by the MIITC from test centers and released on the MIITC official website. Since this policy came into effect, consumers no longer need to rely on reputation and self-justifying brochures from car dealers.

I want to test whether Chinese consumers are sensitive to the fuel economy before the release of official fuel economy data. The Autohome’s car library has begun to use the fuel economy tested by MIITC since the 2010 policy. I follow the most

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[4] In China, foreign auto manufacturers form joint ventures with local car manufacturers to produce vehicles under foreign makes in Chinese factories. Here, Japanese cars and American cars all refer to domestically-produced vehicles from joint venture manufacturers under foreign brands.

comprehensive specification in column 4 in Table 1.2 but instead use vehicle transaction prices and new registration data from before the policy was implemented. There are 14,383 comments on vehicles that were purchased before the 2010 policy that had their fuel economy information updated after the policy. As shown in Table 1.4, the consumers' valuation of fuel economy before the policy is not significantly different from zero in both the price and quantity regressions. This indicates Chinese consumers have been paying more attention to fuel economy after the policy. Some possible explanations are that (i) consumers had a relied-upon source of fuel economy after the government began to release the test center results in 2010 and put more effort calculating the fuel cost, and (ii) consumers have begun to be more aware of the fuel economy due to news coverage on the policy and the physical presence of a label (see Figure A.1) on every car's windshield at the time of sale at dealerships. A major news website, Sina (https://www.sina.com), released a news article in January 2010 calling the mandatory label "the end of the fuel-economy-cheating era."

With the rapid popularity of the internet, another great information source has emerged in all areas of civilian life. People don't need to buy a tourist guidebook to look for good restaurants but instead search on Yelp. The birth of many user-rating websites has made information exchange much easier and has emerged as a new, relied-upon authority for consumers. This is also true when it comes to car purchases. Autohome started in 2008 and has developed a very active community since 2012. Many potential car buyers come to the website to research vehicle attributes and read other buyers' comments. Actual buyers are active in sharing their thoughts on the model they have purchased. To post a comment, the user has to follow a particular format, which includes input on the transaction price and real-world fuel consumption.

The test performed at government-designated centers in China adopted the New European Driving Cycle (NEDC) as the test drive cycle. The NEDC is designed to assess the emission levels of car engines and fuel economy in passenger cars. It has been widely used in Europe since the procedure is simple and easy to duplicate. However, the NEDC was last updated in 1997. It is carried out under a controlled laboratory environment using a low load condition (Tóth et al., 2008; Merkisz et al., 2010). It has become increasingly outdated and unable to represent real-world driving. Many researchers have pointed out that there is an increasing divergence between official and real-world fuel economy or CO_2 values (Kadijk et al., 2012; Tietge et al., 2017; Mock et al., 2012; Mellios et al., 2011, Huo et al., 2011, Ntziachristos et al., 2014). For example, Tietge et al. (2016) find a huge gap between official and real-world CO_2 emission values of new European passenger cars, and the divergence increased from approximately 9% in 2001 to 42% in 2015. Huo et al. (2011) use 2009 data and estimate the gap to be around 15.5% for Chinese passenger vehicles.

In fact, many countries have realized the NEDC is no longer a reliable test method and have been pushing for a new testing system. Since September 2019, all light-duty vehicles in EU countries must comply with the new WLTP standards (world harmonized light-duty vehicles test procedure). Meanwhile, China will be switching to the China Automotive Testing Cycle (CATC) in 2020, which is a China-specific driving cycle designed to assess the emission levels of auto engines and fuel economy in vehicles.

There are a variety of factors other than vehicle attributes that could potentially have a substantial impact on real-road fuel consumption and increase the gap between official results and real-road results. Official test results come from a precisely-controlled environment and cannot take into account real driving conditions such as temperatures, wind speed, precipitation, and traffic conditions. First of all, the temperature has a significant impact on fuel economy in several ways. In both cold and hot weather, the AC will be turned on, which consumes more energy. The surrounding temperature also affects the efficiency of vehicle operation. The optimal operating temperature for engines is around 90 °C (194 °F). If the ambient temperature is significantly below this temperature, the viscosity of the oil and other fluids will increase, causing more friction in the engine. Moreover, the density of air on a 70 °F day is 16% lower than on a day with temperatures around 0 °F, thereby making aerodynamic drag stronger and resulting in increased fuel consumption. In addition to temperature, vehicle fuel economy can also be severely affected if the vehicle needs to drive through snow or water. Tire slippage can occur on wet or icy highways, which wastes energy and decreases fuel economy. Finally, in a crowded urban area, the stop-and-go driving style also should cause an increase in real-road fuel consumption.

The Autohome users' comment data enables me to verify whether the real-road fuel economy is different from the official test results that use the NEDC cycle in a laboratory environment. I extract the self-reported fuel economy from each comment and make a simple plot (see Figure 1.8) between the official test results and self-reported fuel consumption rate in L/100 km (which is the reciprocal of fuel economy). A simple regression of user-reported fuel consumption on official test results yields a coefficient of 1.204 with an R-square of 0.46, shown as the red line in the figure. A 45-degree line is drawn in green as a comparison. The discrepancy increases as the fuel consumption rate increases. This difference of 20.4% is overall consistent with the Huo et al. (2012) finding that fuel consumption in real-road conditions in China is 15.5% higher than official results, as the difference has tended to broaden over time, and I am looking at data in years after that study. The underestimation of official fuel consumption occurs at all levels of fuel economy. This validates the widespread belief among Chinese vehicle buyers that the official fuel consumption number can only serve as a lower bound of real consumption.

When estimating total fuel cost, almost all research uses official fuel economy information released by government agencies. However, with booming user-rating communities and the increasing gap between NEDC test results and real-road fuel economy, potential buyers might be turning to online rating platforms for fuel economy information. I'm interested in testing whether this new information source has become important in Chinese consumers' decision-making processes. I use the average user-reported fuel consumption for each sub-model as an "informed real-world fuel economy" and calculate the average as well as coefficient of variation of all previous user-reported fuel consumption rate. The trend of the two constructed variables over time is shown in **Error! Reference source not found.**. Both average and coefficient of variation of previous fuel consumption rates have a wide range over time. With more comments coming in, the coefficient of variation converges to a narrower range compared with the first several months when the sub-model was just released. Then I repeat the price regression using the following specification:

$$lnP_{ijrt} = \gamma \ ln \ Fuel \ Cost_{ijrt} + \theta \ ln \ CV_{ijt} + \alpha_{m \cdot yr} + \theta_{rt} + \boldsymbol{X}_i \boldsymbol{\beta} + \epsilon_{ijrt} \qquad (1.10)$$

Where $ln \ Fuel \ Cost_{ijrt}$ is the fuel cost (price per kilometer) calculated by using gasoline price at time *t* in region r for user *i*, and the average user-reported real-road fuel economy for sub-model j from all previous comments at the time t user *i* commented. $ln \ CV_{ijt}$ is the log of the coefficient of variation for user-reported fuel economy on Autohome.com for sub-model j from all previous comments at the time t when user *i* commented. A bigger coefficient of variance means a greater uncertainty perceived by potential buyers about the true fuel economy. The rest of the notation is the same as my main regression in Equation (1.6)

I follow the most comprehensive specification in column 4 in Table 1.2 by controlling with various policy controls and class-by-year fixed effects. The result is presented in Table 1.5. The coefficient of unit fuel cost is -0.101, which is larger than that in results using official fuel economy in absolute magnitude and also more significant. This shows that consumers are indeed paying attention to the new information source and adjust their beliefs on inaccurate official fuel economy. Column 2 adds also includes the log of coefficient of variance. The negative sign of the log of coefficient of variance shows consumers dislike uncertainty, which is consistent with what I would expect. A 1% increase in uncertainty would cause a decrease in equilibrium price by 0.002%. The uncertainty could affect consumers' confidence in three ways: (1) It directly increases the uncertainty of learning the true fuel economy of the vehicle and makes it difficult for consumers to make an informed decision on the car; (2) The large divergence of reported fuel economy across users could also indicate instability of the vehicle's performance since fuel economy is very correlated with other vehicle attributes, such as engine quality; (3) The consumers might have doubts about whether the manufacture is cheating on the fuel economy test and have less confidence in the product. The overall magnitude of uncertainty seems small. But as I have argued in the previous section, price generally responds less dramatically than quantity since Chinese automobile manufacturers and dealers have much fewer promotional events compared to the United States.

1.5.2 Gasoline tax simulation

Gasoline prices in China have been controlled by the National Development and Reform Commission (NDRC) since 2008, and usually lag behind international oil prices (Tan et al. 2019). Prior to 2013, the NDRC adjusted prices every 22 business days according to international crude oil prices. Since then, the frequency has increased to every ten business days. The adjustment follows the trend of international crude oil prices with some exceptions. The gasoline price in China will only be adjusted if international crude oil prices change by more than 50 RMB per ton and remain at that level for ten working days. The NDRC also sets an upper bound on adjustments at $130 per barrel and a lower bound at $40 per barrel. If international gasoline prices rise above or fall below these caps, Chinese gasoline prices do not adjust accordingly. Therefore, the gasoline price adjustment mechanism in China serves as a stabilizer to smooth out drastic changes in international gasoline prices.

In general, the international crude oil price accounts for approximately 40% of the retail price; other major factors include refinement cost (approx. 13%), transportation cost (approx. 15%), and various taxes (approx. 30%). In China, the Refined Oil Excise Tax applies to gasoline, naphtha, solvent, and lubricating oil at a uniform rate and has remained relatively low since its introduction in 1994 (Tan et al., 2019). The tax started at 0.2-0.28 RMB per liter in 1994 and increased to 1-1.4 RMB per liter in 2009. It has further increased to the current 1.52 RMB per liter level as of 2015. However, this number is still very low compared with OECD countries (see Figure 1.9).

With the exponential growth of the consumer vehicle market in recent years, the Chinese government has raised concerns over emerging issues related to rapid motorization, such as air pollution, congestion, energy conservation, and climate change mitigation. From 2000 to 2013, China has increased its gasoline consumption by 167%, reaching 95 million tons of gasoline in 2013. On-road vehicles are the main driver for this surge in fuel demand, accounting for 90% of total gasoline consumption (CAERC, 2012). He et al. (2013) project CO_2 emissions for passenger transportation could reach approximately 800 million tons by 2030. In 2015, China formally committed to peaking its carbon emissions and reducing its carbon intensity 60–65% from 2005 levels by 2030. In order to make substantial progress within this time frame, it is necessary for China to significantly lower energy consumption for fossil-fuel-powered vehicles (Wu et al., 2017).

The government has been experimenting with various policy tools targeting the transportation sector to control vehicle emissions. These policies include purchase restrictions as well as subsidies and incentives for fuel-efficient vehicles and new energy vehicles (NEVs). However, these policies do not directly target energy usage. Even though driving restrictions target the usage of vehicles, they restrict all users uniformly rather than by intensity of vehicle usage. For example, one type of restriction allows only vehicle users with a specific last digit on their vehicle's license plate to drive on a certain day of the week, no matter how far the vehicle owners plan to travel. Therefore, an Uber driver using their vehicle all day and a parent who only drives their kids to a nearby school are restricted uniformly, which is not efficient.

Fuel taxes can directly target the intensity of energy usage. In my previous analysis, I found that Chinese consumers are able to almost fully value fuel economy and capitalize the fuel cost and fuel tax could be the most efficient policy instrument in the current environment. I'm interested in simulating how vehicle sales and CO_2 emissions will be reduced if a stricter gasoline tax was in place. A rise in gasoline tax will not only reduce sales by increasing the cost of driving, but it could also affect the composition of the vehicle fleet, which I refer to as the compositional effect. The rationale behind this is when expected fuel cost rises, the demand curve shifts down and all types of vehicles might see a decrease in quantity. However, a more efficient car might have more comparative advantage than less efficient cars when the gasoline price rises, and consumers could potentially switch to more fuel-efficient cars. If this happens, it is likely that the sales of more fuel-efficient cars increase despite the rising future fuel cost. Indeed, Busse et al. (2013) find that the rise in gasoline price decreases the market share of cars in the lowest fuel economy but increases the market share of cars with a higher fuel economy.

To investigate how gasoline tax would affect the composition of the vehicle fleet in the Chinese automobile market, I follow the method of Busse et al. (2013) and divide fuel economy into four quartiles and interact these quartiles with unit fuel cost (price per kilometer). Since I'm interested in the sales response of the total fleet, I use the entire new registration data from 2010 to 2017 instead of the subset that could be matched to transaction prices quoted on Autohome. Then I estimate:

$$lnQ_{jrt} = \sum_{k=1}^{4} \gamma_k \left(ln\, Fuel\, Cost_{jrt} \cdot Tier_k\right) + \alpha_{m \cdot yr} + \theta_{rt} + \boldsymbol{X}_i \boldsymbol{\beta} + \epsilon_{jrt} \qquad (1.11)$$

This equation is similar to the quantity regression in Equation (1.7. The only difference is that I interact the unit fuel cost with a dummy indicating which fuel economy tier the vehicle belongs to. This model assumes that different tiers could have different sensitivity to fuel cost. The rest of the notation is the same as Equation (1.7.

The result is presented in Table 1.6. In the first row I do not split the fuel economy into tiers but run the same specification as Table 1.2 panel B column 4, using the full new registration data from 2010 to 2017. The coefficient on the log of unit fuel cost is similar: it is -0.779 for the smaller, matched subset and -0.700 for the full dataset. This indicates that the small subset that is matched to the Autohome comments library is representative of the overall Chinese vehicle fleet. One reason that the matched subset has a slightly larger coefficient with more significance is that the full new registration dataset contains models that are not popular, locally produced and sold, or experimental. Sales of these models might respond very differently to fuel cost given their niche customer base, and it's common for these niche models to have only one sub-model, making it difficult to exploit the fuel economy variation within the model. In contrast, models that appeared in Autohome's comments tend to be more mainstream and have more variation in fuel economy within the same model.

Rows 2-4 shows results for the coefficient of unit fuel cost for different fuel efficiency quartiles. Quartile 1 has the highest fuel efficiency and quartile 4 has the lowest. Similar to Busse et al. (2013), I find that the two tiers with the highest fuel efficiency do not see a significant decrease in vehicle sales. Tier 3, which is the lower-middle fuel efficiency tier, experiences a significant reduction. Tier 4, which is the lowest fuel efficiency tier, is not significantly impacted by the rise in gasoline price. Further investigation reveals that many of these vehicles are high-end vehicles. One possible explanation is that the potential buyers of these vehicles are high-income earners who are less sensitive to fuel cost and purchase these vehicles as status symbols.

Next, I use the model estimated above and predict what would happen in 2017 if the gasoline tax went up by 50% and 100% of its original level (CNY 1.52 per liter). I keep the total vehicle sales constant and only look at the compositional effect discussed earlier in this section. Here I only focus on how changes in fuel cost affect the composition of vehicle fleet instead of the aggregate sales of the vehicle fleet, for the following two reasons. First, since I have included time fixed effects, my quantity regression won't be able to identify the impact on aggregate sales. Second, people who are deterred by the high fuel cost from new vehicle purchases might turn to an alternative mode of transportation (for instance, taxi) or keep using their old vehicles, which are likely to be more polluting than newer cars. It's difficult to conclude the net change in GHG emissions from not buying a new car. Therefore, I only look at the compositional effect, and the result is shown in Table 1.7. In 2017 there are initially 19.4 million new registrations in my dataset. According to the greenhouse gases equivalencies calculator provided by the EPA, each liter of gasoline generates 2,337 g CO_2 emission. For the vehicle fleet registered in 2017, this is equivalent to 311.1 million tons of CO_2 emission. If a 50% gasoline tax was in place, the CO_2 emission would be reduced by 0.6% to 309.1 million tons. If a 100% gasoline tax was implemented, the CO_2 emission would be reduced by 1.3% to 307.1 million tons.

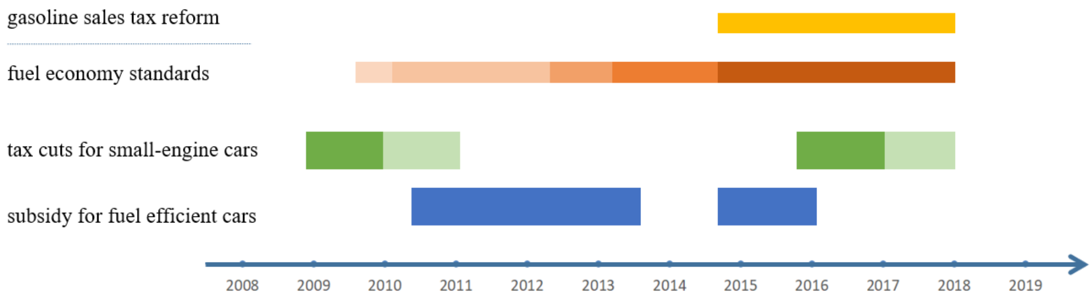
1.6 Conclusion

In this study I estimate Chinese consumers' valuation of fuel economy. It is an essential step to understand whether an energy tax type of policy would be efficient in China's circumstances. As the Chinese automobile market grows rapidly, it is increasingly important for policymakers to choose the most effective policy tool to combat pollution and congestion problems.

Using online website comment data and new vehicle registration data, I find that the new vehicle market in China displays almost full valuation. Assuming demand elasticity of -3, consumers appear to value fuel economy at 85-105% under different specifications and assumptions on annual vehicle kilometer traveled. The release of public fuel economy data in 2010 has a positive effect on consumers' awareness of fuel economy. The rising popularity of the vehicle rating website provides a new information source and leads consumers to focus on real-road fuel consumption data.

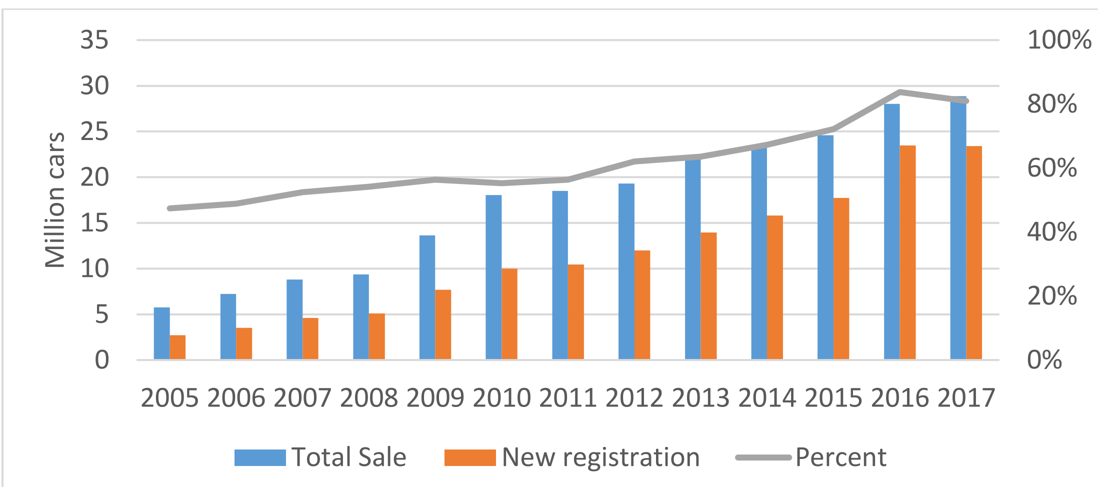
A gasoline tax or carbon tax could be the most efficient tool given the high valuation of fuel economy in the Chinese automobile market. I take the 2017 new vehicle sales as an example and look at the compositional effect on vehicle fleet from increased gasoline tax: if the gasoline tax was set to increase by 50%, the CO_2 emission could be reduced by 0.6% to 309.1 million tons a year. If a 100% gasoline tax was implemented, the CO_2 emission could be reduced by 1.3% to 307.1 million tons a year. This is a promising policy result that can help China fulfill its pledge to peak its carbon emission by 2030.

Figure 1.1: Timeline for vehicle-related policies



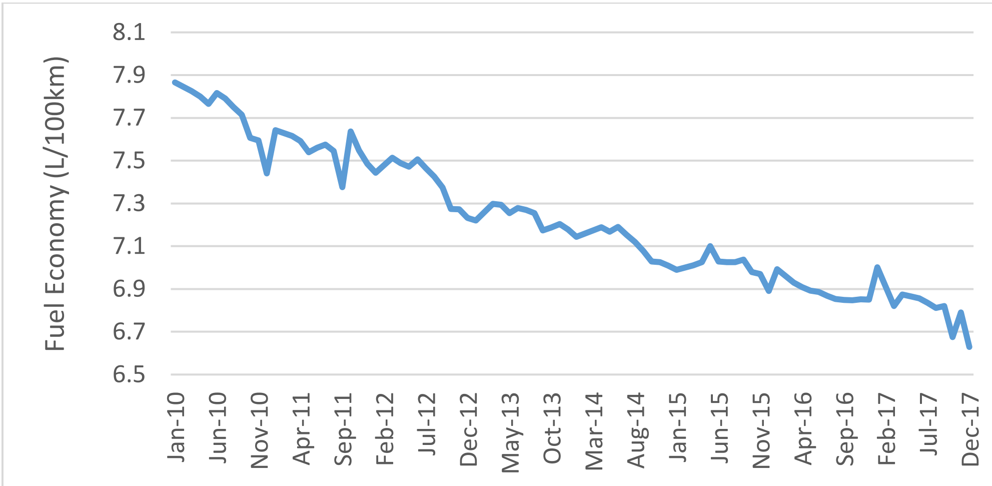
Notes: The figure shows a stylized timeline for vehicle-related policies in China over the study period that aim to reduce energy consumption and emissions. The length of the block indicates the duration and period in which the policy was in place and the color of the block indicates the strength of the policy. For instance, the darkening orange blocks for fuel economy standards suggest that fuel economy standards have been tightened over the years.

Figure 1.2: Total sales vs. new registration data



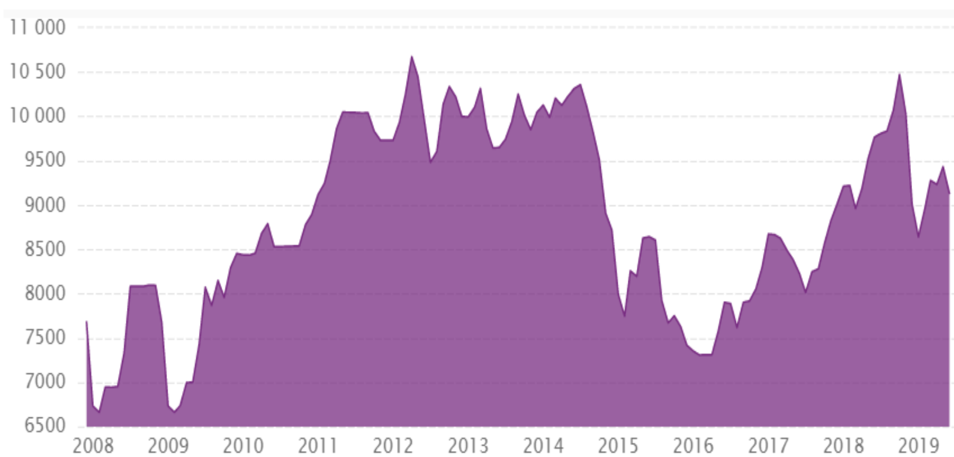
Notes: The figure shows a comparison between total vehicle sales and new vehicle registration over the study period. Overall, the new registration data represents around 70% of the total vehicle sales in China.

Figure 1.3: Trend of average fleet fuel economy (L/100 km)



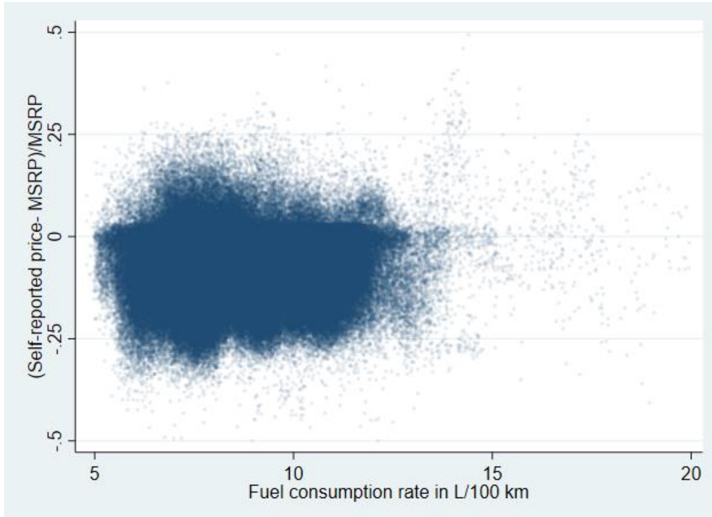
Notes: The figure shows the average fleet fuel economy in China over the study period.

Figure 1.4: Gasoline price (RMB/ton)



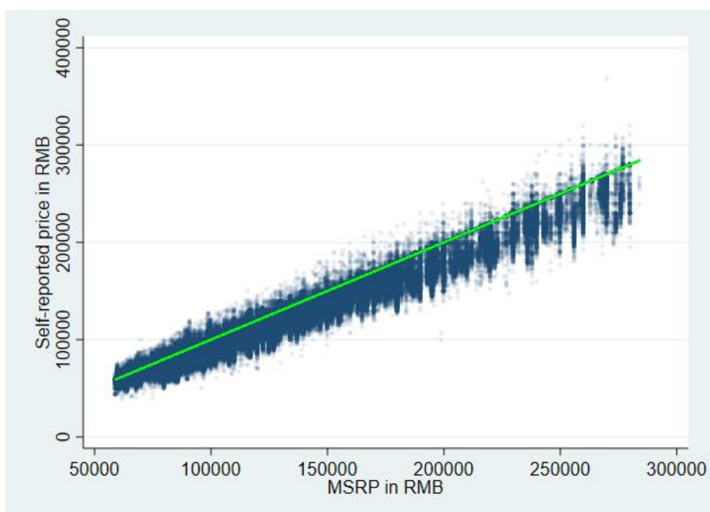
Notes: The figure shows considerable intertemporal variation in gasoline prices in China over the study period. 1 RMB/ton is 3.686×10^{-5} dollar/gallon. Therefore, the gasoline price during the study period fluctuated between 3.43 and 5.81 dollar/gallon, higher than the US average gasoline price during the same period. Source: CEIC's China premium dataset.

Figure 1.5: Percentage discount in self-reported price vs. fuel economy



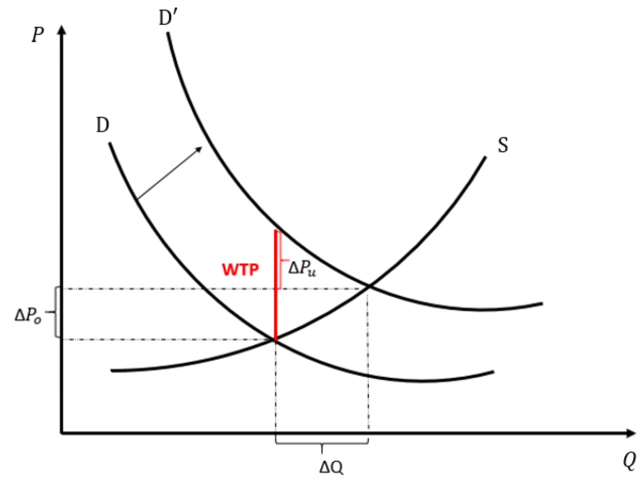
Notes: The figure plots the percentage discount off the MSRP received by the car buyer for each vehicle against the fuel consumption rate of the vehicle.

Figure 1.6: Self-reported transaction price vs. MSRP



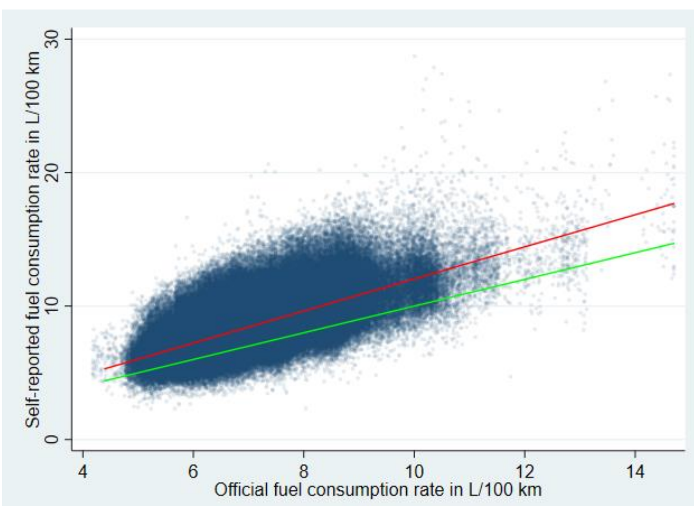
Notes: The figure plots the user-reported vehicle transaction price against the MSRP of the vehicle. The green line is a 45-degree trend line. Transaction prices fluctuate around the MSRP for all price ranges of vehicles.

Figure 1.7: Implication of WTP from a change in fuel cost



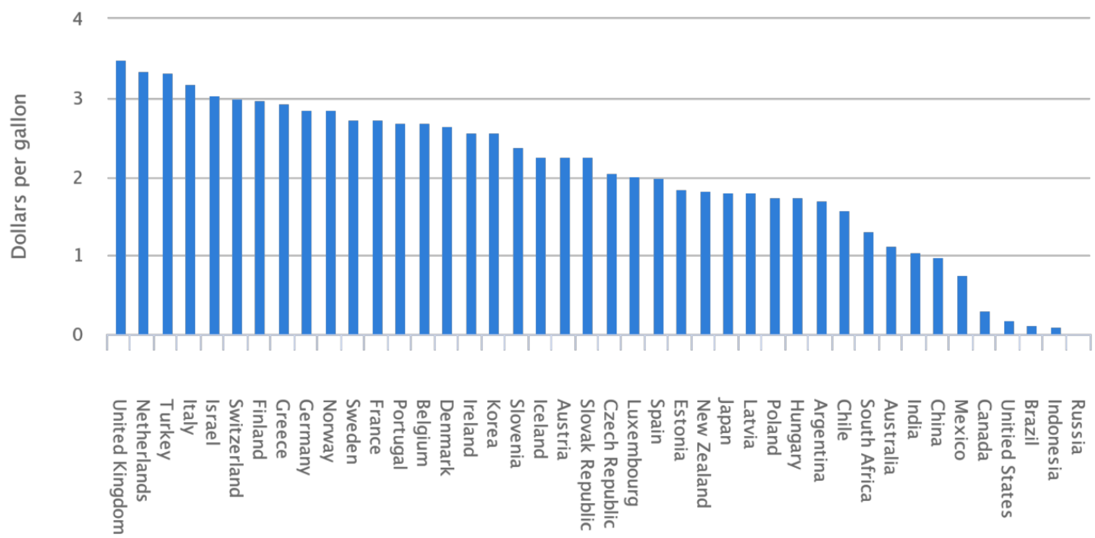
Notes: The figure shows the relationship between the willingness to pay and observed change in vehicle equilibrium when a demand shock occurs, assuming the supply curve does not move.

Figure 1.8: Self-reported vs. official fuel economy



Notes: The figure plots the user-reported fuel consumption rate from each comment on Autohome.com against the official fuel consumption rate of the vehicle. The red line represents the fitted OLS trend line and has a slope of 1.20. The green line is a 45-degree line. The discrepancy increases as the fuel consumption rate increases.

Figure 1.9: Gasoline fuel tax by country



Notes: The figure shows gasoline fuel tax in OCED countries in 2018.

Source: Taxing Energy Use 2018 - OECD 2018 Database.

Conversion Factors: EPA Greenhouse Gas Equivalencies Calculator

Table 1.1: Summary statistics

stats	mean	sd	min	max	p25	p50	p75
Transaction price (RMB)	125452	69449	19000	1028000	77800	106900	149800
MSRP (RMB)	137717	77660	20800	1048000	84900	118800	164800
Fuel economy (L/100km)	6.9	1.0	5.0	13.4	6.2	6.7	7.5
Engine size (ml)	1646	285	798	6208	1490	1591	1798
Gross weight (kg)	1347	206	645	2300	1210	1306	1485
Horsepower	136	35	36	457	112	126	154

Table 1.2: Estimating WTP for fuel economy

	(1)	(2)	(3)	(4)
Panel A: Log transaction price				
Log fuel cost (RMB/km)	-0.089***	-0.094***	-0.094***	-0.094***
	(-3.213)	(-3.604)	(-3.755)	(-3.755)
Policy controls		Yes	Yes	Yes
Class by year fixed effect			Yes	Yes
License restriction dummy				Yes
Number of observations	386,472	386,472	386,472	386,472
R square	0.989	0.989	0.989	0.989
Panel B: Log new registration				
Log fuel cost (RMB/km)	-0.751***	-0.773***	-0.779***	-0.779***
	(-4.245)	(-4.416)	(-4.477)	(-4.477)
Policy controls		Yes	Yes	Yes
Class by year fixed effect			Yes	Yes
License restriction dummy				Yes
Number of observations	197,426	197,426	197,426	197,426
R square	0.721	0.732	0.732	0.732
Panel C: Implied WTP for 1% change in fuel cost (RMB)				
Elasticity: -3	425.7	441.2	443.7	443.7
Elasticity: -4	347.2	360.4	362.2	362.2
Elasticity: -5	300.1	311.9	313.4	313.4
Panel D: Implied valuation for fuel economy				
Elasticity: -3	101%	105%	105%	105%
Elasticity: -4	82%	85%	86%	86%
Elasticity: -5	71%	74%	74%	74%

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions include model-year fixed effects, province-by-month fixed effects, and other car attributes. Observations are weighted by new registration in all price regressions and not weighted in all quantity regressions. Robust t-statistics are shown in parentheses, and standard errors are clustered by model-province.

Table 1.3: Valuation ratio using different assumptions

	Busse et al. (2013) survival rate			Leard et al. (2017) survival rate		
Life expectancy	15	20	25	15	20	25
Elasticity: -3	101%	98%	97%	94%	87%	85%
Elasticity: -4	82%	80%	79%	77%	71%	69%
Elasticity: -5	71%	69%	68%	66%	62%	60%

Table 1.4: WTP before official data is released

Dependent variable:	Log transaction price	Log new registration
Log fuel cost (RMB/km)	0.170	-0.330
	(0.804)	(-0.561)
Number of observations	14,383	8,516
R-square	0.995	0.831

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions include model-year fixed effects, province-by-month fixed effects, and other car attributes. All regressions include policy controls, class-by-year fixed effects, and vehicle purchase restriction dummy. Observations are weighted by new registration in all price regressions and not weighted in all quantity regressions. Robust t-statistics are shown in parentheses, and standard errors are clustered by model-province.

Table 1.5: WTP using real-world fuel economy

	Dependent variable: Log transaction price	
	(1)	(2)
Log predicted fuel cost (RMB/km)	-0.101***	-0.101***
	(-4.75)	(-4.86)
Log coefficient of variation		-0.002***
		(-8.13)
Observations	386,472	386,472
R-squared	0.988	0.988

*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions include model-year fixed effects, province-by-month fixed effects, and other car attributes. Observations are weighted by new registration in all price regressions and not weighted in all quantity regressions. Robust t-statistics are shown in parentheses, and standard errors are clustered by model-province.

Table 1.6: Quantity regression by fuel economy tier

Log new registration	(1)	(2)
Log fuel cost (RMB/km)	-0.700**	
	(-2.47)	
Log fuel cost*Quartile 1		-0.584
		(-1.08)
Log fuel cost*Quartile 2		-0.894
		(-1.43)
Log fuel cost*Quartile 3		-1.462***
		(-2.83)
Log fuel cost*Quartile 4		-0.793
		(-1.48)
Observations	1,877,201	1,877,201
R-squared	0.32	0.36

*** p<0.01, ** p<0.05, * p<0.1

Notes: Quartile 1 has the highest fuel efficiency and quartile 4 has the lowest. All regressions include model-year fixed effects, province-by-month fixed effects, and other car attributes. Observations are weighted by new registration in all price regressions and not weighted in all quantity regressions. Robust t-statistics are shown in parentheses, and standard errors are clustered by model-province.

Table 1.7: Gasoline tax simulation for 2017

	Original	50% increase		100% increase	
	level	level	percent	level	percent
CO_2 (M ton)	311.1	309.1	-0.6%	307.1	-1.3%

Chapter 2: The Effect of Income on Vehicle Demand: Evidence from China's New Vehicle Market

2.1 Introduction

Global oil consumption and greenhouse gas (GHG) emissions from transportation are expected to increase over the next few decades, with lower-income countries causing most of the growth. The US Energy Information Agency projects roughly a 15 percent growth in oil consumption and transportation energy consumption between 2020 and 2040. OECD and non-OECD countries are expected to follow diverging paths: consumption is expected to decline 3 percent for OECD countries and increase nearly 30 percent for non-OECD countries (EIA 2019). Projections from the International Energy Agency and other major organizations are broadly similar.

China is a major driver of these trends. China's oil consumption is expected to grow 20 percent between 2020 and 2040 (EIA 2017). Rising vehicle ownership explains much of the oil consumption growth–both in China and in other non-OECD countries[5]. China's vehicle stock is expected to grow by 200 million units between 2020 and 2040, accounting for nearly all of the global growth in the vehicle stock (BloombergNEF, 2020).

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[5] The situation is comparable to that for anticipated growth in electricity consumption, where growth is concentrated among non-OECD countries and is driven largely by uptake of energy-consuming durable goods such as refrigerators and air conditioners (Auffhammer and Wolfram, 2014; Davis, Fuchs, and Gertler, 2014).

China's GHG policies depend crucially on these forecasts, as is the case for other countries. Under the United Nations Paris Agreement, China has pledged to peak its emissions by 2030 and substantially reduce emissions over the subsequent decades. Total transportation sector emissions, which account for 9 percent of China's GHG emissions (IEA, 2017), equal the emissions rate of vehicles multiplied by the number of vehicles and miles traveled per vehicle. China's transportation policies focus mostly on reducing the emissions rates (not the levels of emissions) of new vehicles. Therefore, to achieve a particular emissions target, the greater is future vehicle ownership and use, the more China has to reduce the emissions rates of its vehicles (Pan et al., 2018); if forecasts are 10 percent too low, GHG policy would have to achieve 10 percent greater emissions than if forecasts are accurate.

Unfortunately, assumptions behind these forecasts rest on little empirical support. In the computational models that generate the forecasts, oil consumption and GHG emissions from passenger vehicles are closely linked to household vehicle ownership. An extensive literature correlates income with vehicle ownership in the United States, Europe, and other OECD countries (Dargay, 2001; Dargay, Gately, and Sommer, 2007; Nolan, 2010; Blumenberg and Pierce, 2012; Oakil, Manting, and Nijland, 2018). Most projections of future vehicle ownership in China and other non-OECD countries from the past two decades rely on the assumption that vehicle ownership and use will follow patterns observed in other countries. For example, Huo et al. (2007) forecast vehicle ownership in China using data from Europe, Japan, and other countries, assuming that the effect of GDP per capita on vehicle ownership in China will be the same as it was for the other countries. He et al. (2005) and Yan and

Crookes (2009) use similar methods, as do forecasts from organizations such as the International Energy Agency that receive a lot of attention from policy makers. However, Wang, Teter, and Sperling (2011) argue that periods of early motorization in the US and Europe may be more relevant to future motorization in China; in that case, basing projections on recent OECD data could yield overly conservative estimates of China's future oil consumption and GHG emissions.

Recently, income and vehicle ownership have exploded in China, with average income per capita growing 11.9 times and new vehicle sales growing 7.6 times between 2000 and 2017 (CEIC Data). This situation presents an opportunity to evaluate the assumptions that underlie the projections of future vehicle ownership and GHG emissions in China. That is, have recent projections of vehicle ownership in China proven to be accurate?

In this paper, we estimate the recent relationship between income and new car ownership in China, and we compare the results with recent forecasts of vehicle ownership. The main data include total new vehicle sales, income, and other socio-economic variables by city and year for 2005-2017. This period includes 9.6 percent annual growth in income and 20 percent annual growth in new vehicle sales. During these years, sales grew from 5.8 to 29 million units, as China became the world's largest new car market.

The objective is to estimate the causal effect of income on car ownership, and a major challenge is that income is endogenous to car ownership due to reverse causality and omitted variables. For example, if vehicle ownership reduces travel costs and allows people to find better jobs, there could be reverse causality from car ownership to income. Omitted factors that may be correlated with income and also affect car ownership, such as cultural trends related to car ownership, would cause omitted variables bias. Besides being potentially endogenous, city-level income may be measured with error.

We adopt an instrumental variables strategy to address the endogeneity and measurement error. We employ a Bartik-style instrumental variable (IV) that is the interaction of a city's education employment in 2004 with China's annual high-technology exports. The relevance of the instrument is supported by the fact that high-technology exports have driven much of China's economic growth over the past two decades, and that cities with high initial education employment have large skilled worker populations who can produce high-technology exports. The exclusion restriction is that 2004 education employment is uncorrelated with subsequent unobserved factors that affect vehicle ownership via channels other than income. We provide evidence supporting this assumption, including a lack of correlation between 2004 education employment and subsequent shocks to other drivers of vehicle ownership such as the quality of public transportation.

We find that a 1 percent increase in income causes total new vehicle sales to increase by 2.5 percent. Moreover, income does not affect the sales-weighted average price of new vehicles sold, meaning that as income has grown, sales of low- and high-price vehicles have grown by the same proportion. Likewise, the elasticity of new vehicle sales to income does not appear to be correlated with a city's initial income, again suggesting proportional growth. The estimate is robust to alternative functional forms and controlling for other socio-economic variables.

Comparing our results with the literature, we conclude that recent projections of future new vehicle sales in China may be vastly understated. Our estimates mean that rising income has increased vehicle sales in China by about 36 percent more than predicted by recent forecasts. In the long run, annual sales are proportional to the new vehicle stock, suggesting that recent forecasts of new vehicle sales have underpredicted the effect of rising income on emissions by roughly 36 percent. As we discuss in the Conclusion, our results indicate that recent forecasts may substantially underestimate China’s future oil consumption and GHG emissions in China.

We contribute to several literatures. First, a number of studies project China’s future vehicle stock. A typical method is to assume that vehicle ownership is an S-shaped function of per-capita gross domestic product (GDP). The rationale for the functional form is that in OECD countries, vehicle ownership increased slowly at low levels of GDP, subsequently rose steeply, and then leveled off (Lu et al., 2018). For instance, Huo et al. (2007) assume the vehicle ownership rate follows an S-shaped Gompertz function of per-capita GDP and conclude the Chinese highway vehicle stock will reach 389-495 million by 2040. Huo and Wang (2012) compare several S-shaped functional forms and they also account for income inequality and vehicle prices. Lu et al. (2018) and Gan et al. (2020) use similar methods and more recent data, projecting that China’s vehicle stock will reach 400-600 million units by 2050.

These forecasts assume parameters for the function linking vehicle stock to income, including a saturation rate. Most previous studies assume saturation rates of 200–800 cars per thousand people (He et al., 2005; Dargay, Gately, and Sommer, 2007; Huo et al., 2007; Huo and Wang, 2012; Lu et al., 2018), which is based on observations from other countries. Gan et al. (2020) comment that transferring parameters from other countries to China is arbitrary, and instead they use household survey data to calibrate their model.

In contrast to this literature, rather than calibrating a curve to data from other countries, we use historical data to estimate the effect of income on total new vehicle sales, accounting for the potential endogeneity of income. To our knowledge, ours is the first study to investigate the impact of income at the city level. Nearly all prior research estimates vehicle growth using national data. However, as we illustrate below, Chinese cities have had imbalanced development and it was a national strategy to prioritize the development of certain regions (Shen, Teng, and Song, 2018). Each city also has its own preferences for public transportation and road systems. As such, different cities might exhibit very different vehicle growth patterns. Our balanced panel of city-level data allows us to exploit cross-sectional as well as time-series variation of income and new car sales, and to consider whether the income-sales relationship varies systematically with other factors.

We also contribute to the broader literature on income and energy-consuming durables and future GHG and oil demand. As noted above, there is little research on the effect of income on new vehicle demand in non-OECD countries, although there is some research on household appliances and residential energy-efficient and renewable energy products such as solar panels. McNeil and Letschert (2010) find that appliance ownership of refrigerators, washing machines, televisions and air conditioners increase with household income, urbanization and electrification rates. They also document an S-shaped relationship between income and appliance ownership. Auffhammer and Wolfram (2014) and Li et al. (2019) report somewhat conflicting evidence on the relationship between income and appliance ownership. Auffhammer and Wolfram (2014) show that the proportion of households above the poverty line affects the uptake of energy-using durable goods in rural China. However, Li et al. (2019) show that the income threshold for ownership is correlated with the cost of the appliance. In contrast to Auffhammer and Wolfram (2014), they find that changes in the income distribution have negligible effects on the penetration rate of household appliances[6].

Finally, There exists a large body of literature on long-run climate policy using integrated assessment models (IAMs) and other aggregate models (Nordhaus and Yang, 1996; Cantore, 2011; Krey et al., 2012; Vliet et al., 2012; Ruijven et al., 2012; Calvin et al., 2013; Steckel et al., 2013; Luderer et al., 2015; Cherp et al., 2016; Calderón et al., 2016; Zwaan et al., 2018; Nieto et al., 2020). These models can be used to estimate the efficient carbon price or the costs of achieving long-run policy objectives such as maintaining expected temperature changes below a certain

[6] There is a vast literature on income and appliance ownership in OECD countries. A few examples include Zhao et al. (2012) and Mundaca and Samahita (2020)

threshold. Often IAMs are calibrated to forecasts of future GDP and emissions. We find that at least for China, those forecasts may vastly understate future transportation emissions. Given China's contribution to global emissions, that would cause the forecasts to understate global transportation emissions by a non-trivial amount–and by even more if our results pertain to other non-OECD countries besides China. Therefore, more accurate predictions of future vehicle ownership in China and perhaps other non-OECD countries could have implications for climate policy analysis in IAMs.

2.2 Data and Summary Statistics

We use data on new vehicle registrations in all of China from 2005-2017. The Chinese Department of National Security collects the data, which contain information on the total number of new vehicles registered by city, month, model, and usage purpose (personal or business). The data include vehicle attributes such as engine size and manufacturer suggested retail price. Because we are interested in the effect of personal income on vehicle ownership, we exclude vehicles that are purchased for business. Imported cars are also excluded due to a lack of price information[7].

We use registration data as a proxy for vehicle sales. Tan, Xiao, and Zhou (2019) compare the new vehicle registration data with statistics on vehicle sales from

[7] We conduct a robust test on the total vehicle sales including both domestic and imported vehicles. We follow our main specification in Table 3 column 2. Compared with our main result, including imported cars generate very similar coefficient on the log of income and significance level. The coefficient is 2.39 for including imported cars and 2.53 for our main result with domestic cars.

the China Automotive Industry Yearbook, and they find that the registration data account for 70 percent of total vehicle sales. However, further investigation suggests that the sales data, rather than the registration data, are misleading. Many agencies and organizations in China compile their own sales statistics, such as the China Association of Automobile Manufacturers, the State Information Center, and the Chinese Passenger Cars Association. Each organization uses its own data collection methodology. For instance, the China Association of Automobile Manufacturers counts in total sales the unrealized orders from manufacturers. In addition, most of these statistics rely on self-reported data from manufacturers. It is not uncommon for vehicle manufactures to fake sales and many automobile industry practitioners are turning to registration data for decision-making.

One potential concern about using registration data is that consumers may not immediately register their vehicles after purchase. In that case, registrations would lag sales. However, the month of registration is a good proxy for the month of sales. Most Chinese car buyers choose to pay an additional service fee and apply for registration through the car dealers immediately after they complete their purchases. The application process usually takes 2-7 days, and driving without registration would add penalty points to the driver's license. Therefore, the registration month and purchase month are the same for the majority of vehicles, and the two may differ by at most a month. This situation likely introduces little measurement error because we aggregate the monthly data to the annual level.

We combine the registration data with a set of socio-economic variables from the China City Statistical Yearbook, which is published annually by the National Bureau of Statistics of China (NBSC). Each year, NBSC distributes questionnaires to municipal statistics departments. Province-level statistics departments and the NBSC check the validity of the responses. For each city, the yearbook includes average income per capita, which is the key independent variable in the econometric analysis; the built area (constructed areas for residential, commercial, or industrial use); area of paved roads (road length multiplied by width); population; number of buses and taxis in the public transportation system; total retail revenue; and the share of education sector employment in total employment, which we use to construct the IV. We also gather information on national-level high-technology exports from the World Bank. The World Bank defines high-technology exports as products with high R&D intensity, such as aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.

Table 2.1 summarizes the car registration and socio-economic variables. The dataset contains 3,627 unique city-year observations. New car expenditures and the number of cars sold are aggregated to the city-year level and average car price is weighted by the number of cars sold. Car sales and the socio-economic variables vary substantially across cities.

Figure 2.1 illustrates income growth for five groups of cities between 2005 and 2017. We compute quantiles of the distribution of city-level average income per capita using 2005 income data, and we assign each city to a quintile group based on its 2005 income per capita. The figure shows the average income of cities in each group, with average income normalized to 1 in 2005 to facilitate comparison of income growth across cities. As shown in the figure, there is tremendous income growth for all five quintiles, as well as a steady pattern of converging income levels across cities. Between 2005 and 2017, the average income for cities in the lowest quantile grew by a factor of 3.64, indicating a remarkable 28 percent average annual growth rate. In contrast, the average income for cities in the highest quantile grew by a factor of 2.51. This convergence eliminated 67 percent of the difference between the average income of the fifth and first quantiles: In 2005, the average income of the highest quantile is 214 percent of the average of the lowest quantile, whereas in 2017 this number decreased to 148 percent.

Table 2.2 provides further insight into the income dynamics during the study period. Each column indicates a city's 2005 income quintile, and each row indicates a city's 2017 income quintile (based on the 2017 rather than the 2005 income distribution). Quintile 1 refers to the lowest quintile and quintile 5 refers to the highest quintile. Each cell reports the percentage of cities that were in the indicated 2005 income quintile and that belong to the 2017 income quintile. For example, 50 percent of cities in the lowest 2005 income quintile belong to the lowest 2017 income quintile, whereas 36 percent of cities in the lowest 2005 income quintile belong to the second 2017 quintile. The table shows that many initially low-income cities catch up to and pass many initially higher-income cities, for example, 15 percent of cities in the lowest income quintile in 2005 belong to the top three quintiles in 2017.

The next two figures present summary statistics about new car registrations and attributes. All monetary values are converted to 2017 RMB using the annual consumer price index. Figure 2.2 reports the growth rate of vehicle sales (panel a) and revenue (panel b) by income quantile, with quantiles defined as in Figure 2.1 and 2005 levels normalized to 1 for comparability across quantiles. Total sales and expenditure have a similar pattern to income growth from Figure 2.1, with sales and revenue increasing more quickly in low-income cities than in high-income cities. The similarity of the patterns across the two figures previews our main finding of a strong connection between income and new car demand; In fact, panel (d) shows that sales outpaced income growth for each group of cities.

Panel (c) shows that the average new car price has been declining during this period when inflation is factored in. The declining average price indicates that although the aggregate demand for new cars increased, households are not systematically buying more expensive cars at the end of the period, relative to the cars they were buying at the beginning. This is consistent with the fact that domestic car manufacturing evolved during the sample, with most domestic brands targeting low-end and middle-end vehicles, putting downward pressure on average prices.

The average new car price declined between 2008 and 2016. During this period, income growth slowed and vehicle policies changed. Between January and December of 2009 as well as from October 2015 through December 2016, China reduced purchase taxes from 10 percent to 5 percent for cars with small engines. These tax changes likely increased demand for cars with small engines, which also tend to be less expensive than cars with large engines. Moreover, in 2008 China introduced a stricter fuel economy standard that required a 10 percent reduction in fuel consumption. Manufacturers attempted to meet this standard by incentivizing consumers to purchase cars with low fuel consumption rates, which also tend to have low purchase prices. Panel (b) shows that fuel consumption rates increased from 2005 through 2008, but after 2008 fuel consumption rates declined as the fuel economy standards tightened (the fuel consumption rate in China, measured in liters per kilometer, is the inverse of fuel economy, measured in miles per gallon).

Panels (c) and (d) show that average horsepower and weight increased over the sample period at similar rates. The overall upward trends are interrupted by temporary decreases in 2008 and 2016, which coincide with the engine tax policy changes.

Overall, the data show dramatic growth of new vehicle sales and income. Growth rates varied considerably across cities, with income and sales across cities converging over time. Average prices decreased between 2005 and 2017, and much of the decrease coincided with tax policy changes and fuel economy regulation.

2.3 Empirical Strategy

The first subsection provides a theoretical framework that yields the estimating equation, and the second subsection discusses the IV estimation that accounts for the endogeneity of income.

2.3.1 Economic Framework and Estimating Equation

We motivate the estimating equation by considering a market for new cars, in which many households are contemplating purchasing new cars. For an individual household, the car would increase the household's utility because of the comfort and convenience of travel. For example, suppose a member of the household commutes by public transportation and owning a car would reduce commuting time. The car may also allow household members to take trips that they had not taken previously. Besides comfort and convenience, owning a car may confer status to the household.

When deciding whether to purchase the car, the household compares the benefit of ownership with the costs. The costs include the purchase price (i.e., the forgone consumption of other goods), fuel costs, and maintenance. If car ownership is a normal good, car ownership increases with income. If we aggregate across households, total new car sales increase with income[8].

The objective is to estimate the causal effect of household income on new vehicle purchases and expenditure, conditional on other factors that could affect new car demand besides income. It is natural to begin by assuming that growth in car

[8] This statement could be formalized by considering a model in which a household derives utility from a car and a composite good. The household's utility from the car depends on the attributes of the car (such as interior space or performance) and an idiosyncratic preference shock. If the utility function exhibits decreasing marginal utility for the composite good, an increase in income raises the probability that the household purchases the car. Aggregating across households, we conclude that total new car sales increase with average income.

purchases and expenditure is proportional to income growth conditional on population growth, which gives rise to the following regression:

$$\ln\ Y_{jt} = \alpha_N \ln\ N_{jt} + \alpha_P \ln\ P_{jt} + X_{jt}\delta + \gamma_j + \tau_t + \epsilon_{jt} \qquad (2.1)$$

The dependent variable is the log of either new vehicle purchases or expenditure in city j and year t. The variable N_{jt} is income, P_{jt} is population, X_{jt} is a vector of controls, γ_j includes city fixed effects, τ_t includes year fixed effects, and ϵ_{jt} is an error term. The equation includes the log of population as an independent variable. Note that instead, we could normalize the dependent variable and income by population. However, such normalization forces the two coefficients to be equal. Because Equation (2.1) allows the coefficient to differ from negative one, this specification is more flexible.

The vector X_{jt} includes factors that could affect new car demand independently of income, such as the built-up area in the city (constructed area for residential, commercial or industrial use), area of paved roads, population, number of buses and taxis in the public transportation system of the city, and total retail revenue of the city. The city fixed effects control for time-invariant attributes such as geographic proximity to other cities (which could affect travel demand), and the year fixed effects control for aggregate shocks that affect car sales proportionately.

The main coefficient of interest in (2.1 is α_N. Because the dependent variable and income enter the equation in logs, the coefficient is interpreted as an elasticity; a coefficient of 1 means that a 1 percent increase in income is associated with a 1 percent increase in car purchases or expenditure. We expect α_N to be positive because an increase in income raises new vehicle demand.

We consider the log-log relationship between average city income and sales to be an approximation to a potentially more complex relationship. For example, sales could be a function of the household income distribution if there is a threshold level of household income below which households do not purchase new vehicles. As the household income distribution shifts to the right over time, sales increase but the relationship between average city income and total sales may not be iso-elastic. However, as we show below, the log-log approximation appears to fit the data reasonably well.

2.3.2 IV Estimation and Interpretation

The theoretical framework at the beginning of the previous subsection indicates three reasons why estimating Equation (2.1) by ordinary least squares (OLS) would yield inconsistent estimates of α_N: reverse causality, omitted variables bias, and measurement error. Reverse causality could arise if owning a car reduces commuting costs, expanding an individual's job opportunities and income from employment.

Omitted variables bias could occur if variables other than income affect the costs and benefits of owning a car. Above, we mentioned the quality of transportation as one example, and there are many others, such as vehicle operating and maintenance costs. Although we attempt to control for variables that affect new car demand independently of income, such as the number of buses and taxis operating in a city, many such variables are unobservable or difficult to measure, such as the quality of public transportation.

Finally, income may be measured with error. We use the average income of a city's population, but the relevant measure may be the income of households considering buying new vehicles. Note that a city's average income and the average income of potential new car buyers are likely to be highly correlated with one another, but using average citywide income likely introduces some measurement error.

Given these concerns, we use a Bartik-style instrument based on high-technology export-driven growth. A classic Bartik instrument is formed by interacting local industry shares and national industry growth rates. This type of instrument is used commonly across many fields in economics, including labor, public, development, macroeconomics, international trade, and finance (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Beaudry, Green, and Sand, 2012; Nunn and Qian, 2014; Baum-Snow and Ferreira, 2015; Jaeger, Ruist, and Stuhler, 2018).

The literature on export-driven income growth motivates the IV strategy, which is the interaction of national high-technology exports with the pre-sample city-level education sector employment. We use high-technology exports defined by The World Bank, which include products with high R&D intensity in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery. Numerous studies find that high-technology exports have substantially improved economic growth. For instance, Hausmann, Hwang, and Rodrik (2007) show that export quality is positively correlated with growth, and Falk (2009) shows that high-technology exports have a positive effect on economic growth in OECD countries. Jarreau and Poncet (2012) confirm that high-technology exports promote economic growth in China. They exploit variation in export sophistication at the province and prefecture-level and find that regions specializing in more sophisticated goods subsequently grow faster.

Moreover, human capital growth has contributed to high-technology exports (Stokey, 1991; Levin and Raut, 1997; Mehrara, Seijani, and Karsalari, 2017; Mulliqi, Adnett, and Hisarciklilar, 2019). Thus, the literature documents a strong connection from human capital growth to high-technology export growth to income growth. Given these findings, we specify the first stage as:

$$\ln N_{jt} = \beta_X \ln (X_t) \cdot E_j + \beta_P \ln P_{jt} + X_{jt}\eta + \gamma_j + \tau_t + \mu_{jt} \tag{2.2}$$

The second stage is:

$$\ln Y_{jt} = \alpha_N \ln \widehat{N}_{jt} + \alpha_P \ln P_{jt} + X_{jt}\delta + \gamma_j + \tau_t + \epsilon_{jt} \tag{2.3}$$

The IV specification is similar to the previous reduced-form [9] OLS model except that we use a Bartik-style instrument for income. The literature on export-driven economic growth cited above establishes the relevance of the instrument. Below we show that the instrument is a strong predictor of income, reducing potential concern

[9] Some literature uses a discrete choice model to study how certain attributes affect appliance ownership. However, a discrete choice model is not necessary given the scope of our paper. Implementing a discrete choice model introduces more structures as well as the need to instrument for endogenous vehicle attributes such as vehicle price. Therefore, we opted for a more straightforward reduced form approach.

about weak instruments bias. Moreover, using pre-sample education employment and aggregate exports addresses potential concerns about reverse causality and omitted variables bias. Specifically, it eliminates reverse causality because city-level new vehicle purchases cannot plausibly affect pre-sample education employment or aggregate exports. Moreover, the IV reduces the likelihood that changes in a city's predicted (i.e., second-stage) income are correlated with other factors affecting demand for cars in a city, such as public transportation.

The IV reduces measurement error because export-driven high-income growth likely affected workers with high human capital, who are more likely than other workers to purchase new cars. That is, if we were using an instrument based on income to low-skilled or agricultural workers, who purchased relatively few cars, we might be exacerbating rather than reducing measurement error.

The exclusion restriction is that a city's 2004 educational employment is uncorrelated with factors that subsequently affect new car sales independently of income, and which are not included in the IV estimation. Omitted variables correlated with the instrument are likely the most important remaining concern about the IV strategy. Although there may be unobserved factors correlated with initial employment, below we show that the city's 2004 educational employment is uncorrelated with 2004 levels and 2004-2017 growth of variables that may affect car ownership independently of income, such as road space, built area, and the number of buses and taxis. The fact that observed factors are uncorrelated with initial employment provides evidence supporting the exclusion restriction, but of course the exclusion restriction cannot be tested directly.

Care must be taken when interpreting the IV coefficient in Equation (2.3). The coefficient identifies the effect of income driven by expanding exports. This coefficient includes effects of income mediated through other factors that are not included in the estimation. For example, if rising income makes owning a new car more fashionable, the IV coefficient includes that effect. As another example, consider traffic congestion. If rising income increases driving and raises congestion, the coefficient includes that (presumably negative) effect on traffic congestion.

If congestion increases for other reasons besides income, the IV estimate would be consistent as long as the instrument is uncorrelated with the initial congestion level. A similar argument pertains to other factors affecting car demand, such as public transportation quality. If rising income causes cities to invest more in public transportation, reducing demand for cars, the IV estimate would capture the effect of income on car sales, net of the opposing effect of public transportation quality.

Before turning to the estimation results, we provide a brief discussion of dynamics. We have assumed a contemporaneous relationship between income and new car sales. However, new car sales could respond to lagged income or a moving average of recent income if household-level income shocks are transitory. Below, we allow for this possibility in the robustness analysis.

2.4 Results

This section reports the main results and robustness analysis and compares our estimates with recent forecasts of new vehicle sales in China.

2.4.1 Main Results

Table 2.3 reports estimates of Equation (2.1) (OLS) and Equation (2.3) (IV). Column 1 shows the OLS estimate of the key coefficient, α_N, from Equation (2.1). The specification includes city fixed effects, year fixed effects, and province by year interactions. Standard errors are reported in parentheses, clustered by city. The coefficient on log income is 0.73 and is statistically significant at the 1 percent level. The estimate means that a 1 percent increase in income is associated with a 0.73 percent increase in new car sales.

As we discussed in the previous section, the OLS estimate of α_N is likely to be inconsistent because of reverse causality, omitted variables bias, and measurement error. Column 2 of Table 2.3 reports the IV coefficient, using the interaction of the city's 2004 education employment with aggregate high-technology exports in the corresponding year. The IV estimate is 2.53, which is significant at the 1 percent level.

The IV coefficient is about 3 times greater than the OLS coefficient in column 1. The fact that the IV coefficient is so much larger could be explained by reverse causality, omitted variables that are negatively correlated with income, or measurement error that causes attenuation bias. We return to the economic interpretation of this estimate at the end of this section. Column 3 shows the first-stage coefficient on the instrument, which is precisely estimated. Column 2 shows that the first-stage effective F-statistic[10] is 83, reducing concerns about weak instruments bias.

Having shown that rising income causes total new registrations to increase, next we consider how income affects the total expenditure on new vehicles and average prices. Columns 4 and 5 are the same as column 2, except that the dependent variable is the log of new car expenditures (column 4) or the log of the sales-weighted average price (column 5). The income coefficient in column 4 is similar to the coefficient in column 2, indicating that an increase in income causes new car registrations and expenditure to increase by the same proportion. Consistent with that result is the fact that the coefficient in column 5 is small and is not statistically significant; the data reject the hypothesis that the coefficient equals 1 at the 1 percent level. These estimates mean that rising income causes total new car sales to increase, but it does not affect the average price of those cars. In other words, as incomes increased during the sample period, consumers purchased more cars but they did not substitute systematically toward more expensive cars.

[10] We use effective F statistics developed by Olea and Pflueger (2013) for detecting weak instruments. The Montiel Olea and Pflueger approach is robust to heteroskedasticity, time series autocorrelation, and clustering, which are likely to occur in our data. However, Montiel Olea and Pflueger approach is only available for settings with one endogenous regressor and there is still no similar heteroskedasticity-consistent weak instrument test for multiple regressors. Since we find that in our specifications with single endogenous regressor, the effective F statistics is almost identical (within 1% difference) to regular F statistics, we report regular F statistics for specifications with multiple endogenous regressors as an approximation.

The finding that income has not affected average prices is perhaps surprising, given that one might expect rising income to increase demand for relatively expensive vehicles. We consider two possible explanations for this result. First, the fuel economy and taxation policy implemented during this period (discussed in the previous section) could encourage sales of small and relatively inexpensive cars. This effect could counteract the effect of rising income on demand for new cars. However, Table B.2 shows that rising income tends to increase the average engine size, fuel consumption, horsepower, and weight. Therefore, the regulation and policy do not appear to explain the finding in columns 4 and 5.

A second possibility is that middle-income rather than high-income consumers may have been driving the growth in new car sales. That is, a change in the composition of new car buyers over time could counteract the effect of within-household income growth. For example, middle-income households may have higher demand for domestic brands, which tend to be relatively inexpensive, than do high-income households. Unfortunately, household-level data on income and vehicle purchases are not available, preventing us from testing this hypothesis.

2.4.2 Robustness

This subsection presents additional estimation results. We consider omitted variables bias, dynamics, and functional form assumptions.

As we discussed in the previous section, identification of the IV coefficient rests on the assumption that the initial level of education employment is uncorrelated with subsequent unobserved shocks to new vehicle sales. Although we cannot test this assumption directly, we can provide some supporting evidence. Specifically, if one assumes that unobserved variables in the IV regression are correlated with observed variables, we can check whether the results are sensitive to adding or dropping control variables. This assumption seems reasonable, as omitted variables such as traffic congestion (which would negatively affect new car demand) are likely to be correlated with observable variables such as the size of the public transportation system.

For convenience, column 1 in Table 2.4 repeats the main IV regression from Table 2.3, which we refer to as the baseline. Column 2 shows that omitting the province by year interactions causes the income coefficient to increase by about one-third. In column 3, we add several socio-economic controls that are likely to be correlated with new car demand, independently of income: built area of the city, the area of paved roads, population, the number of buses and taxis in the public transportation system, and total retail sales. The fact that including these variables causes the income coefficient to decrease only slightly supports the identification strategy.

Moreover, Table B.3 and Table B.4 show that 2005 education employment, which is used to construct the instrument, is uncorrelated with the other socio-economic variables in column 4. Specifically, the appendix tables include interactions of each of the socio-economic variables with a linear time trend or year fixed effects (the latter is more flexible). If education employment were correlated with these socio-economic variables, adding these controls would affect the IV coefficient. However, the income coefficient is reasonably stable across these specifications, further supporting the empirical strategy.

Next, we turn to dynamics. In principle, mean reversion in income and new car registrations could explain the large effect that we estimate. To illustrate this possibility, consider a hypothetical city that experiences simultaneous negative shocks to income and new vehicle demand at the beginning of our sample. If both income and new vehicle demand are mean reverting processes, we would estimate a positive relationship between the two variables even if the relationship is only spurious. To allow for the possibility of such mean reversion, we compute quintiles of city income using the 2005 distribution. Column 4 of Table 2.4 adds to the baseline the interactions of quintile fixed effects with a linear time trend. These time trends control for potential mean reversion, and adding these variables would decrease the income coefficient if mean reversion is an important factor. However, as column 4 shows, adding these trends causes the coefficient to increase. The estimate is significant at the one percent level, but the standard error is also larger than in column 1. This reflects the correlations among the instrumented income and the income-trend interactions; the first-stage F-statistic in column 4 is substantially smaller than in column 1. Thus, notwithstanding the large standard errors, we do not find evidence that mean reversion causes a spurious estimate.

Another issue related to dynamics is the possibility that income has a non-contemporaneous effect on vehicle demand. That is, the baseline IV specification includes the implicit assumption that income affects new vehicle demand within a year. In practice, consumers may delay making a new car purchase after their incomes increase for a variety of reasons, such as whether they want to wait to determine whether the income increase is permanent or transitory. Ideally, we would test for such dynamics by adding lags of income to the baseline specification, but unfortunately current income is highly correlated with lagged income. Therefore, in Table 2.5 in columns 2 through 4 we replace current income with the 1, 2, or 3-year lag (column 1 repeats the baseline). If consumers respond to rising income with a lag, the income coefficient on lagged income would be larger than the current income coefficient, but the table shows that this is not the case. Therefore, we do not find evidence refuting the hypothesis that new vehicle purchases respond to income within a year; or, put differently, if purchases respond with a lag, the lagged response is no larger than the estimated contemporaneous response.

Estimating Equation (2.3 yields the sample average elasticity of new registrations to income. As noted in the previous section, because the income distribution may affect registrations rather than average income, the elasticity could vary across cities or with income. In Table 2.6 we allow the income coefficient to vary across cities according to the city's 2005 income. Column 1 and 2 assign each city to one of two groups, depending on whether the city's 2005 income is below or above the median 2005 income. Columns 3 and 4 include three equal-sized groups based on 2005 income. The table shows that the effect of income on new car registrations is larger for initially high-income than low-income cities, but the difference across city groups is small; columns 1 and 2 show that the high-income city coefficient is about 5-10 percent higher, and columns 3 and 4 show that the effect is 10-20 percent higher, depending on the specification and group. However, note that the first-stage F statistics are smaller than in the baseline, particularly when we consider three groups. This indicates that although the instrument has sufficient variation to identify the baseline specification, unfortunately there is insufficient variation to consider much heterogeneity.

2.5 Comparison with Recent Forecasts

This subsection compares our estimated elasticity of new registrations to income with recent forecasts of the elasticity of new vehicle sales to income. We begin by summarizing recent forecasts published in the literature.

Table 2.7 shows the implied elasticity of new vehicle sales to income from recent forecasts. Some of the studies in the table report forecasts of new vehicle sales and others report forecasts of the entire on-road stock. For the latter, we impute sales following Hsieh et al (2018) and Gan et al (2020) and assuming a survival rate of Chinese vehicles estimated by Lu et al (2018).

The table reports the elasticity of sales to income by decade. Overall, studies forecast a declining elasticity over time, from an average of 3.2 for 2005-2010 to 0.41 from 2040-2050. Because the previous literature uses national data and we use city-level data, to facilitate comparisons with the literature, we need to estimate an elasticity of total sales to income. For each city, we predict the change in log new registrations between 2005 and 2010 by multiplying α_N by the change in log income between 2005 and 2017. Exponentiating this expression, summing across cities, and taking logs yields the predicted change in log national sales between 2005 and 2010.

$$\Delta \ln \text{ Sale}_{05-17} = \ln\left(\sum_i exp\left(\widehat{\beta_{IV}} \cdot \Delta\, ln\ \ Income_i + ln\ \ Sale_{i2005}\right)\right) - \ln\left(\sum_i \ln \text{ Sale}_{i2005}\right) \tag{2.4}$$

To generate a comparable predicted log sale using the income elasticity from the previous literature, we calculate total income across all cities in our data for each year. The predicted change in log total sales for 2005 to 2010 equals the income elasticity from 2005-2010 multiplied by the change in total log income for the corresponding years. We repeat this calculation for the 2010-2017 period as well. Table B.7 shows calculations for each study in Table 2.7, and the first row of Table 2.8 shows the results using the average elasticities in the literature. The literature predicts a change in log sales from 2005 to 2010 of 1.8 and predicts a change in log sales from 2010-2017 of 0.6. Thus, the literature predicts a dramatic slowdown in sales growth from 2010-2017.

To compare with the results from the literature, the second row of Table 2.8 shows the results using our estimates. Our estimates predict an increase in log sales from 2005 to 2010 of 1.4, which is 0.4 less than the 1.8 predicted by the literature. In contrast, from 2010-2017, our estimates predict about twice the increase in log sales as the literature–1.3 versus 0.6. Across the entire 2005-2017 period, our estimates predict greater growth by 0.3 log points, which translates to about 36 percent[11]. Thus, our analysis predicts a larger effect of income on new vehicle sales than does the literature. In particular, the literature has assumed that the growth rate of sales would diminish in the 2010s, when in fact income continued to have a large effect on sales in the 2010s.

2.6 Conclusion

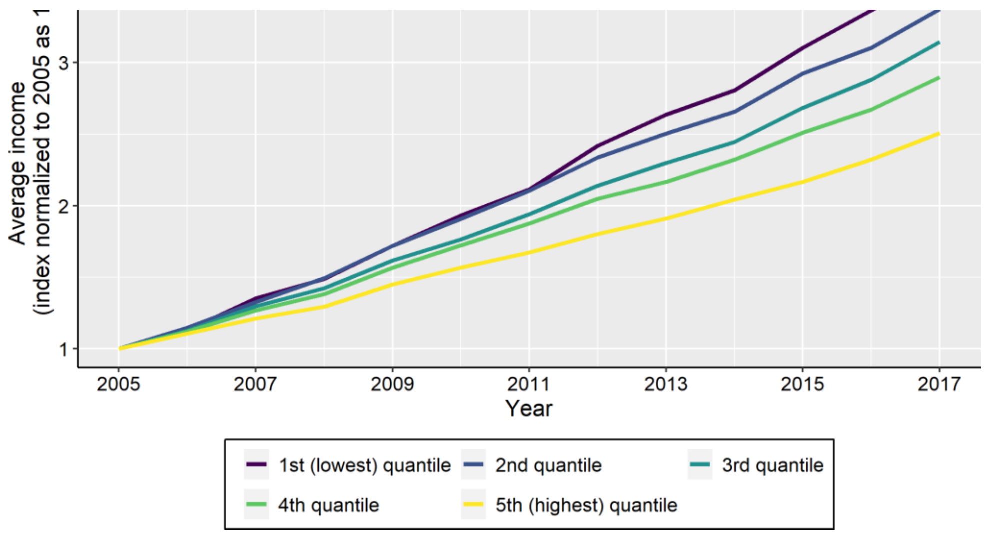
This paper reports a strong connection between growth in income and new vehicle sales in China. We assemble a unique data set of city-level sales, income, and socio-economic characteristics. We use an instrumental variables strategy that isolates income growth driven by high-technology exports, and which addresses potential concerns about endogeneity and measurement error of income. The preferred specification indicates an elasticity of city-level new car sales to income of 2.5.

We show that recent forecasts of vehicle sales in China appear to have substantially underestimated the effect of income on sales between 2005 and 2017. Our estimates indicate that income growth has caused new car sales to grow by 40 percent more than the average growth anticipated in forecasts conducted in the 2000s or early 2010s.

[11] Between 2005 and 2017, actual log sales in China increased by about 1.5. This number is smaller than either our estimates or the literature predicts, likely because our results and the literature isolate the effect of income on sales. There have been other developments in China that oppose the effect of rising income, such as expanding public transportation and traffic congestion.

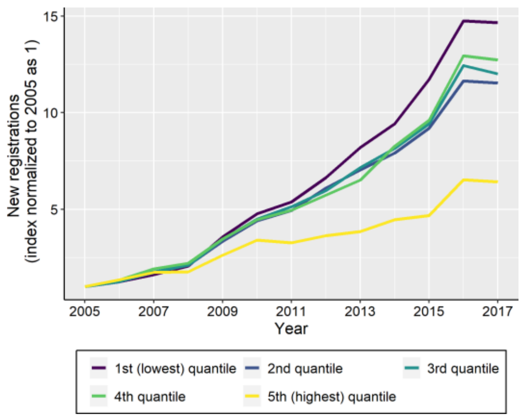
The results suggest that China's future oil consumption and GHG emissions may be higher than recent studies have predicted. These forecasts anticipate that the effect of income growth on sales growth will diminish over the coming decades, as vehicle ownership follows an S-shaped curve. However, given how dramatically these studies under-predicted sales growth in the 2010s, it seems unlikely that sales growth in the 2020s will slow to the low levels these studies anticipate. In that case, oil consumption and GHG emissions (in the absence of policy intervention) would be much higher than expected, and meeting China's pledge under the UN Paris Agreement would require more aggressive policies than if the forecasts prove to be accurate.

Figure 2.1: Income growth pattern by five quantiles

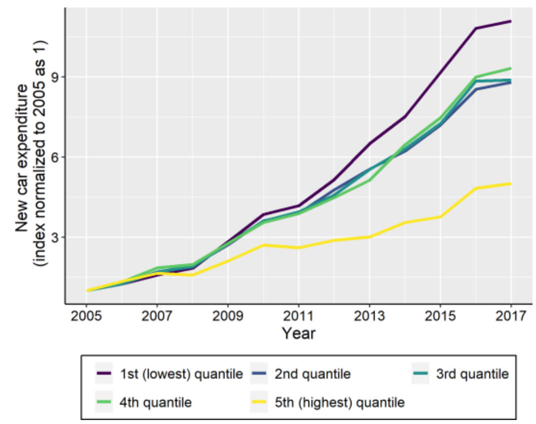


Notes: All cities are divided into five quantiles according to their income in the initial period (2005). For each year, we calculate the average income of cities within each of the five quantiles. Then we normalize all the quantile-level averages by their 2005 value.

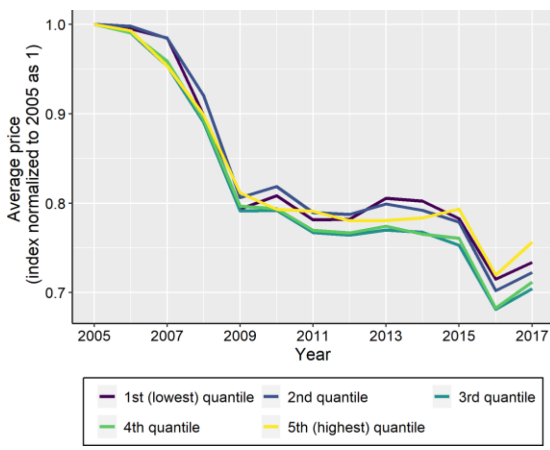
Figure 2.2: Growth rate of sales by income quintile



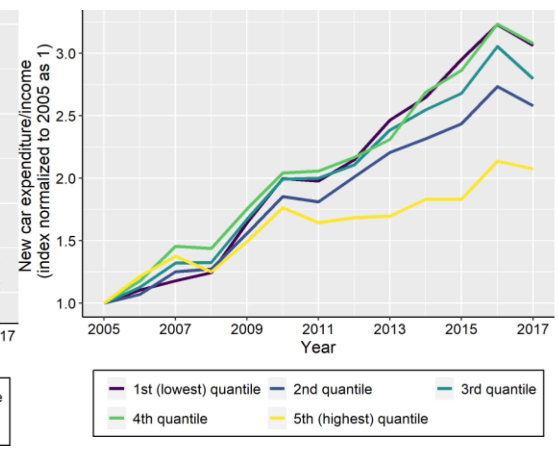
(a) Growth of sales



(b) Growth of expenditure



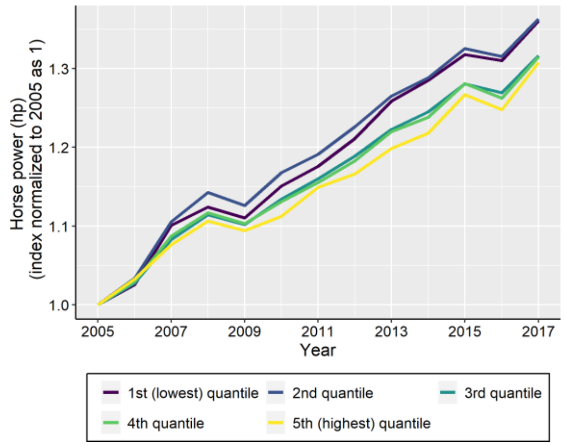
(c) Growth of average price



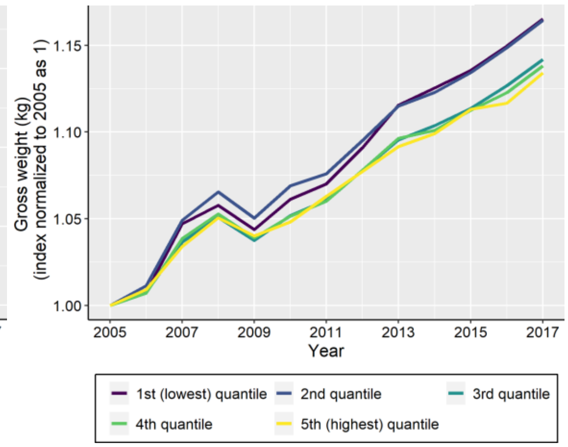
(d) Growth of expenditure/total income

Notes: All monetary values are converted to 2017 RMB using annual CPI.

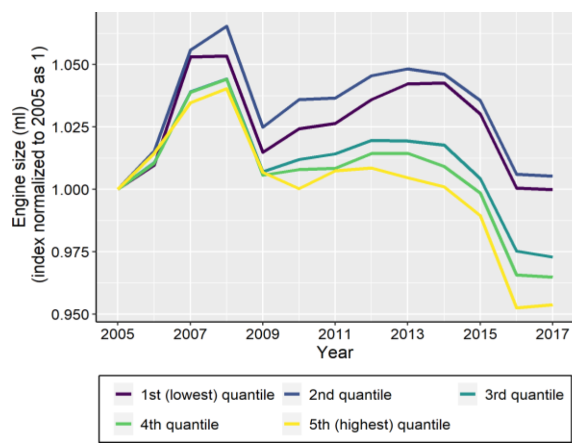
Figure 2.3: Average vehicle attributes by income tier



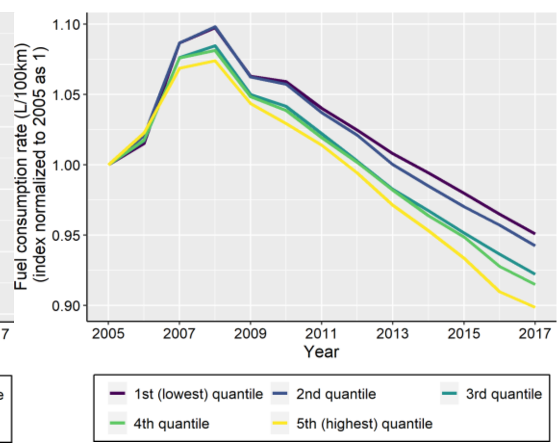
(a) Average engine size by income quantiles



(b) Average fuel consumption by income quantiles



(c) Average horsepower by income quantiles



(d) Average gross weight by income quantiles

Table 2.1: Summary statistics

Main variables	mean	std.dev	coef.var	min	max	median
New cars sold (thousand units)	37.9	62.0	1.6	0.4	727.0	17.0
New car expenditure (billion RMB)	5.9	10.5	1.8	0.1	140.1	2.4
Average car price (thousand RMB)	153.0	27.0	0.2	94.1	259.3	148.9
Income (thousand RMB)	41.4	16.3	0.4	8.8	135.0	40.4
Built-up area (square km)	121.0	165.2	1.4	6.0	1446.0	70.0
Area of paved roads (square km)	15.9	21.7	1.4	0.4	214.9	8.4
Population (thousand people)	4354.2	3098.4	0.7	172.2	34332.3	3700.0
Bus (thousand units)	1.3	2.8	2.1	0.0	35.8	0.5
Taxi (thousand units)	3.1	6.0	2.0	0.1	68.5	1.5
Total retail expenditure (billion RMB)	73.0	111.0	1.5	1.6	1183.0	38.6
Employment percentage in education (2004)	4.8	4.5	0.9	0.1	41.6	3.9
National high-tech export (billion RMB)	3786.0	590.2	0.2	2461.6	4509.9	4001.6

Notes: The data contain 3,627 observations. Built area is the area of land constructed for residential, commercial, or industrial use. Bus and taxi are the numbers of buses and taxis operating in the city. All monetary variables are adjusted for inflation and measured in 2017 RMB.

Table 2.2: Quintile switching

		2005 income level				
		1	2	3	4	5
2017 income level	1 (lowest)	50 %	30 %	13 %	5 %	2 %
	2	36 %	23 %	27 %	14 %	0 %
	3	9 %	29 %	27 %	25 %	11 %
	4	4 %	16 %	32 %	30 %	18 %
	5 (highest)	2 %	2 %	2 %	25 %	69 %

Notes: Each column indicates a city's 2005 income quintile, and each row indicates a city's 2017 income quintile (based on the 2017 rather than the 2005 income distribution). Each cell reports the percentage of cities that were in the indicated 2005 income quintile and that belong to the 2017 income quintile. For example, 50 percent of cities in the lowest 2005 income quintile belong to the lowest 2017 income quintile.

Table 2.3: Effect of income on vehicle registrations, expenditure and average price

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var:	log new registrations	log new registrations	First Stage	log new registrations	log new expenditure	log average price
Estimated by:	OLS	IV	OLS	IV	IV	IV
log income	0.73	2.53		2.07	2.64	0.10
	(0.11)	(0.39)		(0.52)	(0.40)	(0.08)
log income * post 2010				-0.50		
				(0.32)		
log income instrument			2.29			
			(0.25)			
Observations	3,627	3,627	3,627	3,627	3,627	3,627
Effective F stat for IV		83.33	83.33	22.88	83.33	83.33
Kleibergen-Paap stat		44.95	44.95	40.36	44.95	44.95
Underidentification p val		0.00	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. Column headings state the dependent variable and estimation method. All regressions include city fixed effects, year fixed effects, and province-year interactions.

Table 2.4: Effects of adding controls on IV estimates

Dependent var: log new registrations	(1)	(2)	(3)	(4)	(5)
log income	2.53	3.48	2.40	5.58	2.38
	(0.39)	(0.53)	(0.39)	(2.15)	(0.38)
log income * license cap dummy					-0.05
					(0.01)
Province by year FE	YES	NO	YES	YES	YES
Socio-economic controls	NO	NO	YES	NO	NO
2005 income quintile * trend	NO	NO	NO	YES	NO
Observations	3,627	3,627	3,627	3,627	3,627
Effective F stat for IV	83.33	59.73	78.85	8.09	41.16
Kleibergen-Paap stat	44.95	46.85	45.30	7.93	44.80
Underidentification p val	0.00	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. The dependent variable is log registrations. All regressions include city and year fixed effects. Columns 1, 3, and 4 include province-year interactions. Column 3 includes built area, area of paved roads, population, number of buses and taxis in the public transportation system, and total retail revenue. Each city is assigned to a quintile based on its 2005 income. Column 4 includes the interaction of a linear time trend and fixed effects for the city's quintile. Column 5 includes the interaction of log income and a dummy variable indicating if the city has a license cap policy in place at the time.

Table 2.5: Effects of lagged income on vehicle registrations

Dependent var: log new registrations	(1) Current	(2) 1 year lag	(3) 2 years lag	(4) 3 years lag
log income	2.53	2.85	2.96	2.59
	(0.39)	(0.42)	(0.42)	(0.45)
Observations	3,627	3,348	3,069	2,790
Effective F stat for IV	83.33	76.06	67.99	60.59
Kleibergen-Paap stat	44.95	43.62	41.89	39.24
Underidentification p val	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. The dependent variable is the log of registrations. All regressions include city fixed effects, year fixed effects, and province-year interactions. The first column uses current period log income. Columns 2-4 replace current log income with 1, 2 or 3-year lags of log income, instrumented by the corresponding lag of the instrument.

Table 2.6: Effect of income by initial income level

Dependent var:	Two groups		Three groups	
log new registrations	(1)	(2)	(3)	(4)
log income	3.19	5.78	4.46	7.07
	(0.63)	(2.33)	(1.08)	(3.18)
log income * above median	0.31	0.27		
	(0.13)	(0.17)		
log income * middle income			0.45	0.55
			(0.17)	(0.29)
log income * high income			1.01	0.99
			(0.36)	(0.48)
2005 income quintile * trend	NO	YES	NO	YES
Observations	3,627	3,627	3,627	3,627
F statistics for IV	17.53	3.49	5.6	1.60
Kleibergen-Paap stat	24.48	6.88	14.85	4.93
Underidentification p val	0.00	0.01	0.00	0.03

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. The dependent variable is the log of registrations. All regressions include city fixed effects and year fixed effects. Columns 2 and 4 include interactions of a time trend with 2005 income quintiles. We compute the median income across cities in 2005. Columns 1 and 2 include interactions of log income with a dummy variable equal to one if the city's 2005 income is greater than the median. We construct three equal-sized groups of cities according to 2005 income, and columns 3 and 4 include the interaction of log income with income group fixed effects. For each column, we form IVs by interacting the income instrument with the corresponding dummy variable or fixed effects.

Table 2.7: Elasticity of vehicle sale to GDP from other studies

	2005-2010	2010-2020	2020-2030	2030-2040	2040-2050
Wang et al (2006)	3.10	1.61	0.72		
Huo et al (2007)-High		1.54	1.23	0.91	0.76
Huo et al (2007)-Low		1.38	1.07	0.73	0.51
Wang (2011)-High	3.43	0.92	0.94		
Wang (2011)-Low	3.06	0.93	0.83		
Huo and Wang (2012)-High		1.03	0.64	0.45	0.37
Huo and Wang (2012)-Low		1.00	0.61	0.41	0.34
Hsieh et al (2018)		0.54	0.85	0.12	0.05
Gan et al (2020)			0.54	0.30	
Average	3.20	1.12	0.83	0.49	0.41

Notes: The table shows the elasticity of vehicle sales to income from recently published forecasts of oil consumption and GHG emissions in China. For studies that project the vehicle stock rather than new vehicle sales, we use the method adopted from Hsieh et al (2018) and Gan et al (2020) to impute new vehicle sales. We follow the survival rate schedule for Chinese vehicles estimated by Lu et al (2018).

Table 2.8: Comparing our result with previous studies

	$\Delta ln\ Sale_{05-10}$	$\Delta ln\ Sale_{10-17}$	Total: $\Delta ln\ Sale_{05-17}$
Literature average	1.8	0.6	2.4
Our prediction	1.4	1.3	2.7

Notes: See text for details on the calculations. For studies that do not have projections during the 2005 - 2010 period, we use the average income elasticity of other studies during this period. We show prediction result using two methods. In our first prediction, we use the main specification in Table 2.3 column 2 with a single coefficient on log income. In our second prediction, we follow Table 2.3 column 4 with different coefficients on log income before and after 2010.

Chapter 3: The impact of high-emission trucks on NO2: Evidence from a quasi-experiment in Beijing

3.1 Introduction

China has witnessed rapid economic development in the last two decades. It has also seen an increasingly severe pollution problem as a result of industrialization and urbanization. Seven of the ten most air-polluted cities in the world are in China (Ministry of Environmental Protection of the People's Republic of China 2013). According to the Chinese Ministry of Health, air pollution has made cancer China's leading cause of death. Many researchers have studied the effects of air pollution on public health. Infant mortality is found to be positively linked with higher pollution (Chay and Greenstone 2003). A recent study suggests air pollution contributes to 1.6 million deaths per year in China, roughly 17% of all deaths in the country (Rohde and Muller 2015).

Realizing the severity of this pollution problem, the Chinese government has taken various actions to reduce air pollution, such as promoting fuel-gas desulfurization by power plants and shutting down factories. However, new challenges have emerged with time: China has one of the fastest-growing fleets of motor vehicles in the world. The total number of vehicles increased more than tenfold in the last 15 years, reaching 300 million in 2017. Motor vehicles are becoming the primary source of air pollution in urban cities, where more than 57% of the Chinese population live (World Development Report 2016). The exponential growth in number of vehicles is particular notable in Beijing, both the capital and logistics hub of China. Emissions from motorized vehicles contribute to 40% – 70% of the city's air pollution (Clark, Shaul, and Lower 2015).

To tackle this problem, a series of policies were enacted to alleviate vehicular pollution. Driving restrictions introduced at the time of the 2008 Beijing Olympic Games created a natural experiment to study the effectiveness of these measures and have been studied extensively by many researchers. Viard and Fu (2015) investigate the impact of traffic restriction on air quality and found air pollution fell 21% during one-day-per-week restrictions. Using differences-in-differences approaches and aerosol optical depth (AOD) data, Chen et al. (2013) find atmospheric particulates dropped significantly in areas with higher road densities, and the pollution saw a 17% decrease during the Odd-Even policy. However, similar policies tend to fail in major cities of other developing countries (e.g., Mexico City by Davis (2008), Delhi by Kathuria (2002)). Both Viard and Fu (2015) and Chen et al. (2013) attribute Beijing's success to high compliance with emission control policies from an authoritarian regime.

Recent years have seen a rising popularity in environmental policy targeting vehicle pollution. However, much of the research focuses on gasoline vehicles, such as private vehicle driving restrictions (e.g., Chen, Jin, et al. 2013; Sun, Zheng, and Wang 2014; Viard and Fu 2015), or private vehicle license auction systems (e.g., Yang et al. 2014; X. Chen and Zhao 2013). With developments in technology, gasoline vehicles have significantly improved in emission control, and many countries have established strict emission standards for gasoline cars. Furthermore, the popularization of automobiles with alternative fuels might be able to provide a solution to pollution from passenger cars in the near future (Granovskii, Dincer, and Rosen 2006). Unfortunately, such technologies are less adaptive to cargo trucks due to their low energy density, range limitation, and the loss of cargo space from battery tanks. In addition to this, major technological breakthroughs are needed if alternative fuel is to displace the diesel engine (Eberhardt, 2002). Diesel would still remain the primary fuel for cargo trucks, so understanding the impact of truck-related pollution is increasingly important for better pollution management.

Among all vehicles in Beijing – non-local diesel cargo trucks have a sizeable role in traffic-related pollution. These are trucks from other provinces that are subject only to the emission standards of the province where they were registered. Some of them set Beijing as their final destination and carry food, goods, or construction material needed in the city; others are trucks that enter Beijing for its convenient connection to different national expressways (see Figure 3.1). In a recent report by a Beijing municipal environmental monitoring center, issued in September 2017, it was found that diesel cargo trucks accounted for only 4% of total vehicle fleet in Beijing, but contributed 50% of total NO_x and 90% of total PM from vehicle source. Fortunately, the Beijing government has noticed a plateau in the effect of driving restrictions on passenger vehicles and has shifted attention to truck-related pollution.

There is very limited literature on truck-traffic pollution. The majority of existing studies on truck-traffic pollution focus on the assessment of vehicle emission factors under different scenarios based on vehicle testing data (Brunekreef et al. 1997; He et al. 2020). It's challenging for researchers to make an independent estimation of heavy-duty truck pollution (Perugu, Wei, and Yao 2016). Compared with the household automobile, it's much more difficult to gather trip data from heavy-duty trucks. There are several recent studies that try to evaluate the effect of truck emissions on air pollution using event study, especially truck driver's strikes. Dantas et al. (2019) find increased ozone in a study performed for Rio de Janeiro during the 2018 truck strike. Chiquetto et al. (2021) find primary pollutants (CO and NO) decreased by 50% in roadside locations. Perugu, Wei, and Yao (2016) use an integrated data driven model and find 71% of the urban mobile-source $PM_{2.5}$ emissions are caused by trucks in the Cincinnati urban area. To my knowledge, however, there is no paper trying to quantify the impact of cargo trucks on air pollution in China.

This study uses the hourly NO_2 data across 35 monitoring stations in Beijing from April 11, 2014 to January 13, 2018. The new order issued by the Beijing municipal government on September 21, 2017 provides a quasi-experiment study case for testing the emission control policy on trucks. The new order targeted non-local China III diesel cargo trucks and updated the previous policy by extending the forbidden zone from "24 hours forbidden within 5th ring road, 6 am to midnight forbidden between 5th and 6th ring road" to "24 hours forbidden within the 6th ring road." The change occurs in the area between 5th and 6th ring road (referred to as the semi-urban area) between midnight and 6 am (referred to as truck-allowed time). NO_2 works as an excellent indicator to test the effectiveness of the policy since it is closely related to truck traffic in an urban setting. Other major pollutants such as PM, SO_2, or

CO are either greatly affected by other economic activities (power plant, industrial emission, winter heating) or gasoline vehicles.

The settings call for a differences-in-differences-in-differences model. Following the methodology of previous literature, I control for the potential confounders and test the effectiveness of the policy. The NO_2 level in Beijing is estimated to decrease by 1.26 $\mu g/m^3$ or approximately 2.6% by the new ban, and the result remains robust under different specifications and interpretations. Linking the geographic information of each monitoring station and their NO_2 readings, I find three main factors that are vital to the policy effect. Monitoring stations that have more major roads see more significant policy impact compared with stations that are less accessible to major traffic. Areas that do not have many natural resources have 2-5 times policy effect than their counterparts which are surrounded by parks and lakes. Also, areas with high building density benefit more from the policy. The finding verifies that the mechanism of the new order affecting the pollution is through reducing the truck traffic. It also suggests that increasing the green space in the city and reducing the building density could be an efficient way to reduce truck-related pollution.

This study also adds to the literature investigating the negative spill-over effect of pollution between cities. Most of the previous literature studying this topic focuses on wind and diffusion as the channels that pass on the pollution spill-over (Xiao, Brajer, and Mead 2006; Hao and Liu 2016). However, very little literature investigates exporting of pollution by cargo truck transportation. By exploiting the propensity for high compliance with Chinese policy implementation, this study discusses the effectiveness of environmental policy intervention in this new context.

The remainder of this paper is organized as follows: Section 2 describes the new order in detail as well as the Chinese emission standards. Section 3 explains the data. Section 4 outlines the main methodology of the paper and model. Section 5 presents the results. Section 6 provides a conclusion.

3.2 Background

3.2.1 Policy banning non-local diesel cargo truck in Beijing

To improve air quality, the Beijing municipal government issued a new order on September 21, 2017 (Beijing Traffic Management Bureau, 2017, No.179). The new order banned non-local diesel cargo trucks with an emission standard of "China III" in the areas within the 6th ring. This new order took a step further than the previous order issued in early 2014 which banned these high-emission trucks within 5th ring road but still allowed them between 5th and 6th ring road from midnight to 6 am. Figure 3.2 summarizes the timeline of the policy and denotes the newly updated forbidden area. According to Beijing Traffic Management Bureau's 2017 statistics, approximately 71,000 non-local diesel cargo trucks enter Beijing daily, and more than a third of these are trucks which only enter Beijing for its convenient highway connections. According to official estimates, Beijing will see a reduction of about 9,600 inbound China III cargo trucks in daily traffic volume after the order takes effect, leading to a daily reduction of 11 tons of NOx and PM. To better implement the new policy, Beijing Traffic

Management Bureau (BTMB) has released guidance to detour routes for these trucks without entering Beijing. BTMB also set up 24-hour check-points in 26 major roads and highway entrances to Beijing and implemented a truck-by-truck inspection starting on September 21, 2017. The unqualified trucks are required to leave Beijing following the detour guidance.

China issued its first emission regulations for motor vehicles in the 1990s and has released five levels of emission standards to date. The design of Chinese standards is based on European regulations. After the implementation of a new standard, sale and registration of vehicles under the old standard is banned, but already registered vehicles are still allowed on the road. Cities and regions in China may implement the released standard prior to the nationwide implementation dates or implement stricter standards with the approval from the State Council. Beijing has adopted more stringent rules on an accelerated schedule. In 2008 Beijing implemented China IV standards for light-duty vehicles to prepare for the Beijing Olympics and advanced to China V-based standards from 2013. Trucks with "China I" and "China II" standards are already banned from the city since early 2014, and Beijing has had a ban on the sale and registration of light-duty diesel vehicles since 2000. A detailed description of the Chinese emission standard and the policy timeline is depicted in Table 3.1 and Table 3.2.

According to the Ministry of Environmental Protection of the People's Republic of China (MEP) 2017 report, 62.6% of automobiles nationwide in China have achieved at least China IV. This number would be even higher in a city like Beijing.

Even without data on an exact number for the city, from the implementation date we can infer that the majority of current gasoline cars in Beijing are China IV or China V standard (purchased after 2008), which contribute 0.06–0.08 g/km NO*x*. In contrast, the China III heavy-duty truck emits 5g/km, almost 70 times that of gasoline cars. Less polluted light-duty trucks still emit 10 times the NO*x* emission. Figure 3.3 displays a summary of the total number of vehicles by type in China from the MEP 2017 report. The statistical calibration is different, but we can still conclude that heavy-duty cargo trucks affected by the new order (>3.5 ton) should be no less than 4% of the total vehicle population. In a word, the number of light-duty cargo truck is equivalent to 10% of passenger car but have 10 times the NO*x* pollution; the number of heavy-duty cargo truck is equivalent to 5% of the passenger car but generates 70 times NO*x* pollution. Thus, policy targeting China III trucks might have a significant effect in reducing NO*x* in Beijing.

3.2.2 NO_2 and truck traffic

This study focusses on NO_2 as the main pollutant of interest. NO_2 is highly toxic and hazardous on its own. Brunekreef et al. (1997) find exposure to truck traffic may result in declined lung function in children by measuring truck-traffic density, NO_2, and PM_{10} concentrations at sample schools. The vapors are a strong irritant to the pulmonary tract and can cause irritation of the eyes and throat, tightness of the chest, nausea, and headache. A large volume of epidemiological literature (for example, see Chauhan et al. (1998)) find evidence suggesting that exposure to nitrogen dioxide (NO_2) is associated with respiratory symptoms. Additionally, NO_2 has the potential to react with other atmospheric chemicals and produces a variety of environmental damages, ranging from the creation of acid rain (via formation of nitric acid), and $PM_{2.5}$ (via formation of secondary particulates such as ammonium nitrate); regional haze; eutrophication of aquatic ecosystems (via addition of excess nitrogen); and elevated O_3 concentrations (via reaction with hydrocarbons and carbon monoxide). All of these pose a great threat to public health and agriculture (Mauzerall et al. 2005).

NO_2 levels are much higher in Beijing than in other metropolitan cities. During the study period from 2014 to 2018, the average ambient NO_2 in Beijing was 48.6 $\mu g/m^3$. This is 49% higher than the average NO_2 in New York City (32.7 $\mu g/m^3$) and 90% higher than the average NO_2 in London (25.6 $\mu g/m^3$) during the same period[12]. It also was not unusual for NO_2 concentration in Beijing to reach a level that is considered unhealthy by air quality standards. For example, US Federal Standard (NAAQS) requires that 1-hour NO_2 not exceed 188 $\mu g/m^3$ and annual NO_2 not exceed 99.64 $\mu g/m^3$. More progressive states have stricter rules. China updated its ambient pollutants standard in 2016, requiring that average NO_2 not exceed 40 $\mu g/m^3$ annually, 80 $\mu g/m^3$ daily and 200 $\mu g/m^3$ hourly. During the study period in Beijing, 6% of hourly NO_2 exceeds the NAAQS 1-hour standard. 11% of daily NO_2 exceeds China's 2016 standard, and all five years of annual NO_2 exceeds China's annual standard.

Another reason that I choose NO_2 instead of other pollutants is that most of the ambient NO_2 in the urban area is attributable to vehicle emissions, thus avoiding noises

[12] The NO_2 data for NYC and London is obtained from the website of the New York City Department of Health and Mental Hygiene, and the UK Department for Environment Food & Rural Affairs.

from other pollution sources. The primary source of NO_2 in Beijing is vehicle emission, especially diesel truck emission. Lin (2005) conclude vehicle source could account for 74% of ground NO_2 emissions in Beijing whereas power plants and industrial sources could only take up 2% and 13%, respectively. Furthermore, of total NO*x* from vehicle exhaust, diesel truck accounted for nearly 70 percent, with heavy-duty trucks being the main contributors (MEP 2017). Xu et al. (2005) confirm this result and arrived at a similar estimation by using Models-3/CMAQ with the local emissions inventory to predict Beijing ground-level NO_2 concentrations. Therefore, unlike levels of other truck-traffic pollutants (such as SO_2 and PM) which can be affected greatly by activities such as power plant emission, winter heating and constructions, NO_2 can give a clear picture of air pollution from truck traffic without including too many confounders. The main target of the new policy is China III non-local cargo trucks, which generate 10-70 times more NO*x* compared with the gasoline vehicles as discussed above. Thus, NO_2 could serve as an effective indicator to reflect pollution from high-emission trucks and examine the impact of the new policy in reducing truck-traffic pollution.

3.3 Data

3.3.1 Data sources

Hourly NO_2 data in Beijing is recorded by 35 monitoring stations. The stations track down common air pollutants, namely, NO_2, CO, O_3, $PM_{2.5}$, PM_{10}, and SO_2. This pollution data has been published on a real-time basis since April 2014 by the State Environmental Protection Agency and Beijing Environmental Protection Bureau. NO_2 is measured in $\mu g/m^3$ whereas CO is measured in mg/m^3. In this paper, I exploit this relatively rich panel of pollution data and cover NO_2 observations from April 11, 2014 to January 13, 2018. The only traffic order issued in this period is the new ban in this study. The new order started on September 21, 2017, allowing a three-year pre-policy period and a five-months post-policy period.

I also incorporate a pool of GIS variables to better capture the individual characteristics of each monitoring station. Information about the density of major roads, parks and lakes, and buildings is calculated using ArcGIS software. The points of interest and road network data were collected and organized by Jin et al. (2017) and have been made available by the Beijing City Lab (BCL) upon the authors' permission. BCL is an urban research association that unites researchers from all disciplines to discuss methods to quantify urban dynamics and new insights for sustainable urban development. Figure 3.4 shows the locations of all the monitoring stations. These stations are distributed evenly in all 16 county-level divisions (districts).

The control variables include hourly weather data such as temperature, humidity, wind speed, wind direction, visibility, precipitation, and cloud coverage, as well as meteorological events such as the presence of snow, rain, and thunderstorm. This data is taken from the China Meteorological Data Sharing Service System. Temperature is measured at a 2-meter height above the earth's surface (degrees Celsius). Wind speed is expressed as mean wind speed at the height of 10-12 meters above the earth's surface over the 10-minute period immediately preceding the observation (meters per second). Humidity reports relative humidity (%) at the height of 2 meters above the earth's surface. Precipitation measures the millimeters of raindrop at the hour. This paper also used dummies such as hour, day of the week, week of the year, and month to control for time trend.

3.3.2 Summary statistics

Table 3.3 shows a summary of main variables by whether the new ban has been issued. The maximum number of potential observations for the study period is 1,160,880, and all variables have more than 90% of full observations, generating a pretty complete data set and strongly balanced panel data. Turning to the implementation of the new order, the average NO_2 of Beijing has seen a drop since the ban of non-local China III trucks. Since the post-policy data covers from September 2017 to January 2018, the weather variables are significantly different and display the characteristics of winter Beijing, which is very cold and dry. Thus, it is very necessary to control for these weather conditions when studying the effect of the policy. Otherwise, the change in NO_2 could be overly attributed to the policy and ignore the contribution of the change in weather.

In Table 3.4, I summerize the data by location in three categories: within the 5^{th} ring road (urban area), between 5^{th} and 6^{th} ring road (semi-urban), and outside 6^{th} ring road (rural Beijing). The new policy only affected the second category (5-6^{th} ring road). The NO_2 pollution varies significantly according to the location of the monitoring stations because of the difference in traffic patterns and geographic features. Monitoring stations in the urban area (<5^{th} ring) are exposed to the highest NO_2 pollution, 26% higher than NO_2 of stations in the semi-urban area (5-6^{th} ring). The latter is around the average NO_2 across all stations but 38% more polluted than the rural area.

Truck-banned time (6 am to midnight) has lower NO_2 level than truck-allowed time (midnight to 6 am), which indicates the potential pollution problem of truck traffic. After the policy was implemented, in all locations the gap in NO_2 level between truck-allowed time and truck-banned time narrowed. Monitoring stations between the 5th and 6th rings experienced the largest reduction in the gap after policy implementation by approximately 2.2 $\mu g/m^3$.

Figure 3.5 depicts the daily pattern of NO_2 level across monitoring stations. The statistics are calculated by averaging NO_2 data for each hour. Most of the stations share a similar underlying pattern, with a morning spike occurring around 6-9 am, followed by a significant drop in the early afternoon around 3 pm, and then increasing gradually until the end of the day. The NO_2 variation throughout the day coincides with the traffic pattern, as expected. Despite these similarities, the NO_2 pattern still varies significantly across monitoring stations. Some stations have relatively constant NO_2 levels across the day (e.g. No.27, which is located in the Beijing Botanical Garden) and some have very clear morning and evening spike (e.g. No.3, which is located in urban Beijing right off the South 3rd ring road, a major commuter highway for city dwellers). Thus, it is important to consider the monitor-level characteristics when estimating the policy effect. Figure 3.5 also shows graphical evidence that NO_2 is a relatively short-lived GHG on ground level with sizeable daily variation and is sensitive to the local environment and traffic pattern. Compared with the local environment, the spill-over pollution between urban, semi-urban, and rural area should be negligible, and not be able to bias the estimation.

3.4 Empirical strategy

3.4.1 Differences-in-differences-in-differences

The purpose of this study is to estimate the effect of the new ban aiming to limit NO_2 levels. The change with this new order was to extend the all-day forbidden zone in the urban area (within the 5th ring road) to include the semi-urban area (between the 5th and 6th ring roads). Before the new ban, China III cargo trucks were allowed to enter Beijing only at nighttime (from midnight to 6 am, truck-allowed time) and unload at warehouses in the semi-urban area. These trucks were always banned during the daytime. After the new order, these trucks were banned from entering the semi-urban area throughout daytime hours. Thus, the most significant effect of the new order on reducing NO_2 level should only occur during the previously truck-allowed time (treatment hours) on the monitoring stations located in the semi-urban area (5th to the 6th ring road, treatment stations), after the new ban was implemented (treatment date). This setting calls for the "difference-in-difference-in-differences" (DDD) model.

The triple difference model is based on the traditional "difference-in-differences" model, which is popular in policy evaluation. It usually has two dimensions: whether the observation is from the treatment group and whether the data is from the post-policy period. The fundamental principle of the DiD model is that it calculates change before and after policy implementation for each group to get their time trend effects (first difference) and then it compares the two time trend effects. The difference of these two time trends between treatment group and control group (the second difference) is the policy effect. This helps get rid of time-varying confounders and reveal the actual policy effect.

The triple difference model takes a step beyond the "difference-in-differences" model because it adds a third dimension that can better control for the cofounders and underlying trend (Angrist and Pischke 2009; Currie et al. 2009; Nguyen 2013). The triple difference model follows a similar principle to the DiD model. It starts with a binary treatment or policy dummy to indicate the implementation of a policy, then adds two other dimensions, each of which relates to two different groups where only one group is targeted by the policy. Thus, the effect is identified by the interaction of each of the three indicator variables, which has the interpretation of a triple differencing (Flores-Lagunes and Timko 2015).

The three dimensions in my study are: whether the readings are from the monitoring stations that are located in the new forbidden zone (5^{th}-6^{th} ring road); whether the NO_2 is observed after the new order came into effect (starting September 21, 2017); and whether the NO_2 reading is observed during truck-allowed time. One might think it is sufficient to use a DiD model and examine the policy by looking at monitoring stations in the new forbidden zone in the post-policy period. However, ignoring the truck-allowed dimension might lead to an inaccurate estimation of policy effect. For instance, since the post-policy data falls mostly in fall and winter, it is very possible that there would be less road construction and repair work during this period because of the inclement winter weather in Beijing. Moreover, most of the construction and repair work occurs at midnight, which overlaps with the truck-allowed time.

Without controlling for truck-allowed time and post-policy period, we may wrongly attribute the decline in NO_2 to the policy when it may be from the reduction in construction activity.

3.4.2 Model

To include all potentially confounding influences, I employ a triple difference model:

$$NO_{2_{isjt}} = \beta_0 + \beta\,(new\ order)_{sjt} + \gamma_{sj} + \delta_{st} + \pi_{jt} + \tau_s + \omega_j + \mu_{dow\cdot hr} + \tau_{yr\cdot m} + X'_{isjt}\phi + \alpha_{it} + \epsilon_{isjt} \tag{3.1}$$

The rich specification of the triple difference model enables me to control for a variety of unobserved factors that may be simultaneously related to the introduction of the policy. In my model, *s* denotes the new forbidden zone updated by the recent policy (semi-urban Beijing, the area between 5th and 6th ring). j denotes the truck-allowed hours (midnight to 6 am). t denotes the policy implementation period. γ_{sj} is the interaction between the new forbidden zone and the truck-allowed time. It controls for systematic impact on NO_2 level in semi-urban area (between 5th and 6th ring road) during truck-allowed time (midnight to 6 am) that does not vary with the policy implementation. δ_{st} is the interaction between new forbidden zone and the post-policy period. It controls for the common trend for NO_2 level in the semi-urban area before and after the policy. For instance, the inclement weather in post-policy period (Sept 17 to Jan 18) might cause commuters who reside in semi-urban area to drive more often to their workplace in the urban area, rather than take public transportation. π_{jt}

represents the interaction between post-policy period and truck-allowed hours. It controls for the simultaneous change in NO_2 level between midnight and 6 am after the policy implementation across all locations (e.g., a halt of road repair work during the night due to inclement weather). Including these extensive set of interactions in my specification rule out possible unobserved factors that would confound the causal effect of interest. Finally, the interaction of all three dimensions $(new\ order)_{sjt}$ is the interest of the study. It equals 1 when the observation is from a monitoring station that is located in the new forbidden zone, during truck-allowed time, after the policy implementation. The coefficient of this variable indicates the real policy effect.

I also control for the general time trend by including the interaction between day of the week and hour of the day, month of the year and the year dummy. These can help me characterize the general daily traffic pattern and common trend. X'_{isjt} includes a variety of weather variables such as temperature, humidity, wind speed, wind direction, visibility, precipitation, and cloud coverage, as well as meteorological events. I also include interaction between station and time trend to specify the heterogeneity on monitor-level traffic pattern.

The identification assumption underlying the triple difference model is that there is no systematic shock on the NO_2 level besides the new order that affects monitoring stations located between 5^{th} and 6^{th} ring from midnight to 6 am after the implementation of the new policy. I examine the traffic policies and updates issued by Beijing government and did not find other policies or shocks.

3.5 Results

3.5.1 Main results

Table 3.5 reports the estimation results of various specifications using the triple difference model. In all equations the standard errors are clustered by ring road and station to deal with the heteroscedasticity. Column 1 and column 2 do not include station-specific time trend. However, in column 2 I include the interaction between the treated area (semi-urban, between 5^{th} and 6^{th} ring road) and time trend dummies to allow for ring-specific time trend. Column 3 is the most comprehensive and controls for station-specific time trend by including the interaction between station dummies and time dummies. Column 4 excludes the upper and lower 5% extreme NO_2 reading.

In all specifications, the policy on banning non-local China III cargo truck reduces the NO_2 level significantly. Column 4 has the most complete specification which I use as the baseline. The result gives a coefficient of -1.26, indicating that the policy could effectively reduce the NO_2 level by 1.26 μg/ m^3. Recalling from the summary statistics, the mean NO_2 level of the treated area is 48.95 μg/m^3. The policy results in a reduction of 2.6%. This number might not seem very impressive at first, but this is because the current policy is only affecting a subset of all high-emission trucks in Beijing. It is only considered the first phase of a series of policies targeting truck pollution. According to official estimation, 9,600 inbound cargo trucks would be affected by this phase I order, only 13.5% of all inbound trucks that are potential policy targets. Furthermore, local China III heavy-duty trucks (registered in Beijing) are not regulated in this 2017 order but will be banned in the follow-up phase II order to be issued in 2019. Thus, revisiting the fact that vehicle source accounts for 74% of Beijing NO_2 (Chan and Yao 2008); diesel cargo trucks account for 70% of the total NO*x* from vehicle exhausts; and the policy in question targets less than 13.5% of all diesel trucks (MEP 2017); a reduction of 2.6% is reasonable in magnitude. Considering the success of phase I, further reductions in truck pollution should be expected as policies proceed in Beijing.

The inclusion of treated-area / station-specific time trends to the model in column 2 and 3 serves as a check for the most critical triple difference identification. Under the assumption of the triple difference model, the stations would follow a common time trend without the introduction of the ban. While it's unlikely that stations would follow the exact same pattern, if their time trend patterns diverge greatly from one another, the treatment effect estimation would be biased. When this happens, the policy dummy would absorb the differences between underlying time trends. Angrist and Pischke (2009) note that estimation is more robust and convincing with state-specific trends. They cite a labor market study by Besley and Burgess (2004) as a precautionary example. From my result, we can see the significance and magnitude of the new ban are similar with or without station-specific time trend comparing column 1, 2 and column 3. As such, I can be more confident in saying that our specification is reliable and the result is robust. In column 4, I exclude NO_2 levels that lie outside the 5% and 95% percentile. Such extreme values might result from an unexpectedly severe traffic jam near the monitoring station and may bias the estimation. As is shown in the table above, exclusion of such extreme NO_2 levels generates an even higher policy effect.

Besides policy, weather conditions also exhibit a significant impact on the NO_2 level. Wind speed is the most potent factor. Increasing wind speed by 1 m/s could help decrease NO_2 level by 5.32 $\mu g/m^3$, an almost 11% decrease from the mean NO_2 level. Since pollutants are naturally trapped within the city due to Beijing's unique geographical characteristics, it is reasonable that wind would play such a significant role in NO_2 dispersion. An increase by 1 percentage point of relative humidity can decrease the NO_2 concentration by 0.06 $\mu g/m^3$. However, this effect is not significant. On the other hand, precipitation can reduce NO_2 level significantly. This might be due to the fact that water can react with NO_2 to form nitric acid (Baukal 2005). The NO_2 level is also negatively correlated with temperature, since as the weather gets colder one would expect residents to drive more, increasing NO_2 pollution. 1 Celsius degree drop in temperature increases NO_2 level by 0.3 $\mu g/m^3$. Following this logic, we can explain the negative relationship between visibility and NO_2 level. When the sight distance is low, drivers might turn to alternative transportation such as subway.

The coefficients on the double interactions conform to the expectation. The coefficient on the truck-allowed * post-policy interaction can be interpreted as the systematic shock to NO_2 level between midnight and 6 am after the implementation of the policy. The negative coefficient could indicate the reduced activities of road repair and construction work that often occur at midnight. This would be due to the inclement winter weather in the post-policy period. The positive coefficient on new forbidden * post-policy term can be interpreted as people living in this area (semi-urban, housing many commuters) tending to drive more. Again, cold weather would likely cause this preference for driving over public transportation. The new forbidden * truck-allowed interaction controls for the confounders that affect semi-urban area and hours between midnight and 6 am simultaneously with or without the introduction of the new ban. The negative coefficient on this term could indicate the total traffic in the semi-urban area, including both trucks and private vehicles, is less busy during midnight. This is consistent with the fact that the semi-urban area is highly residential – there would be fewer activities there during that time slot.

3.5.2 Robustness checks

To further validate the result, I conduct more tests based on the baseline model, column 3 in Table 3.6 with state-specific time trend. In column 1, I exclude the monitoring stations that locate in rural Beijing (outside 6th ring road). After the Beijing government issued the new policy banning non-local China III cargo trucks between 5^{th} and 6^{th} ring road, they also released a guide to direct those trucks taking alternative detour routes. Some of these detour routes include highways located outside the 6^{th} ring of Beijing and some direct the cargo drivers to highways in the peripheral cities. Thus, it is not clear whether the rural area of Beijing will be more polluted due to the substitution effect or less polluted if cargo drivers do not enter Beijing at all. If either situation happens, the assumption of the triple difference model would be violated since I treat both urban area and rural area as the control group for the semi-urban treated group. To account for either situation, I rerun the model on monitoring stations that are only located within the 6^{th} ring. As is shown in column 1, the NO_2 reduction is more substantial than the baseline level at -1.27 and is significant. This confirms the result is robust, but might also indicate a possible spill-over policy effect on rural Beijing (outside 6^{th} ring). I conduct a test on the monitoring stations located in rural Beijing (outside 6^{th} ring road) and use the same triple difference model to compare it with the urban area which is safely unaffected by the new order (within 5^{th} ring road). In this test, the real treated area (5^{th} to 6^{th} ring) is excluded. As shown in column 2, there is no evidence that the rural area experienced a significant policy effect. Therefore, we can think of the rural Beijing area as a non-treated group, as previously specified, and there is not enough spillover effect to bias the estimation. I also conduct two further pseudo-policy checks on the rural area (outer 6^{th} ring) and urban area (within the 5^{th} ring). For column 3, I take stations in a rural area only and regress the NO_2 level on all fixed effects, time trend, and weather controls as the previous model specified. In addition, I include a pseudo-policy dummy and its interaction with truck-allowed time. The coefficient of the interaction indicates whether the stations in this ring were affected by this policy. As is shown in column 3 and 4, neither stations in rural nor urban areas display significant policy effect. This further suggests our triple difference assumption is held.

3.5.3 Factors on the effectiveness of the new traffic ban

I utilize geographic information to gain further insight into potential mechanisms for the new policy. Ground-level NO_2 is regional and deposited within a few kilometers of its release (Ho et al. 2006). Since the policy targeted non-local China III cargo trucks, we should expect the monitoring stations that are in areas with more highway traffic to see a more significant reduction. Many papers have exploited the variation of influence from pollution sources to each monitoring station (Hanna and Oliva 2015; Viard and Fu 2015; J. M. Currie and Walker 2009). I calculate the major motorway length within a 1 km and 2 km buffer of each monitoring station using

ArcMap (Figure 3.6). The major motorway is defined as all the highways, ring roads, and primary city roads. I then divide all the stations into two categories compared with the city average. The result is shown above in column 1 and 2 in Table 3.7. We can see that for stations that have more highway in the 2 km buffer, the policy can efficiently reduce 1.33μg/ m^3. This is larger than the baseline model in the main result. For the group that is less accessible to the major motorways, the policy effect is less in magnitude and not significant at both a 1 km and 2 km buffer.

Next, I do a similar calculation to construct a indicator of nature site availability. Here I use the total area of natural land within 1 km or 2 km radius of each monitoring station. I divide the stations into two categories comparing the average nature coverage across all stations. As is shown in column 3 and 4, the policy effect for less nature areas is 30–40% higher in magnitude and more significant compared with the baseline model, and 2-5 times more than areas surrounded by lakes and parks. Places rich in nature sites have seen less policy benefit and the effect is not significant. This is possibly because areas with greenery and water are effective at removing pollutants naturally, leaving less to show for the policy effect.

I also test for how the policy effect would react to the building densities. It is possible that buildings may block the diffusion of NO_2, exacerbating the pollution caused by traffic (Chan and Yao 2008). I calculate the total building area within a 1 km and 2 km radius of each monitoring station. The result in column 5 and 6 shows that the policy is very effective in areas with high building density in the 2 km radius. This confirms the theory that building-intensive areas tend to block the NO_2 from spreading out and suffer from an accumulation of pollutants. Because they see the same amount of traffic, the policy targeting NO_2 reduction would show a larger effect. This result is also meaningful because areas with more buildings have a larger population density (residence or indoors/outdoors activities). This indicates more people would be able to benefit from this policy.

3.6 Conclusion

In this paper, I study the effect of a new order issued by the Beijing government on NO_2 levels using hourly NO_2 readings from 35 monitoring stations. The new order put a ban on the non-local China III cargo trucks between the 5^{th} and 6^{th} ring roads. NO_2 works as an excellent indicator to test the policy since it is closely related to truck traffic in an urban setting. A differences-in-differences-in-differences model is carefully adopted to control for the potential confounders and test the effectiveness of the policy. The NO_2 level in Beijing is estimated to be reduced by 1.26 $\mu g/m^3$ or approximately 2.6% by the new ban, and the result remains robust under different specifications and interpretations. Given the scale of target affected by this phase I policy, the result is optimistic. The effectiveness of this phase I policy lays the foundation for future policies from the Beijing government regulating truck pollution. The policy effect of the subsequent policies on this matter and how the policy effects differ and affect each other is subject to future study.

By exploiting the rich geographic information available, I find two main factors that are vital to the policy effect. Monitoring stations that have more major motorways show significant policy impact compared with stations that are less accessible to major traffic. Areas that lack nature sites have seen triple the policy effect of their counterparts surrounded by parks and lakes. Areas with more building density can benefit more from the policy as well. The first finding reaffirms the mechanism the policy takes effect through is the reduction of truck traffic. The second and third findings call for more attention to the importance of green space in city planning.

This study adds to the literature that examines driving restriction policies as well as those that look at the effectiveness of emission control. One takeaway from this study is that synergistic efforts in pollution management will become increasingly critical as transportation systems, economic activities, and residential life are further integrated. For major cities like Beijing and Shanghai, it is no longer viable to limit their focus to economic development. Pollution inequality is as important as economic inequality. More collaboration between cities is needed, and methods to quantify and minimize the pollution spill-over calls for future research.

Figure 3.1: China national expressway system

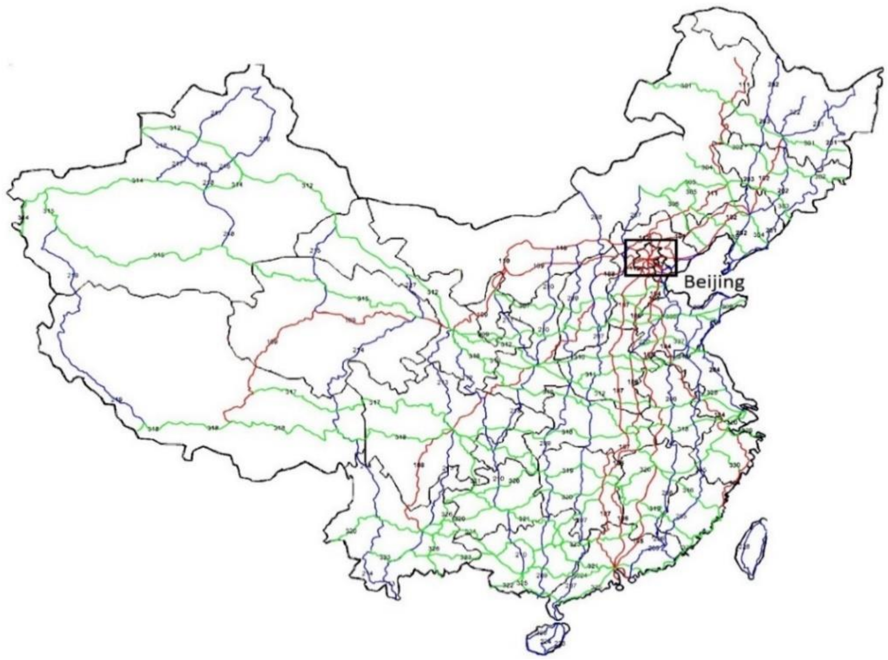


Figure 3.2: Summarization of the new order

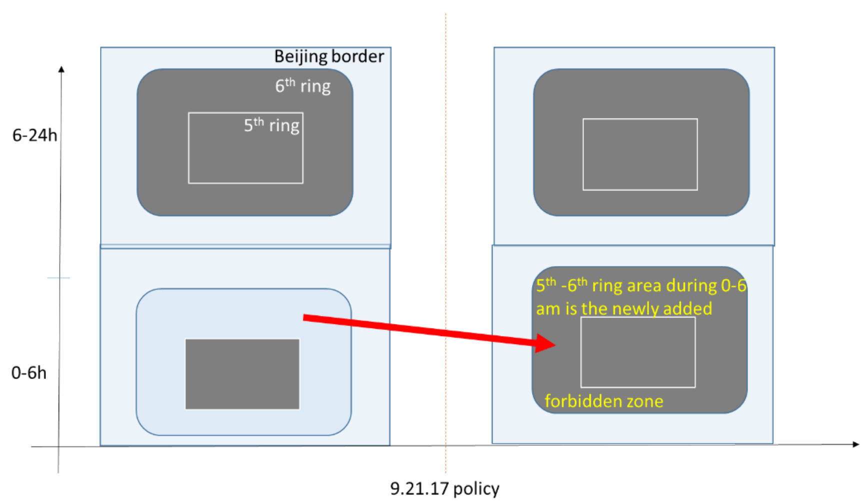


Figure 3.3: Composition of vehicles by type in China

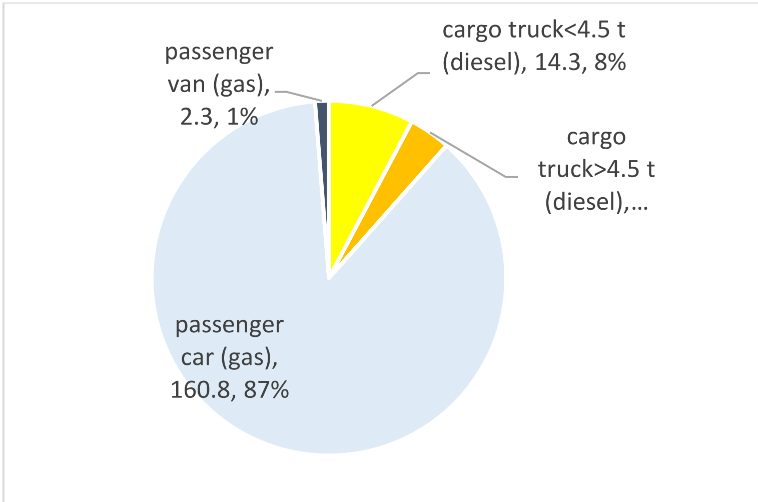
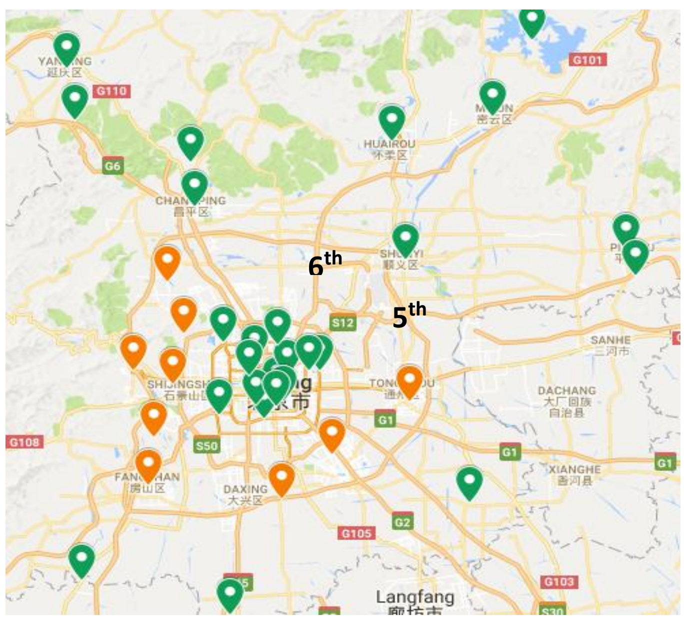


Figure 3.4: Distribution of monitoring stations



Notes: Fig.4. shows the distribution of Beijing 35 monitoring stations from 2014 to 2018. The stations colored in orange are located between 5th ring road and 6th ring road.

Figure 3.5: Hourly NO_2 pattern for all 35 monitoring stations in Beijing

Figure 3.6: Illustration of a monitoring station with 1 and 2 km buffers

Notes: The red line indicates the major motorway. Orange shaded areas indicated buildings and the green area represents natural sites such as parks and lakes. The blue star represents the location of the monitoring station.

Table 3.1: Emission standards on NO*x* for vehicles

Stage	NO*x* (g/km)		
	gasoline vehicle	light-duty truck	heavy-duty truck
China III	0.15	**0.5-0.78**	**5**
China IV	0.08	0.25-0.39	3.5
China V	**0.06**	0.18-0.28	2

Notes: Both light-duty truck and heavy-duty truck in the table above use diesel as fuel. Light-duty truck refers to cargo truck with a reference mass smaller than or equal to 3.5 ton, whereas heavy-duty truck has a reference mass greater than 3.5 ton. Gasoline vehicle includes passenger car and gasoline minivan.

Table 3.2: Emission standard implementation date comparison

standard	gasoline and light-duty truck		heavy-duty truck	
	nationwide	Beijing	nationwide	Beijing
China III	2007.07	2005.12	2008.01	2006.01
China IV	2011.07/ 2015.01	2008.03	2015.01	2011.01
China V	2018.01	2013.02	2017.07	2015.06

Table 3.3: Pre-policy and post-policy summary

Variable	all	pre-policy	post-policy	Obs
NO_2	48.6	48.77	46.71	1,069,466
T	14.51	15.3	5.89	1,134,380
Po	757.99	757.41	764.21	1,134,380
humidity	52.05	52.48	47.35	1,134,380
visibility	11.5	11.2	14.74	1,134,380
windspeed	2.15	2.16	1.95	1,134,380
precipitation	0.21	0.22	0.08	1,134,380

Table 3.4: Location and policy summary for NO_2

	pre-policy			post-policy		
NO_2	<5th ring	5th-6th ring	>6th ring	<5th ring	5th-6th ring	>6th ring
truck-banned	53.10	44.10	36.17	53.84	47.23	38.06
truck-allowed	58.87	50.89	39.31	58.47	51.87	39.67

Table 3.5: The effect of truck ban on NO_2

	(1)	(2)	(3)	(4)
truck-allowed * post policy * new forbidden	-1.23*	-1.02*	-1.26**	-1.53**
	(-2.64)	(-2.77)	(-4.53)	(-4.3)
new forbidden * truck-allowed	1.95	1.93	-11.93***	-14.3***
	(1.68)	(1.65)	(-226.56)	(-82.62)
new forbidden * post policy	4.22	12.64***	12.09***	9.05***
	(2.19)	(26.84)	(29.49)	(19.55)
truck-allowed * post policy	-1.58**	-1.81***	-1.66**	-1.4**
	(-4.45)	(-10.2)	(-7.87)	(-4.97)
T	-0.29*	-0.28*	-0.3*	-0.26**
	(-3.72)	(-3.67)	(-3.8)	(-3.16)
Po	-0.82**	-0.82**	-0.8**	-0.5*
	(-7.34)	(-7.28)	(-7.06)	(-13.74)
humidity	-0.06	-0.06	-0.06	-0.11
	(-1.38)	(-1.36)	(-1.42)	(-2.34)
visibility	-1.06**	-1.06**	-1.06**	-0.99**
	(-5.51)	(-5.5)	(-5.53)	(-6.81)
wind speed	-5.29*	-5.29*	-5.32*	-4.8*
	(-4.04)	(-4.04)	(-4.05)	(-4.34)
precipitation	-0.46**	-0.46**	-0.46**	-0.44**
	(-7.98)	(-7.93)	(-7.87)	(-38.51)
monitor-level fixed effect	NO	NO	YES	YES
treatment*time trend	NO	YES	YES	YES
station*time trend	NO	NO	YES	YES
N	1060878	1060878	1060878	954987

Notes: This table provides OLS estimates of the effect of the new ban on NO_2. In all columns the coefficient of interest is the interaction between the new forbidden zone, truck-allowed time, and post-policy period. Columns 1 and 2 do not include monitor-level fixed effects. Columns 3 and 4 include monitor-level fixed effects and column 4 excludes extreme 5% of NO_2 readings. In all estimations, I control for weather fixed effects and time trend fixed effects. Standard errors are clustered by station and by area (urban, semi-urban, or rural). t statistics in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 3.6: Result of robustness checks

	exclude rural (1)	exclude semi-urban (2)	only rural (3)	only urban (4)
policy	-1.27**	-0.08	-1.93	-2.68
	(-30.08)	(-5.99)	(-1.76)	(-1.81)
T	-0.36**	-0.27	-0.13	-0.35
	(-36.39)	(-2.25)	(-1.16)	(-2.31)
Po	-0.91*	-0.8	-0.63**	-0.97*
	(-11.22)	(-4.49)	(-9.37)	(-10.57)
humidity	-0.11*	-0.05	0.02	-0.12
	(-5.91)	(-0.79)	(0.41)	(-2.38)
visibility	-1.25**	-1.03	-0.74**	-1.32**
	(-14.38)	(-3.52)	(-17.18)	(-20.21)
windspeed	-6.59*	-5.12	-3.09**	-7.09**
	(-11.14)	(-2.55)	(-19.92)	(-23.88)
precipitation	-0.52**	-0.45	-0.36*	-0.54
	(-28.09)	(-5.05)	(-6.39)	(-3.44)
N	666357	788874	394521	394353

Notes: This table provides OLS estimates of the effect of the new ban on NO_2. In all columns the coefficient of interest is the policy variable. For column 1 and 2, the policy variable is the interaction between the new forbidden zone, truck-allowed time and post-policy period, as specified in the baseline model. In column 3 and 4, the policy variable is the interaction between truck-allowed time and the post-policy period. All estimations include monitor-level fixed effects, weather fixed effects, and time trend fixed effects. Standard errors are clustered by station and by area (urban, semi-urban or rural) for column 1 and 2 and by station for column 3 and 4. t statistics in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 3.7: Factors on effectiveness of the policy

	Road length		Nature area		Building area	
	more road	less road	more nature	less nature	more buildings	less buildings
	(1)	(2)	(3)	(4)	(5)	(6)
1 km buffer	-1.13**	-1.04	0.23	-1.62**	-1.39	-1.11
	(-8.25)	(-1.26)	(0.27)	(-9.43)	(-1.6)	(-1.97)
2 km buffer	-1.33**	-1.15	-0.64	-1.49*	-1.75**	-1.14
	(-5.7)	(-1.63)	(-1.24)	(-3.39)	(-50.31)	(-2.73)

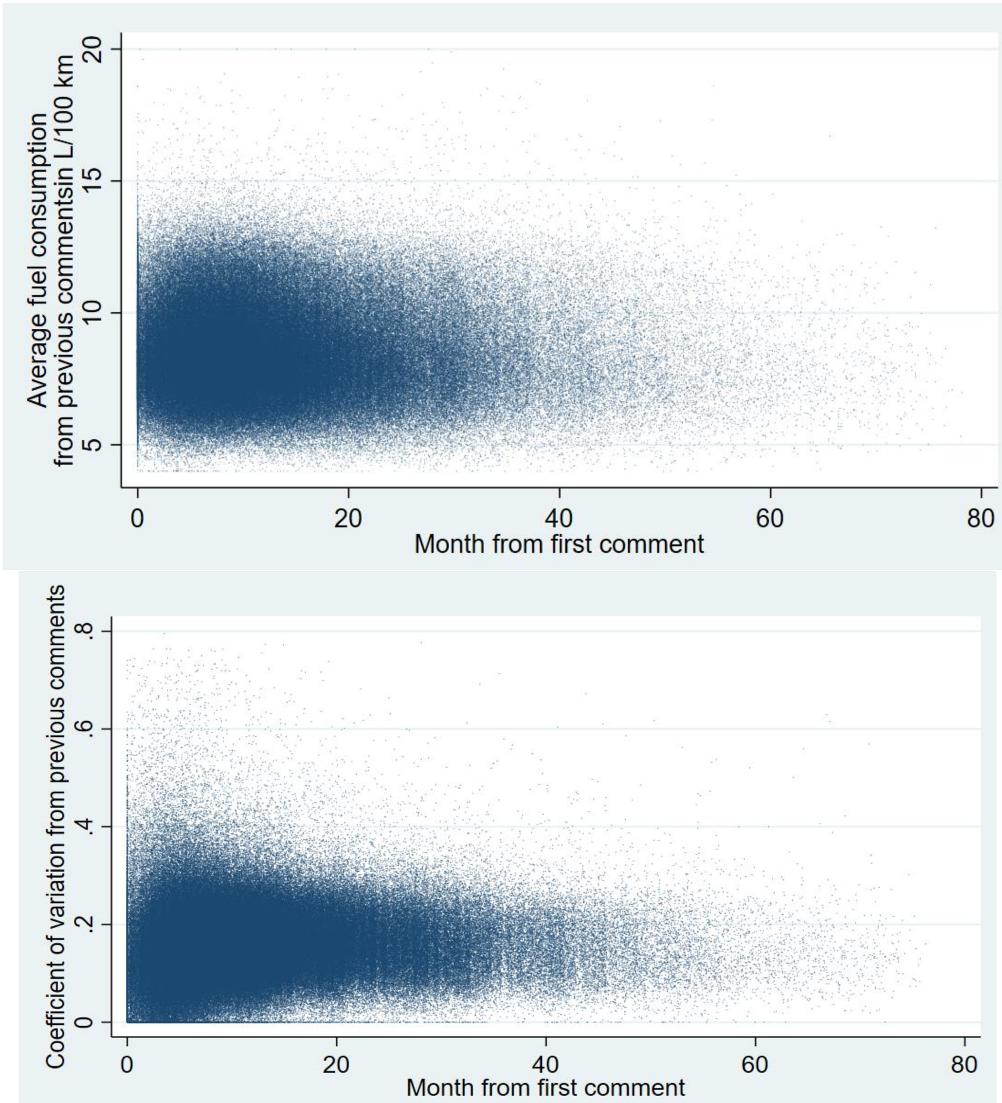
Notes: This table provides OLS estimates of the effect of the new ban on NO_2 in different scenarios. In all columns the result shown is the coefficient of the policy effect. The road length, nature area and building area are calculated in a 1 km radius and 2 km radius for each monitoring station. All estimations include monitor-level fixed effects, weather fixed effects, and time trend fixed effects. Standard errors are clustered by station and by area (urban, semi-urban or rural) for column 1 and 2 and by station for column 3 and 4. t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Appendix A: Appendix for Chapter 1

Figure A.1: Fuel consumption rate label

Source: **https://finance.sina.com.cn/**

Figure A.2: Trend of the coefficient of variation and average fuel consumption rate from previous comments



Notes: This figure plots average fuel consumption rates and coefficient of variation from previous comments and shows how they change over time. X-axis denotes the months since the first comment of the same sub-model.

Table A.1: List of premium features included in fixed effects

List of premium features	
360-degree camera system	Navigation system
Adaptive headlights	Power folding mirrors
Anti-lock brakes (ABS)	Rain detecting wiper
Auto-dimming mirrors	Rear AC
Backing assistance	Rear entertainment systems
Blind spot monitoring	Rear glass wiper
Bluetooth system	Remote start
Brake Assist	Remote start system
Child safety locks	Seat adjustment
Climate control	Seat back beverage holder
Cruise control	Seat material
Driver auto dimming	Side airbags
Electric power steering	Sound enhancement
Electronic stability/skid-control system	Speaker system
Fold-down back Seat	Steering wheel material
Gas tank size	Sunroof
Heated front seats	Trip computer
Heated side mirrors	Turn signal indicator
Hill start/descent assist	Type of headlight
Keyless Entry	Ventilated front seats
Lane keeping assist	Wheel material
LCD monitor	Wheelbase

Table A.2: Parameters for estimating AVKT using Ou et al., (2019)

Parameters		Coefficients
Intercept		7.478*
Age (by month)		0.834*
Geographical area		−0.062*
	North China	−0.065*
	South China	0.051*
	Central China	−0.059*
	Northeast China	−0.001
	East China	−0.040*
Price range	50–80,000 RMB	0.121*
	80–100,000 RMB	0.208*
	100–150,000 RMB	0.213*
	150–200,000 RMB	0.269*
	200–250,000 RMB	0.337*
	250–350,000 RMB	0.362*
	> 350,000 RMB	0.457*
Vehicle type	MPV	0.171*
	SUV	0.061*
	Crossover	0.132*

Table A.3: Average AVKT by vehicle age

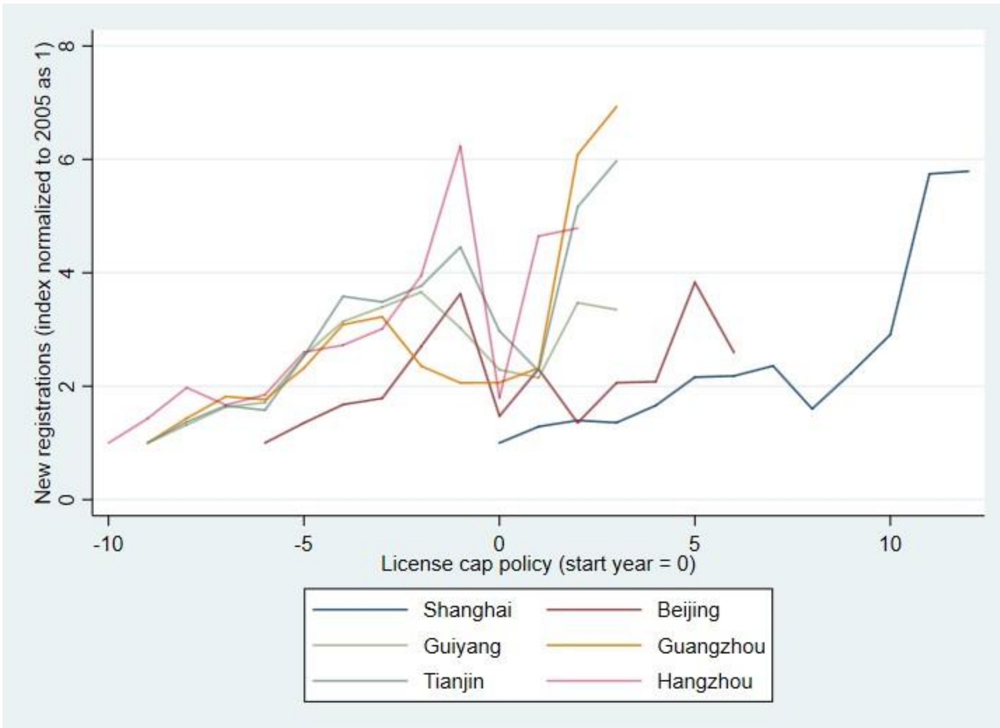
Vehicle age	Average AVKT
1	17081
2	13368
3	12251
4	11578
5	11102
6	10737
7	10443
8	10197
9	9987
10	9804
11	9643
12	9498
13	9367
14	9248
15	9139
16	9039
17	8945
18	8858
19	8777
20	8700
21	8628
22	8561
23	8496
24	8435
25	8377

Table A.4: Survival rate assumption

Vehicle age	Leard et al. (2017)	Busse et al. (2013)
1	0.9972	0.9900
2	0.9944	0.9831
3	0.9897	0.9731
4	0.9823	0.9593
5	0.9714	0.9413
6	0.9564	0.9188
7	0.9367	0.8918
8	0.9122	0.8604
9	0.8828	0.8252
10	0.8488	0.7866
11	0.8168	0.717
12	0.7650	0.6125
13	0.7093	0.5094
14	0.6515	0.4142
15	0.5932	0.3308
16	0.5357	0.2604
17	0.4804	0.2028
18	0.4280	0.1565
19	0.3791	0.1200
20	0.3341	0.0916
21	0.2931	0.0696
22	0.2562	0.0527
23	0.2231	0.0399
24	0.1938	0.0301
25	0.1679	0.0227

Appendix B: Appendix for Chapter 2

Figure B.1: New registrations growth for cities with license cap policy



Notes: This figure plots growth in new registrations for cities with a license cap policy. On y-axis, New registrations are expressed as an index relative to the city's 2005 level. On x-axis, we normalize time to zero in the year that the license cap policy starts. For instance, Beijing's lottery started in 2011. In this chart, we put the 2011 registration data for Beijing at t = 0 and 2012 data at t = 1, and so on.

Table B.1: Summary Statistics by initial income quantiles

Quantiles of 2005 income (1st is lowest quantile)	1st	2nd	3rd	4th	5th
New car sold	19.1	21.6	23.4	37.8	88.5
	(20.6)	(30.4)	(28.4)	(61.5)	(100.5)
New car expenditure	2.5	2.9	3.2	5.7	15.2
	(2.5)	(3.9)	(3.6)	(9.2)	(18.0)
Average car price	142.6	145.4	149.6	155.6	172.2
	(22.4)	(23.3)	(25.0)	(25.3)	(28.0)
Income	33.0	37.5	39.0	43.2	54.4
	(13.1)	(13.8)	(13.6)	(14.3)	(17.9)
Built-up area	63.7	67.4	71.8	135.5	269.5
	(33.4)	(57.3)	(44.1)	(159.4)	(274.3)
Area of paved roads	8.1	8.6	9.6	16.4	37.1
	(5.5)	(9.2)	(7.4)	(21.0)	(34.3)
Population	4821.6	3899.1	4229.7	4306.4	4517.2
	(2776.8)	(2203.5)	(2106.8)	(4523.9)	(3181.4)
Bus	0.4	0.5	0.6	1.4	3.7
	(0.4)	(0.7)	(0.5)	(1.9)	(5.2)
Taxi	1.5	1.7	1.6	3.3	7.3
	(1.0)	(2.3)	(1.6)	(3.8)	(11.6)
Total retail	39.0	37.9	45.2	74.6	170.0
	(30.1)	(37.6)	(37.9)	(100.2)	(189.5)
Employment ratio in education (2004)	4.5	3.9	4.6	4.9	6.3
	(2.4)	(2.4)	(4.3)	(4.7)	(6.7)
National high-tech export	3786.0	3786.0	3786.0	3786.0	3786.0
	(590.5)	(590.5)	(590.5)	(590.5)	(590.5)

Notes: The table shows the mean value for each variable and standard deviation in parentheses. The data contain 3,627 observations. New car expenditures equal the total expenditure on new cars. CV is the coefficient of variation. All expenditure variables (New car expenditure, Total retail, and National high-tech export) are reported in billion RMB. The weighted average of vehicle price and income are expressed in thousand RMB. Built area is the area of land constructed for residential, commercial, or industrial use. Both built-up area and area of paved roads are in square kilometer. New car sold, population, bus and taxi are expressed in thousand unit. Bus and taxi are the numbers of bus and taxis operating in the city. The employment ratio is expressed in percentage points. All monetary variables are adjusted for inflation and measured in 2017 RMB.

Table B.2: Impact of income on vehicle attributes

Dependent variable is	(1) Log avg engine size	(2) Log avg fuel consumption	(3) Log avg horsepower	(4) Log avg gross weight
Log income	0.17	0.13	0.18	0.07
	(0.05)	(0.04)	(0.05)	(0.03)
Observations	3,627	3,627	3,627	3,627
Effective F stat for IV	83.33	83.33	83.33	83.33
Kleibergen-Paap stat	44.95	44.95	44.95	44.95
Underidentification p val	0.00	0.00	0.00	0.00
First stage IV	2.29	2.29	2.29	2.29
	(0.25)	(0.25)	(0.25)	(0.25)

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. Column headings state the dependent variable. All regressions include city fixed effects, year fixed effects, and province-year interactions.

Table B.3: Adding initial level of socio-economic variable * linear time trend

Dependent: Log new registrations	(1)	(2)	(3)	(4)	(5)	(6)
Including t*2005 level of:	Built-up area	Paved road	population	Number of bus	Number of taxi	Total retail
Log income	2.39	2.55	2.11	2.41	2.48	2.49
	(0.42)	(0.44)	(0.42)	(0.41)	(0.40)	(0.41)
Observations	3,627	3,627	3,627	3,627	3,627	3,627
Effective F stat for IV	64.40	60.54	70.98	67.03	75.81	69.34
Kleibergen-Paap stat	38.33	35.85	40.49	39.40	42.00	39.70
Underidentification p val	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. All columns use log new registration as dependent variable. All regressions include city fixed effects and province by year fixed effects. The regression is based on our main regression (Table 2.2 column 2) but for each column we add in the interaction between one initial socio-economic variable and linear time trend. For instance, column 1 adds 2005 level built-up area interacted with a linear time trend t.

Table B.4: Adding initial level of socio-economic variable * year FE

Dependent: Log new registrations	(1)	(2)	(3)	(4)	(5)	(6)
Including t*2005 level of:	Built-up area	Paved road	population	Number of bus	Number of taxi	Total retail
Log income	2.46	2.55	2.11	2.47	2.51	2.53
	(0.42)	(0.44)	(0.42)	(0.41)	(0.41)	(0.42)
Observations	3,627	3,627	3,627	3,627	3,627	3,627
Effective F stat for IV	61.61	59.63	74.70	64.27	73.38	66.10
Kleibergen-Paap stat	36.96	35.13	41.18	38.25	41.11	38.31
Underidentification p val	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. All columns use log new registration as dependent variable. All regressions include city fixed effects and province by year fixed effects. The regression is based on our main regression (Table 2 column 2) but for each column we add in the interaction between one initial socio-economic variable and year fixed effects. For instance, column 1 adds 2005 level built-up area interacted with a linear time trend t.

Table B.5: First stage for Table 2.4

Dependent: Log income	(1)	(2)	(3)	(4)
Log income IV	2.29	2.01	2.21	0.69
	(0.25)	(0.26)	(0.25)	(0.24)
Province by year FE	YES	NO	YES	YES
Socio-economic controls	NO	NO	YES	NO
Avg quantile income in 2005 by year tend	NO	NO	NO	YES
Observations	3,627	3,627	3,627	3,627
Effective F stat for IV	83.33	59.73	78.85	8.09
Kleibergen-Paap stat	44.95	46.85	45.30	7.93
Underidentification p val	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. All columns use log income as the dependent variable. All regressions include city fixed effects. The 1,3 and 4 columns include province-year interactions, whereas column 2 only includes year fixed effects. Column 3 further controls for a set of city-level socio-economic controls including built area, area of paved roads, population, number of buses and taxis in the public transportation system, and total retail revenue. Column 4 also controls for the interaction between the average initial income for each quantile and year trend. The quantiles are also defined using initial income into five groups.

Table B.6: First stage for Table 2.5

	(1)	(2)	(3)	(4)
Dependent: Log income	Current	1 year lag	2 years lag	3 years lag
Log income IV	2.29	2.16	1.98	1.76
	(0.25)	(0.25)	(0.24)	(0.23)
Observations	3,627	3,348	3,069	2,790
Effective F stat for IV	83.33	76.06	67.99	60.59
Kleibergen-Paap stat	44.95	43.62	41.89	39.24
Underidentification p val	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by city. Column headings state the dependent variable. All regressions include city fixed effects, year fixed effects, and province-year interactions. The first column uses current period log income, instrumented with current period IV. The second to the fourth column replace current log income with 1, 2 or 3-year lags, instrumented by the corresponding lag of the instrument.

Table B.7: Vehicle sales projection from previous studies

	$\Delta \ln \text{Sale}_{05-10}$	$\Delta \ln \text{Sale}_{10-20}$	Total: $\Delta \ln \text{Sale}_{05-20}$	$\widehat{\text{Sale}}_{2017}$
Wang et al. (2006)-2009 base	1.7	0.9	2.6	32.3
Huo et al. (2007)-High	1.8	0.8	2.6	32.7
Huo et al. (2007)-Low	1.8	0.8	2.5	30.1
Wang (2011)-High	1.9	0.5	2.4	26.6
Wang (2011)-Low	1.7	0.5	2.2	21.8
Huo and Wang (2012)-High	1.8	0.6	2.3	24.9
Huo and Wang (2012)-Low	1.8	0.5	2.3	24.4
Hsieh et al. (2018)	1.8	0.3	2.1	19.1

Notes: Predicted gross sale in millions of cars. For studies that do not have projections during 2005- 2010 period, we use the average of implied income elasticity of vehicle sales of available studies during this period.

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April 8, 2021

To: Members of Chang Shen's dissertation committee and the graduate school
Re: Chang Shen's contribution on co-authored work included in her dissertation

I am writing to attest to Chang Shen's contributions to the paper that she and I have co-authored. The paper, which is titled "The Effect of Income on Vehicle Demand: Evidence from China's New Vehicle Market", is included as one of her dissertation chapters.

Chang made a substantial contribution to our paper. Specifically, she has performed all data collection and assembly; helped develop the empirical strategy by finding an approach to address the endogeneity of income; and written much of the paper. When we submit the paper to a journal for publication, Chang will be the corresponding author.

During her dissertation defense on April 2, 2021, Chang's committee determined that she made a substantial contribution to this work. The inclusion of this work has the approval of the dissertation committee chair, professor Anna Alberini, and me as Director of Graduate Studies.

Sincerely,

Joshua Linn

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