Energy Policy 59 (2013) 189–197

Contents lists available at SciVerse ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The elasticity of demand for gasoline in China ☆

C.-Y. Cynthia Lin [a,*], Jieyin (Jean) Zeng [a,b]

[a] Department of Agricultural and Resource Economics, University of California at Davis, One Shields Avenue, Davis, CA 95616, United States
[b] Institute of Transportation Studies and Department of Statistics, University of California at Davis, United States

HIGHLIGHTS

- The price elasticity of demand for gasoline in China is between −0.497 and −0.196.
- The income elasticity of demand for gasoline in China is between 1.01 and 1.05.
- The price elasticity of demand for VMT in China is between −0.882 and −0.579.

ARTICLE INFO

Article history:
Received 13 January 2012
Accepted 13 March 2013
Available online 11 May 2013

Keywords:
China
Gasoline price elasticity
VMT elasticity

ABSTRACT

This paper estimates the price and income elasticities of demand for gasoline in China. Our estimates of the intermediate-run price elasticity of gasoline demand range between −0.497 and −0.196, and our estimates of the intermediate-run income elasticity of gasoline demand range between 1.01 and 1.05. We also extend previous studies to estimate the vehicle miles traveled (VMT) elasticity and obtain a range from −0.882 to −0.579.

1. Introduction

On January 1, 2009, China initiated a modest reform on its fuel tax, which led to an increase in the gasoline consumption tax from 0.2 Yuan per liter to 1.0 Yuan per liter and an increase in the kerosene consumption tax from 0.1 Yuan per liter to 0.8 Yuan per liter. Although these tax increases are considered a big breakthrough after 15 years of discussion on fuel tax reform in China, this reform is modest since most of the fuel tax simply replaces pre-existing road maintenance fees and some of the tax revenue is given back to fuel consumers who previously did not pay for the road maintenance fees, including airlines, utilities and the army (Cao and Zeng, 2010). Despite its relatively small magnitude, the fuel tax reform at least reveals the Chinese government's determination to control gasoline consumption in China, where increasing gasoline consumption has led to concerns of oil security, local pollution, and global warming, among other concerns.

In this paper we estimate the price and income elasticities of demand for gasoline in China. A sound understanding of the relationships among gasoline demand, gasoline price and disposable income is important for evaluating the effectiveness of China's tax reform in decreasing gasoline consumption, and has other important implications for energy policy as well.

Fig. 1 plots gasoline prices, diesel prices and the Brent crude oil price over the period 1997–2009. Except for 2009, domestic gasoline and diesel prices followed the trends in the Brent crude oil price, though not exactly. Although China's domestic fuel prices are regulated by the government, they are revised regularly based on the world oil price. As seen in the figure, gasoline prices and diesel prices tend to follow the world oil price. The gasoline price was first liberalized in 1991, and then in 1994, 1998, 2003 and 2009, with several major reforms implemented. Generally, the government usually sets up a base price of crude oil on an irregular basis according to the weighted accumulative price change of several international exchanges such as the Brent, the Minas and the New York. The two main oil companies in China, the China National Petroleum Corporation and China Petrochemical Corporation, are then given the authority to set the ex-plant prices, both wholesale and retail, for gasoline number 90. The two companies sell to the provincial petroleum companies who in

* Corresponding author. Tel.: +1 530 752 0824; fax: +1 530 752 5614.
E-mail addresses: cclin@primal.ucdavis.edu (C.-Y.C. Lin), jzeng@ucdavis.edu (J. Zeng).

☆ We thank the UC-Davis ITS Sustainable Transportation Energy Pathways Program for financial support. The research was also supported by a Grant from the Sustainable Transportation Center at the University of California at Davis, which receives funding from the US Department of Transportation and Caltrans, the California Department of Transportation, through the University Transportation Centers Program. We thank Jing Cao and Yang Xie for providing some of the data used in this paper.

0301-4215/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enpol.2013.03.020

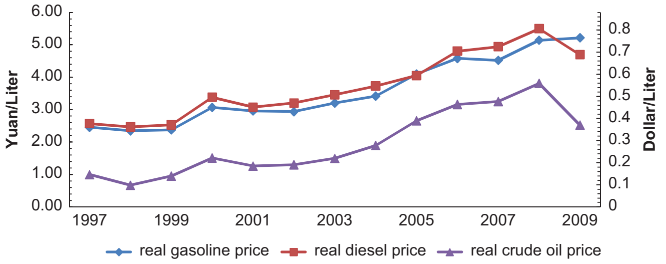

Fig. 1. Real gasoline, diesel and Brent oil price, 1997–2009.
Source: International Petroleum Economics, 1997–2009.
Notes: The national average gasoline price and diesel price are obtained by averaging prices across provinces. Gasoline price is for the #90 type of gasoline. To calculate the real gasoline and diesel prices, we used a regional level CPI with Beijing CPI in 2005 = 100. To calculate the real crude oil price, we used a national level CPI with CPI in 2005 = 100. A conversion to dollar is shown on the right *y*-axes. For simplicity, we set a fixed conversion rate at 6.8 Yuan/dollar, which is the average exchange rate for 2009

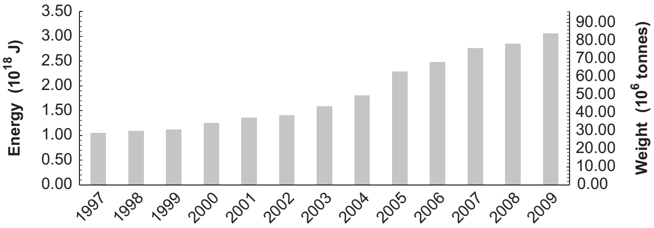

Fig. 2. Annual gasoline consumption for all regions, 1997–2009.
Source: China Energy Statistical Year Book, 1997–2009.
Notes: Total gasoline consumption is obtained by summing up provincial gasoline consumption of 30 provinces. Tibet is not included.

turn oversee the retail service stations (Cheng and Thomson, 2004). The prices charged at the stations are allowed to float between an 8% band above and below the determined prices. Given the price mechanism, the nominal retail gasoline prices grew from almost 2909 Yuan/t in 1997 to 7327 Yuan/t in 2009 with an average annual growth rate of 3.55%. The real gasoline price increased from an average annual growth rate of 0.95%.

Fig. 2 shows annual gasoline consumption for all regions over the years 1997–2009. Fig. 3 shows gasoline consumption per capita over the same years. The growth rates of total gasoline consumption and gasoline consumption per capita are high, and similar in magnitude to China's average real GDP growth rate of 8–10%. Total gasoline consumption grew from 27.82 million t (around 1.28 exajoules[1]) to 83.90 million t (around 3.73 exajoule), with an average annual growth rate of 9.34%. Gasoline consumption per capita increased from 23.23 kg (1.03 gigajoules) to 62.86 kg (2.80 gigajoules), with an average annual growth rate of 8.65%. In 2008, China's motor gasoline consumption of 1,437,000 barrels per day ranked second worldwide after the United States, whose gasoline consumption was 8,989,000 barrels per day, and amounted to 6.7% of the world's total consumption of 21,323,000 barrels per day. However, per capita consumption was still low, at 0.39 barrels per year compared to values in the US (10.78 barrels per year), Japan (2.81 barrels per year), Africa (0.27 barrels per year) and the world average of 1.16 barrels per year. Although the per capita consumption is low, the high total consumption and high consumption growth rate indicate a tremendous potential for gasoline consumption growth in the future.

[1] We use the following conversion rates: 1 t gasoline = 44.5 gigajoules and 1 exajoule = 10^{18} J.

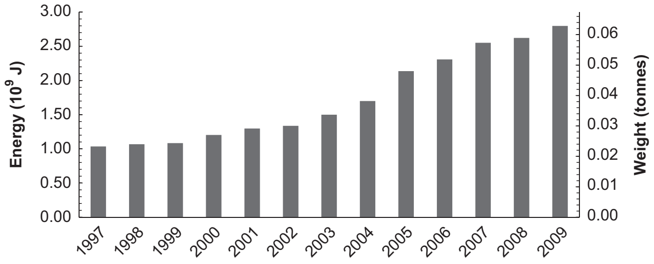

Fig. 3. Annual gasoline consumption per capita, 1997–2009.
Source: China Energy Statistical Year Book, 1997–2009.
Note: Tibet is not included.

To further analyze gasoline consumption in China, Table 1 shows gasoline consumption by sector from 2000 to 2009, and Fig. 4 presents sector shares of gasoline consumption from 2000 to 2009. The transportation and communications sector, which includes transport, storage and post, accounts for the largest share, almost half of the total gasoline consumption, with 46.68% of total consumption in 2009. In 1980, the transportation and communications sector accounted for 41% of the total gasoline consumption. In 1998, the transportation sector alone accounted for approximately 37%. By 2008, the transportation and communications sector grew to 50.29% and is expected to further increase due to the projected increase in private vehicle ownership in the near future. The industry sector experienced a sharp decrease between 2000 and 2005, from 19.46% in 2000 to 9.10% in 2005. The largest increase comes from the residential sector, whose share rose from 6.49% to 16.19% between 2000 and 2009.

The increasing ownership of private cars, buses and cars is a primary reason for the soaring gasoline consumption in the transport sector and it is likely to be a driving factor for the growth of gasoline consumption in the future. While rapid economic development and urbanization over the last three decades have kept an average GDP growth rate of 8–10%, private vehicles in China are experiencing an even bigger growth. Fig. 5 shows the exponential growth in vehicle population in China from 1985 to 2010. Total civil vehicles grew from 12.19 million cars in 1997 to 78.01 million cars in 2010, with an average annual growth rate of 15.35%. It is estimated that the vehicle population in China is likely to grow 13–17% per year from 2010 to 2020, reaching a vehicle population of 359 million by 2024 (Wang et al., 2011). With such a large expected increase in the vehicle population in China, the transport sector's share of gasoline consumption and total gasoline consumption will be much higher than their current levels in the absence of policy.

China's soaring gasoline consumption has resulted in adverse outcomes including carbon emissions, air pollution and oil dependence. Fig. 6 shows the rise in total carbon emissions and carbon per capita from the fossil fuel combustion from 1950 to 2005. Due to the energy and carbon spike that occurred after the year 2002, China has topped the list of carbon emitter countries, exceeding the United States. According to He et al. (2005) carbon emissions from the transportation sector made up a full 7% of total carbon emissions from all sectors in 2002 and the current number may be greater due to the magnitude increase of vehicle population since 2002. In addition, there have been escalating local air pollution threats to human health. Daily and hourly NO_x and ozone concentrations have exceeded national air quality standards, and high concentrations of CO, VOC and SO_2 occur along roads. Vehicle emission has become the main source of air pollution in some big cities including Beijing.

In this paper, we analyze the relationships among gasoline demand, gasoline price and disposable income. Our contribution is that we are the first to estimate the gasoline demand elasticity in China using post-2000 data. To our knowledge, Cheng and

Table 1
Gasoline consumption by sector (10^6 t).
Source: China Energy Statistical Year Book, 2000–2009.

Sector	2000	2005	2006	2007	2008	2009
Agriculture	0.89	1.60	1.68	1.73	1.60	1.68
Industry	6.82	4.42	4.99	5.25	5.86	6.71
Construction	1.16	1.72	1.81	1.79	1.96	2.35
Transportation and communications	15.28	24.30	25.92	26.13	30.90	28.82
Commerce	0.70	1.29	1.23	1.32	1.35	1.48
Other industry	7.93	9.98	10.64	11.20	11.22	10.70
Residential	2.28	5.24	6.16	7.78	8.55	9.99
Total consumption	35.05	48.55	52.43	55.19	61.46	61.73[a]

Notes: The agriculture sector includes farming, forestry, animal husbandry, fishery and water conservancy. The transport and communications sector incorporates transportation, storage, postal and telecommunication services. The commerce sector includes wholesale, retail trade and catering services.

[a] It might be noted the total consumption for all regions in Table 1 for 2009 is different from the value here. The data for Table 1 and Fig. 2 are both from China Energy Statistical Year book. Table 1 lists gasoline consumption by sector, while Fig. 2 is the sum of gasoline consumption by region. The difference is mainly because the National Bureau of Statistics uses different sources when collecting those two datasets. It is likely that the gasoline consumption by sector is underestimated because it is unlikely to have a full coverage of all the sectors. But we list the table here to present the relative shares of each sector and their trends.

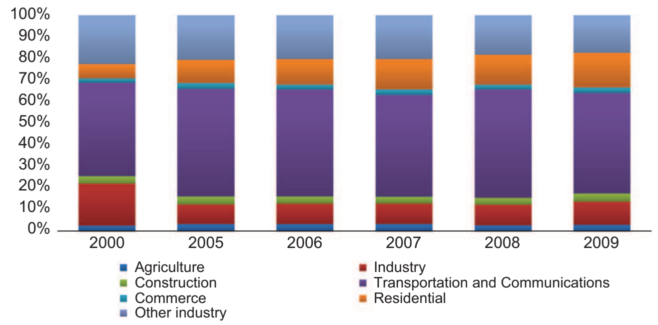

Fig. 4. Sector shares of gasoline consumption, 2000–2009.
Source: China Energy Statistical Year Book, 2000–2009.

Thomson (2004) is the only paper that estimates the gasoline elasticity over the years 1980–1999 at the national level, largely from a statistics perspective instead of an economic perspective. After the implementation of the gasoline tax in 2009, the value of the gasoline demand elasticity is especially important for policy makers who would like to be able to evaluate the effectiveness of a gasoline tax in reducing gasoline consumption. We believe our efforts to utilize comprehensive models and estimate an updated gasoline elasticity at the regional level is an important contribution.

Our estimates of the intermediate-run price elasticity of gasoline demand range between −0.497 and −0.196, and our estimates of the intermediate-run income elasticity of gasoline demand range between 1.01 and 1.05. We also extend previous studies to estimate the intermediate-run vehicle miles traveled (VMT) elasticity and obtain a range from −0.882 to −0.579.

The remainder of the paper is organized as follows. Section 2 provides the methodology and results for estimating the elasticity of demand for gasoline. In Section 3 we estimate elasticity of demand for VMT. Section 4 concludes.

2. Estimating the gasoline demand elasticity

2.1. Data

To estimate the gasoline demand elasticity, we rely on aggregate fuel price and fuel use data combined with income data from the China Statistical Year book, the China Energy Statistical Year book, and a periodical named China's Oil Economy. We collected annual gasoline consumption for 30 provinces from 1997 to 2008, monthly gasoline and diesel prices for 30 provinces from 1997 to 2008, and monthly disposable income for 30 provinces from 1997 to 2008. Prices and income are converted to constant 2005 dollars using the consumer price index. It is noted that the regional gasoline consumption includes gasoline consumption for all industries, in which transport industry accounts for almost 50% in 2008. Due to lack of transport gasoline consumption at regional level, gasoline consumption for all industries is used for the elasticity estimation.

Estimation using regional data is preferred over using aggregate data, as it enables us to capture variation across regions. Annual data are used in our estimation of the gasoline elasticity, as adequate monthly data was not available.

The elasticity of demand for gasoline in western countries has been studied extensively. For example, Bentzen (1994) focused on the study of Denmark over the period 1948–1991. Wasserfallen and Guntensperger studied the elasticity of demand for gasoline in Switzerland over the period 1962–1985. Blum and Foos (1988) estimated the elasticity for West Germany over the period 1968–1983. They estimated the short-run gasoline elasticity for the western countries to be between −0.32 and −0.25. For the United States, Hughes et al. (2008) estimated the short-run price elasticity of gasoline demand for the period from 1975 to 1980 to be between −0.34 and −0.21, whereas for the period from 2001 to 2006 their estimate was much smaller in magnitude, between −0.077 and −0.034. Lin and Prince (2009) provide a summary of elasticity estimates for the United States. Our contribution is that we are the first to calculate the gasoline demand elasticity in China using post-2000 data.

2.2. Basic model

To estimate the gasoline price elasticity, we start with a basic double log model:

$$\ln D_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \varepsilon_{it} \,, \tag{1}$$

where D_{it} is per capita gasoline demand in gallons for region i *in* year t, P_{it} is the real price of gasoline in 2005 constant Yuan for region i in year t, Y_{it} is real per capita disposable income in 2005 constant Yuan for region i in year t, and ε_{it} is a mean zero error term. Because of data limitations, the majority of this analysis is carried out using annual data.

The interpretation of the coefficients of the static model is not entirely clear. We would expect that the price and income elasticities to be:

$$\frac{\partial \ln D_{it}}{\partial \ln P_{it}} = \beta_1 \quad \text{and} \quad \frac{\partial \ln D_{it}}{\partial \ln Y_{it}} = \beta_2,$$

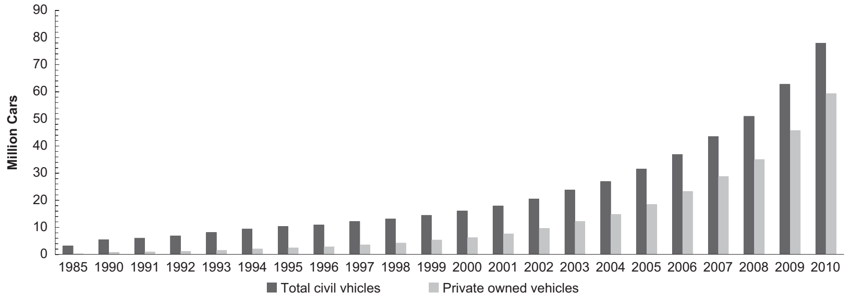

Fig. 5. Total civil vehicles and privately owned vehicles in China (in million cars), 1985–2010.
Source: China Statistical Year Book of Automobile Industry, Appendix Form 22-14, 1985–2009.

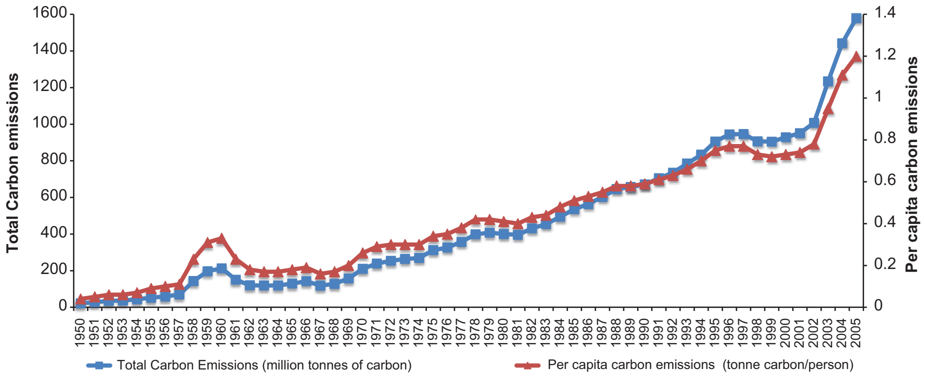

Fig. 6. Total fossil fuel emissions and carbon per capita, 1950–2005.
Source: China Energy Databook.

respectively. Studies have shown that some dynamic models tend to produce higher long-run elasticities than static models, indicating that the elasticity estimate from a static model is an intermediate-run elasticity.

In order to test the sensitivity of the basic model and its results, we employ a number of alternative models in an attempt to address the endogeneity of gasoline price with respect to gasoline consumption, to incorporate the interaction effects between price and income, and to incorporate the real interest rate into the model, respectively.

2.3. Model with instruments

A well-known problem in estimating demand equations arises because price and quantity are jointly determined by the intersection of supply and demand curves. This endogeneity of prices and quantities will lead to a biased parameter estimate. To address the endogeneity of prices and quantities, instruments are needed for price in the regression model (Goldberger, 1991; Lin, 2011). Theoretically, an ideal instrument should satisfy the following requirements: (1) it should be highly correlated with the gasoline price, and (2) it should not be correlated with unobserved shocks to gasoline demand. Ramsey et al. (1975) and Dahl (1979) used the relative prices of refinery goods such as kerosene and residual fuel oil as instruments. However, Hughes et al. (2008) claimed that prices of other refinery goods are likely to be correlated with gasoline demand via the oil price. Instead, they employed crude oil quality and crude oil production disruptions as instrumental variables.

It is quite difficult to determine appropriate instrumental variables for gasoline price. In our paper, we use regional diesel prices and international crude oil prices as instrumental variables. Although diesel prices and gasoline demand are correlated via oil prices, their correlation is through the price channel but not the demand channel because gasoline demand would not affect the diesel price. One underlying reason for choosing the diesel price as an instrument is that both gasoline prices and diesel prices are characterized by regional variation. Although we are unable to capture regional differences with the international crude oil price, the choice of international crude oil prices is mainly aimed at avoiding any unobserved local shock that can possibly affect prices of other refinery products and gasoline demand simultaneously.

In order to test the strength of the instrumental variables, we first estimate a first-stage regression. The results are reported in Table 2. Both the regional diesel prices and the international crude oil prices prove to be appropriate instruments since their *F*-statistics are 4755.48 and 869.07, respectively. However, as seen in specification (3), the instruments do not both have significant coefficients in the first-stage regression when used simultaneously; as a consequence we only report results from regressions using the instruments separately.

Table 3 reports the results from the double log model of gasoline demand. The first specification is OLS while the other two specifications are 2SLS regressions using regional diesel prices and international crude oil prices as instruments, respectively. Our estimates of the intermediate-run gasoline demand elasticity range from −0.432 to −0.23.

2.4. Model with price–income interaction

In order to study the interaction between the price elasticity and income, we employ a simple interaction model that incorporates a price–income interaction term into the regression model:

$$\ln D_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \beta_3 \ln P_{it} \ln Y_{it} + \varepsilon_{it}. \qquad (2)$$

The interaction term reflects the extent to which the responsiveness of consumers to price changes increases or decreases as income

Table 2
First-stage regression.

	Dependent variable is log real gasoline price		
	(1)	(2)	(3)
Log real diesel price	0.983***		0.966***
	(0.014)		(0.034)
Log real oil price		0.557***	0.012
		(0.019)	(0.021)
Log real income	0.031***	−0.047**	0.028***
	(0.006)	(0.015)	(0.008)
Constant	−0.125	5.935***	−0.013
	(0.104)	(0.138)	(0.221)
Observations	284	307	284
R-squared	0.96	0.83	0.96

Notes: Standard errors in parentheses.
*Significant at 5%.
** Significant at 1%.
*** Significant at 0.1%.

Table 3
Double log model of gasoline demand.

	Dependent variable is log per capita gasoline demand		
	OLS (without instruments)	Diesel price as IV	Crude oil price as IV
Log real gasoline price	−0.264**	−0.23**	−0.432***
	(0.088)	(0.090)	(0.097)
Log real income	1.01***	1.01***	1.05***
	(0.038)	(0.038)	(0.039)
Constant	−13.60***	−13.89***	−12.64***
	(0.644)	(0.661)	(0.684)
Observations	275	263	275
R-squared	0.76	0.77	0.76

Notes: Standard errors in parentheses.
*Significant at 5%.
** Significant at 1%.
*** Significant at 0.1%.

changes. A positive coefficient β_3 on the interaction term would mean that the price elasticity of demand decreases in magnitude as income increases. In this specification, the price elasticity of demand is calculated at mean log income: $\varepsilon_p = \beta_2 + \beta_3 \overline{\ln Y_{it}}$.

The regression results are reported in Table 4. Our estimates of the price elasticity when evaluated at mean income range from −0.497 to −0.313. The significant positive estimate of the price–income interaction term, ranging between 0.381 and 0.520, indicates that increasing incomes have resulted in a decrease in the consumer response to gasoline price changes, in the sense that the decreasing budget share of gasoline consumption has made consumers less responsive to higher prices.

2.5. Model with other macroeconomic variables

In this section, we would like to take into account other macroeconomic variables such as the unemployment rate (UE), the inflation rate or the interest rate in addition to income per capita and gasoline prices. Hughes et al. (2008) used a similar model to estimate the gasoline elasticity for the United States. Unlike their model, which plugs in the nominal interest rate and inflation rate separately into the model, we utilized the real interest rate (*RI*)[2] instead. In the regression models, we plug in *RI*, *UE*, *RI* plus *U*E successively using the basic double-log model:

$$\ln D_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \beta_3 \ln RI_t + \beta_4 UE_t + \varepsilon_{it}. \tag{3}$$

The regression results are shown in Table 5. The estimate of price elasticity from the model incorporating the real interest rate is a significant −0.196, and is consistent with that of the previous three models. The model incorporating unemployment rate and the model incorporating both unemployment rate and real interest lead to positive insignificant values of price elasticity. One concern of the model incorporating unemployment rate is that there is hardly any variation of unemployment rate across years: unemployment rates are exactly the same at 3.1 from 1997 to 2000. Thus, we put less weight on the results from the two models incorporating the unemployment rate.

Table 4
Double log model of gasoline demand with price–income interaction.

	Dependent variable is log per capita gasoline demand		
	OLS (without instruments)	Diesel price as IV	Crude OIL Price as IV
Log real gasoline price	−5.048**	−4.575*	−6.959***
	(1.756)	(1.822)	(1.965)
Log real income	−2.173	−1.873	−3.298*
	(1.170)	(1.211)	(1.303)
Log real income × log real gasoline price	0.381**	0.345*	0.520***
	(0.140)	(0.145)	(0.156)
Constant	26.360	22.381	41.882
	(14.661)	(15.219)	(16.397)
Observations	275	263	275
R-squared	0.766	0.772	0.761
Gasoline price elasticity	−0.313	−0.288	−0.497
	(2.472)	(2.563)	(2.760)

Notes: Standard errors in parentheses.
* Significant at 5%.
** Significant at 1%.
*** Significant at 0.1%.

Table 5
Double log model of gasoline demand with macroeconomic variables.

	Dependent variable is log per capita gasoline demand		
	(1)	(2)	(3)
Log real gasoline price	−0.196*	0.078	0.057
	(0.089)	(0.109)	(0.111)
Log real income	1.042***	1.110***	1.106***
	(0.038)	(0.040)	(0.040)
Log real interest rate	0.194***		0.071
	(0.054)*		(0.062)
Log unemployment rate		−1.197***	−1.040***
		(0.233)	(0.273)
Constant	−14.750***	−16.131***	−16.180***
	(0.699)	(0.787)	(0.786)
Observations	263	263	263
R-squared	0.790	0.790	0.790

Notes: Standard errors in parentheses.
**Significant at 1%.
* Significant at 5%.
*** Significant at 0.1%.

2.6. Partial adjustment model

To account for possible frictions in the market that cause adaptation to changes in gasoline price or income not to take place instantaneously, we use a partial adjustment model, which

[2] For the real interest rate, we used the one-year nominal interest rate of savings deposit rates, adjusted by the CPI.

Table 6
Partial adjustment model of gasoline demand.

	Dependent variable is log per capita gasoline demand		
	OLS (without instruments)	Diesel price as IV	Crude Oil price as IV
Lag length	1 Year	1 Year	1 Year
Log real gasoline price	−0.010	−0.019	−0.009
	(0.040)	(0.042)	(0.043)
Log real income	0.153***	0.167***	0.153***
	(0.031)	(0.033)	(0.032)
Log lagged demand	0.868***	0.860***	0.868***
	(0.026)	(0.027)	(0.026)
Constant	−2.181***	−2.320***	−2.186***
	(0.449)	0.478	(0.454)
Observations	249	237	249
R-squared	0.957	0.955	0.956

Notes: Standard errors in parentheses.
*Significant at 5%.
**Significant at 1%.
*** Significant at 0.1%.

Table 7
Short-run and long-run gasoline demand elasticity.

	OLS (without instruments)	Diesel price as IV	Oil price as IV
Short-run price elasticity of gasoline demand	−0.010	−0.019	−0.009
	(0.040)	(0.042)	(0.043)
Long-run price elasticity of gasoline demand	−0.076	−0.136	−0.068
	(0.3040)	(0.3001)	(0.3249)

allows demand in the current period to depend on demand in an earlier period as well as on income and gasoline price:

$$\ln D_{it} = \varphi_0 + \varphi_1 \ln P_{it} + \varphi_2 \ln Y_{it} + \varphi_3 \ln D_{i,t-1} + \varepsilon_{it}. \quad (4)$$

When we estimate this partial adjustment model using OLS, φ_1 can be interpreted as the short-run price elasticity. The long-run elasticity, when fully adjusted to the equilibrium level, is$\varphi_1/(1-\varphi_3)$. However, when the speed of adjustment is relatively short, the fully adjusted elasticity may also be interpreted as a short-run or intermediate-run elasticity (Houthakker et al., 1974; Hughes et al., 2008; Lin and Prince, 2009). Table 6 shows the partial adjustment model results. Table 7 shows the short-run and long-run elasticities that are calculated from the specifications in Table 6. We expect the long-run elasticity to be larger in magnitude, since we expect consumers to be more elastic in the long run.

Note that the short-run elasticity is not significantly different from zero, so that consumers are highly inelastic in the short-run. This is reasonable because in the short run consumers have less time to respond by changing behavior, reducing VMT, or buying more fuel efficient cars, which are usually considered to be long term responses. Although the long-run elasticities are not significantly different from zero either, the point estimates for the long-run elasticities are larger in magnitude than the point estimates for the short-run elasticities. As expected, consumers are more elastic in the long run, when they have more time to adjust to higher prices by changing driving behavior, reducing VMT, or switching for more fuel efficient cars. The estimates of price elasticity from the partial adjustment model are not significant, largely because the lag term, which is highly correlated with the gasoline price due to the stickiness in the gasoline price between periods, explains most of the variation of gasoline consumption in the current period, thus crowding out the effects of price on gasoline consumption.

2.7. Discussion of gasoline elasticity results

The basic double log model and alternative specifications we use to measure the intermediate-run price and income elasticities of gasoline demand between 1997 and 2008 lead to consistent estimates. The basic double log model, the model with instruments, the price–income interaction model, and the macroeconomic model using the real interest rate produce significant estimates of the intermediate-run price elasticity ranging between −0.497 and −0.196. These four models also lead to robust and significant estimates of the income elasticity of gasoline demand, ranging between 1.01 and 1.05. We put less weight on the macroeconomic model incorporating the unemployment rate because there is little variation in the unemployment rate. We also put less weight on the partial adjustment model because the incorporation of the lag term appears to crowd out the effects of price and income on gasoline consumption in the current period.

We compare our results with previous studies of the gasoline demand elasticity for other developing countries since they are closer to China in economic background, income level, energy consumption, urban development, driving behavior and other demographic factors than developed countries are. Table 8 summarizes the results from these previous studies. It is noted that there is a wide range of estimates of gasoline demand elasticity for these countries. Compared with India, which is commonly believed to share similarities with China in its economic development and demographics, our range of estimates for China's intermediate-run price elasticity overlap with India's short-run and long-run price elasticities as estimated by Ramanathan (1999), while our range of estimates for China's intermediate-run income elasticity is just a little lower than India's short-run income elasticity. Our range of estimates for China's intermediate-run price elasticity using more recent regional data overlap with Cheng and Thomson (2004) estimates using national data over the years 1980–1999. All in all, we believe our estimation results are generally consistent and robust across models and consistent with earlier studies for developing countries.

3. Estimating the VMT demand elasticity

3.1. Regional VMT estimation

There is no official report on VMT data in China. A few studies including He et al. (2005) and Lin et al. (2009) have estimated VMT per vehicle across distinct types of vehicles at the national level. The two studies differ in their adopted methods when estimating VMT per vehicle. He et al. (2005) base their estimation on the regularly reported total freight or passenger traffic volume (in billion t/km or passenger/km) over the period 1997–2002. Lin et al. (2009) base their estimation on a survey in which they estimate the relationship between VMT and vehicle age and the distribution of vehicle age in 2007. China Automotive Energy Research Center (CATARC), 2012. summarizes the estimation results from Lin et al. (2009) and other research institutes. These studies' estimates are for distinct periods using varied methods and thus not necessarily the same across studies. But generally, a larger bus or heavier truck tends to have a higher VMT per vehicle than a smaller or lighter one does. A summary of their estimation results is presented in Table 9.

He et al. (2005) estimated the national VMT data for different categories of vehicles over the years 1997–2002. In this paper, we follow the method employed by He et al. (2005) to estimate VMT

Table 8
Review of gasoline demand elasticity estimates for developing countries from earlier studies.

Country	Estimation period	*Price elasticity*			*Income elasticity*			Source
		Short run	Intermediate run	Long run	Short run	Intermediate run	Long run	
Hong Kong	1973–1987	0.055			0.22			McRae (1994)
India	1973–1987	−0.32			1.38			McRae (1994)
Indonesia	1973–1987	−0.20			1.69			McRae (1994)
South Korea	1973–1987	−0.50			0.72			McRae (1994)
Malaysia	1973–1987	−0.13			0.57			McRae (1994)
Pakistan	1973–1987	0.39			2.91			McRae (1994)
Philippines	1973–1987	−0.39			0.15			McRae (1994)
Sri Lanka	1973–1987	−0.34			0.82			McRae (1994)
Taiwan	1973–1987	0.024			0.81			McRae (1994)
Thailand	1973–1987	−0.30			1.77			McRae (1994)
Bangladesh	1973–1987	−0.35			0.016			McRae (1994)
India	1972–1994	−0.21		−0.32	1.18		2.68	Ramanathan (1999)
Kuwait	1970–1989	−0.37			0.47			
China	1980–1999	−0.19		−0.56	1.64		0.97	Cheng and Thomson (2004)
China	1997–2008		−0.497 to −0.196			1.01–1.05		This paper

Table 9
VMT estimation of earlier studies[a].
Source: Lin et al. (2009), He et al. (2005), China Automotive Technology and Research Center (CATARC) and other research institutes.

	Earlier estimates of VMT per vehicle (1000 km)									
	1997	1998	1999	2000		2001	2002		2007	2008
	He et al. (2005)	He et al. (2005)	He et al. (2005)	He et al. (2005)	CATARC	He et al. (2005)	He et al. (2005)	CATARC	CATARC	CATARC
Sedan	27.2	27.3	26.4	26.4	24	26.4	26	26	26.9	
Bus										
Large	68.9	67.3	58.6	52	40	50	48.6	48.6		
Medium	68	66.5	57.8	52	35	50	47.3	47.3		
Small	35.2	34.9	36	34		34	33.6	33.6		
Mini	35	35	35	35		34	34	34		
Trucks										
Heavy	73.6	75.6	72	67.4	40	50	50	50		65
Middle	25	25	25	25	25	24	24	24		40
Light	24.5	23.3	22	20.9	21	20.7	20	20		25
Mini	36.3	39.5	44.8	43.2	20	39.7	38.4	38.4		

[a] Bus is categorized into large, medium, small and mini bus according to vehicle length and the total number of seats. Truck is categorized into heavy, middle, light and mini truck according to load capacity.

for trucks and passenger vehicles respectively over a more recent period, 2003–2008, at the regional level. After deriving the VMT data, we then use a double log model to estimate the VMT elasticity and the income elasticity. The equation used to calculate VMT per vehicle in a given year t is formulated as follows:

$$\mathrm{VMT}_t = \sum_i \frac{\gamma_{it} TV_{it}}{\beta_{it} ALC_{it} VP_{it}}, \tag{5}$$

where TV_{it} is an important parameter reported regularly by the Chinese Statistical Year book and measures the total freight or passenger traffic volume (in billion t/km or passenger/km) of vehicle type i; γ_{it} is volume share of vehicle type i; VP_{it} is vehicle population of vehicle type i; ALC_{it} is the average load capacity (ALC, in t/vehicle or passengers/vehicle); and β_{it} is the average actual load rate of vehicle type i. Noticeably, γ_{it} can be interpreted as the weights used to calculate the average VMT per vehicle across vehicle types. $\beta_{it} \cdot ALC_{it}$, the product of average load capacity and actual load rate, can be interpreted as the actual load per vehicle (in passengers/vehicle or t/vehicle). We assume an identical β_{it} for each region, since we do not expect the actual load rate differ much across regions.[3] On the other hand, due to data limitations, we only obtain total freight or passenger traffic volume, TV_{it}, for buses and trucks, and therefore our estimations of VMT per vehicle are limited to these two types of vehicles.[4]

Fig. 7 shows the average estimated VMT per vehicle and its standard deviation across provinces for passenger vehicles and trucks from 2003 to 2009.

As seen in Fig. 7, there is a decreasing trend of VMT per vehicle for passenger vehicles (buses), while VMT per vehicle for trucks is increasing except for 2009. The decreasing trend of VMT for buses

[3] For the actual load rate, the average results of several cities are used to represent the uniform actual load rate for all regions. For the average load capacity, we used the median value of total seats/t for each category of vehicle i.

[4] Because the VMT we calculate is total VMT, not just VMT from gasoline-fueled cars. However, gasoline-fueled cars comprise the majority of cars in China: in 2007 they were approximately 75% of all vehicles, according to a Chinese government report (Development Center of State Council for Industry Research, 2007). While not perfect, our measure of VMT is highly correlated with the actual gasoline-fueled VMT, and it is the best we can do given the data limitations.

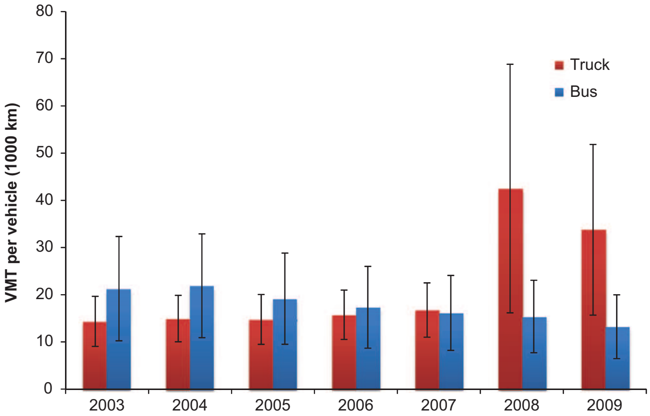

Fig. 7. VMT per vehicle, 2003–2009.
Note: Error bars indicate standard deviation.

Table 10
Double log model for VMT elasticity estimation.

	Dependent variable is log per capita VMT	
	OLS (without instruments)	Diesel price as IV
Log real gasoline price	−0.579**	−0.882***
	(0.193)	(0.214)
Log real income	−0.066	−0.123
	(0.08)	(0.083)
Constant	4.813*	8.107***
	(2.348)	(2.572)
Observations	158	144
R-squared	0.507	0.4579

Notes: Standard errors in parentheses.
* Significant at 5%.
** Significant at 1%.
*** Significant at 0.1%.

conforms to He et al. (2005) estimation over the period 1997–2002, which is mainly due to the intensively increasing population share of small buses. Although there is a rising share of light trucks, the share of heavy trucks is also climbing. Therefore, the combined effects result in an increasing trend of VMT per vehicle for trucks over the period 2003–2008 but a downward trend from 2008 to 2009.

3.2. VMT elasticities

To estimate the VMT price elasticity, we utilize a double log similar to the one we used to calculate the gasoline elasticity:

$$\ln VMT_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \varepsilon_{it}. \quad (6)$$

To be consistent with our estimation of gasoline elasticity, we used VMT per capita as dependent variable in the above model. VMT per capita is derived by multiplying VMT per vehicle by total vehicle population and then dividing by total population. The regression results are shown in Table 10. The intermediate-run VMT elasticity is estimated to be between −0.882 and −0.579.[5]

3.3. Discussion of VMT elasticities

To compare our results with previous studies, a review of the previous literature on VMT elasticities is shown in Table 11.

Our estimates of the VMT price elasticity are somewhat higher in magnitude than the estimates for other countries, but still in a reasonable range. The estimates from previous estimates are for developed countries. A possible reason is that our estimates for China are somewhat more elastic is that drivers in China might be more responsive to gasoline price changes, thus leading to an elastic VMT, whereas the gasoline consumption is relatively inelastic because the gasoline demand from industries other than transportation are relatively rigid while the gasoline consumption share of transportation sector, which may exhibit a relatively greater elasticity of demand for gasoline, has been shrinking over the years.

Our estimates of the VMT per capita income elasticity are statistically insignificant. As shown in the Table 11, most estimates of the income elasticity of total VMT have a positive value, while a few studies of VMT per vehicle indicate that a small negative income elasticity might be reasonable because of the increasing density of cities and improved public transportation system (CATARC, 2012). Thus, while total VMT may increase when incomes increase, the VMT per capita may not necessarily increase.

There are concerns regarding our estimation of the VMT elasticity, mostly due to the poor data quality of VMT data. The R^2's from our regressions are low, ranging from 0.46 to 0.51, suggesting that our model does not fully capture the determinants of VMT. As mentioned above, due to lack of official reports of VMT and limited previous studies, our approximation of VMT from the regularly reported traffic volume is not precise. However, we believe that our estimates at least capture some of the variation in VMT across regions and years, that they are still in a reasonable range consistent with previous estimates of VMT elasticities in the United States and that they shed some light on consumers' demand for VMT.

4. Discussion and conclusion

In this paper we use the basic double log model and several alternative specifications to estimate the price and income elasticities of gasoline demand in China over the period 1997–2008. Our models produce significant estimates of the price elasticity ranging between −0.497 and −0.196 and significant estimates of income elasticity ranging between 1.01 and 1.05. After comparative analysis with earlier studies for developing countries, we believe our estimation results are consistent and robust. The low price elasticity of gasoline demand indicates that consumers are not sensitive to higher prices. One hypothesis is that with the rapid increase of income and thus a lower budget share of gasoline consumption, consumers' responses to higher prices have decreased in magnitude, a hypothesis which is supported by a significant and positive coefficient on the price–income interaction term. In addition, the relatively higher income elasticity implies that increases in disposable income have caused gasoline consumption to soar, largely due to the increasing ownership of cars.

Using the double log model and instrumental variables, we estimate the intermediate-run VMT elasticity to be between −0.882 and −0.579. Although there are some concerns regarding the validity of our estimated VMT data, our estimation results at least shed some light. Given a higher intermediate-run VMT price elasticity than gasoline price elasticity and given improved fuel efficiency, it might be the case the demand for gasoline is relatively more elastic in the transportation sector than it is in

[5] Crude oil price as instrument is not shown because there is no regional variation of crude oil price across province, thus resulting in the model to be unidentified due to a singularity problem. We incorporated fixed effects in the model because the Hausman test preferred fixed effects over OLS with a significant improvement in the R-squared, whereas for the gasoline demand model the Hausman test preferred OLS and the R-squared was not much improved by fixed effects.

Table 11
Review of previous studies of VMT elasticities.

Country	Estimation period	*VMT price elasticity*			*VMT income elasticity*			Dependent Variable	Source
		Short run	Intermediate run	Long run	Short run	Intermediate run	Long run		
US	Pre-1986	−0.16		−0.32				Vehicle/km	Goodwin (1992)
US	Pre-1986	−0.15		−0.30				Vehicle/km	Graham and Glaister (2002)
US	Pre-1974		−0.54			0.30		Vehicle/km	Goodwin et al. (2004)
US	1974–1981		−0.32			0.57	0.21	Vehicle/km	Goodwin et al. (2004)
US	Post-1981	−0.10	−0.24	−0.29	0.30	0.49	0.73	Vehicle/km	Goodwin et al. (2004)
US	Pre-1991	−0.10	−0.51	−0.30	−0.005	0.06	0.17	Per vehicle	Goodwin et al. (2004)
China	2003–2009		−0.88 to −0.58			Insignificant		Per capita	This study

Table 12
Projected gasoline consumption growth rate.

Projected gasoline consumption (and associated CO_2 emissions) growth rate			
Tax rate (%)	*Gasoline price elasticity*		
	Mid-range (−0.35) (%)	Low (−0.497) (%)	High (−0.196) (%)
0	6.18	6.18	6.18
15	0.93	−1.28	3.24
30	−4.32	−8.73	0.30

Notes: We assume the growth rate of real income per capita is 6% and income elasticity of gasoline consumption is 1.03, which is the midpoint of our estimation range. It is also assumed that all increases in the gasoline price come from the tax increase.

other sectors.[6] If this is the case, imposing a gasoline consumption tax to increase gasoline prices might be more effective in reducing gasoline consumption, congestion and roadway pollution within the transportation system than it would be in reducing the gasoline consumption in other sectors, although the current tax may be too low to completely counteract the income effects.

A few policy implications can be drawn from our elasticity results. Currently China is implementing a modest gasoline consumption tax, at 1 Yuan per liter. However, given that the price elasticity is lower in magnitude than the income elasticity, a further increase in the gasoline consumption tax will be needed to achieve the goal of gasoline consumption reduction. Ceteris paribus, given the current income increase rate of 6–8%, an increase of gasoline price by 18%–23% is needed to counteract income effects for one year, not to mention achieve the goal of gasoline consumption reduction. Table 12 presents the projected gasoline consumption growth rate and associated greenhouse gas emissions growth rate the year following the implementation of a tax under three gasoline tax specifications: 0%, 15% and 30%. As shown from the table, a gasoline tax rate of 15%, which is close to the current volume based tax rate of 1 Yuan/l, is not sufficient to achieve the goal of gasoline consumption reduction in the following year. While a more aggressive tax rate of 30% manages to meet the goal, it is likely to be politically infeasible. As it is always politically difficult to implement a high gasoline consumption tax, alternative measures such as public transportation, increases in fuel efficiency and mandates to control potential vehicle population will be needed in the future.

[6] We do not have sufficient data to verify this, but obtaining the data in order to do so will be the subject of future work.

References

Bentzen, J., 1994. An empirical analysis of gasoline demand in Denmark using cointegration analysis. Energy Economics 16 (2), 139–143.
Blum, U.C.H, Foos, G., 1988. Aggregate time series gasoline demand models: review of the literature and new evidence for West Germany. Transportation Research Part A: General 22 (2), 75–88.
Cao, J., Zeng, J., 2010. The incidence of carbon tax in China. In: Proceedings of the Lincoln Institute China Program Annual May Conference, Cambridge, USA, May 17, 2010.
Cheng, K., Thomson, E., 2004. The demand for gasoline in China: a cointegration analysis. Journal of Applied Statistics 31 (5), 533–544.
China Automotive Energy Research Center (CATARC), 2012. China Automotive Energy Outlook 2012. Science Press, Beijing.
Dahl, C.A., 1979. Consumer adjustment to a gasoline tax. The Review of Economics and Statistics 6 (3), 427–432.
Development Center of State Council for Industry Research, 2007. Diesel technology and development policy.
Goldberger, A.S., 1991. A Course in Econometrics. Harvard University Press, Cambridge, MA.
Goodwin, P.B., 1992. A review of new demand elasticities with special reference to short and long run effects of price changes. Journal of Transport Economics and Policy 26, 155–163.
Goodwin, P.B., Dargay, J., Hanly, M., 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transport Reviews 24 (3), 275–292.
Graham, D., Glaister, S., 2002. The demand for automobile fuel: a survey of elasticities. Journal of Transport Economics and Policy 36 (1), 1–26.
He, K., Huo, H., Zhang, Q., He, D., An, F., Wang, M., Walsh, M., 2005. Oil consumption and CO_2 emissions in China's road transport: current status, future trends, and policy implications. Energy Policy 33, 1499–1507.
Houthakker, H.S., Verleger, P.K., Sheehan, D.P., 1974. Dynamic demand analysis for gasoline and residential electricity. American Journal of Agricultural Economics 56 (2), 412–418.
Hughes, J., Knittel, C., Sperling, D., 2008. Evidence of a shift in the short-run price elasticity of gasoline demand. The Energy Journal 291, 93–114.
Lin, C.-Y.C., 2011. Estimating supply and demand in the world oil market. Journal of Energy and Development 34 (1), 1–32.
Lin, C.-Y.C., Prince, L., 2009. The optimal gas tax for California. Energy Policy 37 (12), 5173–5183.
Lin, X., Tang, D., Ding, Y., Yin, H., Ji, J., 2009. Study on the distribution of vehicle mileage travelled in China. Research of Environmental Sciences 22, 3.
McRae, R., 1994. Gasoline demand in developing Asian countries. Energy Journal 15 (1), 143–155.
Ramanathan, R., 1999. Short- and long-run elasticities of gasoline demand in India: an empirical analysis using cointegration techniques. Energy Economics 21 (4), 321–330.
Ramsey, J., Rasche, R., Allen, B., 1975. An analysis of the private and commercial demand for gasoline. The Review of Economics and Statistics 57 (4), 502–507.
Wang, Y., Teter, J., Sperling, D., 2011. China's soaring vehicle population: Even greater than forecasted? Energy Policy 39 (6), 3296–3306.