Energy Economics 45 (2014) 244–253

Contents lists available at ScienceDirect

Energy Economics

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

Modeling gasoline demand in the United States: A flexible semiparametric approach☆

Weiwei Liu *

College of Business and Management, Saginaw Valley State University, 313 Curtiss, 7400 Bay Road, University Center, MI 48710, United States

ARTICLE INFO

Article history:
Received 16 August 2011
Received in revised form 24 May 2014
Accepted 8 July 2014
Available online 24 July 2014

JEL classification:
C14
Q41
Q54

Keywords:
Gasoline demand
Price elasticity
Income elasticity
Semiparametric estimation

ABSTRACT

The focus of this paper is on the modeling and estimation of quarterly state-level gasoline demand in the United States. The existing literature may not appropriately evaluate the price elasticity and income elasticity of gasoline demand. Most studies fail to address the possible heterogeneity in gasoline demand elasticities that may arise from a variety of sources. The endogeneity issue of gasoline price has remained redundant throughout the literature. I address these challenges using a flexible demand model and a recently developed estimation technique. The econometric approach allows for functional coefficients to accommodate the heterogeneity in demand elasticities. Several instrumental variables are used to investigate the endogeneity of gasoline price. The estimation results provide strong evidence of heterogeneous gasoline demand elasticities across states and over time. Some state-level attributes along with income and macroeconomic shocks are the potential sources of heterogeneity.

1. Introduction

Gasoline demand has been widely studied in the last 30 years. After the negotiation of the Kyoto Protocol in 1997, concerns about increasing greenhouse gas emissions and global warming have renewed interests in this area in the last decade. Besides environmental regulations, imposing a gasoline tax is one way to reduce gasoline consumption and greenhouse gas emissions from the transportation sector. The effectiveness of such a tax largely depends on how gasoline demand responds to price changes, the measurement of which calls for a properly specified demand model and precise estimation of the price elasticity.

A reduced-form demand model applied to aggregate data to estimate the demand for gasoline has been, by far, the most preferred and dominant approach in both the academic and non-academic literature. Hundreds of studies have been conducted to assess the price elasticity and income elasticity of gasoline demand at country or region levels. There are also a great number of reviews and surveys attempting to synthesize and compare the results of those studies (e.g., Basso and Oum, 2007; Blum et al., 1988; Dahl, 1995; Dahl and Sterner, 1991a,b; Drollas, 1984; Espey, 1998; Goodwin, 1992; Goodwin et al., 2004; Graham and Glaister, 2002; Sterner and Dahl, 1992). However, there are substantial differences in the estimates of both price elasticity and income elasticity.

Baltagi and Griffin (1983) believe that the inconsistency in the estimates of the price elasticity and the income elasticity is caused by differences in methodologies and data. Goodwin (1992), on the other hand, shows that data type, i.e., cross-section or time-series, only affects the estimates marginally. Another possible explanation for the broad range of gasoline demand elasticity estimates is that they are not homogeneous at all, but rather vary under different conditions. This problem has been addressed in fairly diverse empirical studies, but unfortunately the results are mixed.

Dahl (1982) first investigates whether gasoline demand elasticities change over time in the context of the oil crisis in 1973. A series of Chow tests indicate that the price and income elasticities neither do change even under severe price fluctuations nor do vary with income. However, Dahl (1995) surveys a number of gasoline demand studies for the U.S., and concludes that overall the gasoline demand elasticities tend to decrease over time. The exactly opposite findings are reported by Goodwin (1992) where the values of both the price and the income elasticities have slightly gone up by comparing studies in the 1980s and 1990s with earlier works.

There have been intensive discussions about the effects of gasoline price and income on gasoline demand elasticities. Although Goodwin et al. (2004) prove mathematically that the price elasticity is negatively related to income, their empirical relationship still remains ambiguous.

☆ The author would like to thank Subal C. Kumbhakar, Daniel J. Henderson, Michael S. Delgado and two anonymous referees for insightful comments that greatly improved the paper.

* Tel.: +1 989 964 4904.
E-mail address: wliu1236@svsu.edu.

http://dx.doi.org/10.1016/j.eneco.2014.07.004
0140-9883/

The popular log-linear demand model which gives constant elasticities is unable to answer this question. A translog model on the other hand is preferred in this case. Using the translog specification and CEX household survey data (1972–1973), Archibald and Gillingham (1980) find that low income households are more responsive to changes in gasoline price and income. Hausman and Newey (1995) using the REC survey data (1979–1988) find that the price elasticity is not affected by income but varies with price. Kayser (2000) studies the PSID (1981) household data, and suggests that when income increases, the demand for gasoline becomes less responsive to income changes but more responsive to price changes. In Wadud et al. (2010a) where the CEX household survey data (1997–2002) are adopted, the gasoline demand for higher income households is found to be more responsive to changes in both price and income.

Recent studies have explored more flexible functional forms in the modeling of gasoline consumption. For instance, Hausman and Newey (1995) introduce a semiparametric partially linear model, and find a nonlinear gasoline demand function. Such a flexible demand specification enables further examination of how income and gasoline price affect the price and income elasticities. Schmalensee and Stoker (1999) apply a similar technique to the RTEC survey data (1988 and 1991), but find no evidence that the gasoline demand of higher income households is less elastic. Using a partially linear model and the CEX household survey data (1997–2002), Wadud et al. (2010b) find a "U" shaped relationship between the absolute value of the price elasticity and income.

Despite most studies agree that the demand for gasoline in the U.S. is relatively inelastic, the inconsistency in estimation results brings up the question whether the gasoline demand elasticities are heterogeneous. If they are, what factors may have been driving the heterogeneity? In this paper I address these challenges by applying a flexible functional form and a recently developed estimation technique to 15 years of gasoline consumption data to estimate quarterly gasoline demand in the U.S. at the state level. This study has three major contributions to the existing literature.

First, I thoroughly investigate the endogeneity of gasoline price using a variety of instrumental variables. The endogeneity of gasoline price has been redundant throughout the literature, and even under the assumption of gasoline price being endogenous, finding a strong and valid instrument has been challenging the researchers. In this study, I propose three different instruments for the price of gasoline: the gasoline tax, the domestic crude oil first purchasing price, and the average gasoline price of nonadjacent states. I further conduct a Durbin–Wu–Hausman test for endogeneity using each instrument, and find that the gasoline price is more likely to be exogenous to the quarterly demand at the state level.

Secondly, I employ a semiparametric smooth coefficient model that maintains the basic log-linear demand structure but allows for functional coefficients. The advantage of this specification lies in its ability to incorporate possible heterogeneity and to obtain observation-specific price elasticity and income elasticity. I also conduct a formal model specification test in which the robustness of the smooth coefficient model is supported against the conventional log-linear model. The estimation results suggest that there exists substantial heterogeneity in both the price elasticity and the income elasticity of gasoline demand. In addition, the semiparametric model results in a much smaller income elasticity than suggested by previous studies, which implies that ignoring heterogeneity may have led to overestimate of the income elasticity in the past. More importantly, I demonstrate the meaningful policy implications of heterogeneity by simulating the reduction of gasoline consumption induced by a 10-cent increase in gasoline tax by state.

Thirdly, I further explore the sources of heterogeneity, and consider a series of factors that may be associated with the variation of the price elasticity and income elasticity of gasoline demand across states and over time. The analysis reveals that real personal income, urban form, and average fuel efficiency of vehicles on the road have strong impacts on the gasoline demand and demand elasticities of a particular state. Moreover, fluctuations of gasoline price, changes in the macroeconomic economic environment and other unobserved time effects have caused the demand for gasoline to become more elastic over time. These findings provide implications on how gasoline taxes could be implemented more effectively to achieve the goals of energy conservation and environmental protection.

The remainder of the paper is organized as follows. Section 2 introduces the semiparametric smooth coefficient model and related estimation techniques, followed by the description of data and variables in Section 3. Section 4 discusses the endogeneity of gasoline price including a comparison of various instrumental variables. Section 5 presents the estimation results from various models, and describes the discovered heterogeneity in gasoline demand elasticities. Section 6 explores the sources of heterogeneity, and finally Section 7 concludes and summarizes the policy implications.

2. Methodology

2.1. Model specification

The most commonly used gasoline demand model in the literature is the log-linear model, where the consumption of gasoline is specified as a linear function of real gasoline price, and real income. Other exogenous variables may also be included. Usually, variables are logged, and the coefficients on gasoline price and income can be directly interpreted as the price elasticity and the income elasticity respectively. The main problem attributed to the log-linear specification is the assumption of strict linear relationship between gasoline demand and all the explanatory variables. As a result, the demand elasticities are estimated to be homogeneous across the entire sample. This assumption is questionable, because in reality the price and income elasticities of gasoline demand are far more likely to be heterogeneous in different regions due to a number of factors such as weather, regulations, and driving conditions.

Another popular model among studies of gasoline demand in the literature is the translog model which includes quadratic terms of gasoline price and real income and an interaction term of the two variables. Under this specification, the price elasticity and income elasticity can be derived as linear functions of gasoline price and real income. Hence, rather than being constant as assumed in the log-linear model, the demand elasticities estimated from a translog model can vary with gasoline price and real income. Empirical results from the previous studies (Archibald and Gillingham, 1980; Hausman and Newey, 1995) have shown that varying gasoline demand elasticities are indeed supported by data.

However, gasoline price and real income may not be the only sources that can cause heterogeneity in demand elasticities. Other factors besides gasoline price and income are also likely to affect the elasticities of gasoline demand in a particular area. For instance, to the same increase in the gasoline price, urban residents may react differently from people who live in rural areas. In order for the translog model to capture such a difference, an interaction term between gasoline price and residential location would need to be added. As more interaction terms are added to control for other factors, more degrees of freedoms would have to be given up, which leads to less efficient estimation results. Therefore, finding a more flexible functional form for the estimation of gasoline demand is necessary (Hausman and Newey, 1995).

In order to sufficiently capture the heterogeneity in gasoline demand elasticities, I turn to the following semiparametric smooth coefficient model

$$\begin{aligned} ln\text{Gas}_{it} = {} & \beta_0(\mathbf{Z}_{it}) + \beta_1(\mathbf{Z}_{it})ln\text{Price}_{it} + \beta_2(\mathbf{Z}_{it})ln\text{Income}_{it} + \beta_3(\mathbf{Z}_{it})\text{Unemp}_{it} \\ & + \beta_4(\mathbf{Z}_{it})\text{Q2}_{it} + \beta_5(\mathbf{Z}_{it})\text{Q3}_{it} + \beta_6(\mathbf{Z}_{it})\text{Q4}_{it} + \epsilon_{it}, \end{aligned} \tag{1}$$

where

Gas is the gasoline consumption per capita per day measured in gallons,
Price is the real gasoline price (after-tax) measured in cents per gallon,
Income is the real personal income per capita measured in dollars,

Unemp is the unemployment rate,
Q2, *Q3* and *Q4* are quarter dummies,
Z is a vector of state attribute variables, and
ϵ_{it} is the *i.i.d.* error term.

Compared with the other two models (log-linear and translog), the semiparametric specification in Eq. (1) offers much more flexibility. It is based on a log-linear demand structure, but allows coefficients to be smooth nonparametric functions of a set of attribute variables (**Z**), which includes

PopDens: population density measured in thousand per square mile,
PTFund: state funding on public transit,
TruckPerc: percentage of trucks,
ID: state id, and
Year: time variable.

The price elasticity estimate is $\hat{\beta}_1(\mathbf{Z}_{it})$, and the income elasticity estimate is $\hat{\beta}_2(\mathbf{Z}_{it})$. These expressions of elasticities clearly demonstrate the advantages of the semiparametric setting over the parametric log-linear model. The elasticities are not simply constants, but instead related to several state attributes included in vector **Z** that may affect not only the overall gasoline consumption but also the demand responsiveness. The relations do not have to be in any specific functional form, which allows more flexibility to capture any potential heterogeneity. Meanwhile, the nonparametric estimation yields observation-specific estimates which can be used to investigate how the price and income elasticities vary with gasoline price and real income.

The selection of those attribute variables is based on the following reasoning. As is known to all that trucks are much less fuel-efficient than passenger cars, thus the percentage of trucks could roughly indicate the average fuel efficiency of vehicles in a state.[1] People's driving behavior is greatly affected by the availability and performance of public transportation services in which funding from local and state governments plays an essential role. Variable "PT Fund" (state funding on public transit) is introduced to capture the influence of this attribute. The demand elasticities of gasoline in a state with a large rural population are likely to be different from one with a large urban population. This attribute is signaled by the population density of a state. In addition, two discrete variables "state id" and "year" are included to capture other unobserved state fixed effects and time effects.

2.2. Estimation techniques

For a log-linear model, the parameters to be estimated are the coefficients on all the explanatory variables, which is true for a semiparametric model as well. The difference is that in the semiparametric model (Eq. (1)) the coefficients are estimated as nonparametric functions of **Z** variables, rather than constants as in a log-linear model. Moreover, no functional forms of these coefficients need to be presumed, thus the semiparametric estimation will yield a set of coefficient estimates for each observation (by state and quarter) in the sample, which leads to observation-specific demand model and demand elasticities. In the context of gasoline consumption, the estimates of price and income elasticities for a particular state are not only globally determined by all explanatory variables (e.g., gasoline price, and income), but also dependent on all the attribute variables specified in vector **Z**.

As for the estimation of functional coefficients $\beta(\mathbf{Z}_{it})$, a standard kernel smoothing method is usually applied. For a given observation, say z_{it}, a local sample is selected within a close neighborhood of z_{it}, and each data point in the local sample is given a different weight depending on its distance from z_{it}. The local sample is then used to estimate the fitted value $\hat{\beta}_{it}$ for that observation. This "local fit" could be approximated by taking the average of all observations in the local sample, i.e. "local constant fitting", or by fitting a linear regression line through the observations in the local sample, i.e. "local linear fitting". These local fits are then "smoothed" to construct a global function estimate. The size of the local sample is determined by a smoothing parameter (i.e. the bandwidth), and the weight assigned to each data point inside the local sample depends on the kernel function selected[2].

In this study, coefficient functions will be estimated using the nonparametric generalized method of moments (NPGMM) approach proposed in Cai and Li (2008) where moment conditions are locally weighted by the Gaussian kernel function to allow for a "local-linear fitting". For detailed description of this method and the estimator, please refer to Cai and Li (2008).

The key to reliable nonparametric and semiparametric estimation is to select an appropriate smoothing parameter (bandwidth). In this study I will use the least-squares cross-validation (LSCV) method to select bandwidths for **Z** variables. A variety of automatic, data-driven bandwidth selection methods have been developed, and the general consensus is that the LSCV selector is the most useful one over a wide range of data sets. Although computationally intensive, LSCV is usually able to select optimal bandwidths by minimizing the distance between the actual function and the estimated function.

In this study I frequently use the bootstrapping method (in particular, wild bootstrap) to compute standard errors and confidence intervals of coefficient estimates. For a wide bootstrap, the procedure follows these general steps. First fit the model of interest, and retain the fitted values and the residuals. Then randomly multiply the residuals by a random variable with mean 0 and variance 1, and add them to the fitted values to create synthetic values (for the dependent variable). Next, fit the model again using the resampled data (the original data for explanatory variables and the synthetic data for the dependent variable) to obtain coefficient estimates. Repeat the previous steps over and over again, and record all the resulted coefficient estimates. Finally calculate the standard deviation of the coefficient estimates, which is the standard error.

3. Data

A state-level panel data set consisting quarterly consumption and price of gasoline, real per capita personal income, and all other variables is used for estimation. The study period spans from 1994 to 2008, which secures 3000 observations in the panel (from 50 states and over 60 quarters).[3] Gasoline consumption data are from the U.S. Department of Energy. Since gasoline taxes are collected in most states, it is necessary to use the after-tax prices[4]. Davis and Kilian (2011) have constructed a comprehensive panel of state-level gasoline tax rates and after-tax prices using the price data from the U.S. Department of Energy and the state tax rates from U.S. Department of Transportation. Their gasoline tax rates and after-tax prices are fairly actuate, thus are adopted for this study. State quarterly personal income comes from the Bureau of Economic Analysis. Prices, personal income, and tax rates are all adjusted to constant 2005 dollars (cents) using GDP implicit price deflator provided by the Bureau of Economic Analysis (2009). Per capita gasoline consumption and per capita personal income are calculated using state population estimates from the U.S. Census Bureau.

State attribute variables include the percentage of trucks among all vehicles, state funding on public transit, and state population density.

---

[1] The average fuel efficiency is 18.1 mpg for light trucks, and 24.1 mpg for passenger cars (Heavenrich, 2006. "Light-Duty Automotive Technology and Fuel Economy Trends: 1975 through 2008". Tables 1 and 2. U.S. EPA).

[2] A kernel function $K(u)$ is a weighting function used in non-parametric estimation techniques. It could be any function which satisfies $\int_{-\infty}^{+\infty} K(u)\, du = 1$. Several types of kernel functions are commonly used, such as uniform, Epanechnikov, and Gaussian.

[3] The District of Columbia is excluded due to the presence of too many missing values.

[4] Gasoline prices from the U. S. Department of Energy are before-tax prices, i.e. the federal, state, and local taxes are not included.

Numbers of trucks and all vehicles by state are obtained from Highway Statistics Series (1993–2009), U.S. Department of Transportation. The data for state funding on public transit used here are taken from a series of Government Transportation Financial Statistics (GTFS) reports, U.S. Department of Transportation.[5] The population density (thousand per square miles) of each state is calculated using the state population estimates and the state land area (from the U.S. Census Bureau). See Appendix B for a detailed description of all variables and data sources.

4. Endogeneity issue

The endogeneity of gasoline price has remained ambiguous among studies of gasoline demand. Some authors (Archibald and Gillingham, 1980; Hausman and Newey, 1995; Schmalensee and Stoker, 1999; Wadud et al., 2010a, 2010b), who believe that the price of gasoline is mainly determined by the crude oil price in the world market and that the influence from gasoline demand is negligible, treat the gasoline price as an exogenous variable. While others argue that the quantity demanded and the price are determined simultaneously, simply ignoring the potential endogeneity will likely lead to biased and inconsistent estimates.

If the price of gasoline is indeed endogenous, an ideal instrumental variable should be both correlated with the endogenous regressor (the gasoline price) and orthogonal to the errors. However, finding an appropriate instrument for the price of gasoline has proved to be extremely difficult. Ramsey et al. (1975) and Dahl (1979) use the relative prices of other petroleum products such as kerosene and residual fuel oil as instrumental variables. The validity of this instrument is questionable, as noted in Hughes et al. (2008), that the prices of those refinery outputs are likely to be correlated with gasoline demand shocks. Hughes et al. (2008) consider crude oil production disruptions of three oil producing countries as instrumental variables, but those data are available only at the country level, hence are not suitable for this state level study.

In hope of thoroughly understanding whether the price of gasoline is endogenous, I propose three different instrumental variables. The first one is the gasoline tax (sum of the federal and state taxes) inspired by Davis and Kilian (2011) in which the change in gasoline taxes is used as an instrument for the gasoline price in a log-difference model. The gasoline tax is generally believed to be exogenous to the demand of gasoline, thus could potentially be a valid instrument. However for most states over the study period, the tax rates have shown very little variation, and this raises the doubts about the gasoline tax being a strong instrument in the econometric sense.

International prices of gasoline or crude oil could be ideal instruments for domestic gasoline prices. The difficulty of using those instruments is that the data used in this study are state-level panel data, so the instruments being used would also have to be at state level, which apparently does not apply for international prices. As an alternative to international crude oil price, "the domestic oil first purchasing price" could be a potentially valid instrument, given that the U.S. both import and export crude oil. Meanwhile, the domestic oil price could be a good proximate of the crude oil cost, the major component of the gasoline price. The data are obtained from the U.S. Energy Information Administration, and are available at the state level, which is suitable for this study as well.

One argument for the gasoline price being endogenous is that if the gasoline markets in different states are separated, the price of gasoline in the local market will be affected by the demand. In that case, the price in one state could be instrumented by the price in another state of the same time period, because they are both correlated with the crude oil price in the world market. However if the gasoline markets are not completely separated, then any demand shock in one state is likely to spread out to nearby states and influence the gasoline price in those markets. Taking both sides into account, I construct one more instrumental variable for the gasoline price in a state by taking the average gasoline price of its nonadjacent states at the same time period. For instance, the New York state is neighbor with Vermont, Massachusetts, Connecticut, New Jersey, and Pennsylvania, so the average gasoline price in all states except New York, Vermont, Massachusetts, Connecticut, New Jersey, and Pennsylvania will be the instrument for the gasoline price in New York.

Since the estimation of the semiparametric smooth coefficient model (Eq. (1)) is very computationally intensive, I start with the following fixed effect log-linear model[6] to investigate the issue of price endogeneity.

$$\begin{aligned} ln\text{Gas}_{it} = {} & \alpha_0 + \alpha_1 ln\text{Price}_{it} + \alpha_2 ln\text{Income}_{it} + \alpha_3\text{Unemp}_{it} + \alpha_4\text{PopDens}_{it} \\ & + \alpha_5\text{PTFund}_{it} + \alpha_6\text{TruckPerc}_{it} + \alpha_7\text{Year}_{it} + \alpha_8 Q2_{it} + \alpha_9 Q3_{it} \\ & + \alpha_{10} Q4_{it} + u_i + \epsilon_{it} \end{aligned} \tag{2}$$

Table 1 summarizes the estimation results using the proposed instruments under the log-linear specification (Eq. (2)). The second column presents the results when the price of gasoline is not instrumented as comparison. The correlation between instrumental variables and endogenous regressors (relevance of an instrument) can be assessed by the significance of the first stage regression. Staiger and Stock (1997) suggest that a sufficiently high F-statistic (>10) implies the relevance of the selected instrumental variables. According to their criteria, all three instruments seem relevant given the high F-statistics from the first-stage regressions. It is obvious that the coefficient estimates from "No instrument", "Instrumented by domestic oil price" and "Instrumented by average price of nonadjacent states" are very similar. Most explanatory variables are statistically significant at the 5% level, and their signs are also expected. However when using the gasoline tax as instrument, not only is the price elasticity estimated to be positive, but also the estimate of the income elasticity is surprisingly large. Such counter-intuitive results could be attributed to the lack of variation in gasoline tax rates, hence not reported in the table.

To further examine the validity of these instruments and the endogeneity of gasoline price, I conduct a Durbin–Wu–Hausman endogeneity test for each IV regression. The testing results suggest that when domestic oil price and average price of nonadjacent states are used as instruments, the price of gasoline is exogenous. Such a result is not surprising for a state-level quarterly gasoline demand study. Although the U.S. is the largest consumer of gasoline in the world, the demand of an individual state is unlikely to affect the price of crude oil in the world market, therefore its influence on the price of gasoline is almost negligible. This study is not the first one finding the gasoline price to be exogenous. Both Yatchew and No (2001) and Manzan and Zerom (2010) fail to reject the null hypothesis of price exogeneity when using regional dummy variables as instruments. Based on the above statistical evidence and the economic intuition, I incline to treat the gasoline price as an exogenous variable, at least in a quarterly state-level study. The rest of the analysis in this paper will base on this assumption.

[5] The Bureau of Transportation Statics collects data on transportation revenues and expenditures for Federal, state and local governments, and summarizes them in the Government Transportation Financial Statistics (GTFS) reports.

[6] The fixed effect estimator is in favored by a Hausman Test over the random effect estimator. This way of specification is comparable with the semiparametric model in equation (Eq. (1)) where unobserved state fixed effects are captured by the state "ID". Meanwhile, all other attribute variables are also included in the log-linear model as explanatory variables.

Table 1
Estimation results using various instrumental variables.

Variables	Instruments		
	No instrument	Domestic oil price	Average price of nonadjacent states
Intercept	4.056[a]	4.213[a]	4.807
	(2.322)	(2.404)	(2.360)
ln price	−0.083	−0.082	−0.078
	(0.009)	(0.010)	(0.009)
ln Price	0.215	0.217	0.221
	(0.046)	(0.047)	(0.047)
Unemp	−0.006	−0.006	−0.006
	(0.001)	(0.001)	(0.001)
PopDens	−0.565	−0.564	−0.562
	(0.194)	(0.194)	(0.194)
PTFund	−0.0002	−0.0002	−0.0002[a]
	(0.0001)	(0.0001)	(0.0001)
TruckPerc	0.225	0.225	0.228
	(0.062)	(0.062)	(0.062)
Year	−0.002[a]	−0.002[a]	−0.002[a]
	(0.001)	(0.001)	(0.001)
Q2	0.078	0.078	0.077
	(0.003)	(0.003)	(0.003)
Q3	0.102	0.102	0.102
	(0.003)	(0.004)	(0.003)
Q4	0.044	0.044	0.044
	(0.003)	(0.003)	(0.003)
R^2	0.081	0.081	0.080
First-stage regression			
F-stat	–	5853.28	11869.37
p-Value	–	0.000	0.000

[a] The variable is insignificant at the 5% level.

5. Results

5.1. Model specification test

Although the semiparametric approach has various appealing advantages, whether it is statistically adequate for this data set and superior to the conventional log-linear model is still yet to be proved. For that purpose, I conduct a specification test on the semiparametric model (Eq. (1)) against the log-linear model (Eq. (2)). Formally the null hypothesis and alternative hypothesis are given by

$$\begin{aligned} H_0 &: \beta_j(Z) = \alpha_j \\ H_1 &: \beta_j(Z) \neq \alpha_j \end{aligned} \tag{3}$$

where $\beta_j(Z)$ is the functional coefficient from the semiparametric model (Eq. (1)), whereas α_j is the constant coefficient from the log-linear model (Eq. (2)). Under the alternative hypothesis, the coefficients are nonparametric functions of Z rather than constants as given by the log-linear model. The test statistic is defined as

$$T_n = \frac{RSS_0 - RSS_1}{RSS_1} = \frac{RSS_0}{RSS_1} - 1 \tag{4}$$

where RSS_0 is the residual sum of squares of the H_0 model (i.e. the log-linear model with constant coefficients), and RSS_1 is the residual sum of squares of the H_1 model (i.e. the semiparametric model with functional coefficients).

The distribution of the test statistic T_n is unknown, and an effective way to find that information is the bootstrap approach mentioned earlier in the paper. In particular, I first randomly add the centralized residuals from the semiparametric (H_1) model to the fitted values of the log-linear (H_0) model to create synthetic values for the dependent variable (the consumption of gasoline). Then estimate both models using the synthetic data, and calculate the test statistic. Repeat the above process for a large number of times to get a distribution of all the bootstrapped test statistics. If the actual test statistic (calculated using the original data) is large enough to fall in the tail of the density curve, i.e. the p-value is small, the null hypothesis is rejected.

This test is proposed by Cai et al. (2000). It is a goodness-of-fit type of test that is based on the comparison of residual sum of squares of two specifications. This testing approach is very general, and can be used to test the semiparametric smooth coefficient model (Eq. (1)) against any other specification. For more details of the test, please refer to Cai et al. (2000).

I bootstrap the test statistic 399 times, and plot its density distribution in Fig. 1. The test statistic, $T_n = 13.39$, is shown by the point "T_n" on the horizontal axis. Apparently the test statistic is fairly far away from the center of distribution curve, and the resulted p-value is virtually zero. Therefore, the null hypothesis of constant coefficients is rejected, which suggests that the semiparametric smooth coefficient model (Eq. (1)) is a better specification for the quarterly state-level gasoline demand study than the conventional log-linear model (Eq. (2)).

5.2. Heterogeneity in gasoline demand elasticities

Since the semiparametric smooth coefficient model yields observation-specific estimates, the best way to present the results is the density distribution plot. The solid curve shown in Fig. 2(a) is the density distribution of price elasticity estimates, and the one in Fig. 2(b) is the density distribution of income elasticity estimates. The estimated price elasticity ranges from −0.2 to 0.1, and the estimated income elasticity ranges from 0.05 to 0.3. Both estimates widely spread out around their means, implying the existence of heterogeneity in both elasticities. In addition, the standard deviation of price elasticity estimates is 0.121, and is significantly greater than that of income elasticity estimates (0.063), which suggests that more heterogeneity is observed in the price elasticity of gasoline demand than in the income elasticity.

Density distribution plots are able to depict the heterogeneity in coefficient estimates, but fail to provide any information on other statistical inferences, such as significance and confidence intervals. Thus I use another graphical tool to present the results: the 45° gradient plots with confidence bounds (Fig. 3). It is constructed as follows. The price elasticity estimates for all observations are plotted against themselves, shown as the 45° line formed by solid black dots in Fig. 3(a). The 95% confidence upper bound and lower bound[7] is then plotted above and below the coefficient estimate of each observation. A similar plot is formed for the income elasticity estimates as shown in Fig. 3(b). The intuition for these 45° gradient plots is straightforward. The price (or income) elasticity estimate of any observation is significant at 5% level if the upper and lower confidence bounds both fall in the first or the third quadrant, because the horizontal line at zero runs outside the confidence bounds (i.e., the estimate is significantly different from zero). On the contrary, the observation is statistically insignificant at 5% level if both of the upper and lower confidence bounds fall in the second or the fourth quadrant, because the horizontal line at zero runs between the confidence bounds.

The 45° gradient plots indicate that the estimates of price elasticity and income elasticity for most observations are statistically significant (5%). One may notice from the density plot that for some observations the price elasticity is found to be positive. It is worth pointing out that, 45% of the observations with a positive price elasticity are statistically insignificant, and the ones that are significant repeatedly occur in the same states. Such counter-intuitive results suggest that there maybe other relevant factors affecting the gasoline demand in those states at a certain time. More detailed information may help understand this problem.

[7] The standard errors are estimated using a wild bootstrap. See Section 2.2 "estimation techniques" for details.

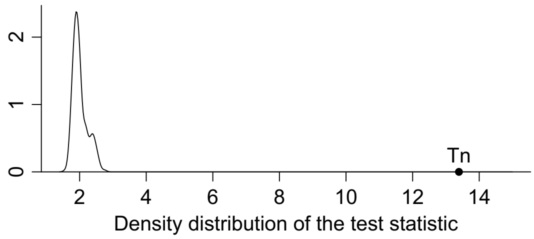

Fig. 1. Model specification test.

For the purpose of comparison, I also apply the following parametric translog model to the same data set[8]:

$$\begin{aligned} lnGas_{it} = {} & \gamma_0 + \gamma_1 lnPrice_{it} + \gamma_2 lnIncome_{it} + \gamma_3 (lnPrice_{it})^2 + \gamma_4 (lnIncome_{it})^2 \\ & + \gamma_5 lnPrice_{it} * lnIncome_{it} + \gamma_6 Unemp_{it} + \gamma_7 PopDens_{it} \\ & + \gamma_8 PTFund_{it} + \gamma_9 TruckPerc_{it} + \gamma_{10} Year_{it} + \gamma_{11} Q2_{it} + \gamma_{12} Q3_{it} \\ & + \gamma_{13} Q4_{it} + u_i + \epsilon_{it} \end{aligned} \tag{5}$$

In common with the semiparametric specification (Eq. (1)), this translog model gives observation-specific price and income elasticities as well. To closely examine the difference in elasticity estimates across various models, in Fig. 2(a), I add a dashed curve to represent the density distribution of price elasticity estimates obtained from the translog model (Eq. (5)), and a vertical line to depict the constant price elasticity given by the log-linear model (Eq. (2)). Same procedure is done in Fig. 2(b) for income elasticity estimates. The translog model yields smaller variation in gasoline demand elasticities, because the elasticities are only allowed to vary with the gasoline price and real income. Whereas in the semiparametric specification, various sources of heterogeneity (i.e. the state attributes) other than the gasoline price and income are also being considered. The semiparametric model tends to give relatively smaller values of gasoline demand elasticities compared with the other two parametric specifications, and this is especially true for income elasticity.

To better show the difference, I compute the mean price elasticity and the mean income elasticity estimates from the translog model and the semiparametric model, and summarize the results in Table 2. The constant elasticity estimates from the log-linear model are also included in the table for comparison. It appears that the more flexible the demand model, the smaller the elasticity estimates tend to be. Using the same data set, the semiparametric model gives the lowest mean income elasticity (0.162) among all three models. The translog model follows with a slightly larger income elasticity estimate (0.199). The log-linear model is the least flexible specification, and it gives the largest income elasticity estimate (0.215).

Note that the demand elasticity estimates from all three models are generally lower than what have been reported in the previous studies. For instance, using meta-analysis Espey (1998) finds a mean price elasticity of −0.38 and a mean income elasticity of 0.60 for state-level studies. Several factors may contribute to the differences. First, the frequency of data and study periods are different. Most of the studies surveyed in Espey (1998) use annual data which tend to give more elastic price and income response than quarterly data would. In addition, the time period in Espey (1998) spans from 1936 to 1986, a decade earlier than the current study, hence the results may not be comparable. Furthermore, the flexible functional coefficients in the semiparametric model incorporate state-level attributes, other unobserved state fixed effects and time effects, some of which are very likely to be correlated with income. If the influences of these factors are not sufficiently controlled for as in most other studies, they may be falsely captured by the income effect, which leads to the overestimate of income elasticity.

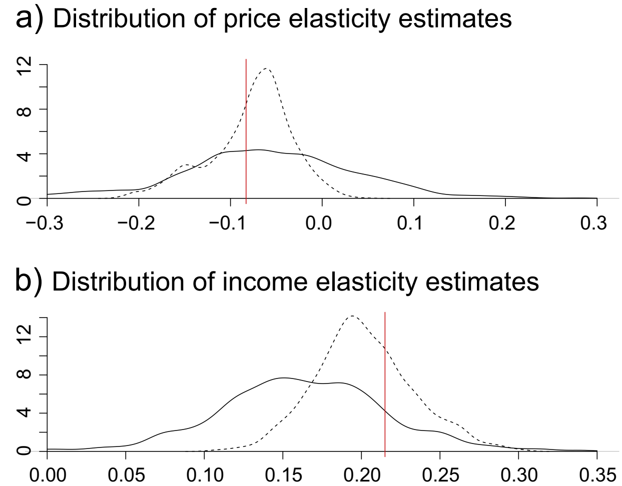

Fig. 2. Density distributions of demand elasticity estimates.

5.3. Effect of a 10-cent increase in gasoline tax

When comparing the results from the log-linear model and the semiparametric approach, it is important to consider what the different estimates imply for the effect of a given change in gasoline tax on gasoline consumption. Although the mean elasticities reported in Table 2 are similar, the induced gasoline reduction could be very different especially at the state level. In this section, I examine a hypothesized scenario in which the gasoline tax rates in all states are increased by 10 cents in December 2008. The percentage reduction in gasoline consumption resulting from this tax raise is

$$\Delta Gas_{it} = 100pe_{it}\left(\frac{10}{Price_{it}}\right). \tag{6}$$

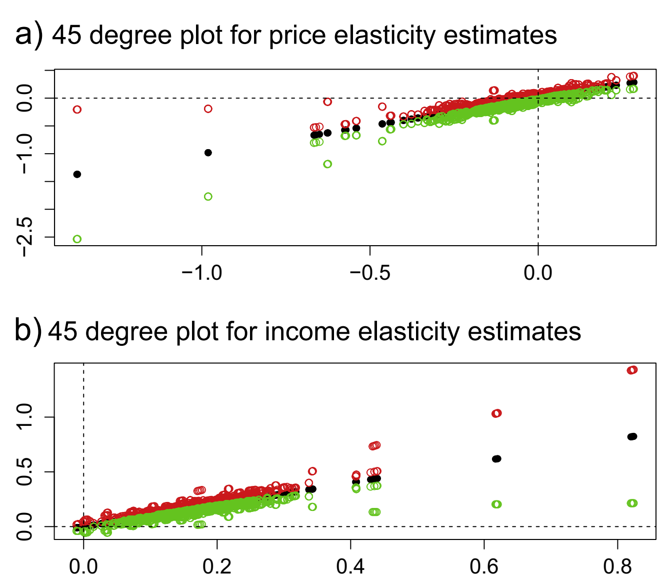

Fig. 3. Significance and confidence bounds of demand elasticity estimates.

[8] See Appendix C for detailed regression results.

Table 2
Comparison of elasticity estimates across models.

	Models		
	Log-linear	Translog	Semiparametric
Price elasticity	−0.083	−0.070	−0.062
Std. dev.	–	0.045	0.121
Income elasticity	0.215	0.199	0.162
Std. dev.	–	0.031	0.063

See Appendix C for the detailed regression results of the translog model (Eq. (5)).

The effect in each state is evaluated at the after-tax gasoline price (in cents) of December 2008 in that state. The price elasticity estimated from the log-linear model is constant at −0.083, and the gasoline prices in December 2008 are not too different across states. Therefore, the reduction in gasoline consumption in most states is similar with an average of 0.41% per day. Using the price elasticity of each state in December 2008 estimated from the semiparametric model, the total reduction in gasoline consumption (including all states) associated with the 10-cent tax increase is found to be 0.53% which is slightly higher than what is estimated from the log-linear model. Moreover, the semiparametric estimates reveal different tax effects across states.

Fig. 4 presents the tax induced percentage reduction in gasoline consumption for each state in December 2008 estimated from the semiparametric model. It is obvious that the impact of the tax raise in some states is quite different from the national average effect. For example, the state of Utah reacts much stronger than other states, and yields almost a 2% reduction in gasoline consumption, whereas in New Jersey the tax raise only reduces the gasoline consumption by 0.1%. These results are much more informative than the average effect (041%) given by the log-linear model shown by the vertical line at 0.41% in Fig. 4. The contrast between the two sets of results clearly demonstrates the advantage of the semiparametric estimation approach. The state specific tax effect implies that a tax raise is not universally effective across states as predicted by the log-linear model.

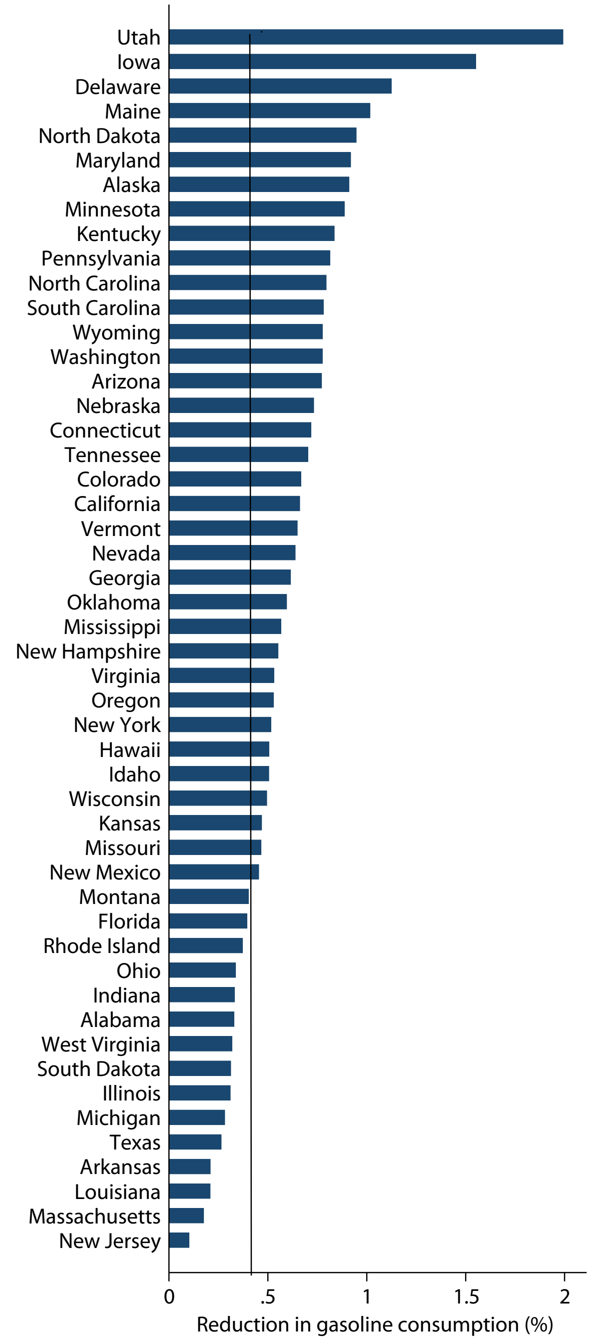

Fig. 4. The effect of a 10-cent increase in gasoline tax by state.

6. Exploring heterogeneity

6.1. Variation across states and over time

To examine the heterogeneity in gasoline demand elasticities across states, I calculate the mean price elasticity and the mean income elasticity for each state over the study period. Fig. 5 displays these mean estimates along with their 95% confidence bounds ((a) for the price elasticity and (b) for the income elasticity).

There are a few counter-intuitive results: positive price elasticities are found in Rhoda Island, Illinois and Arkansas, but these estimates are not significant at the 5% level. Significant differences are observed across states. West Virginia has the highest price and income elasticities, whereas Rhoda Island has the lowest price and income elasticities[9]. The heterogeneity across states may be explained by several state-level attributes and other unobserved state effects, which will be further discussed in the next section.

Previous literature cannot reach an agreement on how the price and income elasticities of gasoline demand have changed over time. According to Goodwin (1992), since 1980s the demand for gasoline has become more sensitive to changes in gasoline price and income; while on the contrary, Dahl (1995) reports that gasoline demand tends to become less elastic over time. Those findings are based on comparing a number of studies that cover different time periods, and the data and methods used for analysis are also fairly diverse. Unless surveying exactly the same or at least a similar collection of studies, finding inconsistent results is inevitable. In this paper under the semiparametric specification, the elasticity estimates are observation-specific by state and time, which makes it possible to examine how the price and income elasticities change over time. The results should be more creditable, because the comparison is made using the same data set and under the same framework.

I calculate the mean price elasticity and the mean income elasticity for each year across all 50 states, and plot them along with their 95% confidence bounds in Fig. 6 ((a) for the price elasticity and (b) for the income elasticity). The two graphs clearly exhibit a common pattern: the (absolute) values of elasticities tend to increase over time. This pattern shows a general trend that over time the demand for gasoline has become more responsive to changes in both gasoline price and income. A number of factors may be associated with this over-time heterogeneity. For example, dramatic fluctuations of gasoline price in the last decade may have affected consumers' driving behavior; the

[9] Technically speaking, the price elasticities of gasoline demand in Rhoda Island, Illinois and Arkansas are equally the lowest, because they are all indifferent from zero.

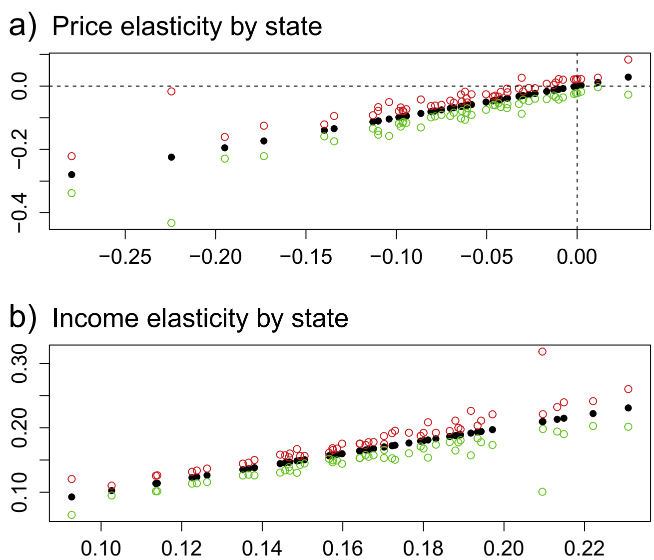

Fig. 5. Variation of demand elasticities across states.

personal income, considered as a strong driver of the demand for gasoline in the literature, has been growing over time. The overall economic environment may have also played a role in consumers' demand for gasoline. The two major macroeconomic shocks over the study period are the "911 attack" in 2001 and the "financial crisis" from 2007 to 2008, and it is worth noting that the steady increasing trend of demand elasticities is interrupted during both periods. In sum, the over-time variation of elasticities is likely to be the integrated effect of all these factors. Without further investigation, it would be difficult to predict exactly which of these factors contribute to the time-varying pattern and how the influences take place.

6.2. Sources of heterogeneity

The previous section has shown that both the price elasticity and the income elasticity of gasoline demand are heterogeneous not only across different states but also over time, following which I will further explore the sources of heterogeneity.

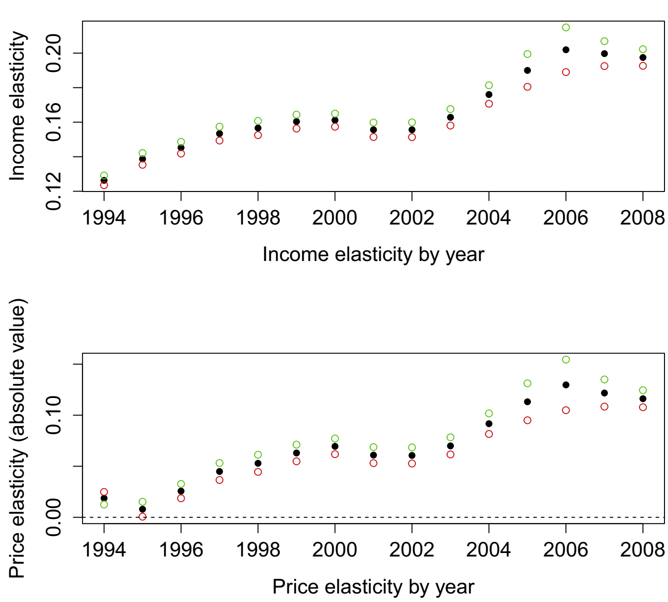

Fig. 6. Variation of gasoline demand elasticities over time.

In the semiparametric model (Eq. (1)), the demand elasticities are unknown smooth functions of **Z** variables, including state attribute variables, state fixed effects and year effects. This specification is able to control the effects of those factors, but the coefficients it estimates are high dimensional nonparametric functions and thus difficult to interpret. One commonly used tool is the counterfactual plot in which a coefficient (price or income elasticity) is plotted against one of the **Z** variables while holding others constant at their mean values. This plot shows the partial effect of the **Z** variable of interest, but holding all others such as state id at their means could lead to less informative results especially when some variables are discrete.

The effects of **Z** variables on gasoline demand elasticities could be complicated, but I assume a linear relationship to start with. Formally I regress the price elasticity and income elasticity estimated from the semiparametric model, respectively, on all the Z variables, the gasoline price (in log), and the real personal income (in log). The results are reported in Table 3. Note that the absolute value of the price elasticity is used as the dependent variable for the convenience of interpretation.

The coefficients of real personal income are found to be negative and significant in both regressions, implying a strong impact of income on consumers' gasoline consumption behavior. As income increases, the demand for gasoline tends to be less responsive to any changes in price or income. This finding is consistent with the economic principle that the demand for a good is less elastic when it takes a smaller share in consumers' overall expenditure. It also empirically proves the mathematical relationship presented by Goodwin et al. (2004) that the price elasticity is negatively related to income, and clears the ambiguity on that matter.

The effect of gasoline price on demand elasticities can be explained by the income effect of a price change. Suppose the price of gasoline goes up, to which consumers would respond as if their income falls, and the demand for gasoline thus become more sensitive to any further changes in price and income. This reasoning is verified by the positive and significant coefficient of gasoline price in the regression of the income elasticity. In the regression of the price elasticity, the coefficient of gasoline price is insignificant at 5% level, which suggests a negligible influence of gasoline price on the price elasticity.

The higher the percentage of trucks, the more responsive the demand for gasoline tends to be. This relationship is fairly intuitive. As mentioned earlier in the paper that the fuel efficiency of trucks is much lower than that of passenger cars. When there is an increase in the price of gasoline or a decrease in personal income, consumers

Table 3
Sources of heterogeneity in demand elasticities.

Independent variables	Dependent variables	
	Elasticity estimates from semiparametric model	
	Price elasticity	Income elasticity
State funding on public transit	0.0004	0.0003
	(0.0001)	(0.0001)
Percentage of trucks	0.451	0.216
	(0.082)	(0.042)
Population density	0.914	0.242[a]
	(0.257)	(0.133)
Unemployment rate	−0.017	−0.011
	(0.002)	(0.001)
Year	0.013	0.007
	(0.001)	(0.001)
Gasoline prices	−0.010[a]	0.014
	(0.011)	(0.006)
Personal income per capita	−0.429	−0.237
	(0.060)	(0.031)
F-test on the joint significance of fixed effects		
F-stat	24.200	19.870
p-Value	0.000	0.000

The absolute value of price elasticity is used as the dependent variable.
[a] The variable is insignificant at the 5% level.

initiate fuel-saving behavior, such as carpooling or combining trips, which leads to a larger reduction in fuel consumption in the states with higher share of trucks. Such an effect would be especially strong in the short run, since there would be little opportunity for consumers to adjust their vehicle stocks. This argument is supported by the large and significant coefficient on variable "percentage of trucks" in both regressions.

Although the influences are small, variable "state funding on public transit" does affect the price elasticity and income elasticity of gasoline demand, shown by the positive and significant coefficient estimates in both regressions. Financial support from state and local governments could be an indicator for the availability and performance of public transportation services. The better the services, the more likely people would use public transit as an alternative to driving when the gasoline price increases or their income falls, which means a larger reduction in gasoline consumption.

Most states have both rural and urban areas, but some states are significantly more rural than others. According to U.S. Census (2010), the most rural state is Vermont, with 82.6% of its population living in either rural areas or small cities; while in New Jersey, the rural population is only 7.8%. There are major differences between rural and urban areas, including road conditions, traffic congestion, distance between physical facilities, and the lifestyles of residents. All these differences may directly or indirectly affect people's driving behavior and their demand for gasoline. The urban form of a state is represented by variable "population density", the effect of which is large, positive and significant when explaining the heterogeneity of price elasticity, implying that the demand for gasoline is more responsive to price changes in more urbanized states. The intuition is that in larger cities, especially metropolitan areas, driving is obviously not a necessity, and can be easily replaced by walking or taking public transit. Therefore when the price of gasoline increases, a large reduction in the demand for gasoline is expected. However, the income elasticity is not significantly affected by the population density or urban form of a state.

Macroeconomic shocks indubitably influence consumers' perspectives on current economic situation and expectations of future. During a recession, most consumers are less willing to spend when faced with uncertainty and decreased purchasing power, which can be reflected on changes in driving behavior and consumption of gasoline. Initially consumers decrease discretionary driving to ease pressure on spending budgets. When a recession is perceived as long-lasting, consumers react by shifting to smaller, more fuel-efficient vehicles. Therefore, when the economy experiences a downturn, the consumption of gasoline may have already been reduced to the minimum possible amount, leaving a very little room to respond noticeably to changes in the gasoline price and income. This effect is also suggested by the negative and significant coefficients of "unemployment rate" in both regressions.

In addition to the factors mentioned above, other unobserved state fixed effects and time effects may have also contributed to the heterogeneity of gasoline demand elasticities. In the regressions of both price and income elasticities, the joint significance of fixed effects is tested to be significant (both p-values are zero). The time effect is shown by the coefficient of variable "year" which is positive and significant, suggesting that the demand for gasoline has become more elastic over time.

7. Conclusion

Neither the log-linear model nor the translog model can sufficiently capture the heterogeneity in the price elasticity and income elasticity of gasoline demand. Moreover, simply ignoring heterogeneity may result in misleading estimates of demand elasticities. This paper has shown that these problems can be overcome by a semiparametric smooth coefficient model. To illustrate this method, I have constructed a flexible gasoline demand model using 15 years of gasoline consumption data and other relevant information to incorporate possible demand heterogeneity. I have also explored a variety of alternative instrumental variables designed to account for possible endogeneity of gasoline price. The use of a recently developed estimation technique enables the estimation of observation-specific demand elasticities. The estimated income and price elasticities are smaller than those suggested by the previous studies in which heterogeneity is not sufficiently counted for.

The estimation results suggest that there exists substantial heterogeneity in both the price elasticity and the income elasticity of gasoline demand. The heterogeneity is shown by across-state and over-time variations. I have further investigated the sources of heterogeneity, and found that a series of factors, including the urban form of a particular state, the average fuel efficiency of vehicles, and state funding on public transit have played important and significant roles in explaining the variation in demand elasticities across states. Meanwhile, the fluctuation of gasoline price, the growth of personal income, changes in the macroeconomic economic environment, and other unobserved time effects have caused the demand for gasoline to become more elastic over time.

The analysis in this study provides insights on the effect of gasoline taxes on gasoline consumption and how the taxes could be implemented more efficiently in practice. Overall speaking, the demand for gasoline in the United States is fairly inelastic, therefore a tax would need to be sufficiently large in order to induce a noticeable reduction in gasoline consumption. Heterogeneity in price elasticity implies that the gasoline taxation or any pricing policy would be more effective for states with more elastic demand.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2014.07.004.

Appendix B. Data description and sources.

Variable	Source
Gasoline consumption*	Prime supplier sales volumes (1994-2008), Consumption/sales, Petroleum and other liquids, U.S. Energy Information Administration
Price of gasoline	Gasoline prices by formulation, grade, sales type (1994-2008), Prices,
after taxes **	Petroleum and other liquids, U.S. Energy Information Administration
Personal income	State quarterly personal income, Regional economic accounts, Bureau of Economic Analysis, U.S. Department of Commerce
Federal and state	Highway statistics (1994-2008), Federal Highway Administration,
gasoline taxes	U.S. Department of Transportation
State population	State Population Estimates (1990-1999) and State Intercensal Estimates (2000-2010), U.S. Census Bureau
State land area	Census 2010 Summary File 1, U.S. Census Bureau
Unemployment rate*	Local Area Unemployment Statistics (LAUS), Bureau of Labor Statistics
Number of trucks and all vehicles**	Highway statistics series(93-09), Federal Highway Administration, U.S. Department of Transportation
State funding on**	State Transportation Statistics, Bureau of Transportation Statistics,
public transit	U.S. Department of Transportation
Domestic crude oil	Domestic Crude Oil First Purchase monthly Prices by Area (94-08), Prices,
first purchase price*	Petroleum and other liquids, U.S. Energy Information Administration
GDP deflator	Bureau of Economic Analysis, U.S. Department of Commerce

Notes:
^ Trucks include private, commercial and public owned light trucks (vans, pickup trucks, and sort utility vehicles) and heavy duty trucks.
^ State funding on public transit: the data before 2000 are collected from individual states, and the data after 2000 are from the summary reports.
^ Monthly data (*) and annual data (**) are converted to quarterly data.
^ Domestic crude oil first purchase price: for states that have no data recorded in a particular time period, use the PADD average price of the same time period to fill in the missing values.

Appendix C. Estimation results using the translog model.

Variable	Coefficient	Std. Err
Intercept	-11.054	-9.851
ln *Price*	-0.436*	0.507
ln *Income*	1.046*	1.479
(ln *Price*)^2	-0.093	0.018
(ln *Income*)^2	-0.072*	0.079
ln *Price* * ln *Income*	0.127	0.054
U nemployment	-0.007	*0.001*
PopDensity	-0.678	0.225
PT F und	-0.0003	*0.0001*
TruckPerc	*0.201*	0.062
Y ear	*-0.001**	*0.001*
Q2	0.079	0.003
Q3	0.104	0.003
Q4	0.044	0.003

* The variable is insignificant at the 5% level.

References

Archibald, R., Gillingham, R., 1980. An analysis of the short-run consumer demand for gasoline using household survey data. Rev. Econ. Stat. 62, 622–628.

Baltagi, B., Griffin, J., 1983. Gasoline demand in the OECD: an application of pooling and testing procedures. Eur. Econ. Rev. 22, 117–137.

Basso, L.J., Oum, T.H., 2007. Automobile fuel demand: a critical assessment of empirical methodologies. Transp. Rev. 27 (4), 449–484.

Blum, U., Foos, G., Gaudry, M., 1988. Aggregate time series gasoline demand models: review of the literature and new evidence for West Germany. Transp. Res. A22, 75–88.

Cai, Z., Fan, J., Yao, Q., 2000. Functional-coefficient regression models for nonlinear time series. J. Am. Stat. Assoc. 95 (451), 941–956.

Cai, Z., Li, Q., 2008. Nonparametric estimation of varying coefficient dynamic panel data models. Econ. Theory 24, 1321–1342.

Dahl, C., 1979. Consumer adjustment to a gasoline tax. Rev. Econ. Stat. 61 (3), 427–432.

Dahl, C., 1982. Do gasoline demand elasticities vary? Land Econ. 58, 373–382.

Dahl, C., Sterner, T., 1991a. Analyzing gasoline demand elasticities: a survey. Energy Econ. 13, 203–210.

Dahl, C., Sterner, T., 1991b. A survey of econometric gasoline demand elasticities. Int. J. Energy Syst. 11, 53–76.

Dahl, C., 1995. Demand for transportation fuels: a survey of demand elasticities and their components. J. Energy Lit. 1, 3–27.

Davis, L.W., Kilian, L., 2011. Estimation the effect of a gasoline tax on carbon emissions. J. Appl. Econ. 26, 1187–1214.

Drollas, L., 1984. The demand for gasoline: further evidence. Energy Econ. 6, 71–82.

Espey, M., 1998. Gasoline demand revisited: an international meta-analysis of elasticities. Energy Econ. 20, 273–295.

Goodwin, P., 1992. A review of new demand elasticities with special reference to short and long run effects of price changes. J. Transp. Econ. Policy 26, 155–163.

Goodwin, P., Dargay, J., Hanly, M., 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transp. Rev. 24 (3), 275–292.

Graham, D., Glaister, G., 2002. The demand for automobile fuel: a survey of elasticities. J. Transp. Econ. Policy 36, 1–26.

Hausman, J., Newey, W., 1995. Nonparametric estimation of exact consumer surplus and dead weight loss. Econometrica 63, 1445–1476.

Heavenrich, R.M., 2006. Light-duty Automotive Technology and Fuel Economy Trends: 1975 to 2006. Office of Transportation and Air Quality. U.S. Environmental Protection Agency, Ann Arbor.

Hughes, J., Knittel, C., Sperling, D., 2008. Evidence of a shift in the short-run price elasticity of gasoline demand. Energy J. 29 (1), 113–134.

Kayser, H., 2000. Gasoline demand and car choice: estimating gasoline demand using household information. Energy Econ. 22, 331–348.

Manzan, S., Zerom, D., 2010. A Semiparametric analysis of gasoline demand in the united states: reexamining the impact of price. Econ. Rev. 29 (4), 439–468.

Ramsey, J., Rasche, R., Allen, B., 1975. An analysis of the private and commercial demand for gasoline. Rev. Econ. Stat. 57 (4), 502–507.

Schmalensee, R., Stoker, T.M., 1999. Household gasoline demand in the United States. Econometrica 67 (3), 645–662.

Staiger, D., Stock, J.H., 1997. Instrumental variables regression with weak instruments. Econometrica 65 (3), 557–586.

Sterner, T., Dahl, C., 1992. Modelling transport fuel demand. Int. Energy Econ. Chapman and Hall, London, pp. 65–79.

Wadud, Z., Graham, D.J., Noland, R.B., 2010a. Gasoline demand with heterogeneity in household responses. Energy J. 31 (1), 47–74.

Wadud, Z., Graham, D.J., Noland, R.B., 2010b. A semiparametric model of household gasoline demand. Energy Econ. 32, 93–101.

Yatchew, A., No, J., 2001. Household gasoline demand in Canada. Econometrica 69, 1679–1709.