An estimation of U.S. gasoline demand: A smooth time-varying cointegration approach

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ABSTRACT

In this paper the U.S. gasoline demand from 1976 to 2008 is estimated using a time-varying cointegrating regression. We find that price elasticity increased rapidly during the late 1970s and then decreased until 1987. After a relatively small-scaled "increase–decrease" cycle from 1987 to 2000, the price elasticity rose again after 2000. The time-varying change of the elasticities may be explained by the proportion of gasoline consumption to income and fluctuation of the degree of necessity. The result of the error correction model shows that a deviation from a long-run equilibrium is corrected quickly, and the welfare analysis illustrates there may be a gain by shifting the tax scheme from income tax to gasoline tax.

1. Introduction

While a great deal of attention has been paid to the empirical investigation of price and income elasticities of gasoline demand (see, for example, Archibald and Gillingham, 1980; Puller and Greening, 1999), only a few studies have attempted to estimate the elasticities beyond 2000.[1] Small and Van Dender (2007) used annual cross-sectional time-series data from 1966 to 2001 to investigate the rebound effect, improvements in vehicle fuel efficiency encouraging more vehicle utilization, in the U.S. market. They found that the short-run price elasticities of miles driven and fuel consumption decreased by 50% and 25% over the last 15 years, respectively. Using the 2001 National Household Travel Survey (NHTS), Kim (2007) obtained an estimate of −0.269 for the price elasticity, which is similar to many previous studies. Wadud et al. (2007) adopted a cointegration analysis and found that the gasoline demand and lifetime income had a long-term stable relationship after the oil shock in 1978. Their

estimate for the price elasticity from 1978 to 2004 was much lower than many previous estimates. Hughes et al. (2008) modeled the gasoline demand in a traditional way and found that the short-run price elasticity reduced considerably from the periods 1975–1980 to 2001–2006, but there were no statistically significant differences in the income elasticity between these two periods.

Previous studies can be classified into two classes by the type of data used for the analysis: micro data or aggregate data. The micro data can capture the effect of demographic characteristics and household structure. Since the micro panel data usually uses the time-series cross-sectional variation to identify the elasticities, the estimate embodies the long-run or, possibly, a mixture of the long-run and short-run behaviors. The aggregate data usually use the time variation for identification. The long-run and short-run elasticities can be estimated using the data with different frequencies. Previous studies usually considered monthly or quarterly data to analyze the short-run price and income elasticities of the U.S. gasoline demand. For the time series data, the non-stationarity should be considered if the series has the unit-root behavior. One of the most frequently used methods for the non-stationary time series is the cointegrating regression approach. However, the cointegration analysis is rarely used in this field (for example, Eltony and Al-Mutairi, 1995, Cheung and Thomson, 2004, etc.). And some of them failed to find a cointegrating relationship

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[1] According to Dahl and Sterner (1991) and Espey (1998), there are more than one hundred papers on gasoline demand since 1966, and most of them use U.S. data.

between U.S. gasoline demand and income or gasoline price, for example, (Wadud et al., 2007). This evidence may be due to the parameter instability. It is hard to assume that the long-run relationship between gasoline demand and income or gasoline price remains constant, say, from 1949 to 2004.

In this paper, we adopt the time-varying cointegrating regression technique proposed by Park and Hahn (1999) to estimate the time-varying price and income elasticities of U.S. gasoline demand. Our paper is different from the previous studies in two respects. First, we use most recent data to estimate elasticities. The price of gasoline rose again in 2000, and started to increase rapidly from 2004. The retail price of the regular gasoline exceeded 4.1 dollars per gallon in July 2008, which is two or three times of the gasoline price in the 1990s. Such high price may change people's style of living, and therefore, alter the short-run elasticities. Secondly, we offer some evidence that the price and income elasticities have been changing over the last few decades and show when and why these changes happened.

Our models are based on the aggregate monthly data from January 1976 to July 2008 for a total of 391 observations. We consider two model specifications, Eqs. (M1) and (M2). Eq. (M1) is the traditional log–log linear specification, that is, the logarithm of price and income explain the behavior of the logarithm of gasoline demand. It is always possible to consider other appropriate macroeconomic variables as additional covariates in the regression equation. In Eq. (M2), the interest rate is included as an additional covariate. The empirical results show that the price elasticities increased from 1976 to 1980 and then decreased until around 1986. After 1986, price elasticities had another "increase–decrease" cycle which ended in 2000. With the rise of the gasoline price in recent years, price elasticities increased gradually. The income elasticities share a similar pattern of variation with the price elasticities, however, their magnitudes and variations are much smaller than those of the price elasticities. The variations of the proportion of gasoline consumption to the disposable income and degree of necessity of gasoline can be regarded as two main causes of the time-varying changes of elasticities. The results of the error correction model (ECM) show that a deviation from a long-run equilibrium is adjusted quickly. In addition, the absence of income in the selected ECM can strengthen the notion that the income may not be very important in the short-run dynamics of gasoline demand. The welfare analysis shows the gasoline tax may have some merit compared to income tax.

The organization of the paper is as follows. Section 2 presents the econometric issues including model specifications, estimation method and cointegration test statistics. The results from the estimation, and examination of the time-varying price and income elasticities for the gasoline demand, along with the estimation results of the error correction model and welfare analysis, are reported in Section 3. Finally, Section 4 offers some concluding remarks.

2. Econometric model

Consider a cointegrating regression model in which coefficients are time-varying rather than fixed,

$$g_{mj} = \beta_0 + \beta_1(mj)p_{mj} + \beta_2(mj)y_{mj} + \varepsilon_m + \varepsilon_{mj}, \ m = 1, 2, \cdots, 12, \ j = 1, 2, \cdots, T, \quad \text{(M1)}$$

where g_{mj}, p_{mj} and y_{mj} denote the per capita gasoline demand in gallons, the real price of gasoline, and the real per capita disposable income, respectively, and subscripts m and j represent the month and year. All the variables are expressed in natural logarithm. ε_m is the unobserved demand factor that varies monthly, and error term, ε_{mj}, has zero mean. We consider ε_m as fixed month effects to capture the seasonality presented in gasoline demand. Actually, Eq. (M1) is a

time-varying coefficient version of the traditional log–log linear model. Previous studies have considered the above specification with fixed coefficients to analyze gasoline demand (see, for example, Hughes et al., 2008). Therefore, we can immediately compare our results with other studies.

It is known that the gasoline price is often correlated with the business cycle, especially after 1975 (Mork, 1989, Clements and Krolzig, 2002, Blanchard and Galí, 2007). Thus, there could be a relationship between macroeconomic variables and gasoline demand. In such a case, the estimates of coefficients based on Eq. (M1) could be biased. Thus we consider another model in which a macroeconomic variable is added to Eq. (M1) as an additional covariate,

$$g_{mj} = \beta_0 + \beta_1(mj)p_{mj} + \beta_2(mj)y_{mj} + \beta_3(mj)r_{mj} + \varepsilon_m + \varepsilon_{mj}, \quad \text{(M2)}$$

where r_{mj} denotes the interest rate.[2]

There are two distinct advantages of the cointegrating regression model with time-varying coefficients specification. Hughes et al. (2008) analyzed the differences of the price and income elasticities between two periods 1975–1980 and 2001–2006 by splitting samples correspondingly. However, this ad-hoc way leads to reducing the sample size considerably and may yield inefficiency of the estimator. In contrast, all the samples are used to estimate the time-varying parameters in our model specification. Moreover, the model also helps to detect the elasticities' turning points. The traditional cointegrating regression model assumes a "*constant*" long-run relationship. Thus, when there are structural changes in the long-run relationship, the traditional model cannot accommodate such changes, and therefore, rejects the existence of the cointegration relationship. However, such structural changes can be implemented in our model by smooth time-varying coefficients.

Park and Hahn (1999) showed that a consistent and efficient estimator for Eqs. (M1) and (M2) could be obtained in a nonparametric way using suitably transformed series. Denoting $x_{mj} = (p_{mj}, y_{mj})'$ and $\beta_{mj} = (\beta_1(mj), \beta_2(mj))'$, Eq. (M1) can be expressed by

$$g_{mj} = \beta_0 + \beta'_{mj}x_{mj} + \varepsilon_m + \varepsilon_{mj}, \quad (1)$$

where β_{mj} is assumed to vary in a smooth way. In particular, we let

$$\beta_{mj} = \beta\left(\frac{t}{n}\right), \quad (2)$$

where n is the sample size, and t is the order of observation in the total sample given by $t = 12(j - 1) + m$. Thus, β_{mj} is a smooth function defined on [0,1].

The basic idea of Park and Hahn (1999) is to approximate the time-varying parameters, β_{mj}, by the Fourier flexible form (FFF) functions,

$$\beta_k(\lambda) = \alpha_{k,1} + \alpha_{k,2}\lambda + \sum_{i=1}^{k} (\alpha_{k,2i+1}, \alpha_{k,2(i+1)})\varphi_i(\lambda), \quad (3)$$

where $\alpha_{k,j} \in R^2$ for $j = 1, 2, \cdots, 2(k+1)$ and some k, and $\varphi_i(\lambda) = (\cos 2\pi i\lambda, \sin 2\pi i\lambda)'$. Thus the n variations of β_{mj} is approximated with trigonometric polynomial functions with $2k+2$ parameters. Moreover, if β_{mj} is sufficiently smooth, k will be adequately small.[3] Alternatively, letting $f_k(\lambda) = (1, \lambda, \varphi'_1(\lambda), \cdots, \varphi'_k(\lambda))'$ with $\lambda \in [0,1]$ and $\alpha_k = (\alpha'_{k,1}, \alpha'_{k,2}, \cdots, \alpha'_{k,2(k+1)})'$, the functions β_k can be rewritten by

$$\beta_k = (f'_k \otimes I_2)\alpha_k, \quad (4)$$

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[2] We also tried various other model specifications, but they are either rejected by the cointegration test or possibly misspecified in the sense of the elasticities' signs.
[3] In our empirical results, $k = 4$ and 3 are chosen for Eqs. (M1) and (M2), respectively.

where I_2 is a 2×2 identity matrix and $\otimes$ is the kronecker product. Therefore, the model is represented by

$$g_{mj} = \beta_0 + \alpha'_k x_{kmj} + \varepsilon_j + \varepsilon_{kmj}, \tag{5}$$

where

$$x_{kmj} = f_k\left(\frac{t}{n}\right) \otimes x_{mj} \text{ and } \varepsilon_{kmj} = \varepsilon_{mj} + \left[\beta\left(\frac{t}{n}\right) - \beta_k\left(\frac{t}{n}\right)\right] x_{kmj}.$$

Park and Hahn (1999) show that if k increases along with sample size n, we can obtain a consistent estimate of $\Pi(\beta)$. However, due to the endogeneity of the error term, the ordinary least square (OLS) estimators of the model (5) are asymptotically inefficient, and, in general, non-Gaussian, which invalidates the standard OLS-based inferential procedures. In order to obtain an efficient estimator and a valid inferential basis for the parameters, the canonical cointegrating regression (CCR) method (see, Park, 1992) can be used.

Once we get the CCR estimator, we can recover β_k with the Eq. (4). Park and Hahn (1999) show that the CCR estimator of β_k is a consistent estimator of β and its limit distribution is normal,

$$M^*_{nk} - 1/2(\Pi(\hat{\beta}k) - \Pi(\beta)) \to_d N(0, \omega^2_* I_{2d}) \text{ as } n \to \infty, \tag{6}$$

where $\Pi(\beta) = (\beta(\lambda_1)', \cdots, \beta(\lambda_d)'$ and $\Pi(\hat{\beta}_k) = (\beta_k(\lambda_1)', \cdots, \beta_k(\lambda_d)')'$ with $\lambda_i \in [0,1], \forall i = 1, \cdots, d$; I_{2d} is a $2d \times 2d$ identity matrix; M^*_{nk} is a $2d \times 2d$ matrix and ω^2_* is the conditional long-run variance of the errors (ε_{mj}) given the innovations of regressors in the original regression (1).[4]

To test the null hypothesis of the time-varying coefficient cointegration against the alternative of the spurious regression with non-stationary errors, Park and Hahn (1999) used the superfluous regressors approach (see Park, 1990). The test statistic is

$$\tau^* = \frac{RSS_{TVC} - RSS^s_{TVC}}{\omega^2_*}, \tag{7}$$

where RSS_{TVC} and RSS^s_{TVC} are, respectively, the sum of squared residuals from CCR estimation for regression (5) and the same regression augmented with s additional superfluous regressors. Under the null hypothesis that the true model is a time-varying coefficient cointegration model, the limit distribution of τ^* is a chi-square with s degree of freedom. Note that if the true cointegration relation contains time-varying coefficients, the fixed coefficients cointegration model becomes a spurious regression. Hence we may test for the validity of the time-varying cointegration model against the fixed coefficients cointegration model by testing whether the fixed coefficients model is cointegrated. The test statistic for this null hypothesis is given by

$$\tau^*_1 = \frac{RSS_{FC} - RSS^s_{FC}}{\omega^2_*} \tag{8}$$

where RSS_{FC} and RSS^s_{FC} are the sums of the squared residuals from the CCR estimation for the regression (1) keeping the parameters constant over time and the same regression augmented with s additional superfluous regressors, respectively. The limit distribution of τ^*_1 is the χ^2_s if the fixed coefficient model is cointegrated, otherwise it diverges.

3. Empirical analysis

3.1. Description of the data

Data cover the period from January 1976 to July 2008 for a total of 391 observations. The U.S. Energy Information Administration (EIA)

reports the average monthly retail price of gasoline and the average daily supply each week, which equals the sum of domestic production, net import and the stock's decrease in gasoline. For the gasoline prices we consider the city average prices for the unleaded regular. The gasoline supplied is chosen as a proxy for the gasoline demand. In order to match the frequency, the weekly supply data are transformed into monthly data. The population data are from the U.S. Census Bureau, which provides monthly estimates of the number of U.S. residents. The disposable personal income, interest rate and consumer price index (CPI) are all obtained from the Federal Reserve Bank of St. Louis. The price and disposable income per capita are deflated by the consumer price index in dollars of the year of 2000. The 10-year U.S. Treasury Bill is used for the interest rate.[5]

The gasoline consumption per capita, real price of gasoline, real disposable income and interest rate are plotted in Fig. 1. We can see from the first panel that the gasoline demand per capita peaked at 46 gallons per month in 1978 and then reduced sharply when the second oil crisis happened in 1979. Between 1980 and 2008, the gasoline demand per capita usually remained below 40 gallons per month. The second panel illustrates there are two peaks in the real price of gasoline. The first was about 2.7 dollars per gallon in 1982, and the second was greater than 3 dollars per gallon in 2008. For the real disposable income there exists an increasing time trend.

We perform the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit-root tests. The lag length for the ADF test is selected by the Bayesian information criteria (BIC). The Parzen window is used to estimate the long-run error variance for the PP test, and the lag truncations are chosen according to the data-dependent method proposed by Andrews (1991). Seasonally adjusted series are used for the unit-root tests.[6] The results of those two tests are presented in Table 1.a. The PP test statistic supports the presence of the unit-root for both the demeaned and detrended series of all variables, except the gasoline demand. However, the ADF test statistics strongly suggests that all series are unit-root processes.

Although the ADF and PP tests are the most widely used unit-root tests, they are known to suffer potentially finite sample power and size problems. A variety of alternative procedures have been proposed to resolve these problems. The tests developed by Ng and Perron (2001) not only work well in such case but also are relatively easy to apply. Ng-Perron tests constitutes of four tests statistics: MZ_α and MZ_t that are the modified PP test; MSB that is related to the Bhargava (1986) R_1 test; and MP_t that is a modified version of Elliott et al. (1996) Point Optimal test. All of them improve the power and size of previous unit-root tests through two modifications: firstly, they apply a GLS estimator to demean or detrend the time series; secondly, they select the lag truncation with a class of modified information criteria. In our paper, we use the modified AIC (MAIC). The results of Ng-Perron are illustrated in the Table 1.b. All the Ng-Perron tests support the presence of the unit root in all series.

3.2. Model estimation and empirical results

To determine the lag truncation number of pairs of trigonometric functions in Eq. (3) and the inclusion of the constant and/or the linear time trend, we use BIC to select a parsimonious model. For Eqs. (M1) and (M2), $k = 4$ and 3 are chosen (including the constant term), respectively. The CCR transformation is based on the differences of the detrended regressors, the nonparametric estimators of the long-run variances Ω and the one-sided long-run variances Δ of the error term

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[4] See Park and Hahn (1999) for the specific forms of M^*_{nk} and ω^2_*.

Gasoline Consumption per Capita

Real Price of Gasoline

Real Disposable Income per Capita

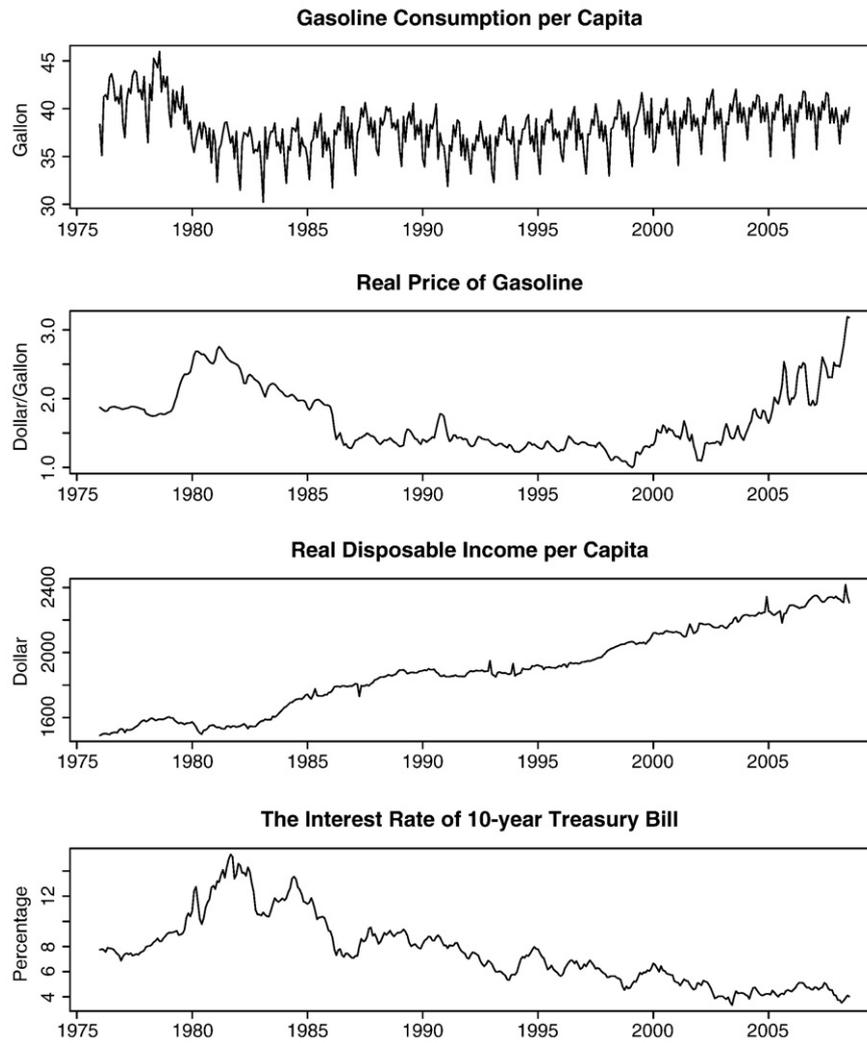### The Interest Rate of 10-year Treasury Bill

Fig. 1. Data series.

in the transformed model (see, Park and Hahn, 1999). The long-run covariance matrix, Ω, is estimated nonparametrically using the Parzen window, with the lag truncation number selected by the data-dependent selection rule (see, Andrews, 1991).

We examine the validity of the model using the specification tests τ^* and τ_1^*, respectively. We consider four time polynomial terms (t, t^2, t^3, t^4) as additional superfluous regressors. Table 2 reports the test statistics τ^* and τ_1^* for Eqs. (M1) and (M2). The results of τ_1^* show that the fixed coefficients cointegrating regression model is rejected. Moreover, the statistic τ^* cannot reject the time-varying cointegration model at the 10% significance level for Eqs. (M1) and (M2). This implies there is a time-varying long-run equilibrium among the variables.

The estimated elasticities based on Eq. (M1) are plotted in Fig. 2. The solid and dashed lines represent the estimates of elasticities and 90 percent confidence interval bands, respectively. In Fig. 2 it can be noted that the price and income elasticities share a quite similar pattern of variation, except during the 1990s. They increased at the beginning of 1975 and started to decrease after 1979. Both elasticities began to rebound from 2000. From 1985 to 2000, the income elasticities remained roughly constant, while the price elasticities showed another U-shape although the fluctuation was not as big as they were in 1976–1985. During 1976–1980 the highest price elasticity was 0.273 and the average elasticity was approximately 0.247 which is very similar to that of many previous studies. Wildhorn et al. (1974)

estimated a short-run price elasticity of 0.26 using the U.S. time series data from 1950 to 1973. Drollas (1984) estimated a short-run price elasticity of 0.35 over the period 1950–1980. Dahl and Sterner (1991) surveyed the gasoline demand literature and found that mean of short-run price elasticities is 0.29. Using the Consumer Expenditure Survey, West and Williams (2004) obtained a price elasticity of 0.27 for two-adult households.[7]

Nevertheless, there are studies in which the estimates are quite different from our estimates. Especially, the estimates based on micro data often show larger price elasticity. For example, the estimates of Archibald and Gillingham (1980), Hausman and Newey (1995), Puller and Greening (1999), Sipes and Mendelsohn (2001) and Yatchew and No (2001) vary between 0.35 and 0.9 over the period 1972–2000. This could be due to the use of micro data, for example, cross-sectional or pooled cross-sectional data, in which the elasticities are identified by the variations of gasoline consumptions and income levels among households. Since the vehicles or other facilities using gasoline, and income levels of different households at a certain time are determined by some long-run factors, for example, education and

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[7] Because the long-run labor supply elasticity and short-run gasoline demand elasticity are estimated jointly in West and Williams (2004), none of the elasticities in West and Williams (2004) is strictly short-run or long-run.

Table 1
Unit-root test.

(a) PP and ADF test					
	Demeaned series			Detrended series	
Variables	PP	ADF		PP	ADF
g_{mj}	−4.69 [6]	−2.13 [2]		−4,72 [6.2]	−2.17 [2]
p_{mj}	0.17 [10]	0.02 [2]		−0.93 [11]	−0.99 [2]
y_{mj}	−0.76 [5]	−0.52 [3]		−2.58 [5]	−2.66 [1]
r_{mj}	−0.84 [9]	−0.70 [2]		−2.97 [9]	−2.93 [2]
10% critical values	−2.57			−3.13	
5% critical values	−2.87			−3.42	

(b) Ng-Perron test							
	Demeaned series				Detrended series		
Variables	MZ_α	MZ_t	MSB	MP_T	MZ_α	MZ_t	MSB	MP_T
g_{mj}	−2.86	−1.15	0.40	8.43	−5.26	−1.61	0.31	17.31
p_{mj}	2.42	1.82	0.75	53.74	−6.81	−1.65	0.24	13.61
y_{mj}	1.24	1.99	1.60	176.49	−8.32	−2.01	0.24	11.05
r_{mj}	−1.40	−0.57	0.41	11.85	−5.40	−1.60	0.30	16.75
10% critical values	−5.70	−1.62	0.28	4.45	−14.20	−2.62	0.19	6.67
5% critical values	−8.10	−1.98	0.23	3.17	−17.30	−2.91	0.17	5.48

Notes: ADF and PP are, respectively, the augmented Dicky-Fuller and Phillips-Perron statistics for the hypothesis that the series has a unit root. The brackets in ADF and PP represent the selected lag order and bandwidth, respectively. As for Ng-Perron test, the selected lag orders are 12, 15, 12 and 2 for the demeaned series; the selected lag orders are 12, 15, 3 and 2 for the detrended series.

Table 2
Model Specification Test.

	τ_1^*	τ^*
Model (M1)	3201.01	4.19
Model (M2)	1411.31	5.31
10% critical value	7.78	

Notes: τ_1^* and τ^* are the test statistics for the null hypothesis that the variables are fixed coefficient cointegrating and time-varying coefficient cointegrating, respectively. The additional superfluous regressors are time polynomial terms, t, t^2, t^3 and t^4. If the null hypothesis is true, the corresponding statistics converges to χ_4^2 in distribution. Otherwise, it will diverge as the sample size increases.

family background, elasticities based on micro data may capture the long-run, or a mixture of long-run and short-run adjustment. In fact, some studies do not distinguish long-run from short-run elasticity in this type of studies (Hausman and Newey, 1995; Yatchew and No, 2001).

Lastly, we can see the level (in absolute value) and degree of fluctuation of the estimated income elasticities are relatively smaller than those of the estimated price elasticities. The average income elasticity is 0.073 and the gap between the highest and lowest values is 0.04. Our estimates for the income elasticity are much smaller than the majority of previous studies.[8]

For Eq. (M2) the estimates for the price and income elasticities are plotted in Fig. 3. They show quite similar pattern of variation to those of Eq. (M1). For the interest rate it had statistically significant positive effect over the periods 1977–1990 and 1997–2001. However, it turned to negative values around 2005.

In summary, for both models the price elasticities were higher during the late 1970s and early 1980s than other periods, and showed an increasing pattern after the year of 2000. The estimated income elasticities are quite similar except for the hump shape during the 1990s. These time-varying changes can be explained by the proportion of gasoline demand to income and the degree of necessity of the gasoline. We present the interpretations of the time-varying changes of the elasticities in the Subsection 3.4.

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[8] In Dahl and Sterner (1991), the average estimate for income elasticity with the monthly/quarterly data is 0.52.

3.3. Error correction model and short-run adjustment

A cointegration relationship among variables implies the existence of a long-run equilibrium. A stable equilibrium requires a positive (negative) deviation accompanied by a negative (positive) subsequent correction. The error correction model (ECM) is used to explore this short-run adjustment. In our model, an error correction term can be obtained from the CCR estimates of the time-varying cointegrating regression and represented by

$$ec_{mj} = g_{mj} - \hat{\beta}_0 - \hat{\beta}_{mj}' x_{mj} - \hat{\varepsilon}_m, \tag{9}$$

where the $\hat{\beta}_{mj}$ is recovered from the CCR estimates, and $\hat{\beta}_0$ and $\hat{\varepsilon}_m$ denote the CCR estimates of the intercept and the seasonal effect, respectively. Since β_0 and ε_m are uncorrelated with the price, income and interest rate, we have the mean- and seasonal-adjusted demand series $\tilde{g}_{mj} = g_{mj} - \hat{\beta}_0 - \hat{\varepsilon}_m$. The ECM for the gasoline demand can be expressed by

$$\Delta \tilde{g}t = b_1 ec_{t-1} + \sum_{k=1}^{q_1} b_{2k} \Delta \tilde{g}_{t-k} + \sum_{k=1}^{q_2} b_{3k}' \Delta x_{t-k} + u_{mj}, \tag{10}$$

where $t = 12(j-1) + m$, Δ denotes the difference operator and $x_t = (p_t, y_t)'$ for Eq. (M1), $x_t = (p_t, y_t, r_t)$ for Eq. (M2). The lag truncation numbers, q_1 and q_2 are selected by BIC in the estimation process.

The estimation results are reported in Table 3. First, both the models have high goodness-of-fit. More than 60% variation can be captured by ECM and the residuals seem to have no first order serial correlation. Secondly, ECM results for the two models are quite similar, however, this is not surprising since the estimates of elasticities of two models are very similar as shown in Figs. 1 and 2. We can confirm the cointegration relationship in Eqs. (M1) andM2) by checking whether $\hat{b}_1$ is significantly different from zero. In Table 3, both $\hat{b}_1$s are significant and have the expected sign. Since the value of $\hat{b}_1$ for Eqs. (M1) and (M2) are −1.134 and −1.112, respectively, we can say that gasoline demand adjusts toward its long-run equilibrium level quickly. Finally, the absence of the income variable in the selected ECM confirms the low income elasticities in long-run equilibrium. Thus we can say that even if there exists a short-run disequilibrium in the gasoline demand due to a certain shock, this disequilibrium is corrected to the long-run equilibrium very quickly.
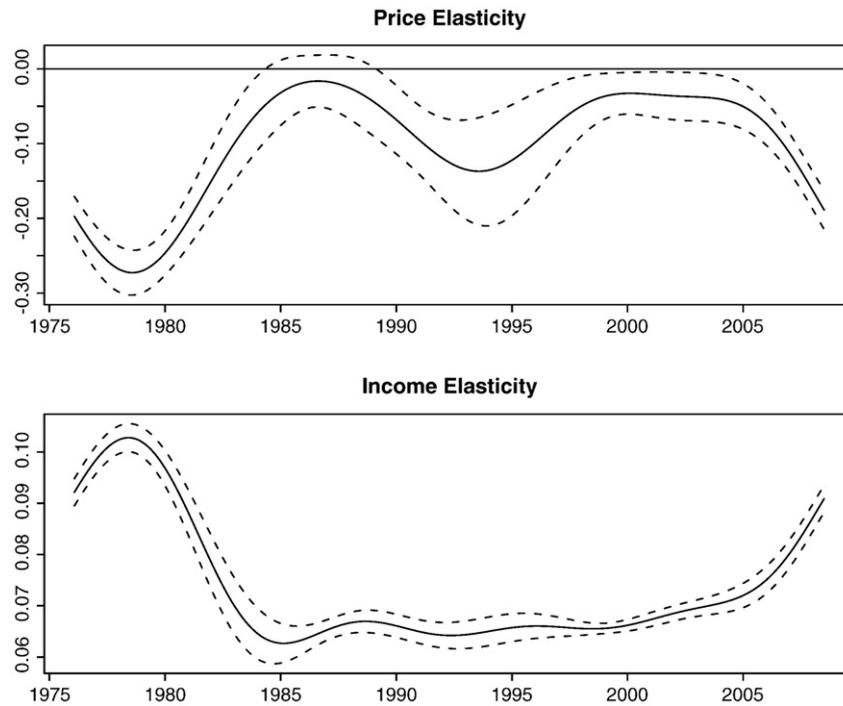
Price Elasticity

Income Elasticity

Fig. 2. Estimated elasticities: Model (M1).

3.4. Discussion

Theoretically, there are four basic determinants of the price elasticity: characteristic of the good, a luxury or necessary good; availability of substitutes; proportion of cost of the good to the consumer's budget; and the time horizon (Taylor, 1995; McTaggart et al., 1996; Gans et al., 2003). The proportion of cost of the good to the budget is also known to affect the income elasticity. Time is not considered as a factor in our model since the data frequency is fixed by month, and the availability of substitutes may not be an important factor leading to the variation of the price elasticity either. Even though diesel is the best substitute for gasoline, households cannot change their gasoline engines to diesel ones quickly. Moreover, the price of diesel usually covaries with the gasoline price. Henceforth, we focus on the other two determinants.

Variation in the proportion of gasoline consumption to the total budget is of importance to explain the behavior of price and income elasticities. It is natural to argue that when the proportion of gasoline consumption to the total budget is high, gasoline demand becomes more elastic. From Figs. 2–4 we can find that the time-varying pattern of the proportions of gasoline consumption to income is quite similar to the estimated income and price elasticities of Eqs. (M1) and (M2). To show the relationships between these variables we plot the proportions with the price and income elasticities in Fig. 5. It can be seen that there are negative and positive relationships between the proportion and the price and income elasticities, respectively. And we regress the price and income elasticities on the proportions and find that the proportions of gasoline consumption to income have a quite strong explanatory power. The adjusted R^2s of the estimated regression model with the price and income elasticities are, respectively, 0.42 and 0.48 for Eq. (M1) and 0.66 and 0.57 for Eq. (M2).

Based on the formula,

$$proportion = \frac{\text{gasoline price} \times \text{gasoline demand}}{\text{income}},$$

the variations of the proportions can be decomposed into three factors: fluctuation of (i) gasoline price; (ii) income; and (iii) gas-

oline demand. From Figs. 1 and 4 we can see that, for most of time, the fluctuation of price is the most important factor and the income is the second important factor, especially in the two periods, 1980–1982 and 2006–2008. The real price and gasoline demand in 2006–2008 were either higher than or similar to those in 1980–1982. However, the proportion in 2006–2008 was less than that in 1980–1982 due to the increase in income. Thus, the recent price elasticities were still less than those in the early 1980s. As for gasoline demand per capita, it increased very little from 1980 and it contributed negatively to the proportion for the most of time between 1980 and 1995. This might be due to improvements in fuel economy. Improvements in fuel economy lessen expenditure on gasoline given the distance required to travel. Fig. 6 shows the effects of fuel economy on gasoline demand. The big jump of the gasoline price in 1979 made consumers reduce the miles traveled, and the miles traveled per vehicle recovered and increased again with the decrease in the gasoline price and the increase in income after 1981. After the oil crisis several bills were enacted to improve fuel economy in the U.S., which stimulated automobile manufacturers to develop more fuel-efficient cars.[9] As a result, gasoline per mile declined about a quarter from 1975 to 1990. If the fuel economy had been kept at the level of 1976, people would have spent more money on gasoline and the elasticities would not be as low as the actual elasticities. In summary, the above three factors determine the proportion of gasoline demand to the total income and this, in turn, affects the price and income elasticities. In the short-run, the response of elasticity to the price change may be higher than other factors.

The degree of necessity of gasoline is also important. There is no doubt that gasoline is a necessity rather than a luxury good in the U.S.. However, the degree of necessity may change over time. Over the postwar period, many developed countries experienced

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[9] In 1975, the Energy Policy and Conservation Act was issued and in 1982 the Motor Vehicle Information and Cost Savings Act was issued, which has been amended in 1988. Afterwards, more bills have been issued for the conservation of energy.
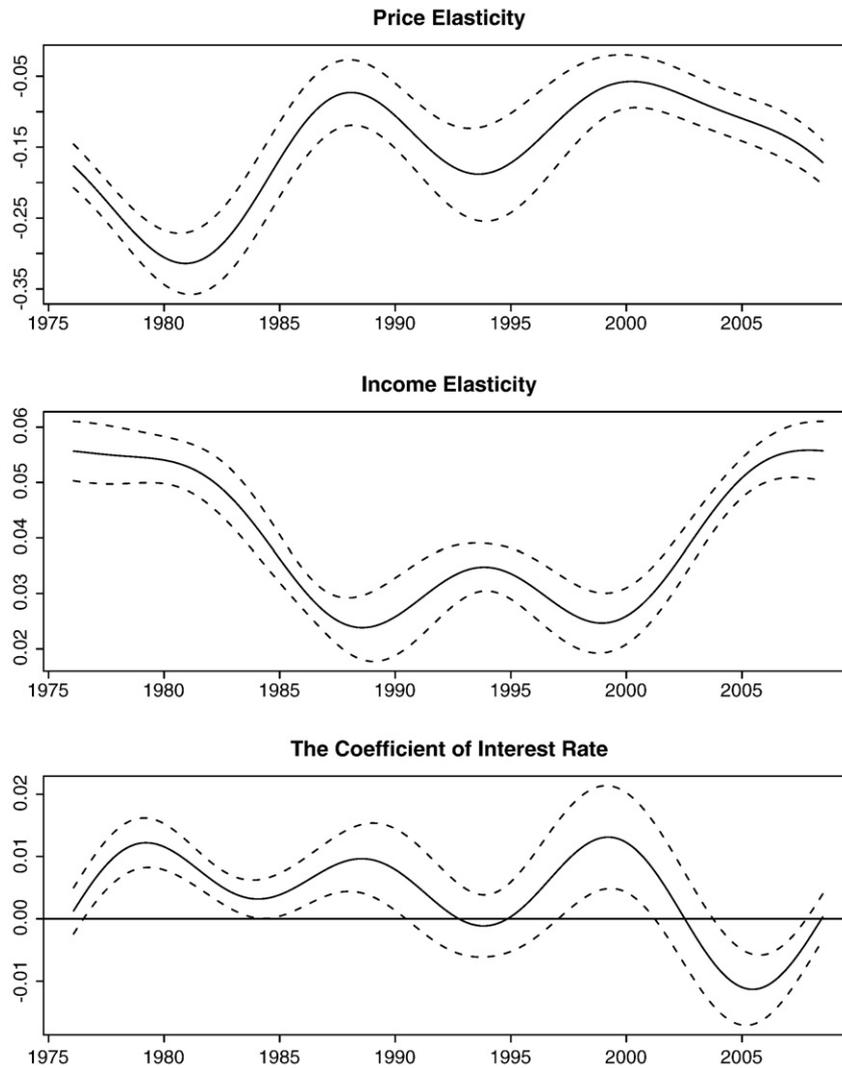
Price Elasticity

Income Elasticity

The Coefficient of Interest Rate

Fig. 3. Estimated elasticities: Model (M2).

suburbanization: more people live in the metropolitan statistical areas (MSAs), while fewer people live and work in the central cities. Suburbanization proceeded faster in the U.S.. According to the population census, 69%, 75% and 77% of the U.S. population lived in MSAs in 1970, 1980 and 1990, respectively. However, 43%, 40% and 37% of residents lived in the central cities in 1970, 1980 and 1990, respectively (Mieszkowski and Mills, 1993). Compared to urban households, suburban households drive 31% more than urban households (Kahn, 2000). Thus we can say that the suburbanization makes the U.S. household more vehicle dependent.[10] This implies that gasoline became more necessary, and thus, more inelastic.

Although elasticities increased recently, they are still very low. Such low price and income elasticities have strong policy implications. It is difficult to reduce the gasoline consumption unless some extremely high tax rate is imposed, which may not be quite appropriate. Instead, over the high fuel price period, the government can provide more subsidies to industries that engage in the fuel-efficient technology and new energy development.

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[10] Mieszkowski and Mills (1993) classified theory of suburbanization into two classes: natural evolution theory and fiscal–social problems theory. The two theories have a number of interactions and intersections. Consequently, it is difficult to distinguish between them empirically.

3.5. Welfare analysis

We use a Cobb-Douglas demand function when we estimate the elasticities of gasoline demand. In the spirit of the Hicksian equivalent variation, the deadweight loss (DWL) is expressed by

$$DWL = EV - G_1(P_1 - P_0) = e(P_1, u_1) - e(P_0, u_1) - G_1(P_1 - P_0),$$

where P_1 and P_0 are the gasoline prices with and without tax, respectively, u_1 is a utility level, G_1 is gasoline demand at P_1 and some given income level, and $e(\cdot, \cdot)$ is the expenditure function.

Table 3
Results of error correction model.

Variables	Model (M1)	Model (M2)
ec_{t-1}	−1.134 (−23.39)	−1.112 (−22.43)
$\Delta \tilde{g}_{t-3}$	0.104 (3.22)	0.096 (2.89)
$\Delta \tilde{g}_{t-9}$	0.138 (4.28)	0.138 (4.16)
$\Delta \tilde{g}_{t-12}$	0.081 (2.50)	0.091 (2.74)
Δp_{t-2}	0.063 (3.07)	0.078 (3.73)
Δp_{t-10}	0.053 (2.57)	–
$\bar{R}^2$	0.64	0.62
Dubin-Watson statistics	1.880	1.864

Notes: The numbers in parentheses are the associated *t*-values.

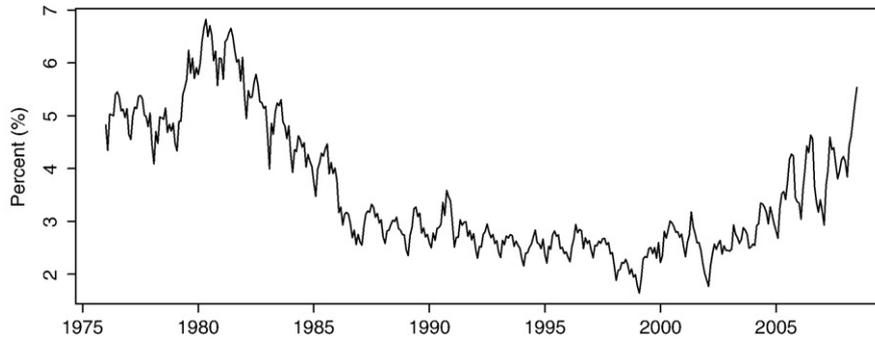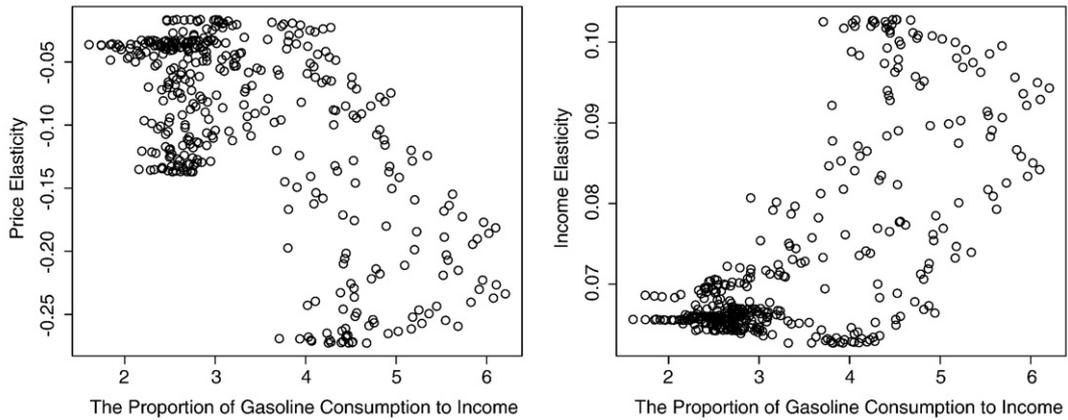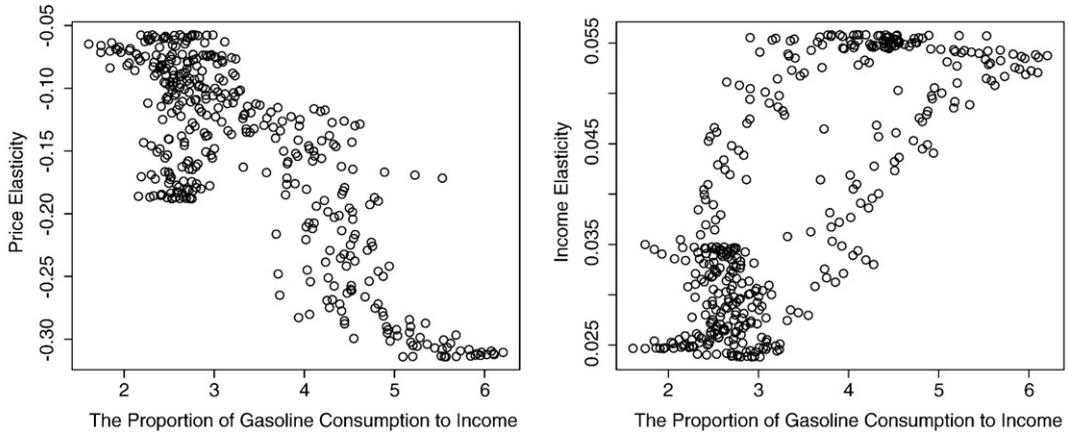**Fig. 4.** The proportion of gasoline demand to real disposable Income.

Fig. 5. Proportion of gasoline consumption to disposable income vs elasticities.

Hausman (1981) derived the indirect utility function and expenditure function for the Cobb-Douglas demand. Based on his work the DWL can be written as

$$DWL = Y - \left\{ \frac{1-\beta_2}{(1+\beta_1)Y^{\beta_2}} [P_0 G(P_0, Y) - P_1 G(P_1, Y)] + Y^{1-\beta_2} \right\}^{1/(1-\beta_2)} - G_1(P_1 - P_0),$$

where Y is the income, $G(\cdot, \cdot)$ is the gasoline demand given some price and income levels, and β_1 and β_2 are the price and income elasticities, respectively. Note that the price and income elasticities are time-varying in our model.

Kim (2004) indicated that the effective gasoline tax rate, that is, the ratio of the total gasoline tax paid to aggregate gasoline expenditure, ranged from 20% to 40% during the most of postwar period. Thus we calculate the DWL under five different effective tax rates, 20%, 25%, 30%, 35% and 40%.[11] The results are shown in Figs. 7 and 8, where we plot the ratios of DWL to income and tax revenues. Compare them to Figs. 2 and 3, we can find that the shapes of the

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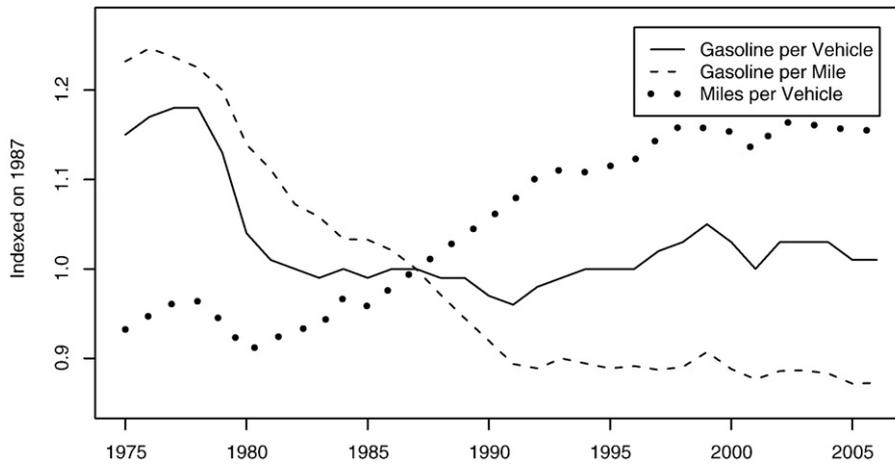[11] We also calculate the DWL under five different specific duty rates, which have similar results.

Fig. 6. The gasoline per vehicle, gasoline per mile and miles per vehicle as indices. Notes: Federal Highway Administration, highway statistics, 2006.
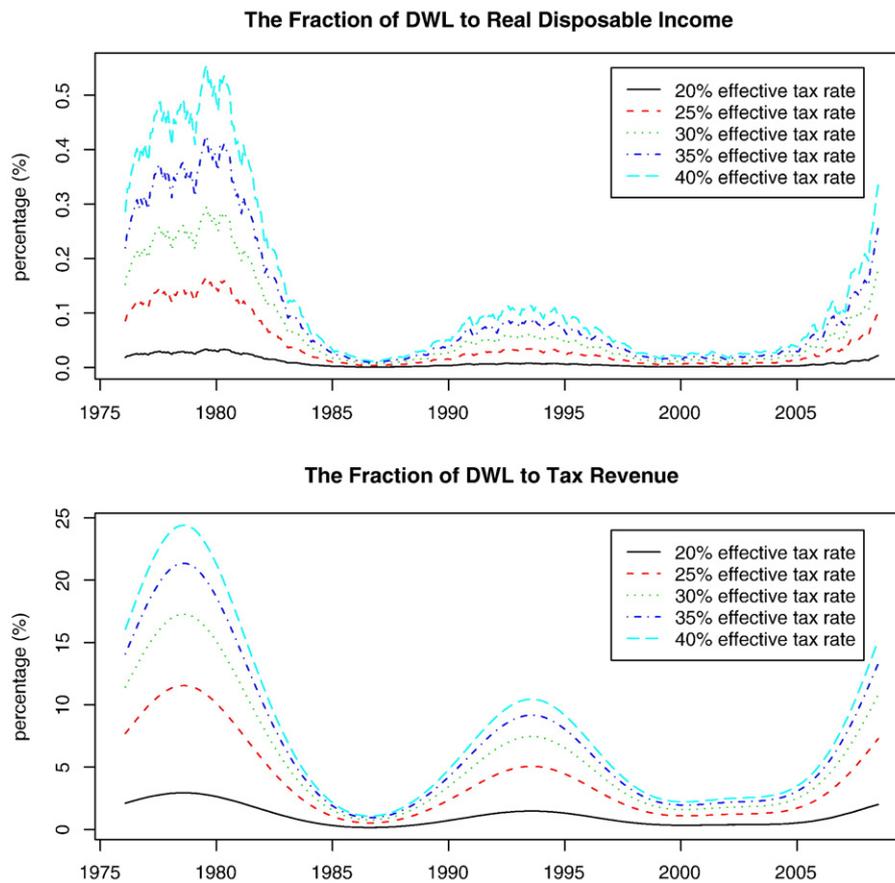

Fig. 7. Welfare analysis: M1 and ad valorem tax.

ratios look quite similar to that of the price elasticities. In addition, given some tax rate the higher the price elasticity, the more the welfare cost of tax, and, moreover, high tax rates amplify the effect of price elasticity on welfare cost. These imply that price elasticity is an important determinant of the deadweight loss.

Since gasoline tax in the U.S. is a specific duty, rather than an ad-valorem tax, the effective tax rate decreases when the gasoline price increases if there is no change in the tax rate. Therefore, if the increasing price would not lead to a rise in price elasticity, the welfare cost of the gasoline tax might decline as the gasoline price rises.

Actually, the price change causes variations of effective tax rate and the price elasticity at the same time, so the effect on welfare cost of tax is more complex.

Feldstein (1999) reported an estimate for the deadweight loss based on 1994 U.S. data and found that the income tax rate could lead to a deadweight loss as much as 30% of the tax revenue. However, in our estimates, the ratio of deadweight loss to revenue is no more than 10% in model (M1), and 15% in model (M2) in 1994 when the effective tax rate is assumed to be 40%. In the period of the late 1970s and early 1980s in which the price elasticity was highest over the whole period,
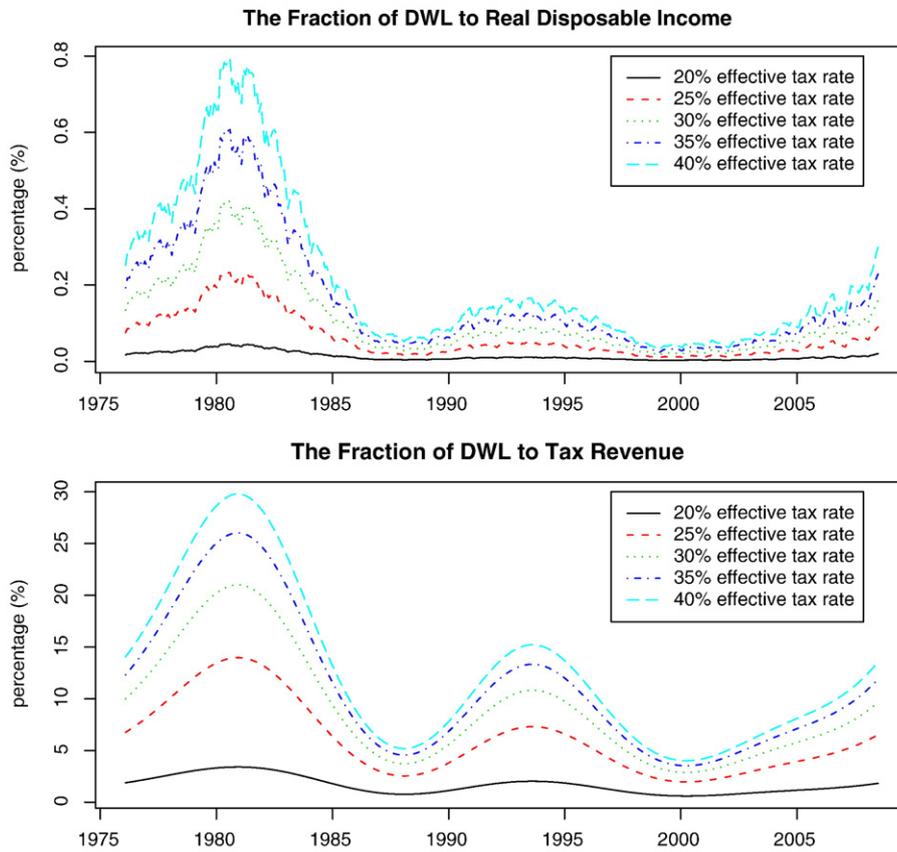
The Fraction of DWL to Real Disposable Income

The Fraction of DWL to Tax Revenue

Fig. 8. Welfare analysis: M2 and ad valorem tax.

the deadweight loss is not more than 30% of the tax revenue. As a result, the gasoline tax is more efficient than income tax, and there could be a gain by shifting the tax scheme from income tax to gasoline tax, at least in short run.

4. Concluding remarks

In this paper we analyze the U.S. gasoline demand from January 1976 to July 2008 using a cointegrating regression with smooth time-varying coefficients approach. Validity of the proposed time-varying cointegration model specification is tested against the alternatives of the spurious regression and the fixed coefficients cointegration model by the Wald-type variable addition tests. We examine two specifications and found that both of them reject the fixed coefficients cointegration model, but cannot reject the time-varying cointegration model at the 10% significance level.

The estimated results show that the price elasticities increased quickly before 1980 and then decreased until 1986. In the late 1980s and 1990s, the price elasticities experienced another relatively small-scaled "increase–decrease" cycle, and they began to increase again after 2000. The income elasticities have a similar behavior to that of the price elasticities during the above periods, but the magnitude and variation are much smaller. These time-varying changes of elasticities can be explained by fluctuation in the degree of necessity and the proportions of gasoline consumption to the total disposable income. We also investigate the short-run adjustment of the gasoline demand and find that a deviation from the long-run equilibrium is corrected quickly. The welfare analysis illustrates that the deadweight loss is, to a large extent, determined by the price elasticity. Compared to the deadweight loss of income tax, the deadweight loss can be shrunken by collecting revenue from gasoline tax.

References

Andrews, D.W.K., 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. Econometrica 59, 817–858.

Archibald, R., Gillingham, R., 1980. An analysis of the short-run consumer demand for gasoline using household survey data. Review of Economics and Statistics 62, 622–628.

Bhargava, A., 1986. On the theory of testing for unit roots in observed time series. The Review of Economic Studies 53, 369–384.

Blanchard, O.J., Galí, J., 2007. The macroeconomic effects of oil price shocks: why are the 2000s so different from the 1970s? NBER Working Papers 13368.

Cheung, K.Y., Thomson, E., 2004. The demand for gasoline in China: a contegration analysis. Journal of Applied Statistics 31, 533–544.

Clements, M.P., Krolzig, H.M., 2002. Can oil shocks explain asymmetries in the US business cycle? Empirical Economics 27, 185–204.

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

Drollas, L.P., 1984. The demand for gasoline: Further evidence. Energy Economics 6, 71–82.

Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64, 813–836.

Eltony, M.N., Al-Mutairi, N.H., 1995. Demand for gasoline in Kuwait: an empirical analysis using cointegration techeniques. Energy Economics 17, 249–253.

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

Feldstein, M., 1999. Tax avoidance and the deadweight loss of the income tax. The Review of Economics and Statistics 81, 674–680.

Gans, J., King, S., Mankiw, G., 2003. Principles of Microeconomics. 2nd ed. Thomson, South Melbourne.

Hausman, J.A., 1981. Exact consumer's surplus and deadweight loss. American Economic Review 71, 662–676.

Hausman, J.A., Newey, W.K., 1995. Nonparametric estimation of exact consumers surplus and deadweight loss. Econometrica 63, 1445–1476.

Hughes, J., Knittel, C.R., Sperling, D., 2008. Evidence of a shift in the short-run price elasticity of gasoline demand. Energy Journal 29, 113–135.

Kahn, M.E., 2000. The envrionmental impact of suburbanzation. Journal of Policy and Management 19, 569–586.

Kim, S.R., 2004. Environmental taxes and economic welfare: The welfare cost of gasoline taxation in the U.S. 1959–99. The ICFAI Journal of Environmental Economics 2.

Kim HG. 2007. An Analysis of Income Distribution Effects of A Gasoline Tax: evidence from the U.S. Micro-level Data. Ph.D. thesis, University of Missouri-Columbia.

McTaggart, D., Findlgy, C., Parkin, M., 1996. Economics. Addison-Wesley, Sydney.

Mieszkowski, P., Mills, E.S., 1993. The cause of metropolitan suburbanization. Journal of Economic Perspective 7, 135–147.

Mork, K.A., 1989. Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. Journal of Political Economics 97, 740–744.

Ng, S., Perron, P., 2001. Lag length selection and the construction of unit root tests with good size and power. Econometrica 69, 1519–1554.

Park, J.Y., 1990. Testing for unit roots and cointegration by variable addition. In: Rhodes, G., Fomby, T. (Eds.), Advances in Econometric. JAI Press, Greenwich, pp. 107–133.

Park, J.Y., 1992. Canonical cointegrating regressions. Econometrica 60, 119–143.

Park, J.Y., Hahn, S.B., 1999. Cointegrating regressions with time varying coefficients. Econometric Theory 15, 664–703.

Puller, S.L., Greening, L.A., 1999. Household adjustment to gasoline price change: an analysis using 9 years of US survey data. Energy Economics 21, 37–52.

Sipes, K.N., Mendelsohn, R., 2001. The effectiveness of gasoline taxation to manage air pollution. Ecological Economics 36, 299–309.

Small, K.A., Van Dender, K., 2007. Fuel efficiency and motor vehicle travel: The declining rebound effect. Energy Journal 28, 25–51.

Taylor, J.B., 1995. Principles of Microeconomics. 3rd ed. Houghton Mifflin, Boston.

Wadud, Z., Graham, D.J., Noland, R.B., 2007. A cointegration analysis of gasoline demand in the united states. Applied Economics 1–10 iFirst.

West, S.E., Williams, R.C., 2004. Empirical estimates for environmental policy making in a second-best setting. NBER Working paper 10330.

Wildhorn, S., Burright, B.K., Ennis, J.H., Kirkwood, T.F., 1974. How to save gasoline. Technical Report R-1560-NSF. RAND Corporation, Santa Monica, CA.

Yatchew, A., No, J.A., 2001. Household gasoline demand in Canada. Econometrica 69, 1697–1709.