Differential demand response to gasoline taxes and gasoline prices in the U.S.

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Abstract

This paper offers new evidence concerning the difference in consumers' reactions to changes in gasoline taxes relative to changes in gasoline prices. Using microdata from the 2007 to 2009 rounds of the U.S. Consumer Expenditure Survey, we estimate a complete system of demand augmented with information on gasoline excise taxes. By relying on a complete system of demand, rather than on single equations, we are able to estimate elasticities that take behavioral responses into account. In addition, we allow gasoline taxes to affect demand in two distinct ways: through relative prices and as policy signals. Elasticities of gasoline demand with respect to gasoline excise taxes and gasoline retail prices are computed and contrasted. A gasoline price increase of 13.2 ¢/gallon, corresponding to a \$15/tCO_2 carbon tax, is then considered for simulation. We find that, on average, the reduction in gasoline demand caused by a tax increase is, in the long run, almost ten times as big as that induced by an equal (tax-unrelated) price increase. The same measure of differential demand response is computed both for four U.S. broad regions and by income quintile. We discuss the implications of our findings for the design of energy policies.

JEL codes: C3, D1, H3, Q4

Keywords: gasoline taxation, consumers reactions, demand analysis

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1. Introduction

A growing literature questions the standard assumption in public finance that consumers respond to commodity tax changes in the same way as they do to price changes[1] (Chetty, 2009; Chetty *et al.,* 2009; Finkelstein, 2009; Congdon *et al.,* 2009; Goldin and Homonoff, 2013; Davis and Kilian, 2011; Li *et al.*, 2014; Rivers and Schaufele, 2013). These studies vary in the goods considered, the approaches used, but also in the explanations given for such difference. Behavioral economics contributions focus on the visibility, or salience, of taxes as a determinant of consumer choice. Finkelstein (2009), for example, shows the demand curve for driving is more inelastic when tolls are charged electronically as compared to manual collection. In a similar vein, Chetty *et al.* (2009) demonstrate that making sales taxes more salient by including them in posted prices increases demand responsiveness.[2] Another perspective is that tax payments may be perceived as a greater burden than equivalent non-tax payments, a phenomenon called tax aversion (McCaffery and Baron, 2006).[3] But explanations more consistent with rational behavior are provided too. With reference to gasoline demand, Davis and Kilian (2011) and Li *et al.* (2014) relate different reactions to gasoline tax and price changes to the difference in persistence between the two types of variations and their respective effects on price expectations. That is, as tax changes are usually longer lasting than price changes, they are more likely to influence expectations on gasoline prices and, thereby, also long-run decisions that impact on gasoline consumption, such as purchasing a more fuel-efficient car, changing transport mode, living closer to work. The same authors, however, allow that effects merely related to subjective perceptions of taxation may also play a role. Indeed, all these interpretations are not mutually exclusive, as they describe mechanisms that in some measure may all underlie the differences observed between demand responses to tax and price changes.

The present study deals with different responses of U.S. consumers to changes in gasoline taxes and gasoline prices. Gasoline taxes in the U.S. are very low compared to other countries, notably European ones (OECD, 2013). Nonetheless, they generate more revenue than any other commodity tax, both at State and federal levels. In recent years, growing concerns related to declining fiscal revenues and high CO_2 emissions meant the option of raising gasoline taxes has

[1] In this paper, unless differently specified, "gasoline prices" are intended as tax-inclusive gasoline retail prices. Similarly, "gasoline taxes" are intended to be gasoline excise taxes.

[2] Tversky and Kahneman (1974) are precursors of this conceptual strand in stressing that consumers, when making decisions, heavily rely on information that is prominent or readily available.

[3] Experimental evidence of tax aversion is growing (Kallbekken *et al.*, 2010 and 2011; Blaufus and Möhlmann, 2014), but there is no empirical evidence of such framing effect based on choice, rather than experimental, data.

received increasing consideration in the public policy debate. Raising gasoline taxes, however, is anything but a popular measure, all the more so in an economy heavily dependent on private transportation. In such a context, the hypothesis that consumers may be more responsive to gasoline taxes than to gasoline prices is of special interest. Notably, it would imply that a tax increase would induce lower gasoline use (and emissions) than "standard" price elasticities, which do not distinguish between tax and tax-unrelated price changes, would indicate. If so, of course, it would also mean less revenue would be raised than expected.

Indeed, there is growing empirical evidence which shows that consumers respond differently to gasoline tax changes as compared to price changes unrelated to taxation (Davis and Kilian, 2011; Li *et al.*, 2014; Rivers and Schaufele, 2013). This paper differs from the existing literature in three fundamental respects. First, it posits that changes in gasoline taxes impact on gasoline consumption in two main ways and identifies the respective effects within a single model. On the one hand, since gasoline taxes are a component of gasoline prices, tax changes alter relative prices and, therefore, the allocation of current consumption. On the other, changes in gasoline taxes are policy signals per se, affecting long-run consumer decisions which in turn impact on gasoline consumption. The effectiveness of gasoline taxes in reducing gasoline use, in the long run, is given by the sum of these two effects. Second, the analysis is conducted within a complete demand system framework. This means complementarities and substitution relationships among the goods considered are accounted for, thus improving identification of the effects under study. Third, by virtue of using household survey microdata, we are able to compare demand responses to changes in gasoline taxes and to equal changes in gasoline prices along different dimensions, such as households' location and income level. In addition, we provide new estimates of demand elasticities for a bundle of energy goods, including gasoline. Only a few studies on gasoline demand in the U.S. use micro-founded demand systems while also taking account of household heterogeneity (Nicol, 2003; Oladosu, 2003; West and Williams, 2004 and 2007).[4]

The rest of the paper is organized as follows. Section 2 illustrates the model and the measure of differential demand response to tax and price changes. Section 3 describes the data. Section 4 presents and discusses the results. Section 5 concludes.

[4] Schmalensee and Stoker (1999) is one example, although they do not employ a demand system nor a tightly parameterized model based on household utility.

2. Empirical Specification

2.1 The QAIDS model

The functional form chosen for our model is the Quadratic Almost Ideal Demand System (QAIDS, Banks *et al.*, 1997), which generalizes the popular AIDS (Deaton and Muellbauer, 1980) by adding a non-linear income term to the expenditure share equations. The QAIDS allows for flexible income and price responses which depend on the level of expenditure, thus providing a practical specification for demands across many commodities. By contrast, the AIDS imposes that all goods have Engel curves varying linearly with the log of expenditure. This may be a reasonable specification for demand systems with few commodities (e.g., West and Williams, 2004 and 2007, in the literature relevant to this paper). However, empirical studies have often found nonlinear Engel curves (Banks *et al.* 1997), especially when dealing with rather disaggregated demand systems and bundles of energy goods, as in our case. Furthermore, when using household survey data, an additional advantage of rank-three demand systems[5] such as the QAIDS is that they make it possible to account easily for household heterogeneity, thus enriching the demand model and leaving less space for misspecification (Nicol, 2001 and Labandeira *et al.* 2006).

The QAID specification is obtained starting from the following indirect utility function:

$$lnV(p, y^h) = \left[\frac{B(p)}{lny^h - lnA(p)} + G(p)\right]^{-1} \tag{1}$$

where y^h is total expenditure of household h; p is a price vector; the term $B(p)/[\ln y^h - \ln A(p)]$ is the inverse of the indirect utility function of a PIGLOG demand system; A and B are functions of prices and the extra term G is a third function of prices.

Specifically, $lnA(p)$ has a translog form and is linear homogeneous; $B(p)$ is a Cobb-Douglas price index homogeneous of degree zero in the price vector p, and $G(p) = \sum_i \lambda_i lnp_i$ is homogeneous of degree zero in the price vector p. The corresponding system of Marshallian demand functions for household h and goods $i=1,\dots,n$ expressed as expenditure shares is given by:

$$w_i^h = \alpha_i + \sum_k \alpha_{ik} d_k^h + \sum_j c_{ij}\, ln\, p_j + \beta_i\, ln\left[\frac{y^h}{A(p)}\right] + \frac{\lambda_i}{B(p)}\left\{\ln\left(\frac{y^h}{A(p)}\right)\right\}^2 \tag{2}$$

[5] I.e. demand models depending on three independent price functions.

where α_{ik} are the coefficients of a set of demographic variables modeled as translating intercepts $d^h = d_1^h..d_k^h$.

The translating technique (Pollak and Wales, 1992), a special case of the modifying function technique proposed by Lewbel (1985), consists in positing an additional set of linear, auxiliary relationships between the α_i in the share equations (2) and demographic or other non-price non-income variables. The demand functions (2) satisfy integrability, i.e. are consistent with utility maximization, if the following parametric restrictions hold: $\sum_i \alpha_i = 1, \sum_i \beta_i = \sum_j c_{ij} = 0$, $\sum_i \alpha_{ik} = 0$ $\forall k$ (Adding up); $\sum_j c_{ij} = 0$ (Homogeneity); $c_{ij} = c_{ji}$ for all i, j (Symmetry). Compared to the AIDS, the QAIDS adds a quadratic term in the log of income, which allows for non linear changes in the budget shares following a price or income change. A simple way to test for the presence of such non linear effects is to test the null hypothesis that λ_i=0[6].

To deal with the presence of zeroes in the dependent variables, we use the two-step estimator proposed by Shonkwiler and Yen (1999) [7]. The procedure involves probit estimation in the first step and a selectivity-augmented equation system in the second step[8].

The system of equations (2) is thus estimated in the following form (subscript *h* is omitted to ease notation):

$$s_i = \Phi(z_i^{'}\tau_i) w_i(p, y; \theta) + \delta_i \phi(z_i^{'}\tau_i) + \xi_i \tag{3}$$

where s_i is the observed expenditure share for good i; z_i is a vector of exogenous variables; τ_i is a parameter vector; θ is a vector containing all parameters (α_i, α_{ik}, b_i, g_i and c_{ij}) in the demand

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[6] We ran a likelihood ratio test to test the hypothesis λ^i =0. The test rejected the null hypothesis, thus we chose the QAID rather than AID specification.
[7] Shonkwiler and Yen (1999); Yen, Lin and Smallwood (2003) and Yen and Lin (2006) provide useful literature review on estimation procedures for censored demand systems.
[8] A different two-step procedure, developed by Heien and Wessells (1990), has often been used in applied demand analysis to address the problem of estimating systems of equations with limited dependent variables. West and Williams (2004 and 2007) are two studies adopting this procedure. However, as stated by Shonkweiler and Yen (1999, p. 972), "the Hein and Wessells procedure is built upon a set of equations which deviate from the unconditional mean expression for the conventional censored dependent variable specification". Instead, the procedure by Shonkweiler and Yen (1999) adopted in this study provides a consistent two-step estimator.

system; $\xi_i = s_i - E(s_i)$, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density function (pdf) and cumulative distribution function (cdf), respectively.

The system of equations (3) is estimated in two steps: (i) Maximum Likelihood (ML) probit estimates $\hat{\tau}_i$ of τ_i are obtained using binary outcomes $s_i = 0$ and $s_i > 0$; (ii) $\Phi(z_i', \hat{\tau}_i)$ and $\phi(z_i' \hat{\tau}_i)$ are computed for all i, and $\theta, \delta_1, \delta_2, ..., \delta_n$ are estimated in the augmented system (3) by ML. This two-step estimator is consistent, but the error terms are heteroscedastic. The estimated elements of the second-step conventional covariance matrix are therefore inefficient. For this reason we empirically calculate the standard errors of the elasticities using nonparametric bootstrapping (with 500 replications). The dependent variable in the first-step probit estimates is the binary outcome defined by the expenditure in each good. The predicted pdf and cdf from the six probit equations are included in the second step of the procedure (see Yen, Lin and Smallwood, 2003, p. 464). The exogenous variables used in the first-step probit estimates are quarterly disposable income (also available in the CE survey) and a set of demographic and geographic variables, which are described in the next section. As for the second-step estimates, we impose homogeneity and symmetry through parametric restrictions, while adding-up is accomodated by dropping the equation for "Other goods and services". Economic theory also requires the matrix of Slutzky substitution effects to be negative semi-definite, which here we impose using the Cholesky decomposition. Furthermore, to address concerns of endogeneity of total expenditure, we use quarterly disposable income instead of total expenditure.

Finally, differentiation of equation (3) gives demand elasticities for the first *n-1* goods, and the elasticities for the n^{th} good are recovered exploiting the Cournot and Engel restrictions (Deaton and Muellbauer, 1980, p. 16). The corresponding uncompensated, compensated (Hicksian) and expenditure elasticities for good *i* are, respectively:

$$e_{ij}^M = \frac{\mu_{ij}}{w_i} - \delta_{ij} \tag{4}$$

$$e_{ij}^C = e_{ij}^M - e_i w_i \tag{5}$$

$$e_i = \frac{\mu_i}{w_i} + 1 \tag{6}$$

Where δ_{ij} is the Kronecker delta, $\mu_i = \beta_i + \frac{2\lambda_i}{B(p)} \left\{ ln \left[\frac{y}{A(p)} \right] \right\}$ and

$$\mu_{ij} = \frac{\partial w_i}{\partial lnp_j} = c_{ij} - \mu_i \left(\alpha_i + \sum_i \sum_k \alpha_{ik} d_k \ + \sum_j c_{ij} lnp_j \right) + \frac{2\lambda_i}{B(p)} \left\{ ln \left[\frac{y}{A(p)} \right] \right\}^2 \quad (6a)$$

2.2 Incorporating gasoline taxes in the demand system

While the literature offers plausible explanations for observed differential responses to gasoline taxes and gasoline prices, such arguments do not inform model specifications. Both Li *et al.* (2014) and Rivers and Schaufele (2013) enter gasoline taxes and tax-exclusive gasoline prices separately in single equation models for gasoline demand. However, no particular role of taxes in relation to consumer choices is tested or assumed. The same is true for the study by Davis and Kilian (2011), who identify the tax effect indirectly by instrumenting tax-inclusive gasoline prices with gasoline taxes. We depart from the literature in positing specific roles for gasoline taxes in a demand system framework.

Our approach hinges on the presumption of a dual effect of changes in gasoline taxes *a)* through relative prices and *b)* as policy signals affecting relevant long-run decisions, such as buying a more fuel-efficient car, changing transport mode, living closer to work. Accordingly, gasoline taxes, *t*, enter our model in two distinct ways. First, as price component, they are embedded in gasoline prices, p^G. Second, together with socio-demographic variables (the d's in (2)), gasoline taxes enter the model explicitly as translating intercepts adjusting equilibrium demands. The same translating intercepts approach has been used in other demand system studies to analyze the effects of non-price, non-income variables such as quality information (Jensen *et al.*, 1992, Chern *et al.*, 1995), innovation (Moro *et al.*, 1996) and advertising (Duffy, 1995, Brown and Lee, 1997).

Such a specification implies that *t* as price component does not have a special role (i.e., it is no different from other components) in determining gasoline demand. In other words, when deciding on allocating current consumption, consumers are assumed to consider p^G, not its composition. Even if drivers were well informed about the level of taxation, or had an approximate sense of it[9], it is difficult to imagine they would refill the tank depending on the composition of the price they pay and not just its level. Conversely, it seems to us plausible that gasoline taxes as policy signals can influence long-run decisions which in turn determine future gasoline demand. As changes in gasoline taxes are not frequent and tend to receive attention from the media (e.g., Li *et*

[9] Posted prices on big signs at gasoline stations are tax-inclusive.

al., 2014), they may affect expectations of future gasoline prices[10] and, at the same time, may induce responses greater than utility maximization would justify given subjective perceptions or beliefs concerning taxation.

2.3 Simulating demand responses to tax increases and tax-unrelated price increases

After estimating the model in (3), inclusive of gasoline taxes, tax and price elasticities of gasoline demand are computed at given points. They are then used to separately simulate the impacts on gasoline demand of equal increases in gasoline prices due to, respectively, a tax increase and an increase in the pre-tax price. The ratio of the two local demand changes, θ_0, measures the effectiveness of gasoline taxes at reducing gasoline demand, in the long run, relative to non-tax price increases. That is, given $p^G = \pi + t$, and considering two scenarios sharing equal changes in *t* and π, respectively (i.e., $\Delta t = \Delta\pi$),

$$\theta_0 \equiv \frac{\Delta q_0^G(\Delta t)}{\Delta q_0^G(\Delta \pi)} = \frac{\eta_0 \times \frac{\Delta t}{t_0}}{\nu_0 \times \frac{\Delta \pi}{\pi_0}} = \frac{\eta_0 \times \frac{\Delta t}{t_0}}{\varepsilon_0 \times \frac{\Delta \pi}{p_0^G}} \tag{7}$$

where: η is the elasticity of gasoline demand to gasoline taxes, ν is the own price elasticity of gasoline demand to tax-exclusive prices, and ε is the own price elasticity of gasoline demand to tax-inclusive prices.[11,12]

As we estimate the model using price indices of tax-inclusive prices, we derive θ using the right hand side formulation in (7); that is, using ε, estimated as per (4), instead of ν. Furthermore, the

[10] Anderson *et al.* (2013) find no evidence supporting this particular hypothesis. However, their test arguably warrants further investigation. Indeed, it is not unconceivable that the respondents to the survey used by the authors expressed their expectations on gasoline prices five years into the future considering only market forces and not taxation. This could be the case since tax changes are relatively rare events, virtually impossible to predict over a five-year horizon.

[11] It is easy to show that if $q = f(p)$ and $p = \pi + t$, then $\left(\frac{\partial q}{\partial \pi}\frac{\pi}{q}\right)\frac{\Delta\pi}{\pi} = \left(\frac{\partial q}{\partial p}\frac{p}{q}\right)\frac{\Delta\pi}{p}$.

[12] This definition of θ is analogous to the one in Davis and Kilian (2011). It differs from the one in Chetty *et al.* (2009) only in that the elasticities to the tax and to tax-exclusive prices are multiplied by the respective percentage variations. For Chetty *et al.* (2009), comparing the two elasticities suffices because the authors consider the case of an *ad valorem* tax.

elasticity of gasoline demand to gasoline taxes, η, encompasses both the effects of Δt, through p^G and as a policy signal:

$$\eta = \frac{\mu_{ii}+\mu_{it}}{w_i} \tag{8}$$

where: i corresponds to gasoline; $\mu_{ii} = \frac{\partial w_i}{\partial lnp_{ii}}$; $\mu_{it} = \frac{\partial w_i}{\partial lnt}$.[13]

A result $\theta_0 = n$ indicates that, at the given point 0, an increase in gasoline taxes is n-times as effective at reducing gasoline demand in the long run as an equal increase in gasoline prices not due to a tax rise.

3. Data

3.1 Household budget shares, total expenditure and socio-demographics

The U.S. Consumer Expenditure Survey (CEX) produced by the Bureau of Labour Statistics (BLS) is the main data source for our application. We use microdata of the quarterly Interview Survey (IS) from the 2007, 2008 and 2009 rounds of the CEX.[14] Each CEX round has five IS cross-sections: one per calendar quarter in which the interviews took place, including the first quarter of the following year.[15]

We draw on 15 cross-sections and about 90,000 observations, as each cross-section has approximately 6,000 observations. The model, however, is estimated on a subset of 43,457 observations, those for which information on the Metropolitan Statistical Area (MSA) is given. We use such a subset because more price variation is obtained with indices that vary by MSA than with State-level indices. The sample spans 39 months, from January 2007 to March 2010, and 20 MSA (see Tables A1 and A2, in the Appendix).

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[13] $\mu_{it} = \frac{\partial w_i}{\partial lnt} = \alpha_{it} - \beta_i\left(\sum_j \alpha_{jt} + \sum_j c_{ij} lnp_j\right) + \frac{2\lambda_i}{B(p)}\left\{ln\left[\frac{y}{A(p)}\right]\right\}$

[14] See Chapter 16 of the Bureau of Labor Statistics Handbook of Methods for a description of the Consumer Expenditure Survey.

[15] The IS is a panel rotation survey. Each panel is interviewed for five consecutive quarters and then dropped from the survey and replaced with a new one.

In the IS, each household's expenditures, which refer to the three months before the interview, are classified into 60 consumption categories. Our system of demand only considers current expenditures (durables and occasional purchases are ignored), which correspond to 40 of the 60 categories. Specifically, the model is estimated for the following shares of total current expenditure:

1) Food at home
2) Electricity
3) Natural gas
4) Other home fuels
5) Motor fuels (gasoline)
6) Public transport
7) All other expenditures

where: *Food at home* is the total expenditures for food at grocery stores (or other food stores) and food prepared by the consumer unit on trips; *Other home fuels* is the sum of expenditures on fuel oil, non-piped gas and other fuels (heating fuels); *Public transport* is the sum of fares paid for all forms of public transport, including buses, taxis, coaches, trains, ferries and airlines.

Table 1 shows summary statistics of these expenditure shares as they appear in the sample. On average, expenditure on food consumed or prepared at home accounts for 22.8% of total current expenditure, followed by motor fuels and electricity, which represent 9.1% and 5.8%, respectively; the residual category, *All other expenditures*, represents 56.7% of total current expenditure. The coefficients of variation indicate that variability is greatest for *Other home fuels*, *Public transport* and *Natural gas*, in that order. Large proportions of households reported zero expenditure for these expenditure aggregates (see the shares in the last column of Table 1). Consumption of the respective goods or services is conditional on certain prerequisites, such as the possession of specific appliances and high substitutability between private and public transport, which may not hold for many households.

[TABLE 1]

Different types of socio-demographic characteristics are also extracted from the IS dataset. Descriptive statistics of those and of total current expenditure are reported in Table 2. The household profile is categorised through six dummy variables identifying the following types: *a)* Single; *b)* Husband and wife; *c)* Husband and wife, with oldest child under 6; *d)* Husband and wife, with oldest child under 18; *e)* Husband and wife, with oldest child over 17; *f)* Other households. Geographic location is rendered through four dummy variables, one for each of the Census-defined regions: Northeast, Midwest, South and West. A dummy variable brings in information on the composition of earners in the household: it takes the value 1 if both reference person and spouse are income earners; 0, otherwise. A categorical variable classifies the education level of the reference person in nine levels. Moreover, the model controls for the number of cars owned by the household.

[TABLE 2]

3.2 Price indices and gasoline taxes

Insufficient price variation is a common problem when estimating demand models with cross-sectional data and price indices. We avoid this issue by using monthly indices varying by MSA, which exhibit sufficient time and spatial variation.[16] Another potential problem is some degree of inaccuracy in the correspondence between demand and price data. In our application, this issue does not arise because price indices, also produced by the BLS, follow the same classification as household expenditure. The BLS uses the CEX to periodically revise the expenditure weights of the Consumer Price Index (CPI). There is, therefore, perfect correspondence between IS and CPI statistics with respect to the expenditure aggregates. In the Appendix, Table A3 shows summary statistics of price indices; also, Figure A1 shows the evolution over time of price indices averaged by region.

In the U.S., three layers of taxes apply to consumption of gasoline and auto diesel, namely, federal taxes, State taxes and local taxes. The federal tax rate on gasoline is currently 18.4 ¢/gallon and has not changed since 2006.[17] By contrast, State taxes can differ significantly from one State to another and they are occasionally subject to revisions. The data used on monthly rates of State taxes are published by the Federation of Tax Administrators (FTA).[18] Local taxes are not considered due to lack of information.

[16] Only, as price indices by MSA are not available for *Other home fuels* nor for *Public transport*, national level indices are considered in these cases.
[17] Source: U.S. Energy Information Administration.
[18] Two rates are added up: "State motor gasoline taxes" and "Other State taxes", in FTA's nomenclature.

Figure 1 shows the sum of federal and State gasoline taxes across the States where the tax rate changed at least once over the the time period considered (9 States out of the 23 in the sample) and over the months (39) covered by the sample.[19] It is apparent that changes in gasoline taxes are relatively rare events and that variation between States is much greater than variation within States. Figure 2 focuses on the two States where gasoline taxes varied the most in the years considered, namely Maine (MA) and Washington (WA).[20] In both cases, taxes remain within a distance of 5% from the mean of the period, with one exception for Washington, in early 2007. By contrast, prices rose as high as almost 50% above the mean of the period and then fell to as low as 30% below the mean. In general, price and tax changes very clearly differ both in size and persistence.

[FIGURE 1]

[FIGURE 2]

4. Results

In this section, we first discuss the estimation results concerning the demand system and its derived parameters (elasticities). We then focus on differential demand responses to simulated gasoline price- and tax changes.

4.1 QAIDS coefficients and elasticities

Table A4, in the Appendix, shows the estimated coefficients of the first-step probit models under Shonkwiler and Yen's procedure. Income is significant in all probit equations and takes on the expected positive sign. The education level of the household's reference person is significant in all equations, except for gasoline, and also takes on the expected sign. Focusing on the gasoline equation, compared to living in the Midwest (the reference location), living in the Northeast has a negative impact on the probability of purchasing gasoline, whereas living in the South or in the West has a positive impact on the probability of buying gasoline. Having children has a positive

[19] Figure A2, in the Appendix, shows the frequency distribution of State tax rates in our sample.
[20] The graphs for the other States, which are similar, are not shown for space reasons. They are available from the authors upon request.

impact on the probability of buying gasoline compared to a childless couple (the reference household type). Being single has instead a negative impact on the probability of purchasing gasoline compared to a childless couple.

Table 3 reports the results of some of the second-step QAIDS parameters.[21] Here we focus on the coefficients of the gasoline budget share equation. All geographic dummy variables (α_{NE}, $\alpha_{SO,}$ α_{WE}) are statistically significant. Their values indicate that, relative to the Midwest (the reference category), living in the West has a positive impact on gasoline consumption, followed by the South and the Northeast (in descending order). As expected, the number of cars owned by a household (α_{NCAR}) has a positive impact on gasoline consumption. The same is true for the presence of two income earners in the household (α_{TWOE}), possibly due to cumulatively longer distances between home and the respective workplaces. The dummy variables for household demographics (α_{N1}, $\alpha_{N3,}$ α_{N4}, $\alpha_{N5,}$ α_{N6}) are all statistically significant. The size of the coefficients, whose values are relative to that of the "Household and wife" base category, seems to reflect the number of household members old enough to have a driving license.[22] A higher education level of the head of household (α_{EDUC}) turns out to have a negative impact on gasoline consumption. As expected, the same is true for higher gasoline taxes (α_{TAX}).

[TABLE 3]

[TABLE 4]

Concerning the elasticities, compensated own- and cross-price elasticities (e^{c}_{ij}), along with income elasticities (e_i) and estimated budget shares (w_i), are shown in Table 4. All of these are evaluated at the sample means of exogenous variables. On average, 18.2% of total current outlay is spent on energy related products (the sum of the budget shares of *Electricity*, *Natural gas*, *Other home fuels* and *Gasoline*), with *Gasoline* on its own making up 9.0% of total current expenditure. With regard to income elasticities, all the commodities but *Other goods* turn out to be necessities. In general, all own-price elasticities seem plausible, ranging between -0.878 and -0.179, these being the elasticities for *Electricity* and *Natural gas*, respectively.[23] For *Gasoline*, we find an own-price elasticity of -0.421, which is in line with the U.S. literature estimating complete systems of demand (e.g., West and Williams, 2007; West and Williams, 2004; Nicol, 2003; Oladosu, 2003). Table 5 shows some

[21] For space reasons, price coefficients and c.d.f. coefficients are not reported. These parameters are available from the authors upon request.

[22] In the U.S., the minimum age for obtaining a driving license is 16 years old.

[23] Alberini *et al.* (2011) estimate price and income elasticities of U.S. household demand both for electricity and gas. For electricity, own-price elasticities range between -0.860 and -0.667; for gas, between -0.693 and -0.566.

recent estimates of own-price elasticities of U.S. household demand for gasoline, distinguishing between demand systems and single equation models. Single equation studies tend to find lower price elasticities. This is probably due to systems of demand accounting for behavioral responses after a price change, i.e. for how households reallocate their budget on the bundle of consumption goods after a change in one of the prices. The nature of the data used may also play a role, inasmuch as time-series data tend to yield short-run responses and cross-sections tend to yield long-run responses, especially in the case of energy demand (Baltagi and Griffin, 1984; Pesaran and Smith, 1995).

[TABLE 5]

Cross-price elasticities measure the degree of substitution or complementarity between the goods considered. Each entry of Table 4 shows the percentage change in the quantity demanded of the goods listed in the rows following a 1% change in the price of the goods listed in the columns. For *Gasoline*, relationships of complementarity arise with *Natural gas*, *Electricity and Public Transport*. In all these cases, the relationship is symmetric, meaning e^C_{ij} and e^C_{ji} have the same sign (e^C_{35} = -0.296 and e^C_{53} = -0.143; e^C_{25} = -0.359 and e^C_{52} = -0.219; e^C_{65} = -0.578 and e^C_{56} = -0.453). A possible interpretation of these findings is that such complementarities may be the consequence of a budget constraint tightening following an increase in the price of a necessity (gasoline). The complementarity between *Gasoline* and *Public transport* (e^C_{65} = -0.578) is perhaps even more surprising. One tentative explanation is that an increase in the price of *Gasoline* makes *Public transport* more expensive too.

We find instead substitution between *Other (home) fuels* and *Gasoline* (e_{45} =0.242). No immediate explanation presents itself for this result, but the mean budget share for *Other (home) fuels* is very small, 0.7%, which makes such substitution not a critical finding.

Finally, we find weak substitution between *Electricity* and *Natural gas* (e^c_{23}=0.061). However, the elasticity is actually very small, implying that a 1% increase in the price of *Natural Gas* would cause *Electricity* demand to increase by 0.061%.

4.2 Differential demand response to tax and price changes

The results presented in the previous section can be used to simulate and measure demand responses to equal changes in gasoline taxes and gasoline prices. We do this by computing θ_0, defined in (7), at different points of interest. In all the simulations, 13.2 ¢/gallon increases are envisaged in gasoline taxes and gasoline prices respectively, which correspond to a $15/t$CO_2$ carbon tax.[24] Such a level of carbon tax is realistic given the rates considered in recent U.S. legislative proposals aiming to reduce national CO_2 emissions.[25]

At sample mean values, the tax elasticity of gasoline demand, $\widehat{\eta_0}$, is -0.644; greater (in absolute value) than the price elasticity, $\widehat{\varepsilon_0}$, which is -0.499. Using (7), and plugging in $\Delta t = \Delta \pi = 13.2$ ¢/gallon and the sample mean values for t (t_0= 39.3 ¢/gallon) and p^G ($p_0^G = 271$ ¢/gallon), θ_0= 9.9 is obtained. This means, in the long run, the reduction in gasoline demand induced by a 13.2 ¢/gallon tax rise would have been on average almost ten times the effect caused by an equal price increase. This result is significantly larger than, but still comparable with, those of the most closely related literature, which uses different data and econometric approaches. For example, Rivers and Schaufele (2013) find British Columbia's carbon tax reduced gasoline demand by an amount 7.1 times greater than that an equal price increase would have caused. The θ obtained by Davis and Kilian (2011) ranges between 2.4 and 4.6, while Li *et al.* (2014) find θ = 3.

The literature offers different explanations for differential demand responses to changes in gasoline taxes and gasoline prices. One is that consumers expect tax changes to be more persistent than price changes. As a result, gasoline taxes affect long-run consumer decisions which in turn determine gasoline demand (Davis and Kilian, 2011; Li *et al.*, 2014). As the QAIDS presupposes rational behavior, this is in principle the type of effect that such a model is best suited to capture. Nonetheless, differential demand responses to gasoline taxes and prices may be observed also for other reasons. The behavioral economics approach points to a number of cognitive biases that can affect individual decision making. For example, as gasoline tax changes tend to attract larger media coverage than equal price changes (Rivers and Schaufele, 2013; Li *et al*, 2014), consumers may be more responsive to the former than to the latter. Moreover, people may perceive an additional burden associated with tax payments as compared to economically equivalent payments labeled differently, a phenomenon called tax aversion (McCaffery and Baron, 2006, Kallbekken *et al.*,

[24] Assuming a CO_2 emission factor for gasoline of 19.44 lbs/gallon.
[25] For example, the 2009 Congress bill *Raise Wages, Cut Carbon Act* (H.R. 2380, 111th Congress) set an initial rate of \$15/tCO_2, in 2010. The 2013 *Climate Protection Act* (S. 332, 113th Congress) set an initial rate of \$20/tCO_2.

2010, Kallbekken *et al.*, 2011, Blaufus and Möhlmann, 2014). All these explanations are not mutually exclusive and, in fact, they are most likely complementary to one another.

A formal investigation of the mechanisms underlying differential responses to gasoline tax and price changes is beyond the scope of this study. However, it should be noted that our approach and interpretation are consistent with the findings of Li *et al.* (2014), who are the only ones, to our knowledge, directly addressing this question. Using U.S. household-level data on vehicles purchased and miles travelled, the authors conclude that *a)* vehicle purchase decisions, as reflected in miles per gallon, respond more strongly to tax changes than price changes, and *b)* no differential effect with respect to miles travelled is found. These results support our presumption that specific effects of gasoline taxes unfold mostly, if not entirely, in the long run.

Differential demand responses across regions

Given sufficient variation in gasoline taxes across the States in the sample, we measure differential demand responses to changes in gasoline taxes and gasoline prices for four broad U.S. regions, namely Northeast (NE), Midwest (MW), West (WE) and South (SO). The results are illustrated through the graphs in Figure 3.

[FIGURE 3]

The top left graph shows estimated gasoline tax and price elasticities at mean values of the four regions. The Northeast exhibits the highest tax elasticity, followed by the Midwest, the West, and the South. As to the price elasticities, this time the Northeast exhibits the lowest demand response, while there are virtually no differences among the other regions. The top right graph shows the resulting θ's for the scenarios of 13.2 ¢/gallon tax- and (non-tax) price increases, respectively: $\theta_{NE} = 13.3$; $\theta_{MW} = 9.4$; $\theta_{WE} = 9.3$; and $\theta_{SO} = 8.7$. Relative to the other regions, the higher θ observed for the Northeast reflects the combination of higher tax elasticity and lower price elasticity. Furthermore, the bottom left graph highlights a direct relationship between the tax level and the tax elasticity over the four regions, suggesting that the higher the gasoline taxes, the more sensitive are consumers to tax changes. Such a result seems consistent with the interpretation of changes in gasoline taxes as policy signals: the higher the tax level, the stronger the signal – and the perception – of a tax increase.

Differential demand responses across income levels

Income level is also likely to affect households' demand responsiveness to changes in gasoline taxes, especially in the long run. Thus, for the same two scenarios of 13.2 ¢/gallon tax- and price increases, we measure θ across five income levels corresponding to the quintiles of the sample income distribution. The results are illustrated through the graphs in Figure 4.

[FIGURE 4]

The left graph contrasts the gasoline tax and price elasticities at mean values of the income quintiles. The right graph shows the respective θ's. With the exception of the first quintile, while the tax elasticity slightly increases with income, the price elasticity decreases slightly. One possible explanation for this is that richer households are less inclined to change their habits following a price change, as the welfare loss they incur following a price increase is smaller. At the same time, however, richer households are more responsive to tax changes because they can afford, or are in a better position, to make choices that allow reducing gasoline consumption in the long run, such as buying a more fuel efficient car, living closer to work or switching to public transport, if richer neighborhoods are better served.

5. Conclusions

In recent years, gasoline taxes have gained renewed importance in the U.S. public policy debate due to increasing concerns about public finances and the environment. At the same time, new ideas have refreshed the economic literature of gasoline taxation. Notably, a handful of studies (Davis and Kilian, 2011; Rivers and Schaufele, 2013, *Li et al.*, 2014) have found that changes in gasoline taxes have significantly larger impacts on gasoline demand than equal changes in gasoline prices do. Two main interpretations have been provided for this finding, which respectively hinge on the greater persistence and the greater salience of tax changes relative to price changes. In the first case, it is argued that changes in gasoline taxes are more likely to influence relevant long-run consumer choices, such as buying a more fuel-efficient car, changing transport mode or living closer to work. In the second case, the argument is that as tax changes receive more attention from the media, consumers are more aware of them and, therefore, are more reactive. A tax-aversion explanation has also been hypothesized, whereby some consumers may react more if they know the price increase they face is due to a tax increase. Most probably, all these factors are complementary to one another to some extent.

This paper adds new evidence and insights to the literature in question. First, to our knowledge, it is the first study to analyze differential demand response to gasoline taxes and gasoline prices within a complete system of demand. This implies a) complementarities and substitution relationships between the goods considered are accounted for, and b) demand elasticities taking behavioral responses into account are derived. Second, we estimate a QAIDS model, with seven goods, in which gasoline taxes affect demand response in two ways, namely through relative prices and as long-run policy signals. We deem this distinction to be important and, indeed, we expect future research to delve further into the roles of taxes and prices in relation to short- and long-run consumer decisions. Third, our use of household-level data for estimating the model allows for heterogeneity in the resulting tax and price elasticities.

As to the numerical results, the demand elasticities computed at sample means are generally within the realm of plausible values. In particular, the price elasticity of gasoline (-0.499), which is central for our analysis, turns out to be very close to those found in some well-known studies of the U.S. literature. This strengthens our confidence about the quality of the results, including the evaluation of differential demand response to gasoline taxes and gasoline prices. For a 13.2 ¢/gallon tax increase, corresponding to a \$15/tCO_2 carbon tax, we find the reduction in gasoline demand, in the long run, would have been on average almost ten times greater than that caused by a price increase of the same amount. Such a difference in effects between taxes and prices is notable, and greater than those found in the literature. The policy implications are qualitatively the same nonetheless: a) gasoline taxes are much more effective at reducing gasoline demand than gasoline price elasticities indicate; b) the extra revenue generated by a tax rise is overestimated if using gasoline price elasticities instead of tax elasticities.[26]

Finally, we evaluate differential demand response to gasoline taxes and prices both for four U.S. broad regions and across income levels. With the exception of the Northeast, for which relatively higher tax elasticity and lower price elasticity are observed, the differences observed across the regions are very small. The same regional results suggest a direct relationship between the level of

[26] Rivers and Schaufele (2013) note, ex-post, that British Columbia's carbon tax generated substantially less revenue than the government had estimated.

gasoline taxes and the demand response to tax changes. As concerns the comparison of differential demand response across income levels, we find the price elasticity slightly decreases with income, while the tax elasticity increases slightly. This evidence signals an important distributional effect, whereby richer households can afford consumer choices which allow them to reduce gasoline consumption in the long run.

References

Alberini, A., W. Gans and D. Velez-Lopez (2011), "Residential consumption of gas and electricity in the U.S.: the role of prices and income", *Energy Economics*, 33, pp. 870-881.

Baltagi, B.H. and J.M. Griffin (1984), "Short and long run effects in pooled models", *International Economic Review*, 25(3), pp. 631-645.

Banks, J., R. Blundell and A. Lewbel (1997), "Quadratic Engel Curves and Consumer Demand", *The Review of Economics and Statistics*, 79(4), pp. 527-539.

Blaufus, K. and A. Möhlmann (2014), "Security Returns and Tax Aversion Bias: Behavioral Responses to Tax Labels", *Journal of Behavioral Finance*, 15(1), pp. 56-69.

Brown, M.G. and J.Y. Lee (1997), "Incorporating Generic and Brand Advertising Effects in the Rotterdam Demand System", *International Journal of Advertising*, 16, pp. 211-220.

Chern, W., E. Loehman, S. Yen (1995), "Information, Health Risk Beliefs, and the Demand for Fats and Oils", *Review of Economics and Statistics*, 77, pp. 555-564.

Chetty, R. (2009), "The Simple Economics of Salience and Taxation", NBER Working Paper 15246.

Chetty, R., A. Looney and K. Kroft (2009), "Salience and Taxation: Theory and Evidence", *American Economics Review*, 99(4), pp. 1145-1177.

Congdon, W.J., J.R. Kling and S. Mullainathan (2009), "Behavioral Economics and Tax Policy", *National Tax Journal*, LXII(3), pp. 375-386.

Davis, L.W. and L. Kilian (2011), "Estimating the Effect of a Gasoline Tax on Carbon Emissions", *Journal of Applied Econometrics*, 26, pp. 1187-1214.

Deaton, A. and J. Muellbauer (1980), "An Almost Ideal Demand System", *the American Economic Review*, 70, pp. 312-336.

Deaton, A. and J. Muellbauer (1980b), "Economics and Consumer Behavior", Cambridge University Press.

Duffy, M. (1995), "Advertising in Demand Systems for Alcoholic Drinks and Tobacco: A Comparative Study", *Journal of Policy Modeling*, 17(6), pp. 557-577.

Finkelstein, A. (2009), "E-ztax: Tax Salience and Tax Rates", *Quarterly Journal of Economics*, 124(3), pp. 969-1010.

Goldin, J. and T. Homonoff (2013), "Smoke Gets in Your Eyes: Cigarette Tax Salience and Regressivity", *American Economic Journal: Economic Policy*, 5(1), pp. 302-336.

Heien, D. and C.R. Wessells (1990), "Demand System Estimation with Microdata: a Censored Regression Approach", *Journal of Business and Economic Statistics*, 8(3), pp. 365-371.

Hsu, S. (2009), "Psychological Barriers to Gasoline Taxation", *Critical Issues in Environmental Taxation, Vol. VI*, Oxford University Press.

Hughes, J.E., Knittel, C.R., and D. Sperling (2008), "Evidence of a shift in the short-run price elasticity of gasoline demand", *The Energy Journal*, 29(1), pp. 113.-134.

Kallbekken, S., S. Kroll, and T. L. Cherry (2010), "Pigouvian Tax Aversion and Inequity Aversion in the Lab", *Economics Bulletin*, 30, pp. 1914-1921.

Kallbekken, S., S. Kroll, and T. L. Cherry (2011), "Do You Not Like Pigou or Do You Not Understand Him? Tax Aversion and Revenue Recycling in the Lab", *Journal of Environmental Economics and Management*, 62, pp. 53-64.

Kilian, L. (2010), "Explaining fluctuations in U.S. gasoline prices: a joint model of the global crude oil market and the U.S. retail gasoline market", *The Energy Journal*, 31(2), pp. 105-130.

Jensen, H.H., T Kevasan and S.R. Johnson (1993), "Measuring the Impact of Health Awareness on Food Demand", *Review of Agricultural Economics*, 14, pp. 299-312.

Labandeira, X., J.M. Labeaga and M. Rodriguez (2006), "A Residential Energy Demand System for Spain", *The Energy Journal*, 27(2), pp. 87-111.

Lewbel, A. (1985), "A unified approach to incorporating demographic or other effects into demand systems", *Review of Economic Studies*, 52, pp. 1-18.

Li, S., J. Linn and E. Muehlegger (2014), “Gasoline Taxes and Consumer Behavior”, *American Economic Journal: Economic Policy,* 6(4), pp. 302-342.

McCaffery, E. J., and J. Baron (2006), “Thinking about Tax”, *Psychology, Public Policy, and Law*, 12, pp. 106-135.

Manzan, S. and D. Zerom (2010), “A Semiparametric Analysis of Gasoline Demand in the United States reexamining the Impact of Price”, *Econometric Reviews*, 29(4), pp. 439-468.

Marion, J. and E. Muehlegger (2011), “Fuel Tax Incidence and Supply Conditions”, *Journal of Public Economics*, 95, pp. 1202-1212.

Moro, D., S. Boccaletti and P. Sckokai (1996), “Innovation and Consumers’ Choice”, in: Galizzi, G. and L. Venturini, eds., *Economics of Innovation: the case of Food Industry*, Heidelberg: Physica-Verlag.

Nicol, C. (2001), “The Rank and Model Specification of Demand Systems; An Empirical Analysis Using United States Microdata”, *Canadian Journal of Economics,* 34, pp. 259-289.

Nicol (2003), ”Elasticities of Demand for Gasoline in Canada and the United States”, *Energy Economics,* 25, pp. 201-214.

OECD (2013), “Taxing Energy Use: A Graphical Analysis”, OECD, Paris.

Oladosu (2003), “An Almost Ideal Demand System Model of Household Vehicle Fuel Expenditure Allocation in the United States”, *Energy Journal*, 24, pp. 1-21.

Pesaran, M.H., and R. Smith (1995), “Alternative approaches to estimating long-run energy demand elasticities – An application to Asian developing countries”, in Ekins, P. and T. Barker, eds., *Global warming and energy demand*, Routledge.

Pollak, R.A. and T.J. Wales (1992), “Demand System Specification and Estimation”, Oxford University Press, New York.

Rivers, N. and B. Schaufele (2013), “Salience of Carbon Taxes in the Gasoline Market”, Unpublished Working Paper.

Sentenac-Chemin, E. (2012), “Is the price effect on fuel consumption symmetric? Some evidence from an empirical study”, *Energy Policy*, 41, pp. 59-65.

Schmalensee, R. and T.M. Stoker (1999), "Household Gasoline Demand in the United States", *Econometrica*, 67(3), pp. 645-662.

Shonkwiler, J.S. and S. Yen (1999), "Two-Step Estimation of a Censored System of Equations", *American Journal of Agricultural Economics*, 81, pp. 972-982.

Small, K. and K. Van Dender (2007), "Fuel Efficiency and Motor Vehicle Travel: the Declining Rebound Effect" *The Energy Journal*, 28(1), pp. 25-51.

Su, Q. (2011), "The effect of population density, road network density, and congestion on gasoline household congestion in U.S. urban areas", *Energy Economics,* 33, pp. 445-452.

Tversky, A. and D. Kahneman (1974), "Judgment Under Uncertainty: Heuristics and Biases", *Science,* 185(4157), pp. 1124-1131.

West, S.A. and R.C. Williams (2004), "Estimates from a consumer demand system: implications for the incidence of environmental taxes", *Journal of Environmental Economics and Management, 47,* pp. 535-558.

West, S.A. and R.C. Williams (2007), "Optimal Taxation and cross-price effects on labor supply: Estimates of the optimal gas tax", *Journal of Public Economics, 91,* pp. 593-617.

Yen, S.T., K. Kan and S.J. Su (2002), "Household demand for fats and oils: two-step estimation of a censored demand system", *Applied Economics*, 14, pp. 1799-1806.

Yen, S.T. and B. Lin (2006), "A Sample Selection Approach to Censored Demand Systems", *American Journal of Agricultural Economics*, 88(3), pp. 742-749.

Yen, S.T., B. Lin and D. Smallwood (2003), "Quasi- And Simulated-Likelihood Approaches to Censored Demand Systems: Food Consumption by Food Stamp Recipients in the United States", *American Journal of Agricultural Economics*, 85(2), pp. 458-478.

Table 1 – Summary statistics of total current expenditure shares.

Variable	Observations	Mean	Standard deviation	Coeff. of variation	Min	Max*	Zeros
Food at home	43,457	22.8%	13.7%	0.60	0.0%	100.0% (15)	0.9%
Electricity	43,457	5.8%	5.3%	0.92	0.0%	100.0% (3)	8.5%
Natural gas	43,457	2.9%	4.3%	1.50	0.0%	63.4%	38.5%
Other home fuels	43,457	0.7%	3.1%	4.59	0.0%	72.8%	91.2%
Motor fuels	43,457	9.1%	7.7%	0.84	0.0%	100.0% (2)	12.9%
Public transport	43,457	2.0%	5.4%	2.63	0.0%	81.4%	73.4%
All other expend.	43,457	56.7%	17.5%	0.31	0.0%	100.0% (128)	0.1%

* In brackets is the number of observations with 100% budget share.

Table 2 – Summary statistics of socio-demographics and total current expenditure.

Variable	Obs.(#)	Mean	Standard deviation	Min	Max
Single	43,457	0.28	0.45	0	1
H&W	43,457	0.19	0.40	0	1
H&W, child(ren) <6	43,457	0.05	0.21	0	1
H&W, child(ren)<18	43,457	0.14	0.34	0	1
H&W,child(ren) >17	43,457	0.08	0.27	0	1
Other households	43,457	0.26	0.44	0	1
Northeast	43,457	0.31	0.46	0	1
Midwest	43,457	0.20	0.40	0	1
South	43,457	0.24	0.43	0	1
West	43,457	0.26	0.44	0	1
Composition income earners	43,457	0.23	0.42	0	1
*Education reference person**	43,457	5.44	1.82	1	9
Number of cars	43,457	0.91	0.89	0	15
Total current expenditure, $	43,457	7,178	7,298	35	321,316

***** 1 “Never attended school”, 2 “1st through 8th grade”, 3 “9th through 12th grade”, 4 “High school graduate”, 5 “Some college, less than college graduate”, 6 “Associate’s degree”, 7 “Bachelor’s degree”, 8 “Master’s degree”, 9 “Professional/Doctorate degree".

Figure 1 – Gasoline taxes across States in the sample: States where rates changed at least once.

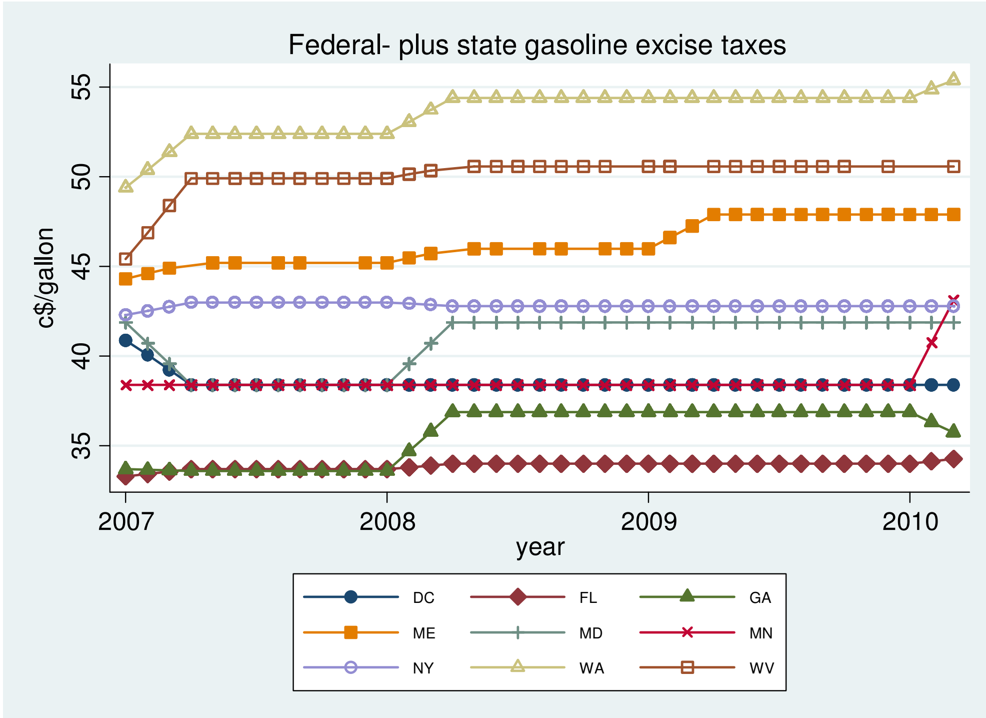


Figure 2 – Gasoline taxes and prices within States in the sample: Maine and Washington

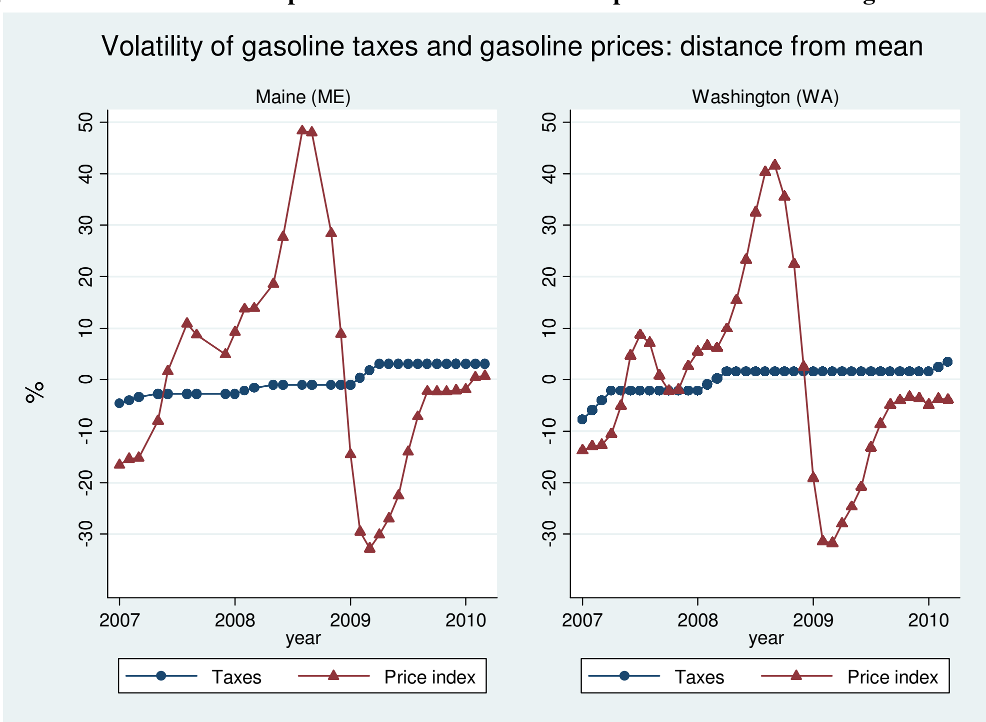


Table 3 – Estimated QAIDS coefficients.

	i=1	i=2	i=3	i=4	i=5	i=6
Coefficient	Food	Electricity	Natural gas	Other fuels	Gasoline	Pub. transp.
α_i	**0.204**	**0.057**	**0.037**	**-0.102**	**0.112**	**0.002**
	0.001	0.001	0.005	0.083	0.001	0.022
β_i	**-0.034**	**-0.004**	**-0.006**	**0.007**	**-0.008**	**0.006**
	0.001	0.001	0.001	0.002	0.001	0.003
λ_i	**-0.004**	**-0.001**	**-0.001**	**-0.002**	**-0.002**	**-0.001**
	0.001	0.000	0.000	0.000	0.001	0.000
$\alpha_{i,NE}$	**0.0**	0.001	**-0.007**	**0.051**	**0.008**	-0.004
	0.002	0.001	0.001	0.08	0.001	0.004
$\alpha_{i,SO}$	**0.019**	**0.035**	**-0.023**	0.051	**0.014**	0.006
	0.002	0.001	0.001	0.009	0.001	0.004
$\alpha_{i,WE}$	**0.043**	**-0.008**	**-0.040**	-0.015	**0.019**	**0.018**
	0.002	0.001	0.001	-0.01	0.001	0.004
$\alpha_{i,NCAR}$	**-0.017**	**-0.001**	**0.001**	**0.009**	**0.009**	**-0.008**
	0.001	0.000	0.000	0.001	0.001	0.001
$\alpha_{i,TWOE}$	**-0.004**	-0.000	-0.000	**-0.015**	**0.011**	0.004
	0.001	0.001	0.001	0.004	0.001	0.003
$\alpha_{i,N1}$	**-0.034**	0.001	**0.005**	0.020	**0.019**	**-0.000**
	0.003	0.001	**0.002**	0.018	0.001	0.004
$\alpha_{i,N3}$	**0.032**	-0.001	**0.005**	0.007	**0.013**	**-0.018**
	0.003	0.001	0.002	0.009	0.001	0.005
$\alpha_{i,N4}$	**0.043**	**0.005**	**-0.003**	-0.000	**0.012**	**-0.017**
	0.002	0.001	0.001	0.006	0.001	0.005
$\alpha_{i,N5}$	**0.039**	**0.005**	-0.002	**-0.021**	**0.014**	-0.014
	0.002	0.001	0.001	0.010	0.001	0.004
$\alpha_{i,N6}$	**0.033**	**0.006**	0.001	-0.012	**0.020**	**-0.008**
	0.002	0.001	0.001	0.011	0.001	0.004
$\alpha_{i,EDUC}$	**-0.009**	**-0.004**	**-0.002**	**-0.004**	**-0.008**	**0.009**
	0.000	0.000	0.000	0.001	0.000	0.001
$\alpha_{i,\ TAX}$	**-0.045**	**0.014**	**-0.017**	**0.170**	**-0.066**	**0.046**
	0.006	0.002	0.003	0.012	0.004	0.009
LogLikelihood	337.700					
R^2	0.18	0.13	0.10	0.06	0.12	0.03
N obs	43,256					

Note: Standard errors are reported below the coefficients. Bold entries indicate rejection of $H_0: e=0$ at the 5% significance level for a two tailed test.

Table 4 – Estimated budget shares, income and compensated price elasticities.

	j=1	j=2	j=3	j=4	j=5	j=6	j=7
	Food	Electricity	Natural gas	Other fuels	Gasoline	Pub. transp.	Other goods
w_j	0.223	0.057	0.028	0.007	0.090	0.021	0.576
e_j	**0.850**	**0.930**	**0.855**	**0.944**	**0.935**	**0.916**	**1.086**
	0.004	0.007	0.009	0.023	0.006	0.021	0.002
e^C_{1j}	**-0.428**	**-0.132**	**0.077**	**-0.117**	**0.091**	0.022	**0.488**
	0.036	0.012	0.01	0.020	0.015	0.028	0.051
e^C_{2j}	**-0.428**	**-0.878**	**0.061**	-0.035	**-0.359**	**-0.504**	**2.142**
	0.041	0.026	0.016	0.033	0.027	0.050	0.062
e^C_{3j}	**0.505**	**0.098**	**-0.179**	**0.145**	**-0.296**	**-0.178**	-0.095
	0.045	0.022	0.038	0.032	0.033	0.043	0.070
e^C_{4j}	**-0.146**	0.018	**0.101**	**-0.691**	**0.242**	**0.141**	**0.335**
	0.052	0.026	0.018	0.165	0.037	0.0399	0.124
e^C_{5j}	**0.234**	**-0.219**	**-0.143**	**0.127**	**-0.421**	**-0.453**	**0.874**
	0.031	0.016	0.014	0.029	0.026	0.040	0.058
e^C_{6j}	0.053	**-0.394**	**-0.125**	**0.111**	**-0.578**	**-0.380**	**1.313**
	0.080	0.042	0.025	0.040	0.055	0.140	0.131
e^C_{7j}	**0.147**	**0.181**	-0.002	**0.026**	**0.098**	**0.132**	**-0.583**
	0.019	0.007	0.005	0.011	0.01	0.015	0.030

Note: Standard errors are reported below the coefficients. Bold entries indicate rejection of $H_0: e=0$ at the 5% significance level for a two tailed test.

Table 5 – Recent estimates of price elasticities of U.S. household gasoline demand.

System of demand models		
Study	*Own price elasticity of gasoline demand*	*Data type*
West and Williams (2007)	-0.75; -0.27 (range)	Pooled cross-section
West and Williams (2004)	-0.46	Pooled cross-section
Nicol (2003)	-0.59; -0.02 (range)	Pooled cross-section
Oladosu (2003)	-0.70; -0.36 (range)	Pooled cross-section
Single equation models		
Study	*Own price elasticity of gasoline demand*	*Data type*
Li *et al.* (2014)	-0.10	Panel
Sentenac-Chemin (2012)	-0.30	Time-series
Su (2011)	-0.39	Cross-section
Davis and Kilian (2011)	-0.46; -0.19 (range)	Panel
Manzan and Zerom (2010)	-0.35	Pooled cross-section
Hughes *et al.* (2008)	-0.07	Time-series
Small and Van Dender (2007)	-0.43	Pooled cross-section

Figure 3 – Price and tax elasticities of gasoline demand and differential demand response, by region.

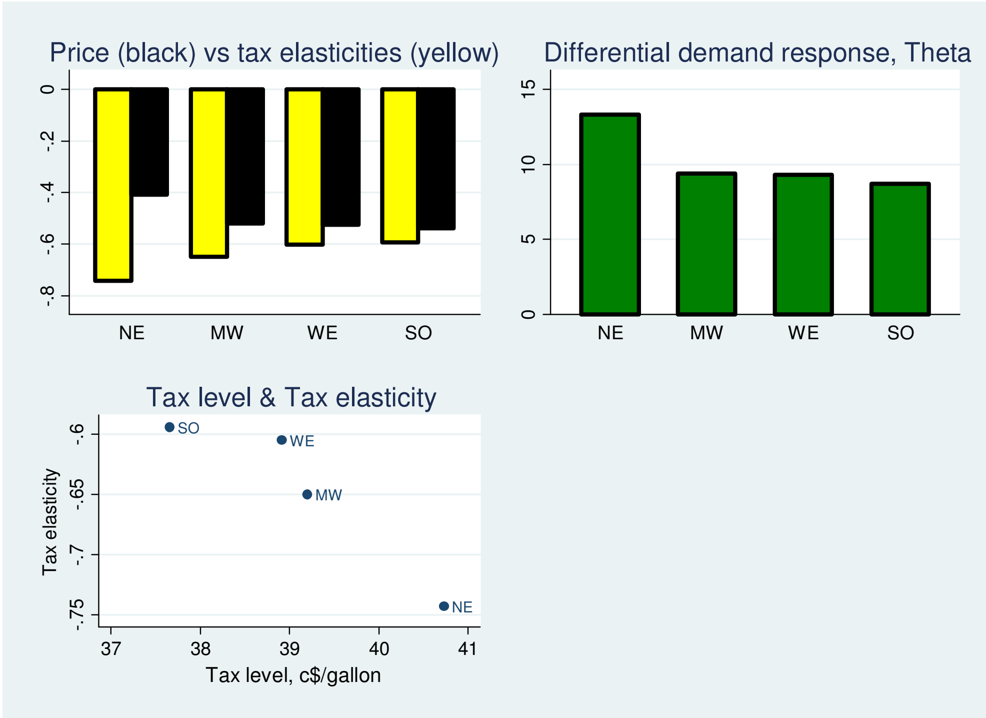
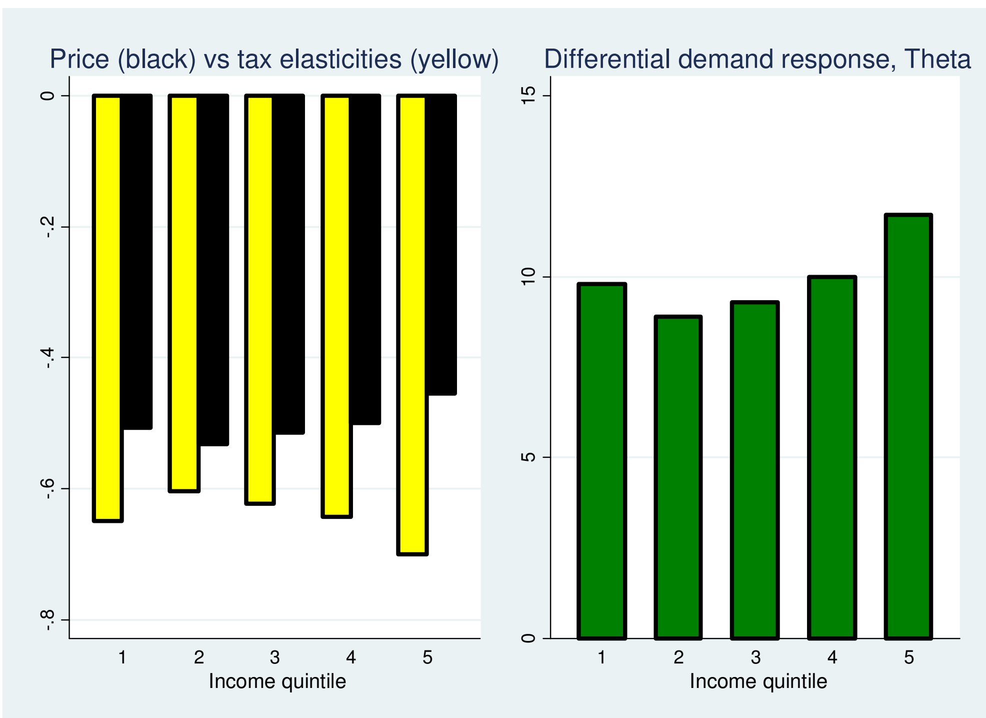


Figure 4 – Price and tax elasticities of gasoline demand and differential demand response, by income quintile



Appendix

Table A1 – Distribution of observations across time (year and month of the interview).

	Year				
Month	**2007**	**2008**	**2009**	**2010**	**Total**
January	989	1,878	1,906	1,019	5,792
February	936	1,898	1,916	1,016	5,766
March	1,004	1,914	1,924	1,034	5,876
April	969	951	979	0	2,899
May	948	951	962	0	2,861
June	972	957	1,002	0	2,931
July	960	941	980	0	2,881
August	921	928	989	0	2,838
September	950	937	1,023	0	2,910
October	978	912	1,036	0	2,926
November	963	949	986	0	2,898
December	931	933	1,015	0	2,879
Total	11,521	14,149	14,718	3,069	43,457

Note: The first three months of 2008 and 2009 have twice as many observations as the others because subsequent CE waves overlap in correspondence of the first calendar quarter, which is covered by two IS cross-sections.

Table A2 – Distribution of observations across MSA.

Metropolitan Statistical Area	State(s)	Frequency	Percent
Philadelphia – Wilmington – Atlantic City	PA – NJ – DE – MD	2,680	6.17%
Boston – Brockton – Nashua	MA – NH – ME – CT	2,472	5.69%
New York	NY	2,984	6.87%
New York, Connecticut suburbs	NY – CT	2,969	6.83%
New Jersey suburbs	NJ	2,474	5.69%
Chicago – Gary – Kenosha	IL – IN – WI	4,039	9.29%
Detroit – Ann Arbor – Flint	MI	2,264	5.21%
Cleveland – Akron	OH	1,058	2.43%
Minneapolis – St. Paul	MN – WI	1,368	3.15%
Washington	DC – MD – VA – WV	2,105	4.84%
Baltimore	MD	1,062	2.44%
Dallas – Ft. Worth	TX	2,038	4.69%
Houston – Galveston – Brazoria	TX	1,676	3.86%
Atlanta	GA	1,782	4.10%
Miami – Ft. Lauderdale	FL	1,398	3.22%
Los Angeles – Orange	CA	4,157	9.57%
Los Angeles suburbs	CA	1,388	3.19%
San Francisco – Oakland – San Jose	CA	2,708	6.23%
Seattle – Tacoma – Bremerton	WA	1,622	3.73%
San Diego	CA	1,213	2.79%
Total		43,457	100.00%

Table A3 – Price indices (1982-84 = 100).

Index	Obs.(#)	Mean	St. deviation	Min	Max
Food at home	43,457	208.40	24.61	124.23	236.79
Electricity	43,457	195.16	42.81	102.03	311.82
Natural gas	43,457	214.95	38.67	112.18	371.55
Other home fuels	43,457	273.30	44.96	228.03	384.30
Motor fuels	43,457	233.48	49.92	143.60	453.11
Public transport	43,457	237.77	10.85	219.86	267.72
All other expenditures	43,457	177.12	17.11	123.00	222.55

Note: All indices are Laspeyres price indices, for all urban consumers, not seasonally adjusted.

Figure A1 – Price indices averaged by region (Northeast, Midwest, South, West), over time.

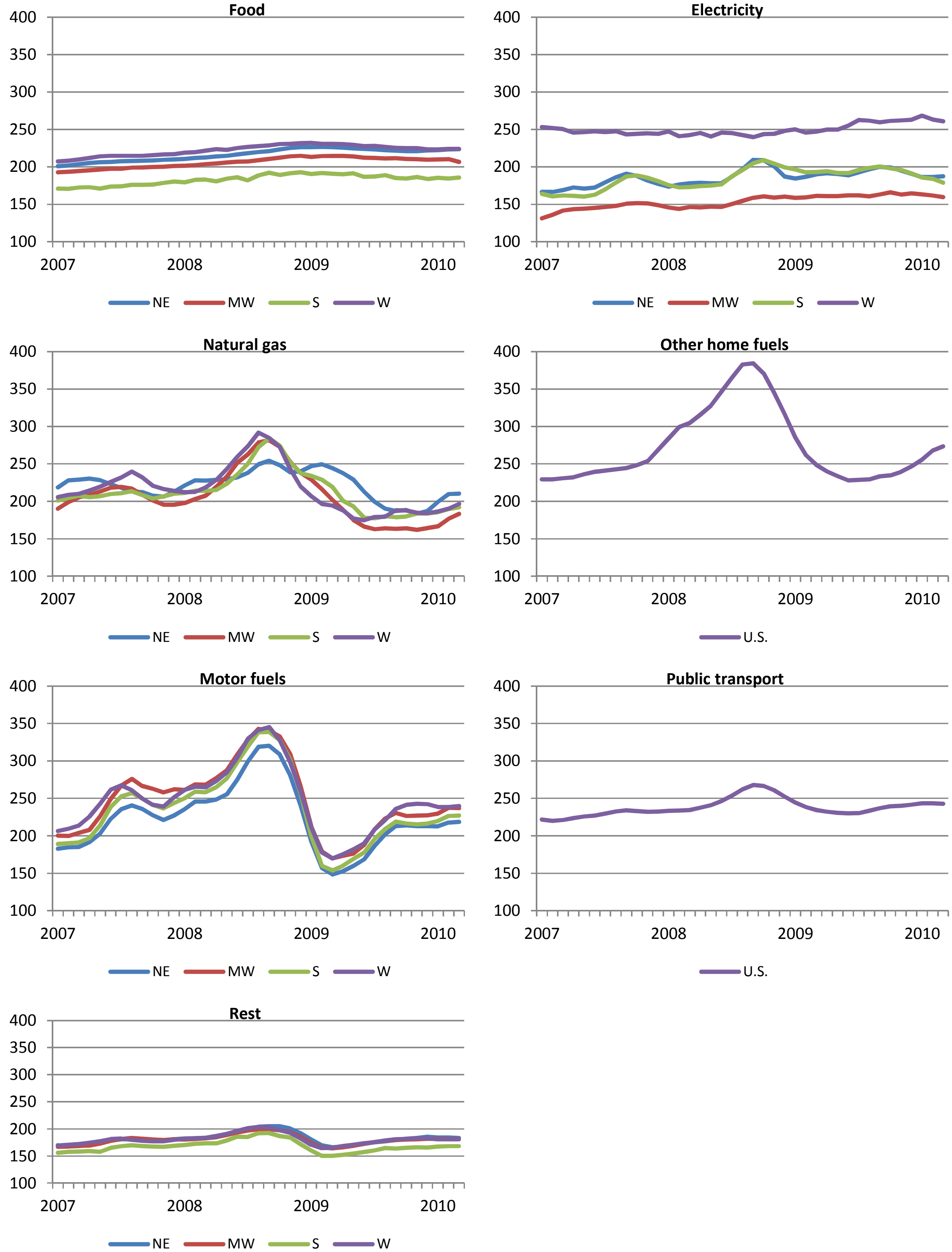


Figure A2 – Gasoline tax rates in the sample.

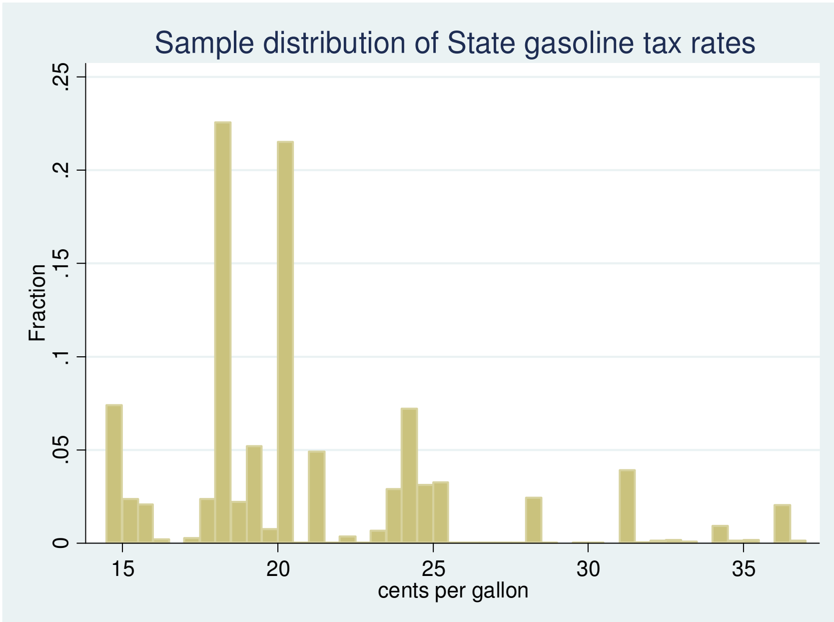


Table A4: First-step probit estimates.

n. obs. = 43,256	i=1	i=2	i=3	i=4	i=5	i=6
Coefficients	Food at home	Electricity	Natural Gas	Other Fuels	Gasoline	Pub. Transp.
Constant	**2.331**	**1.332**	**0.215**	**-1.571**	**1.026**	**-0.801**
	0.041	0.014	0.009	0.013	0.014	0.009
Income	**0.424**	**0.186**	**0.107**	**0.078**	**0.452**	**0.144**
	0.045	0.013	0.007	0.008	0.015	0.006
N1	**-0.677**	**-0.595**	**-0.378**	**-0.455**	**-0.727**	**0.184**
	0.081	0.032	0.021	0.030	0.030	0.022
N3	0.136	**-0.157**	**-0.110**	**-0.155**	-0.090	-0.037
	0.183	0.053	0.033	0.044	0.057	0.034
N4	0.192	**0.165**	**0.067**	**-0.108**	**0.161**	**-0.152**
	0.128	0.043	0.023	0.030	0.044	0.024
N5	0.763	**0.305**	**0.208**	**-0.191**	**0.306**	0.012
	0.296	0.053	0.029	0.037	0.051	0.029
N6	-0.121	**-0.189**	**-0.099**	**-0.264**	**-0.370**	**0.131**
	0.088	0.033	0.021	0.028	0.031	0.022
Northeast	0.101	**-0.419**	**-0.742**	**0.884**	**-0.562**	**0.351**
	0.055	0.027	0.019	0.028	0.024	0.019
South	0.063	**-0.138**	**-0.961**	**0.176**	**0.078**	**-0.108**
	0.058	0.030	0.020	0.032	0.028	0.021
West	0.110	**-0.199**	**-0.203**	-0.44	**0.071**	**0.160**
	0.058	0.029	0.020	0.034	0.028	0.020
Two earners	-0.067	**0.077**	**-0.019**	0.018	**0.187**	0.033
	0.101	0.341	0.020	0.025	0.035	0.020
Education r.h.	**0.067**	**0.057**	**0.029**	0.004	**0.108**	**0.074**
	0.009	0.005	0.003	0.005	0.004	0.004
mean of dep. Var.	0.990	0.914	0.614	0.088	0.870	0.270
Log Likelihood	-2082	-11450	-26390	-11500	-13320	-23930
Scaled R-Squared	0.017	0.0599	0.114	0.064	0.162	0.051
Predicted Power	0.99	0.91	0.66	0.912	0.88	0.74

Standard Errors below coefficients. Bold entries correspond to rejection of $H_0 : e = 0$ at the 5% significance level for a two tailed test.