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Abstract

In this paper we contribute new results on the different consumers' reaction to tax or price changes. We separately compute the compensated gasoline retail price elasticity and the gasoline tax elasticity and show that consumers overreact to taxes as compared to price variations. A novel element in our analysis is that we compare reactions to tax-inclusive retail prices to reactions to information on excise taxes that is made available to consumers. We estimate a complete system of demand for the U.S. population of households using quarterly data from the Consumer Expenditure Survey from 2007 to 2009. Relying on a complete system of demands rather than on single equations avoids imposing an implausible separability restriction, thus allowing estimation of accurate elasticities that take behavioral responses into account, i.e. that account for the way in which consumers reallocate their expenditure on a bundle of goods after a price/tax change in one of the goods. Our analysis shows that the reaction to a gasoline tax change is, on average, about 20% stronger than the reaction to a corresponding price change. We discuss the implications of our findings for the design of energy policies.

Keywords

Gasoline taxation, tax salience, demand analysis

JEL codes: D12, H2, H3, Q4

1. Introduction[*]

This paper is concerned with different responses of U.S. consumers to changes in gasoline prices and gasoline taxes. Gasoline taxes in the U.S. raise more revenue than any other commodity tax both at state and federal levels. They also play an important role as corrective taxes, since gasoline use entails many negative externalities, notably CO2 emissions, air pollution and traffic congestion. Though Pigouvian taxes are widely recognized as the most effective tool to address negative externalities and to shape behavior, the fact that gasoline demand is inelastic to its price makes this tool rather ineffective as an incentive. At the same time, any price increase in presence of a rigid demand curve would disproportionately impact poor households, raising distributional issues.

The idea that agents may respond differently to tax and price changes is central to a number of recent contributions (Chetty, 2009; Chetty *et al.*, 2009; Finkelstein, 2009; Congdon *et al.*, 2009; Goldin and Homonoff, 2013; Davis and Killian, 2011; Li *et al.*, 2012; Rivers and Schaufele, 2012) questioning a central assumption in public finance according to which people respond to tax changes in the same way as they respond to price changes. These contributions vary in the taxed good domain and the methodological approach, but also in the explanation given for such difference.

Davis and Killian (2011) and Li *et al.* (2012) consider different reactions to taxes and prices as consistent with rational behavior. Since tax changes are usually more long lasting and less volatile than price changes, consumers react to announcements of increasing commodity taxes by changing their expectations of future prices accordingly. Behavioral economics contributions, instead, focus on the visibility of taxes (salience, in psychological parlance) as the main reason for observing a different reaction. For example, Finkelstein (2009) shows that the demand curve for driving is more inelastic when tolls are charged electronically as compared to manual collection. Chetty *et al.* (2009) use both experimental evidence and choice data to demonstrate that making sales taxes visible increases demand responsiveness. The salience or prominence of taxes seems to be a major factor affecting consumers' reactions. Tversky and Kahneman (1974) were probably the first to focus on the relevance of salience in consumers' decision making. They identified several heuristics affecting individual decision-making and noticed that individuals often rely heavily on information that is readily available or prominent, ignoring information that they do not see or that is not readily available.

Information availability is therefore crucial. Indeed "availability" is one of the judgemental heuristics mentioned by Tversky and Kahneman (1974). More importantly, they indicated salience as one of the crucial factors affecting the degree of "availability" of information useful to make sound decisions (Cfr. Op. Cit. p. 1127). Whether information is easily available or not is therefore crucial and the degree of salience of such information affects the degree of its availability. In the tax domain, there is one important distinction to be made, between information on taxes that is "available", but not prominent or salient, and information on taxes that is not "available" and therefore invisible. Sales taxes are an example of the first type. Most consumers know about sales taxes, but they might not think about them when they make their purchasing decision. Information on sales taxes is available but not salient. Excise taxes are an example of the second type. Consumers may know they exist, but since such taxes are bundled with the posted price, they are in practice invisible to them and impossible to ferret out. Information on excise taxes is not readily available to consumers. Consumers may also be completely unaware of such taxes, because excise taxes are in fact much less salient than visible-but-not-prominent taxes like sales taxes. Studies in behavioral public economics exploring the impact of tax salience have usually considered taxes included in the posted price, like excise taxes, as highly salient (Chetty *et al.* 2009; Goldin and Homonoff, 2013). In fact, gasoline excise tax information is invisible to most consumers. Therefore, in the present study we treat information on such taxes as

[*] This research was supported by a Marie Curie International Outgoing Fellowship (PIOF_GA_298094) awarded to Silvia Tiezzi within the 7th European Community Framework Programme.

new, additional information that is made available to the consumers when making their purchase decisions.

An additional explanation for the difference in consumers' responses to taxes and prices, suggested by the economics and psychology literature, is that people may perceive an additional burden associated with tax payments compared to economically equivalent payments labeled differently, a phenomenon called Tax Aversion (McCaffery and Baron, 2006). Experimental evidence of Tax Aversion is growing (Kallbekken *et al.*, 2010 and 2011; Blaufus and Möhlmann, 2012), but there is no empirical evidence of such framing effect usingchoice, rather than experimental, data.

All of these explanations are not mutually exclusive, but what they have in common is the consistent result that consumers exhibit more elastic demand responses to tax than to price changes.

Starting from this idea, empirical evidence has been accumulating (Davis and Killian, 2011; Li *et al.*, 2012; Rivers and Schaufele, 2012) that consumers overreact to gasoline tax changes as compared to price changes. This suggests an interesting way in which Pigouvian taxes' effectiveness, for example, could be increased. These contributions, however, rely on single-equation estimates of the price and tax elasticity of demand for gasoline. A major inconvenience of single-equation models is the imposition of implausible separability restrictions and, thus, their inability to estimate cross price effects between different energy goods. For this reason, single equations tend to produce elasticities that on average are lower (in absolute value) than those computed by estimating complete demand systems.

In this paper, we compute gasoline tax and price elasticities by estimating a complete demand system, thus addressing this important methodological point. The main advantage of relying on demand analysis rather than on single equation estimates is that we can account for how each household reallocates its total current expenditure among a bundle of current consumption goods after a price change in one of them. Exploiting complementarities and substitution relationships among commodities implies larger, on average, own price elasticities compared to those obtained from single equations. In turn, this implies that estimates of the degree of under/overreaction to gasoline taxes are more accurate than those obtained from single equations. In general, for a given tax elasticity, the lower (the higher) the price elasticity in absolute value, the higher (the lower) the degree of overreaction. Single equations tend to produce lower price elasticities, thus biasing the degree of overreaction to taxes away from one.

In fact, little previous work has been done on gasoline demand in the U.S. at the household level and using a complete system of demands consistent with duality theory (Nicol, 2003; Oladosu, 2003; West and Williams, 2004 and 2007), and even less has taken full account of households' heterogeneity, i.e. of differences in household composition and location (Schmalensee and Stoker, 1999, even though they do not employ a demand system nor a tightly parameterized model based on household utility).

To estimate the differential response to taxes and prices, Li *et al.* (2012) and Rivers and Schaufele, (2012) decompose the retail price of gasoline into two components: a tax-exclusive price and a tax component. Davis and Killian (2011) instead estimate two gasoline demand equations. In the first they use the retail price (inclusive of all taxes) of gasoline as explanatory variable. In the second, they use taxes rather than prices. In this paper we instead consider retail prices (inclusive of all taxes) and excise taxes as distinct explanatory variables. Because excise taxes are bundled into the retail price they are usually invisible: consumers may know they exist, but in practice they are invisible and impossible to ferret out. Consumers may also be completely unaware of such taxes. By adding taxes to the set of explanatory variables we study the effect of making excise tax information readily available to the consumers, in the Tversky and Kahnemann (1974) sense.

This paper adds to the existing literature in the following ways. First, we provide accurate measures of own and cross price elasticities for a bundle of energy related goods, including gasoline, estimating a complete system of demand, thus accounting for the behavioral responses of the households. Information on gasoline taxes is treated as additional information that is made available to the consumers when making their purchasing decision. We find robust evidence that U.S. consumers overreact to excise tax changes compared to price changes. Our degree of overreaction is however smaller than previous estimates have found. This is likely to be due to the fact that elasticities from single equation estimates tend to be lower, inflating the degree of over (or under) reaction to taxes.

Second, we compute the degree of overreaction to gasoline taxes accounting for a number of demographic variables that capture heterogeneity among U.S. households. Overreaction to taxes tends to be larger in the Northeast and Midwest regions of the country and for households owning zero or one car at most. The remainder of the paper is organized as follows. Section 2 describes our empirical specification. Section 3 presents the data. Section 4 analyzes the estimation results and the measures of overreaction to tax changes relative to price changes. Section 5 concludes.

2. Empirical Specification

The functional form chosen to specify our model is the Quadratic Almost Ideal Demand System (QAIDS, Banks, Blundel and Lewbel, 1997) that generalizes the popular AIDS (Deaton and Muellbauer, 1980) by adding a non-linear income term to the share equations. This demand system allows for flexible income and price responses and it does not have constant elasticities, as they depend on the level of expenditure. As reported by Labandeira *et al.* (2006), the interest of rank-three models, like the QAIDS, is particularly relevant in demand systems using data from the U.S. CEX or the Canadian FAMEX consumer expenditure surveys. We start from the 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 $B(p)/\left[\ln y^h - \ln A(p)\right]$ 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. In particular, *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 $G(p) = \sum_i g_i lnp_i$ is homogeneous of degree zero in the price vector p. The corresponding system of Marshallian demand functions for household h and goods $i=1,\ldots,n$ expressed as expenditure shares is given by:

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

where the parameters c_{ij} are defined as $c_{ij} = \frac{1}{2}(c_{ij}^* + c_{ji}^*) = c_{ji}$ and α_{ik} are the coefficients of the translating intercepts $d^h = d_1^h \ldots d_k^h$. The demand functions (2) satisfy integrability, i.e. are consistent with utility maximization, when the following parametric restrictions hold:

$$\sum_i \alpha_i = 1, \sum_i \beta_i = \sum_j c_{ij}^* = 0, \ \sum_i \alpha_{ik} = 0 \ \ \forall k \ \text{(Adding up)}; \ \sum_j c_{ij} = 0 \ \text{(Homogeneity)}; \ c_{ij} = c_{ji}$$

for all i, j (Symmetry). Compared to AIDS, this functional specification adds a quadratic term in the log of income, thus allowing for non linear changes in the budget shares following a price or income change. An easy way to test for the presence of such non linear effects is to test the null hypothesis that λ_i=0[1].

The presence of zeros in the dependent variables is quite important for our sample. To deal with this problem we use the two-step estimator proposed by Shonkwiler and Yen (1999) which involves probit estimation in the first step and a selectivity-augmented equation system in the second step[2]. The system of equations (2) is thus estimated in the following form (we omit the subscript *h* 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 system; $\xi_i = s_i - E(s_i)$ and where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density (pdf) and distribution (cdf) functions, respectively. The system of equations (3) is estimated in two-steps: (i) we obtain Maximum Likelihood (ML) probit estimates $\hat{\tau}_i$ of τ_i using the binary outcome $s_i = 0$ and $s_i > 0$; (ii) we calculate $\Phi(z_i^{'},\hat{\tau}_i)$, $\phi(z_i^{'}\hat{\tau}_i)$ for all i and estimate $\theta,\delta_1,\delta_2,...,\delta_n$ in the augmented system (3) by ML.

Such two-step estimator is consistent, but the error terms are heteroscedastic, thus the estimated elements of the second-step conventional covariance matrix are inefficient. For simplicity, we empirically calculate the standard errors of the elasticities using nonparametric bootstrapping and running 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). First-step Probit models were used for all commodities except Food, for which the number of zeroes is very low. Exogenous variables used in the first-step probit estimates are: disposable income proxied by total current expenditure, demographic and geographic dummies as described in the following section. In all estimates we impose homogeneity and symmetry. Economic theory also requires the matrix of Slutzky substitution effects to be negative semi-definite. Such a requirement is satisfied at the point of sample means and there is no need to impose it using the Cholesky decomposition. Finally, we drop the "other goods and services" equation to accommodate adding up.

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

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

1 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.

2 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.

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

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

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

$$\mu_{ij} = c_{ij} - \mu_i\left(\alpha_i + \sum_i\sum_k \alpha_{ik}d_k \; + \sum_j c_{ij} ln p_j\right) + \frac{2\lambda_i}{B(p)}\left\{ln\left[\frac{y}{A(p)}\right]\right\}^2.$$

2.1 Incorporating Information on Taxes into Demand Functions

To account for the effects of gasoline taxes on consumer behavior we include them among the explanatory variables of the share equations using the translating technique (Pollak and Wales, 1992), a special case of the modifying function technique proposed by Lewbel (1985) and often used to analyze the effect of non-price, non-income variables like information (Jensen *et al.*, 1992; Chern *et al.*, 1995), innovation (Moro *et al.*, 1996), or advertising (Duffy, 1995; Brown and Lee, 1997), in demand systems. This technique consists of positing an additional set of linear, auxiliary relationships between the α_i in the share equations (2) and the logarithmic values of the sum of federal and state taxes on gasoline. This model implies that the pattern of consumer demands will vary not only as incomes and prices change. Information on taxes may also induce changes in budget shares. The corresponding gasoline (i) tax (T) elasticity of demand is:

$$e_i^T = \frac{\rho_i}{w_i}$$

where $\rho_i = \alpha_{iT} - \beta_i\left(\sum_j \alpha_{jT} + \sum_j c_{ij} ln p_j\right) + \frac{2\lambda_i}{B(p)}\left\{ln\left[\frac{y}{A(p)}\right]\right\}$ (7)

3. Data

3.1 Household budget shares, total expenditure and socio-demographics

The U.S. Consumer Expenditure Survey (CE) produced by the Bureau of Labour Statistics (BLS) is the main data source for our application. We use micro-data of the quarterly Interview Survey (IS) from waves 2007, 2008 and 2009 of the CE.[3] Each CE wave has five IS cross-sections: one per calendar quarter in which the interviews took place, including the first quarter of the following year.[4] We thus 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 the Metropolitan Statistical Area (MSA) is indicated. 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).

3 The CE consists of two components, a quarterly Interview Survey (IS) and a weekly Diary Survey, each with its own questionnaire and sample.

4 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. About 20 percent of the addresses are new to the survey each month.

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 set of budget shares:

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

where: *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 budget 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 categories (see the shares in the last column of the Table). 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 be there for many households.

Table 1 – Summary statistics of budget shares

Variable	Obs.(#)	Mean	Standard deviation	Coeff. of variation	Min	Max	Zeros
Food at home	43,457	22.8%	13.7%	0.60	0.0%	100.0%	0.9%
Electricity	43,457	5.8%	5.3%	0.92	0.0%	100.0%	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%	12.9%
Public transport	43,457	2.0%	5.4%	2.63	0.0%	81.4%	73.4%
All other expenditures	43,457	56.7%	17.5%	0.31	0.0%	100.0%	0.1%

Different types of socio-demographic characteristics are also extracted from the IS dataset. Descriptive statistics of those and total current expenditure are reported in Table 2. The household profile is categorised through 6 dummy variables identifying the following types: *a)* Single; *b)* Husband and wife; *c)* Husband and wife, with oldest child under 6 (years old); *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 9 levels. Finally, the model controls for the number of cars owned by the household.

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	13.41	1.98	0	17
Number of cars	43,457	0.91	0.89	0	15
Total current expenditure, $	43,457	7,178.8	7,298.6	35.0	321,316.0

* 0 "Never attended school", 10 "1st through 8th grade", 11 "9th through 12th grade", 12 "High school graduate", 13 "Some college, less than college graduate", 14 "Associate's degree", 15 "Bachelor's degree", 16 "Master's degree", 17 "Professional/Doctorate degree".

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.[5] 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 BLS, follow the same classification of household expenditure. BLS uses the CE 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 18.4 cents per gallon and has not changed since 2006.[6] By contrast, State taxes can differ significantly from one State to another and they are occasionally subject to revisions. The data we use on monthly rates of State taxes are published by the Federation of Tax Administrators (FTA).[7] Local taxes are not considered due to lack of information. Figure A2, in the Appendix, shows the frequency distribution of State tax rates in our sample.

5 Only, as price indices by MSA are not available for *Other home fuels* nor for *Public transport*, U.S. level indices are considered in these cases.

6 Source: U.S. Energy Information Administration.

7 Two rates are added up: "State motor gasoline taxes" and "Other State taxes", in FTA's nomenclature.

4. Results

4.1 Coefficients and elasticities

Table 3 reports some of the estimated parameters of the two-stage QAID model, in (3).[8] In commenting on those, we focus on the equation for the gasoline budget share. All the geographic dummies (α_{NE}, $\alpha_{SO,}$ α_{WE}) are statistically significant and their values indicate that, relative to the Midwest (the base category), living in the West has a positive impact on gasoline consumption, followed by the South and the Northeast (in decreasing order). As expected, the number of cars owned by a household (α_{NCAR}) has a positive impact on gasoline consumption. The same is also true for the presence of two income earners in the household (α_{TWOE}), possibly due to longer cumulative distances to reach the workplaces. Conversely, a higher education level of the head of household (α_{EDUC}) turns out to have a negative impact on gasoline consumption. In addition, the quadratic term of total expenditure (λ) is statistically significant in all the equations, which proves that the QAID model fits the data better than the AID model could do.

Concerning the elasticities, compensated own-and cross-price elasticities, along with expenditure elasticities and estimated budget shares, are shown in Table 4. All of these are evaluated at the sample means of exogenous variables. On average, 18.4% 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 about 9% of total current expenditure. With regard to expenditure elasticities, *Home food*, *Natural gas* and *Gasoline* turn out to be necessities,[9] while the remaining goods and services appear to be luxuries to different degrees.[10] All own-price elasticities are generally plausible, ranging between -0.855 and -0.293, for *Electricity* and *Natural gas*, respectively.[11] For *Gasoline*, we find an own-price elasticity of -0.50, 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]). Indeed, we observed that single equation studies tend to find lower price elasticities (in absolute value). We reckon that this has probably to do with both differences in model specification and nature of the data, as typically – not always – demand systems and single demand equations are estimated with cross-sectional data and time-series data, respectively. To back this hypothesis, we report, in Table 5, some recent estimates of own-price elasticities of U.S. household demand for gasoline, distinguishing between demand systems and single equation models.

8 Price coefficients and c.d.f. coefficients are not reported to save space. These parameters, as well as first-step probit coefficients, are available from the authors upon request.

9 The expenditure elasticities for *Home food*, *Natural gas* and *Public transport* are close to those derived by Labandeira *et al.* (2006), in a similar application with Spanish data.

10 Perhaps, expenditure elasticities greater than 1 both for *Electricity* and *Public transport* are unexpected. The reason may lie in the specific nature of the data: *Electricity* includes expenditures for second, third and *n-th* homes; similarly, *Public transport* includes air travelling.

11 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.

Table 3 - Second-step QAID estimates

Coefficient	i=1 Food	i=2 Electricity	i=3 Nat. Gas	i=4 Oth. F.	i=5 Gasoline	i=6 Pb. Tr.
α_i	**0.200**	**0.054**	**0.036**	**0.647**	**0.106**	**0.119**
	0.001	*0.001*	*0.006*	*0.031*	*0.002*	*0.025*
β_i	**-0.109**	**-0.029**	**-0.019**	**-0.044**	**-0.039**	**0.032**
	0.001	*0.001*	*0.001*	*0.001*	*0.001*	*0.006*
λ_i	**-0.003**	**0.001**	**-0.004**	**-0.041**	**-0.013**	**-0.007**
	0.001	*0.000*	*0.000*	*0.002*	*0.001*	*0.001*
$\alpha_{i,NE}$	**0.030**	**0.012**	**-0.006**	**-0.083**	**0.009**	**-0.033**
	0.002	*0.001*	*0.004*	*0.015*	*0.001*	*0.005*
$\alpha_{i,SO}$	**0.017**	**0.039**	**-0.027**	**-0.021**	**0.013**	**0.012**
	0.002	*0.001*	*0.005*	*0.008*	*0.001*	*0.004*
$\alpha_{i,WE}$	**0.041**	**-0.005**	**-0.038**	**-0.002**	**0.018**	**-0.013**
	0.002	*0.001*	*0.001*	*0.009*	*0.001*	*0.004*
$\alpha_{i,NCAR}$	**-0.011**	**0.001**	**0.001**	**0.008**	**0.011**	**-0.007**
	0.001	*0.000*	*0.000*	*0.001*	*0.001*	*0.001*
$\alpha_{i,TWOE}$	**-0.001**	**-0.001**	**-0.002**	**-0.021**	**0.011**	**0.002**
	0.001	*0.000*	*0.001*	*0.003*	*0.001*	*0.003*
$\alpha_{i,N1}$	**-0.056**	**-0.009**	0.001	**0.107**	**0.003**	**-0.030**
	0.002	*0.001*	*0.002*	*0.007*	*0.001*	*0.005*
$\alpha_{i,N3}$	**0.028**	-0.001	-0.002	0.035	0.011	**-0.014**
	0.003	*0.001*	*0.001*	*0.006*	*0.002*	*0.004*
$\alpha_{i,N4}$	**0.053**	**0.007**	0.001	**0.024**	**0.018**	**0.002**
	0.002	*0.001*	*0.001*	*0.004*	*0.001*	*0.004*
$\alpha_{i,N5}$	**0.048**	**0.008**	-0.000	**0.022**	**0.022**	-0.011
	0.002	*0.001*	*0.001*	*0.001*	*0.001*	*0.004*
$\alpha_{i,N6}$	**0.024**	**0.003**	0.001	**0.039**	**0.016**	-0.026
	0.001	0.001	0.001	0.001	0.001	0.004
$\alpha_{i,EDUC}$	**-0.005**	**-0.002**	**-0.001**	**-0.001**	**-0.004**	**0.001**
	0.000	*0.000*	*0.000*	*0.001*	*0.000*	*0.001*
LogLikelihood	392.200					
R^2	0.34	0.18	0.11	0.07	0.15	0.04
N obs	43,256					

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

Table 4 - Estimated Budget Shares, Expenditure and Compensated Elasticities

	j=1 Food	j=2 Electricity	j=3 Nat. Gas	j=4 Oth. Fuels	j=5 Gasoline	j=6 Public Transport	j=7 Other Goods
w_j	0.228	0.058	0.029	0.007	0.090	0.021	0.567
e_j	**0.871**	**1.260**	**0.712**	**2.882**	**0.405**	**1.389**	**1.098**
	0.021	*0.033*	*0.060*	*0.151*	*0.032*	*0.117*	*0.010*
e^C_{1j}	**-0.852**	**-0.051**	**0.101**	0.005	-0.021	**0.497**	**0.648**
	0.039	*0.013*	*0.013*	*0.025*	*0.018*	*0.034*	*0.050*
e^C_{2j}	-0.075	**-0.855**	-0.024	0.066	**-0.150**	-0.056	**1.801**
	0.047	*0.028*	*0.023*	*0.042*	*0.029*	*0.071*	*0.080*
e^C_{3j}	**0.515**	-0.047	**-0.293**	**0.384**	**-0.297**	**0.599**	**-0.848**
	0.067	*0.032*	*0.043*	*0.063*	*0.040*	*0.096*	*0.107*
e^C_{4j}	**-0.196**	-0.017	**0.192**	**-0.768**	0.021	**0.495**	**2.267**
	0.091	*0.038*	*0.043*	*-0.384*	*-0.253*	*0.154*	*1.585*
e^C_{5j}	**-0.179**	**-0.152**	**-0.155**	-0.003	**-0.496**	-0.050	**0.719**
	-0.041	*0.018*	*0.019*	*0.039*	*0.029*	*0.047*	*0.067*
e^C_{6j}	**1.551**	-0.033	**0.366**	**0.388**	-0.004	**-0.796**	**-1.150**
	0.110	*0.057*	*0.057*	*0.130*	*0.062*	*0.215*	*0.197*
e^C_{7j}	**0.299**	**0.136**	**-0.014**	**-0.032**	**0.118**	**-0.194**	**-0.396**
	0.018	*0.007*	*0.006*	*0.013*	*0.011*	*0.017*	*0.011*

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

Table 5 – Estimates of price elasticities of U.S. household demand for gasoline

Systems of demand	
Study	**Own price elasticity of gasoline demand**
West and Williams (2007)	-0.75; -0.27 (range)
West and Williams (2004)	-0.46
Nicol (2003)	-0.598; -0.026 (range)
Oladosu (2003)	-0.70; -0.36 (range)
Single equations	
Study	**Own price elasticity of gasoline demand**
Li *et al.* (2012)	-0.39
Sentenac-Chemin (2012)	-0.30
Su (2011)	-0.397
Davis and Kilian (2011)	-0.46
Manzan and Zerom (2010)	-0.35
Hughes *et al.* (2008)	-0.077
Small and Van Dender (2007)	-0.43

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* and *Electricity*. In both cases, the relationship is symmetric, meaning e^C_{ij} and e^C_{ji} have the same sign (e^C_{35} = -0.297 and e^C_{53} = -0.155; e^C_{25} = -0.150 and e^C_{52} = -0.152). While a theoretical explanation for these complementarities is not immediately obvious, it is good news for environmental policy that an increase in the price of *Gasoline* would also induce lower consumption of *Natural gas* and *Electricity*. Surprisingly, perhaps, the same is not true for *Gasoline* and *Public transport*, as both the cross-price elasticities relating the two are not statistically different from zero. Similarly, no price relationship emerges between *Electricity* and *Natural gas*.

4.2 Overreaction to Gasoline Taxes

The purpose of this section is to analyse the different responses of consumers to changes in gasoline taxes and gasoline prices. To do that, as in Rosen (1976) and Chetty *et al.* (2009), we compare the tax elasticity of *Gasoline*, e^T, and the compensated (tax inclusive) price elasticity of *Gasoline*, e^C_{55}. The ratio of these elasticities, θ, measures the degree of overreaction, or underreaction, to gasoline taxes relative to the responsiveness to changes in gasoline prices: $\theta = \frac{e^T}{e^C_{55}}$.

Under the alternative hypothesis of different demand responses to price and tax variations, θ must be different from 1. We thus computed θ at sample mean values, first for the whole sample and, then, for different macro-regions and different numbers of cars owned by households. For the whole sample, θ turns out to be equal to 1.199. This means that, on average, households overreact to taxes and, specifically, their reaction to gasoline taxes is 20% larger than their reaction to price changes.[12]

The existing literature offers a number of explanations for this differential response. Some of these explanations consider a different reaction to taxes as rational behavior consistent with full optimization. For example, Davis and Killian (2011) and Li *et al.* (2012) also find a larger response to taxes relative to prices in the gasoline market. One explanation they provide is that consumers can

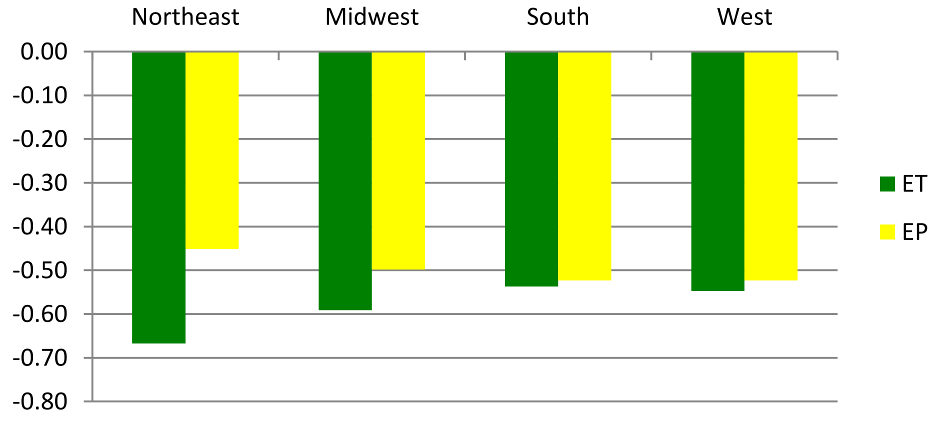
[12] In all estimates, we checked that θ is significantly different from one. At the sample mean, $\theta - 1 = 0.199$ (0.097). Standard errors are bootstrapped with 500 replications

consider a change in taxes as more persistent than a change in prices and rationally adjust their expectations and consumption behavior accordingly. Other, behavioral economics explanations, consider the differential responses to taxes as the result of a number of (not mutually exclusive) cognitive biases affecting individual decision making. First, Gasoline tax changes may be more salient than price changes because they attract larger media coverage. As a result, consumers are more responsive to more salient price or tax changes. Second, people may perceive an additional burden associated with tax payments compared to economically equivalent payments labeled differently, a phenomenon called tax aversion (McCaffery and Baron, 2006; Kallbekken *et al.*, 2010 and 2011; Blaufus and Möhlmann, 2012). These explanations are not mutually exclusive.

What distinguishes this paper from previous contributions is that we compare reactions to retail prices to reactions to separate information on excise taxes. In doing that we assume that excise taxes included in the posted price are completely invisible. Because excise taxes are bundled into the advertised price, they are actually completely hidden, asconsumers cannot separate the excise tax component from the production price component. Excise taxes on various commodities are often largely unknown and very low salient. In order to analyze how consumers react to variations in excise taxes we treat information on excise taxes as new, separate information that is made available to the consumers and is therefore highly salient.

That consumers react more to tax than to price changes is also confirmed when we compute the tax overreaction parameter, θ, by some relevant demographic variable. Figure 1 contrasts estimated tax (ET) and price (EP) elasticities for *Gasoline*, by macro-region. The Northeast exhibits both the lowest price elasticity and the highest tax elasticity across the regions.[13] The sum of these two results explains why θ is significantly higher in that region as compared to the others, as Figure 2 shows. For the Northeast, the parameter of overreaction to gasoline taxes reaches as much as 1.479, which is 20% to 30% higher than for the other regions. In fact, we find that θ is not statistically different from 1, both for the South and the West. That is, for those regions, there is no evidence (at mean values) of overreaction, or underreaction, to tax changes.

Figure 1: ET and EP, by region



[13] The sample mean of gasoline taxes for the Northeast is 7% to 14% higher than the same statistics for the other regions. Thus, this suggests that the higher tax elasticity might be related to the higher level of taxation. We will test the potential nonlinearity of the relationship between gasoline taxes and gasoline demand in a future extension of the paper.

Figure 2: Theta, by region

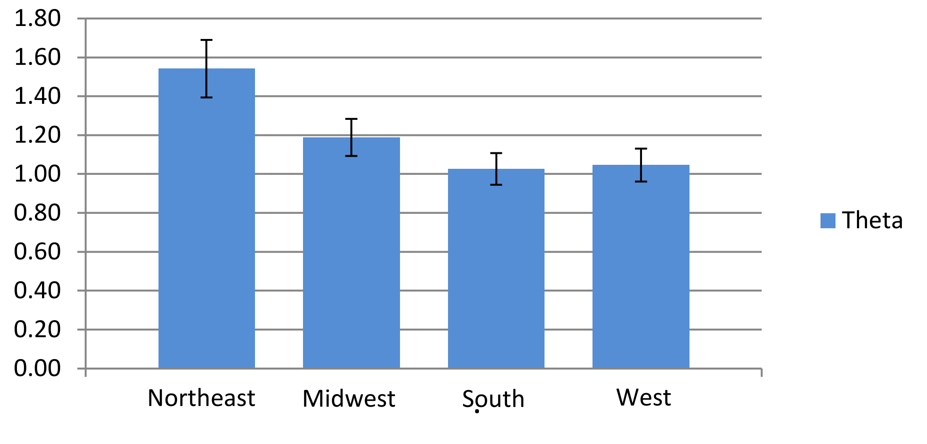
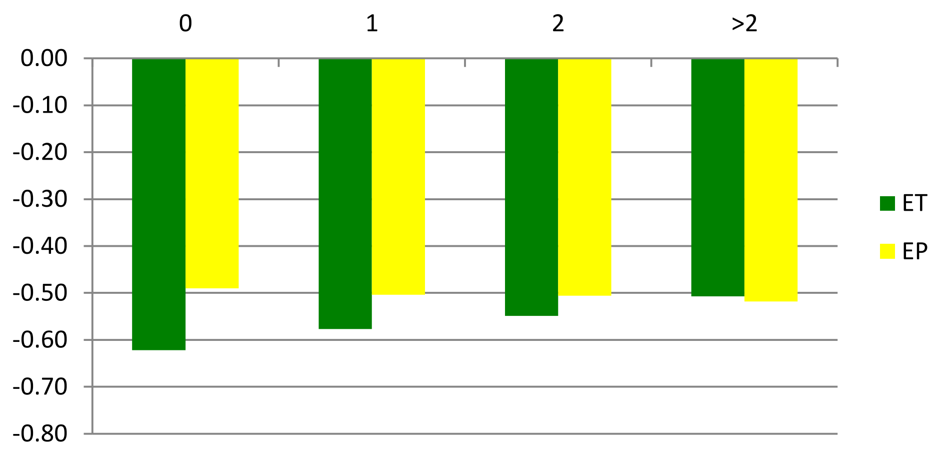


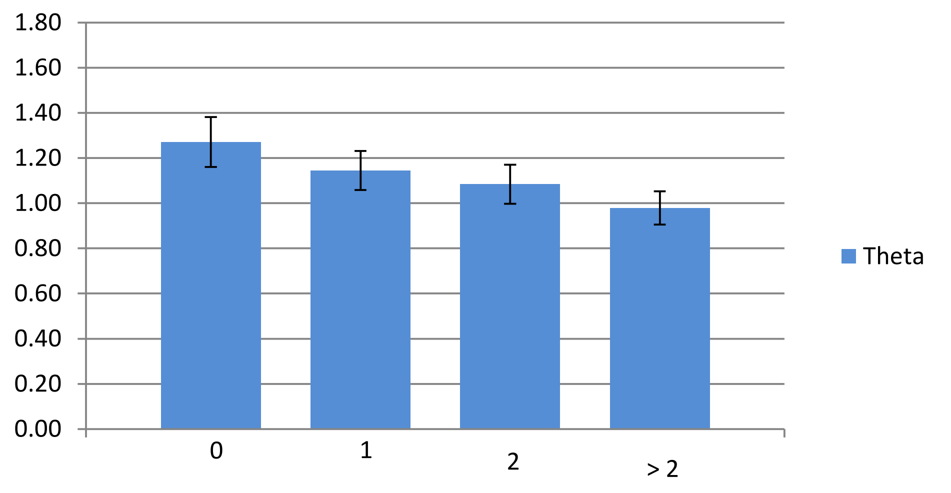
Figure 3 contrasts estimated tax and price elasticities of gasoline demand, this time by the number of cars in the household. The corresponding estimates of θ are then pictured in Figure 4. Households with one car overreact to tax changes by about 15%, compared to equivalent price changes. Households with no cars overreact to tax changes by about 27%. In general, the degree of overreaction appears to be negatively related to the number of cars: the more the cars owned by the household, the lower the degree of overreaction to tax changes relative to price changes. In fact, θ is not statistically different from 1 (at mean values) if more than one car is owned by the household. A possible explanation for this finding is the following. In presence of a direct relationship between income level and number of cars, the degree of attention to taxes could be inversely related to the level of income. That is, low income households having no car or one car at most, may be more sensitive to tax changes (relative to price changes) than richer households are. This argument is supported by recent findings of Goldin and Homonoff (2013), which show that low income consumers are more attentive to tax changes than high income consumers are.[14] To investigate this possibility, we computed θ at different levels of total current expenditure, but none of the results were statistically significant.

Figure 3: ET and EP, by number of cars



[14] In particular low-income consumers are likely to be especially attentive to taxes on goods that represent a larger budget share compared to high income consumers. Gasoline is an excellent example of necessary commodities of this type.

Figure 4: Theta, by number of cars



Our degree of overreaction to Gasoline taxes compares to the existing literature in the following ways. Li *et al.* (2012) estimate a single equation for Gasoline consumption and their θ = 2.107.[15] Davis and Killian (2011) also use a single equation approach to gasoline demand. We use their tax and price elasticity in Table 7 (AIC lag order, last column) to compute θ = 2.143. Our degree of overreaction is much smaller in magnitude (around 1.200 at the sample mean). As we explain in the introduction, the use of single equation approaches implies the imposition of a separability assumption and, as a result, price elasticities may be biased downwards because they do not account for the possibilities of substitution among consumption goods. If this is the case, price elasticities from single equation estimates would inflate the denominator of θ. This is an important point. Since the different reaction to tax and price changes provides important information for the design of tax policies, accurate estimates of gasoline elasticities are necessary in order to predict consumers reactions in a precise way.

5. Discussion

This paper adds empirical evidence to the growing literature observing that people respond differently to tax and price changes. We offer a number of contributions to the existing literature. First, we compute own and cross price Gasoline elasticities by estimating a complete system of demand. This avoids imposing implausible separability restrictions among commodities demands and allows to compute elasticities that take behavioral responses into account. Obtaining accurate elasticity measures is crucial, because the indiscriminate use of Gasoline elasticities may generate inaccurate forecasts. Second, the ratio of the Gasoline tax elasticity and the compensated Gasoline price elasticity is computed for a number of demographic variables accounting for households heterogeneity in the U.S.. We consistently find that households overreact to Gasoline taxes as compared to Gasoline prices (by 20% at the sample mean). Finally, rather than comparing reactions to tax-exclusive price and to taxes, we compare reactions to tax-inclusive prices and to separate information on excise taxes that is made available to consumers. Current excise taxes on Gasoline in the U.S. are clearly low salient and less prominent than separate information on those same taxes. Consumers may be completely unaware of excise taxes that are bundled into the advertised price and that may be difficult to disentangle. Gasoline prices are an excellent example of this. They are probably the most salient among

[15] We consider estimated coefficients in Table 7, column 4 of the Li *et al.* (2012) paper. Since their Gasoline equation specification is log-log form, the elasticities ratio is simply given by the ratio of the coefficients -0.769 and -0.365 and the computed θ = (-0.769/-0.365) = 2.107.

commodity prices. Consumers pay exactly the price they see on big signs at the pumps, but they are unable to separate the market price and excise tax components. In this paper we compare reactions to retail price changes and reactions to information on excise taxes that is made available to the consumers. This approach is close in spirit to Tversky and Kahneman's idea of salience as one of the crucial factors affecting the degree of "availability" of information useful to make sound decisions.

Our findings have relevant implications for the design of efficient taxes, because they confirm that salience manipulation can influence consumers responsiveness to price incentives. The recent and emerging literature on tax salience suggests that the degree to which taxes are salient is a choice variable for policy makers. When policy makers choose to keep some taxes hidden, or not prominent, this will contribute to keep consumers reaction low. This has obvious implications for the carbon tax debate in the U.S.. There is now near unanimity among U.S. economists spanning the political and academic spectrum (Hsu, 2009) in recognizing carbon taxes as the most efficient means of reducing large-scale pollution problems. Yet public support for fiscal efficiency-enhancing policies remains fragile. Our results suggests that the carbon tax rate that would reduce greenhouse gases emissions to any targeted level could be set lower than predicted by the current literature, if consumers' reactions to carbon taxes can be increased by increasing their visibility[16]. A lower carbon tax rate would, in turn, probably be perceived as more acceptable than a correspondingly higher tax rate. By contrast, designing Pigouvian taxes as low salient excise taxes is inappropriate not only because they are intended to affect behavior and thus should be prominent, but also because they should be set at a higher rate which would make them less acceptable.

There is usually a tradeoff between the effectiveness and the acceptability of policies. Because policies that are effective in changing behavior, such as price incentives, also tend to have greater impacts on consumers, they also usually receive less public support, and therefore are less politically palatable, producing a negative relationship between effectiveness and acceptability of such policy measures. Manipulating tax salience, by manipulating information availability, can change this tradeoff. Making excise taxes information visible can increase consumers' reaction to them and shift the effectiveness-acceptability tradeoff upwards so that a higher level of effectiveness is associated with a given level of acceptability.

[16] One easy way to increase Gasoline tax salience by making information on taxes readily available is to design the posted price, on big signs at the pumps, as Price per gallon = \$(price) + \$(taxes) = \$, rather than Price per gallon = \$, in exactly the same way as Chetty *et al.* (2009) do in their exhibit 1.

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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

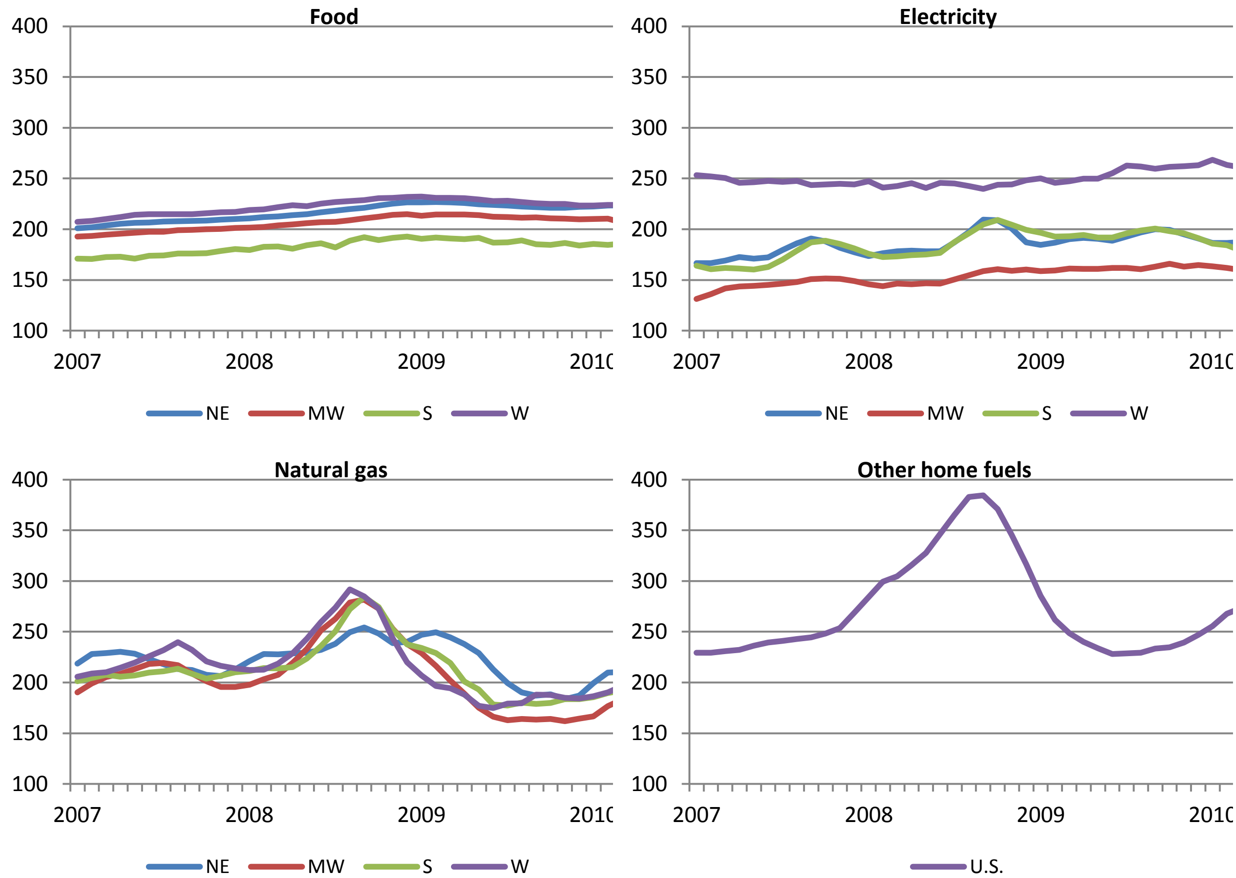
Metropolitan Statistical Area	State(s)	Frequency	Percent
Philadelphia – Wilmington – Atlantic City	PA – NJ – DE – MD	2,680	6.17%
Boston – Brockton – Nashua	MA – NH – ME – CT	2,472	5.69%
New York	NY	2,984	6.87%
New York, Connecticut suburbs	NY – CT	2,969	6.83%
New Jersey suburbs	NJ	2,474	5.69%
Chicago – 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



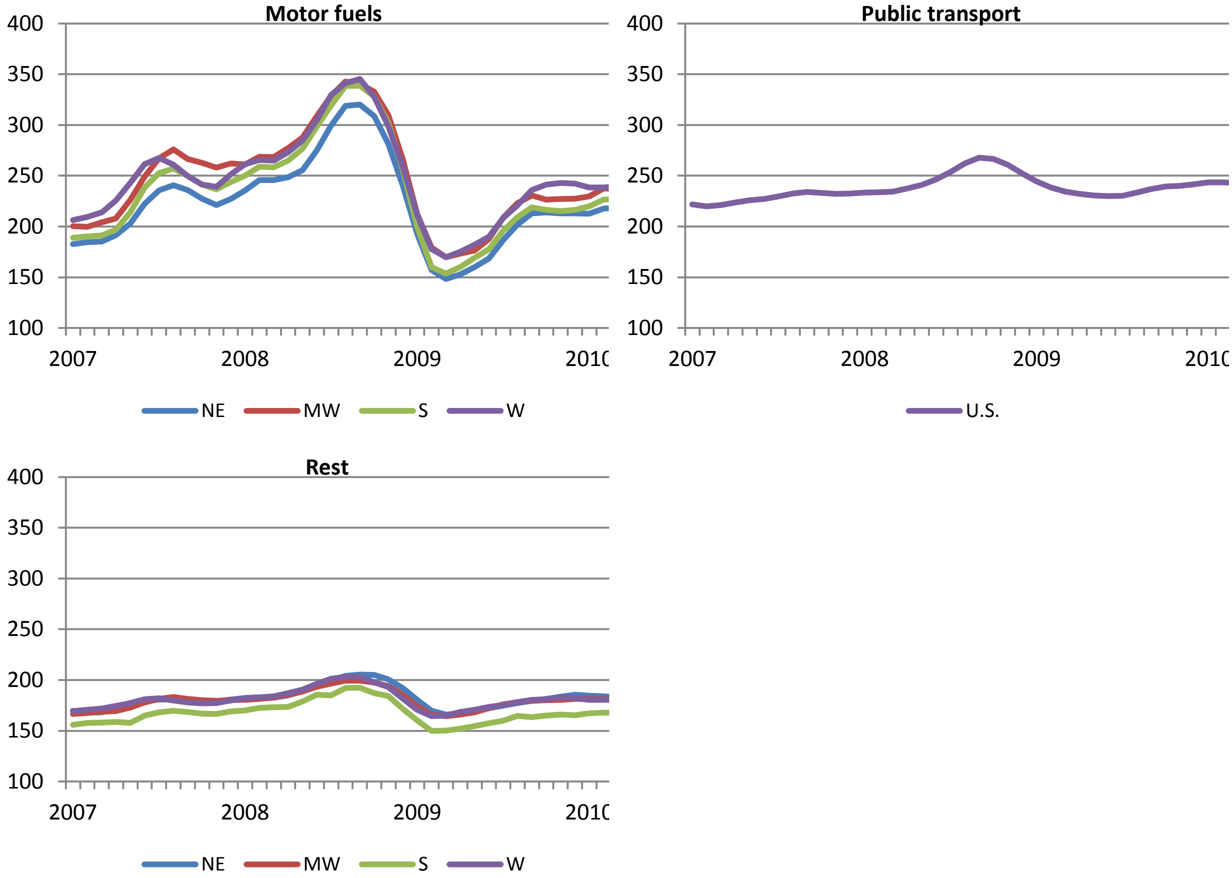
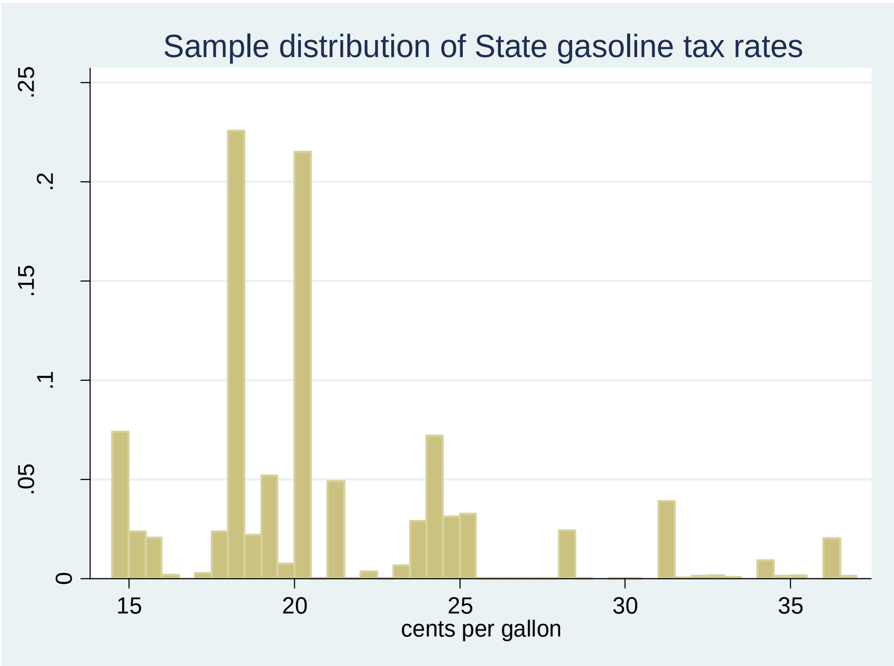


Figure A2 – Distribution of gasoline taxes



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