

## Distributional and Efficiency Impacts of Gasoline Taxes: An Econometrically Based Multi-market Study

By ANTONIO M. BENTO, LAWRENCE H. GOULDER, EMERIC HENRY, MARK R. JACOBSEN,  
AND ROGER H. VON HAEFEN\*

Because of its potential to improve the environment and enhance national security, reducing automobile-related gasoline consumption has become a major U.S. public policy issue. Recently, many analysts have called for new or more stringent policies to discourage gasoline consumption. Proposals include a tightening of corporate average fuel economy (CAFE) standards and subsidies to retirements of older (gas-guzzling) vehicles, as well as increments to the federal gasoline tax. This paper examines the gas-tax option, employing an econometrically based multi-market simulation model to explore the policy's efficiency and distributional implications.

This study differs from earlier work in several ways. Some prior studies have investigated gasoline consumption either by employing a demand function for gasoline or by deriving this demand from households' vehicle-miles traveled (VMT).<sup>1</sup> These studies treat the composi-

tion of the automobile fleet as fixed. However, a gasoline tax can be expected to influence the fleet composition (e.g., the market share of more fuel-efficient cars) as well as the amount of driving. This study allows for both impacts. As in Steven Berry et al. (1995), Pinelopi Goldberg (1995), and Amil Petrin (2002), we account for the imperfectly competitive nature of the new-car market. However, in contrast with these studies, we consider interactions between the markets for new, used, and scrapped cars.<sup>2</sup> The impacts of a gasoline tax can importantly depend on such interactions. Higher gasoline taxes could stimulate higher rates of scrappage of older, fuel-inefficient cars and could also promote shifts in demand from used cars to especially fuel-efficient new cars. Studies that ignore these adjustments could understate a gas tax's impacts on fuel consumption.

Another set of differences from earlier work is in the econometric approach. By allowing the structural parameters entering preferences to vary randomly across households, we can account for rich patterns of unobserved preference heterogeneity. Also, in contrast with nearly all prior work, we adopt an estimation approach that simultaneously estimates in a utility-consistent manner each household's automobile choice and its choice of VMT.<sup>3</sup> This is important for evaluating welfare impacts.<sup>4</sup>

<sup>†</sup> *Discussants:* Kenneth Small, University of California; Richard Arnott, Boston College; Karen Palmer, Resources for the Future; Clifford Winston, Brookings Institution.

\* Bento: School of Public Policy, University of Maryland, College Park, MD 20742 (e-mail: abento1@umd.edu); Goulder, Henry, and Jacobsen: Department of Economics, Stanford University, Stanford, CA 94305 (e-mails: goulder@stanford.edu, chenry@stanford.edu, and mrj@stanford.edu); von Haeften: Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, NC 27695 (e-mail: roger\_von\_haefen@ncsu.edu). We are grateful to David Austin, Tim Bresnahan, Don Fullerton, Ken Small, James Sweeney, Kenneth Train, Kurt van Dender, and Frank Wolak for very helpful suggestions, and to the William and Flora Hewlett Foundation for financial support.

<sup>1</sup> Richard Schmalensee and Thomas M. Stoker (1999) and Sarah E. West and Robertson C. Williams III (2004) use household-level data on gasoline consumption to estimate the income and price elasticity of demand for gasoline. In contrast, James Berkovec (1985), Fred Mannering and Clifford Winston (1985), Kenneth E. Train (1986), and West (2004) sequentially estimate automobile ownership and VMT decisions using discrete-choice and linear-regression

techniques. These studies derive the elasticity of demand for gasoline from the VMT elasticity and the fuel economy of the different vehicles. James Poterba (1991) generates elasticities of demand for gasoline use by transforming Train's (1986) estimates of elasticities for VMT.

<sup>2</sup> Berkovec (1985) develops a model with interactions among these markets. His model assumes pure competition among auto producers, however.

<sup>3</sup> The one exception is a recent working paper by Ye Feng et al. (2004).

<sup>4</sup> Prior studies have tended to focus on policies' impacts on prices or quantities, rather than the welfare consequences.

An appendix to this paper, available on the AER web site, details the simulation model's structure, data, estimation approach, and solution method.

We examine policy impacts both in the aggregate and across households distinguished by income, car-ownership, and other characteristics. Simulation results show that whether a gas-tax increase is regressive in its impact depends on the manner in which the tax revenues are recycled (returned) to the economy. The results also reveal significant heterogeneity in welfare impacts within household income groups, thus highlighting the importance of accounting for household heterogeneity in tastes and car-ownership in evaluating distributional impacts.

## I. Structure of the Simulation Model

### A. Household Demands

Households obtain utility from car ownership and use, as well as from consumption of other commodities. Utility from driving depends on characteristics of the automobile and vehicle-miles traveled. Each household has exogenous income; most households also are endowed with cars. If a household has a car endowment, it chooses whether to hold or relinquish (sell or scrap) that car; if it relinquishes the car it also decides whether to purchase a different car (new or used). Households without car endowments simply choose whether to purchase a car.

U.S. auto markets include thousands of types of new and used cars and trucks, and many households own several vehicles. Households enjoy a huge number of possible household car choices, far more than would be tractable econometrically or in a simulation model. To achieve manageable dimensionality, we group cars and trucks into 284 categories based on the vehicle's age, class, and manufacturer. In addition, to deal with multiple-car households, we adopt a variation of the repeated discrete-continuous modeling approach of Igal Hendl (1999) and Jean-Pierre Dubé (2004).<sup>5</sup> Here we

assume that household automobile choices arise from decisions made on  $T$  separable choice occasions, where  $T$  depends on the number of adults in the household. On each occasion, the household makes a discrete choice of whether to choose one of the 284 composite cars. If the  $j$ th automobile is chosen, the household then makes a continuous choice of VMT for the automobile. A virtue of this approach is that it significantly limits the dimensionality of the choice problem. The disadvantage is that it implicitly assumes that the household's automobile decisions with respect to different cars in its fleet are separable from each other.<sup>6</sup>

More specifically, we assume that household preferences on the  $t$ th choice occasion ( $t = 1, \dots, T$ ) for the  $j$ th automobile ( $j = 1, \dots, J$ ) can be represented by the conditional indirect utility function  $U_{ij} = V_j(y/T - r_j, u_j, \mathbf{q}_j, \mathbf{z}, \boldsymbol{\beta}) + \varepsilon_{ij}$ , where  $y$  is household income,  $r_j$ ,  $u_j$ , and  $\mathbf{q}_j$  are automobile  $j$ 's one-year rental price, per-mile utilization price (i.e., operating cost), and non-price characteristics, respectively. The vector  $\mathbf{z}$  contains household's characteristics,  $\boldsymbol{\beta}$  is a parameter vector that varies randomly across households, and  $\varepsilon_{ij}$  represents additional unobserved heterogeneity that varies across households, automobiles, and choice occasions. Similarly, if the household chooses not to rent an automobile (i.e., chooses car 0), its preferences can be represented by  $U_{i0} = V_0(y/T, \mathbf{z}, \boldsymbol{\beta}) + \varepsilon_{i0}$ . The rational household chooses the alternative that maximizes its utility. Assuming that each  $\varepsilon_{ij}$  is an independent draw from the type-I extreme-value distribution with common scale parameter  $\mu$ , the probability that the household chooses the  $j$ th automobile conditional on  $\boldsymbol{\beta}$  takes the standard conditional logit form. Because we employ a theoretically consistent preference specification, we can use Roy's identity to derive the conditional VMT demand for the chosen automobile.

<sup>5</sup> Most previous studies have avoided the difficulties arising with multiple-car households by considering single car purchases in the new-car market (e.g., Berry et al., 1995; Goldberg, 1995) or by focusing on the roughly 85 percent of households with two or fewer cars (West, 2004).

<sup>6</sup> Work in progress adopts an alternative approach in which households choose alternative bundles of cars. Feng et al. (2004) have tried this approach, which has the attraction of permitting greater interdependencies among a household's automobile choices. A drawback is that, in order to keep tractable the dimensionality of the consumer's choice set, it requires a great deal more automobile aggregation as well as restrictions on the number of cars households can own.

### B. Supply of New and Used Cars

The model distinguishes five age categories, ten car classes, and seven manufacturer (make) categories.<sup>7</sup> This yields 350 possible age-class-manufacturer combinations, but since some combinations are not realized the model actually includes 284 cars.

Each of the seven producers acts in accordance with Bertrand competition, setting the prices for its fleet of automobiles to maximize profits, given the prices set by its competitors. New cars differ by class and manufacturer. Let  $k$  index a given producer. Let  $\Phi$  represent the set of all new cars and let  $\Phi_k \subset \Phi$  represent the  $n_k$  new cars manufactured by producer  $k$ . The profit-maximization problem for producer  $k$  is

$$\max_{\{p_j\}} \sum_{j \in \Phi_k} (p_j - m_j) \times q_j(\mathbf{p})$$

subject to

$$\sum_{j \in T} q_j(\mathbf{p}) \times (e_j - \bar{e}_T) \geq 0$$

$$\sum_{j \in C} q_j(\mathbf{p}) \times (e_j - \bar{e}_C) \geq 0$$

where  $p_j$ ,  $m_j$ , and  $q_j$  are the price, marginal cost, and quantity demanded of car  $j$  (which is made by firm  $k$ ). Marginal cost ( $m$ ) is exogenous and assumed to be constant;  $\mathbf{p}$  denotes the vector of all new car prices. The two constraints above acknowledge the presence of CAFE standards.<sup>8</sup> Above,  $\bar{e}_T$  and  $\bar{e}_C$  refer to the fuel economy (miles per gallon) requirements for light trucks and passenger cars, respectively, and  $e_j$  refers to the fuel economy of car  $j$ . Thus, the two constraints express the requirement that the given manufacturer achieve fleet-wide average fuel economy above  $\bar{e}_T$  and  $\bar{e}_C$ , respectively, for the

light trucks and cars it produces. To obtain the equilibrium, all car prices (and associated mark-ups) must be solved for simultaneously.

The stock of used cars is equal to an exogenously specified maximal amount, less the number of scrapped cars. The amount of scrapage is endogenous. For each car type, there is a probability distribution for maintenance costs. If a household owns a car requiring exceptionally high maintenance, it will prefer to scrap the car rather than pay the costs of keeping the car in operation.

Each car type, or age-class-manufacturer combination, has its own market price. The model determines the set of prices for all car types that is consistent with each new-car producer's profit-maximization (first-order) conditions and that clears the used-car market. Since the demand for every car depends on the prices of all other cars (new and used), all car prices need to be solved for simultaneously.

## II. Data and Econometric Estimation

We estimated the parameters entering household preferences for automobile demand with the 2001 *National Household Travel Survey* (NHTS), the most recent and comprehensive survey of U.S. automobile demand. The NHTS contains a cross-section of households' complete automobile holdings and VMT demands as well as economic, demographic, and geographic data. From several other sources (see Appendix on the AER web site) we obtained information on car characteristics (e.g., weight, horsepower, wheelbase, and fuel-economy) and operating costs.

In designing an estimation approach, two issues were especially important. First, for consistent welfare assessments we wanted to estimate simultaneously and consistently the household's choice of VMT and car type. The two-step estimation strategies in previous studies (e.g., Goldberg, 1998; West, 2004) did not fully integrate these decisions. Second, we were concerned about unobserved preference heterogeneity, which has the potential to bias our parameter estimates and yield implausible predictions about substitution patterns.

To address these concerns, we developed a random-coefficient repeated discrete-continuous model permitting simultaneous estimation of households' car and VMT choices.

<sup>7</sup> The age categories are less than 1 (new), 1–2, 3–6, 7–11, and 12–19 years old. The car classes are compact, luxury compact, mid-size, full-size, luxury mid-size/full-size, small SUV, large SUV, small truck, large truck, and minivan. The manufacturer categories are Ford, Chrysler-Daimler, General Motors, Honda, Toyota, other East Asian, and European.

<sup>8</sup> Some manufacturers elect to pay a fine rather than meet the constraint. In future work we will incorporate this option, which involves very minor changes to the objective function and solution procedure.

Random-coefficient specifications can generate more plausible structures of substitution relative to fixed parameter models (Train, 2003), and recently developed simulation-based techniques now make the estimation of these models computationally feasible. We estimate our random-coefficient model with the Bayesian framework, using a variation of Gregory Allenby and Peter Lenk's (1994) Gibbs sampling algorithm.

The posterior means of our parameter estimates were generally consistent with our a priori expectations and suggested posterior mean VMT operating cost and income elasticities on the order of  $-0.70$  and  $0.64$ , respectively. We also found mean automobile holding elasticities with respect to the own rental price of roughly  $-0.75$  for all cars and trucks and  $-1.78$  for new cars and trucks.

### III. Results

We simulate the impact of raising the federal gasoline tax by 10, 30, or 50 cents per gallon. The benchmark gross-of-tax price of gasoline (which varies by state) averages around \$1.45,<sup>9</sup> so the gas-tax increments imply relative price increases between 6 and 35 percent. We explore two types of revenue-recycling: "tax-based recycling," in which revenues are recycled to households in proportion to their gasoline-tax payments, and "income-based recycling," where revenues are recycled in proportion to their benchmark income.

#### A. Gross Efficiency Costs and Changes in Gasoline Consumption

Table 1 indicates impacts on efficiency and aggregate gasoline use, as well as underlying changes in average VMT, average fuel-efficiency, and fleet-composition. The (gross) efficiency costs, expressed by the negative of the equivalent variation (EV), are about \$12, \$38, and \$68 per household for gas tax increases of 10, 30, and 50 cents, respectively. The efficiency costs are gross in that they take no account of environmental and other external benefits from the policy change. The corresponding average excess burdens (efficiency

<sup>9</sup> This includes 18.5 cents in federal gasoline taxes and (on average) 23 cents in state taxes.

TABLE 1—ECONOMY-WIDE IMPACTS OF GAS-TAX INCREASES

Measure	Base	Gas-tax increase		
		\$0.10	\$0.30	\$0.50
A. Tax-Based Revenue Recycling:				
Avg EV		−\$11.55	−\$38.00	−\$68.28
Total EV/gallons avoided		−\$0.78	−\$0.88	−\$0.98
Avg gas-tax payment		\$77.97	\$225.40	\$362.28
Avg excess burden		0.148	0.169	0.188
Avg gas consumption (gallons) <sup>a</sup>	794.5	−1.86	−5.43	−8.80
Avg VMT (thousands) <sup>a</sup>	19.2	−1.82	−5.33	−8.63
Avg MPG (VMT weighted) <sup>a</sup>	24.2	0.04	0.11	0.18
Fleet size (thousands) <sup>a</sup>				
All cars	44,814.4	−0.17	−0.52	−0.85
New cars	3,845.0	−0.53	−1.55	−2.52
Used cars	40,969.4	−0.14	−0.42	−0.69
High-MPG cars <sup>b</sup>	27,027.4	−0.15	−0.45	−0.74
Low-MPG cars	17,787.0	−0.21	−0.63	−1.03
B. Income-Based Revenue Recycling:				
Avg EV (\$)		−\$11.77	−\$37.49	−\$67.48
Total EV/gallons avoided		−\$0.73	−\$0.79	−\$0.86
Avg gas tax payment		\$77.83	\$224.19	\$358.09
Avg excess burden		0.151	0.167	0.188
Avg gas consumption (gallons) <sup>a</sup>	794.5	−2.03	−5.94	−9.86
Avg VMT (thousands) <sup>a</sup>	19.2	−1.99	−5.82	−9.64
Avg MPG (VMT weighted) <sup>a</sup>	24.2	0.05	0.13	0.24
Fleet size (thousands) <sup>a</sup>				
All cars	44,814.4	−0.18	−0.52	−1.02
New cars	3,845.0	−0.56	−1.65	−2.38
Used cars	40,969.4	−0.14	−0.41	−0.89
High-MPG cars <sup>b</sup>	27,027.4	−0.15	−0.44	−0.84
Low-MPG cars	17,787.0	−0.21	−0.63	−1.29

Notes: One gallon = 3.785 liters; 1 mile = 1.609 kilometers; MPG = miles per gallon. Dollar amounts are in 2001 dollars. "Avg" indicates a weighted average figure per household.

<sup>a</sup> For these rows, the rightmost three columns report percentage changes.

<sup>b</sup> High-MPG cars include those classes with average fuel economy over 23.6 MPG (five out of ten classes).

cost divided by taxes collected) are 0.15, 0.17, and 0.19. The size of this burden is not significantly influenced by the type of revenue-recycling. About 70 percent of the cost occurs as deadweight loss in the gasoline market, as implied by the wedge between producer and consumer prices of gasoline over the induced change in gasoline consumption. Other efficiency costs stem from the tax's impact on the level and composition of new-car production.

From Table 1, the implied (short-run) elasticity of demand for gasoline use is about  $-0.27$ . The gas-tax increase induces a reduction in fleet size (increase in scrappage), a decline in quantity demanded of new cars relative to used cars,

TABLE 2—DISTRIBUTIONAL IMPACTS OF GAS-TAX INCREASE  
(FOR \$0.30 INCREASE)

Group	Income (\$ thousands)			
	<25	25–50	50–75	>75
<i>A. Tax-Based Recycling:</i>				
EV (percentage of base income)				
All households	–0.103	–0.108	–0.098	–0.092
Retired	–0.093	–0.105	–0.089	–0.094
Not retired, no children	–0.104	–0.105	–0.103	–0.092
Not retired, children	–0.119	–0.113	–0.099	–0.091
High-probability car owner	–0.110	–0.110	–0.098	–0.092
Low-probability car owner	–0.084	–0.089	–0.099	–0.091
Percentage change in VMT				
All households	–5.43	–5.69	–5.59	–5.35
Retired	–4.87	–5.70	–5.42	–5.70
Not retired, no children	–5.45	–5.60	–5.69	–5.11
Not retired, children	–6.39	–5.78	–5.58	–5.49
High-probability car owner	–5.48	–5.61	–5.53	–5.24
Low-probability car owner	–5.31	–6.29	–6.59	–7.38
<i>B. Income-Based Recycling:</i>				
EV (percentage of base income)				
All households	–0.216	–0.205	–0.077	0.079
Retired	0.033	0.038	0.132	0.189
Not retired, no children	–0.311	–0.164	–0.116	0.093
Not retired, children	–0.482	–0.403	–0.113	0.046
High-probability car owner	–0.429	–0.281	–0.102	0.063
Low-probability car owner	0.356	0.393	0.360	0.368
Percentage change in VMT				
All households	–5.42	–5.75	–5.67	–5.23
Retired	–4.74	–5.59	–5.33	–5.36
Not retired, no children	–5.49	–5.63	–5.77	–5.00
Not retired, children	–6.50	–5.99	–5.70	–5.40
High-probability car owner	–5.56	–5.73	–5.63	–5.14
Low-probability car owner	–5.05	–5.91	–6.20	–6.81

and a relative increase in quantity demanded of more fuel-efficient cars. Over 95 percent of the reduction in gasoline consumption derives from reduced VMT, rather than from increases in average fuel efficiency from changes in fleet composition. The main reason for the small fleet-composition change is that these simulations only consider the impacts in the first year following a policy's implementation. Thus the effects through changes in the new-car market are muted. Work in progress examines impacts over the longer term.

### B. Distributional Impacts

Table 2 displays the distributional impacts of a 30-cent gas-tax increase for households grouped by income, family size (measured by the number of children) and stage of life (retired or not). The welfare impact (EV) of the policy is reported as a percentage of benchmark income. Under tax-based recycling, the gasoline-tax in-

crease is close to proportional in its impact.<sup>10</sup> The cost of policy for households with annual income less than \$25,000 is about 0.10 percent of their income, while for households with income greater than \$75,000 it is about 0.09 percent. The cost of the policy relative to income is highest for households not retired and with children. These households tend to drive more than others.

The results under income-based recycling are very different. Here the impacts are highly regressive. Under income-based recycling, relatively low-income (high-income) households enjoy much lower (higher) transfers than they do under tax-based recycling. Households earning over \$75,000 per year enjoy a welfare gain from the policy change.

Income-based recycling is relatively beneficial to households that do little driving, since these households nevertheless can enjoy significant recycled gas-tax revenues. Thus the retired suffer welfare losses under tax-based recycling but enjoy welfare gains under income-based recycling. Similarly, while all car owners experience welfare losses under tax-based recycling, only the high-probability car owners lose under income-based recycling.<sup>11</sup> The presence or absence of car-ownership is especially significant for the poorest households. Indeed, these results suggest that there is considerable heterogeneity in the impacts of a gas tax on the poorest households: among these households, the impacts depend importantly on the nature of recycling, whether the household is retired, and presence or absence of car-ownership.

### IV. Future Work

This is our first application of the model. Several improvements and new applications are planned. The present model only considers a policy's impacts in the year of its implementation. We currently are expanding the model to

<sup>10</sup> It would be exactly proportional in the absence of relative price changes. Such changes differentially affect the values of household endowments and the commodities (cars) they prefer to purchase, thus causing slight departures from proportionality.

<sup>11</sup> Every household has some positive probability of purchasing or retaining a car. High-probability car owners here are those for which the probability of purchasing or retaining a car exceeds 25 percent per choice occasion.



enable it to examine long-run effects associated with the gradual evolution of the automobile fleet. We also are exploring alternative ways to deal with the potentially very high dimensionality that arises from the multitude of car types and car combinations. In subsequent applications we hope to perform a more comprehensive assessment of distributional impacts, considering other demographic dimensions such as race and region of residence. We would also like to consider other policies to reduce gasoline consumption, including changes to CAFE standards and subsidies to retirements of low-mileage vehicles.

#### REFERENCES

- Allenby, G. and Lenk, P.** "Modeling Household Purchase Behavior with Logistic Normal Regression." *Journal of the American Statistical Association*, 1994, 89(428), pp. 669–79.
- Berkovec, James.** "New Car Sales and Used Car Stocks: A Model of the Automobile Market." *Rand Journal of Economics*, 1985, 16(2), pp. 195–216.
- Berry, Steven; Levinson, James and Pakes, Ariel.** "Automobile Prices in Market Equilibrium." *Econometrica*, 1995, 63(4), pp. 841–90.
- Dubé, J. P.** "Multiple Discreteness and Product Differentiation: Demand for Carbonated Soft Drinks." *Marketing Science*, 2004, 23(1), pp. 66–81.
- Feng, Ye; Fullerton, Don and Gan, Li.** "Vehicle Choices, Miles Driven and Pollution Policies." Working paper, University of Texas at Austin, July 2004.
- Goldberg, P. K.** "Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry." *Econometrica*, 1995, 63(4), pp. 891–951.
- Goldberg, P. K.** "The Effects of the Corporate Average Fuel Efficiency Standards in the US." *Journal of Industrial Economics*, 1998, 46(1), pp. 1–33.
- Hendel, I.** "Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns." *Review of Economic Studies*, 1999, 66(2), pp. 423–46.
- Manning, Fred and Winston, Clifford.** "A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization." *Rand Journal of Economics*, 1985, 16(2), pp. 215–36.
- Poterba, James.** "Is the Gasoline Tax Regressive?" National Bureau of Economic Research (Cambridge, MA) Working Paper No. W3578, 1991.
- Petrin, A.** "Quantifying the Benefits of New Products: The Case of the Minivan." *Journal of Political Economy*, 2002, 110(4), pp. 705–29.
- Schmalensee, Richard and Stoker, Thomas M.** "Household Gasoline Demand in the United States." *Econometrica*, 1999, 67(3), pp. 645–62.
- Train, Kenneth E.** *Qualitative choice analysis*. Cambridge, MA: MIT Press, 1986.
- Train, Kenneth E.** *Discrete choice analysis with simulation*. Cambridge, UK: Cambridge University Press, 2003.
- West, Sarah E.** "Distributional Effects of Alternative Vehicle Pollution Control Policies." *Journal of Public Economics*, 2004, 88(3–4), pp. 735–57.
- West, Sarah E. and Williams, Robertson C., III.** "Estimates from a Consumer Demand System: Implications for the Incidence of Environmental Taxes." *Journal of Environmental Economics and Management*, 2004, 47(3), pp. 535–58.

**This article has been cited by:**

1. Haotian Chen, Russell Smyth, Xibin Zhang. 2017. A Bayesian sampling approach to measuring the price responsiveness of gasoline demand using a constrained partially linear model. *Energy Economics* **67**, 346-354. [[Crossref](#)]
2. Diana Reckien, Felix Creutzig, Blanca Fernandez, Shuaib Lwasa, Marcela Tovar-Restrepo, Darryn Mcevoy, David Satterthwaite. 2017. Climate change, equity and the Sustainable Development Goals: an urban perspective. *Environment and Urbanization* **29**:1, 159-182. [[Crossref](#)]
3. David Klenert, Gregor Schwerhoff, Ottmar Edenhofer, Linus Mattauch. 2016. Environmental Taxation, Inequality and Engel's Law: The Double Dividend of Redistribution. *Environmental and Resource Economics* . [[Crossref](#)]
4. Samuel Faye Gamtessa. 2016. The effects of energy price on energy intensity: evidence from Canadian manufacturing sector. *Energy Efficiency* . [[Crossref](#)]
5. Adam T. Jones. 2016. Mileage tax, property tax, sales tax, or fee: the best way to pay for commercial infrastructure that isn't free. *Review of Regional Research* **36**:1, 81-98. [[Crossref](#)]
6. Claudio A. Agostini, Johanna Jiménez. 2015. The distributional incidence of the gasoline tax in Chile. *Energy Policy* **85**, 243-252. [[Crossref](#)]
7. Elisheba Spiller, Heather Stephens, Christopher Timmins, Allison Smith. 2014. The Effect of Gasoline Taxes and Public Transit Investments on Driving Patterns. *Environmental and Resource Economics* . [[Crossref](#)]
8. Laure B.A. Lampin, Franck Nadaud, Fabio Grazi, Jean-Charles Hourcade. 2013. Long-term fuel demand: Not only a matter of fuel price. *Energy Policy* **62**, 780-787. [[Crossref](#)]
9. Antonio M. Bento. 2013. Equity Impacts of Environmental Policy. *Annual Review of Resource Economics* **5**:1, 181-196. [[Crossref](#)]
10. 2012. Measuring the price responsiveness of gasoline demand: Economic shape restrictions and nonparametric demand estimation. *Quantitative Economics* **3**:1, 29-51. [[Crossref](#)]
11. W. Ross Morrow, Steven J. Skerlos. 2011. Fixed-Point Approaches to Computing Bertrand-Nash Equilibrium Prices Under Mixed-Logit Demand. *Operations Research* **59**:2, 328-345. [[Crossref](#)]
12. Abdelkrim Araar, Yazid Dissou, Jean-Yves Duclos. 2011. Household incidence of pollution control policies: A robust welfare analysis using general equilibrium effects. *Journal of Environmental Economics and Management* **61**:2, 227-243. [[Crossref](#)]
13. Benjamin Bureau. 2011. Distributional effects of a carbon tax on car fuels in France. *Energy Economics* **33**:1, 121-130. [[Crossref](#)]
14. Nazneen Ferdous, Abdul Rawoof Pinjari, Chandra R. Bhat, Ram M. Pendyala. 2010. A comprehensive analysis of household transportation expenditures relative to other goods and services: an application to United States consumer expenditure data. *Transportation* **37**:3, 363-390. [[Crossref](#)]
15. Lei Zhang, B. Starr McMullen, Divya Valluri, Kyle Nakahara. 2009. Vehicle Mileage Fee on Income and Spatial Equity. *Transportation Research Record: Journal of the Transportation Research Board* **2115**:1, 110-118. [[Crossref](#)]
16. Nicholas Brozović, Amy Whritenour Ando. 2009. Defensive purchasing, the safety (dis)advantage of light trucks, and motor-vehicle policy effectiveness. *Transportation Research Part B: Methodological* **43**:5, 477-493. [[Crossref](#)]
17. Eleni Sardianou. 2008. Estimating differences in gasoline consumption among socio-economic groups in Greece. *International Journal of Consumer Studies* **32**:6, 596-606. [[Crossref](#)]