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Is There an Energy Paradox in Fuel Economy?

A Note on the Role of Consumer Heterogeneity and Sorting Bias

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RESOURCES FOR THE FUTURE

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Abstract

Previous literature finds that consumers tend to undervalue discounted future energy costs in their purchase decisions for energy-using durables. We argue that this finding could result from ignoring consumer heterogeneity in empirical analyses as opposed to true undervaluation. In the context of automobile demand, we show that, if not accounted for, consumer heterogeneity could lead to sorting, which in turn biases toward zero the estimate of marginal willingness to pay for discounted future fuel costs.

Key Words: energy paradox, fuel economy, consumer heterogeneity

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1. Introduction

Although economic theory suggests that rational consumers should be willing to pay $1.00 more for a vehicle that saves them $1.00 in discounted future fuel costs, a growing body of literature finds a marginal willingness to pay (MWTP) for reduced discounted future fuel costs ranging from $0.35 to $0.79 (Helfand and Wolverton 2010; Greene 2010). This perceived undervaluation of future fuel costs is an example of *energy paradox* in the automobile market. The energy paradox concept is used to understand the unexpectedly slow diffusion of apparently cost-effective, energy-efficient technologies that involve similar trade-offs between up-front capital costs and future operating costs (Jaffe and Stavins 1994). The energy paradox has also been studied in the context of other energy-using durables (Hausman 1979).

With increasing concerns related to climate change, energy security, and local pollution, policies to promote energy efficiency in various sectors of the economy are subject to increased attention from policymakers. In the automobile sector, the debate over such policies focuses on the comparison between the gasoline tax and corporate average fuel economy (CAFE) standards, as well as the design of future CAFE standards. Precise estimates of the MWTP for reduced discounted future fuel costs are central to this debate (Parry et al. 2010). If consumers correctly value future fuel costs, gasoline taxes are found to be less costly than CAFE standards in achieving targeted fuel reductions (Fischer et al. 2007; Jacobsen 2010). However, the opposite is true if consumer undervaluation is sufficiently large.

Is there really an energy paradox in fuel economy? Our concern is that prior literature has answered this question by relying on hedonic and discrete choice models that ignore the

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underlying consumer heterogeneity in MWTP for future reductions in fuel costs. If consumers are heterogeneous in their MWTP, they will sort into vehicles based on vehicle fuel efficiency: those with high MWTP for reduced fuel costs will sort into fuel-efficient vehicles and those with low MWTP will sort into fuel-inefficient ones. In a (multinomial) logit specification of vehicle demand, this will imply that a portion of the utility that is captured in the error term will be positively correlated with the vehicle's fuel costs. As a consequence, the estimate of MWTP for future fuel costs will be biased toward zero, suggesting undervaluation. Although we are not arguing that there is no undervaluation of fuel economy, our point is that an empirical analysis that ignores consumer heterogeneity may overstate the magnitude of undervaluation. Similar concerns of bias due to sorting were raised in a recent study of the value of a statistical life using labor market data (Deleire et al. 2009).

We illustrate this point by comparing the estimated MWTP for future reductions in fuel costs from a logit model and a random coefficients logit model using data generated from an equilibrium model of the automobile market.[1] Our analysis shows that, when undervaluation of fuel costs is not present in the data-generating mechanism, the logit model could erroneously suggest significant undervaluation, whereas the random coefficients logit model recovers the true average MWTP.

2. Methods

2.1 The Equilibrium Model

The equilibrium model for data generation is composed of a demand side and a supply side.

Demand: On the demand side, each consumer chooses to buy a new vehicle, from among J models or products, or not to make any purchase (labeled *choosing the outside good*) in a given period. The utility of consumer i from vehicle j is defined as

$$u_{ij} = \alpha_i p_j + \beta_i fc_{ij} + \gamma_i x_j + \varepsilon_{ij} \tag{1}$$

[1]Given that consumers have multiple vehicle models from which to choose, the empirical methods are multinomial logit models, but we suppress the word *multinomial* to save space throughout our paper.

where α_i, β_i, and γ_i are individual-specific taste parameters. We define $\theta = \{\alpha_i, \beta_i, \gamma_i\}$. p_j is price of model *j*. fc_{ij} is the present value of the total expected discounted fuel cost of the vehicle; it is defined by

$$fc_{ij} = \sum_{t=0}^{T_j} \delta_i^t * AVMT_{itj} * gp_{it}^{\ e} / MPG_j \tag{2}$$

where T_j is the expected lifetime of vehicle model *j*, δ_i is an individual-specific discount factor, $AVMT_{itj}$ is annual vehicle miles of travel in year *t* (which usually decreases with the vehicle's age), and $gp_{it}^{\ e}$ is the expected gasoline price at year *t* of consumer *i*. Heterogeneity can arise from any of the elements used to calculate the lifetime fuel cost of the vehicle. x_j is a vector of other vehicle attributes, and ε_{ij} is assumed to have a type I extreme value distribution. We normalize the utility from the outside good, u_{i0}, to zero. The probability of household *i* choosing vehicle *j* is given by

$$P_{ij} = \frac{\exp(\overline{u}_{ij})}{1 + \sum_h \exp(\overline{u}_{ih})} \tag{3}$$

where $\overline{u}_{ij} = u_{ij} - \varepsilon_{ij}$. Given individual choice probabilities, the aggregate demand can be obtained through summation.

Supply: The supply side is composed of several firms, each producing multiple vehicle models. They engage in Bertrand competition in that each firm chooses prices to maximize its total profit in a given year, taking the products available as fixed. Following the literature, we assume that the marginal cost of each product is constant. The total profit of firm *f* is

$$\pi^f = \sum_{f \in F} [(p_j - mc_j) q_j(p, \theta)] \tag{4}$$

where *F* is the set of all products produced by firm *f*, mc_j is the marginal cost, and q_j is the aggregate demand. *p* is the price vector; the equilibrium price vector is obtained through the first-order conditions

$$p = mc + \Delta^{-1} q(p, \theta) \tag{5}$$

where the element of Δ, Δ_{jr} is zero if *j* and *r* are produced by different firms. Otherwise, it is equal to $-\partial q_r / \partial p_j$. Given the demand function and marginal cost, this equation can be used to compute equilibrium prices and sales.

2.2. Data Generation

Through our data generation approach, we aim to mimic the U.S. auto market. Vehicle information comes from the 2001 Ward's Automotive Yearbook; vehicle characteristics include miles per gallon (MPG), horsepower, weight, and manufacturer. We construct marginal cost, a function of MPG, horsepower, and weight, for each model based on estimates from Berry et al. (1996).[2] We randomly choose a set of vehicle models (25 in the baseline simulation) and assume that these models are available in each year from 2001 to 2006, the time span for our analysis.

For ease of exposition, we make several demand-side assumptions. For preference parameters, we assume that all consumers have the same preference on all characteristics except fuel costs. In calculating fuel costs, we assume that the discount factor δ, annual vehicle miles of travel $AVMT$, and expected gasoline price gp^e are all constant across consumers for any given vehicle. We assume a 10 percent yearly discount rate. Vehicle lifetime and age-specific annual miles of travel for passenger cars and light trucks are from Lu (2006). We further assume that expected gasoline prices during a vehicle's lifetime are equal to current annual gasoline price (i.e., gasoline price follows a random walk). Annual gasoline prices during 2001–2006 are from the Energy Information Administration. These simplifying assumptions, innocuous for our conclusion, imply that consumer heterogeneity is manifested only through the consumer-specific taste parameter on fuel cost, β_i. In the baseline simulation, we assume that β_i has a uniform distribution; the range of the distribution affects the degree of consumer heterogeneity.

We generate data in two steps. First, we generate equilibrium prices for each model, assuming the whole market with 50,000 consumers in each year. Second, based on equilibrium prices, we generate vehicle choices for 20,000 consumers in each year.

2.3 Estimation

The goal of the estimation is to recover the underlying preference parameters and to obtain consumers' MWTP for reduced fuel costs. For ease of exposition, we assume that the econometrician observes all vehicle characteristics relevant to consumers.[3] We employ two methods: a logit model and a random coefficients logit model. The logit model is estimated using

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[2] We also add a random error term to the marginal cost of each attribute and to the marginal cost of each product based on the standard errors estimated by Berry et al. (1996). All costs are converted to 2001 dollars.

[3] In real applications, it is important to control for unobserved product attributes. Most recent literature on the energy paradox has explicitly dealt with this issue.

the standard maximum likelihood method. As discussed in Train (2003), the appeal of the random coefficients model comes from its ability to incorporate unobserved consumer heterogeneity, which in our context avoids sorting bias. This model is estimated using the simulated maximum likelihood method. To conduct numerical integration in the simulated method, we employ Halton sequences, which are more efficient than direct Monte Carlo sampling.

3. Results

We find three main results from the Monte Carlo analysis.

Result 1: In the presence of heterogeneity, the logit model suggests undervaluation of the MWTP for reduced future fuel costs, even when undervaluation is not present in the data.

Support: Panel A in Table 1 shows that consumers undervalue fuel costs by 29 percent. The parameter estimates on vehicle price and fuel cost implies that consumers are only willing to pay $0.71 for a $1.00 reduction in discounted future fuel costs. The bias comes from individuals sorting into vehicles based on their MWTP: those very averse to fuel costs (e.g., with very negative MWTP) purchase vehicles with low fuel costs. The correlation between fuel cost and the average MWTP among consumers who purchase corresponding vehicles is depicted on the left panel of Figure 1 (the correlation coefficient is 0.83). The correlation implies that the error term in the logit model will be positively correlated with fuel cost, biasing the MWTP estimate toward zero. We believe that at least part of the undervaluation found in prior literature could be attributable to this type of sorting bias.

Result 2: The random coefficients logit model correctly identifies the MWTP.

Support: Table 1, Panel A shows that, by explicitly modeling consumer heterogeneity, the random coefficients logit model is able to recover the underlying parameters on vehicle price and fuel cost. The implied MWTP is –1, indicating that consumers are willing to pay $1.00 for a $1.00 reduction in discounted future fuel costs.

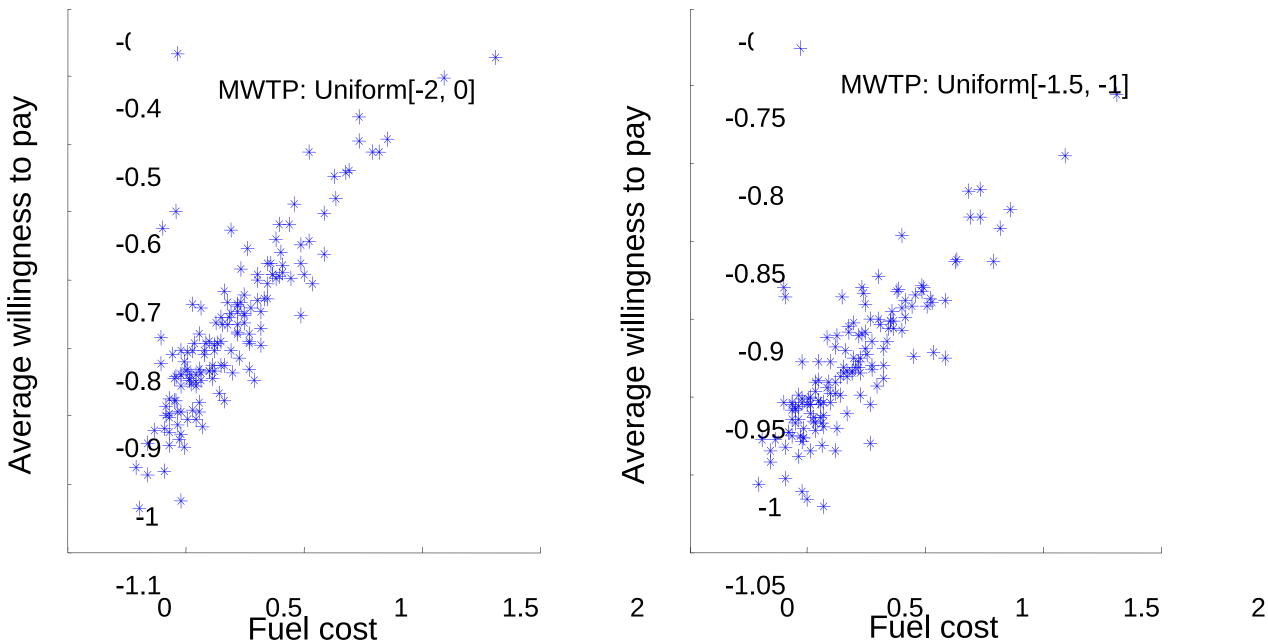
Result 3: The greater the heterogeneity, the larger the bias from the logit model.

Support: The underlying data-generating process in Panel A of Table 1 implies twice the heterogeneity of Panel B. As a consequence, the undervaluation for the logit model in Panel A, 29 percent, is larger than the 10 percent undervaluation in Panel B.

Table 2 presents Monte Carlo results for alternative specifications. Panel A suggests that increased market power magnifies the bias from the logit model, with the undervaluation going to 37 percent from 29 percent in the baseline model in Table 1. Increasing the number of vehicle draws (Table 2, Panel B) slightly decreases the undervaluation from 29 percent to 27 percent.

The three findings discussed above still hold when the distribution of MWTP takes a log-normal distribution (Table 2, Panel C).

Figure 1. Fuel Cost and Average Marginal Willingness to Pay among Buyers



Notes: Figure 1 plots the average MWTP for reduced future fuel cost among consumers who purchase vehicles with a given fuel cost. Fuel cost is the lifetime discounted fuel cost divided by 10,000. The left figure corresponds to Panel A in Table 1 and the right figure to Panel B.

Table 1. Monte Carlo Results

	True	Estimates			
Panel A: baseline model		Logit		Random coef logit	
		Para	S.E.	Para	S.E.
Constant	1	0.60	0.05	1.05	0.07
Price	–2	–2.02	0.01	–2.00	0.01
Fuel cost	–2	–1.43	0.03	–2.01	0.07
Weight	4	4.49	0.15	3.83	0.17
Horsepower	8	7.68	0.14	8.18	0.15
Sigma[a]	4			4.18	0.26
Log-likelihood		228,335		228,268	
Implied valuation for $1 drop in fuel cost		$0.71		$1.00	
Implied undervaluation		29%			
Panel B: smaller heterogeneity		Logit		Random coef logit	
		Para	S.E.	Para	S.E.
Constant	1	0.93	0.05	1.08	0.06
Price	–2	–2.01	0.01	–2.01	0.01
Fuel cost	–2	–1.82	0.03	–2.03	0.06
Weight	4	3.99	0.15	3.80	0.16
Horsepower	8	8.05	0.14	8.21	0.14
Sigma[a]	2			2.31	0.31
Log-likelihood		225,942		225,933	
Implied valuation for $1 drop in fuel cost		$0.90		$1.01	
Implied undervaluation		10%			

[a] Sigma measures the degree of heterogeneity for MWTP for fuel cost. The value of sigma is multiplied by random draws from a uniform distribution [–0.5, 0.5]. In Panel A, the range of the MWTP for fuel cost is [–2, 0], whereas in Panel B it is [–1.5, –0.5].

Table 2. Robustness Checks

	True	Estimates			
Panel A: monopoly instead of oligopoly		Logit		Random coef logit	
		Para	S.E.	Para	S.E.
Constant	1	0.62	0.06	1.10	0.09
Price	–2	–2.02	0.02	–2.01	0.02
Fuel cost	–2	–1.27	0.03	–2.14	0.14
Weight	4	4.38	0.19	3.80	0.21
Horsepower	8	7.86	0.18	8.32	0.19
Sigma	4			4.55	0.42
Log-likelihood		158,480		158,437	
Implied valuation for $1 drop in fuel cost		$0.63		$1.07	
Implied undervaluation		37%			
Panel B: 50 vehicle models instead of 25		Logit		Random coef logit	
		Para	S.E.	Para	S.E.
Constant	1	0.62	0.03	1.00	0.05
Price	–2	–2.02	0.01	–2.00	0.01
Fuel cost	–2	–1.48	0.03	–1.99	0.06
Weight	4	4.18	0.12	3.99	0.13
Horsepower	8	7.75	0.11	8.01	0.11
Sigma	4			4.01	0.21
Log-likelihood		326,436		326,351	
Implied valuation for $1 drop in fuel cost		$0.73		$1.01	$0.99
Implied undervaluation		27%			
Panel C: lognormal MWTP instead of uniform distribution		Logit		Random coef logit	
		Para	S.E.	Para	S.E.
Constant	1	0.74	0.07	0.94	0.10
Price	–2	–2.01	0.02	–2.00	0.02
Fuel cost		–1.65	0.04	N/A	
Weight	4	4.38	0.21	4.21	0.21
Horsepower	8	7.78	0.19	7.96	0.20
Mean of underlying normal distribution	0.57			0.59	0.05
Sigma of underlying normal distribution	0.50			0.45	0.09
Implied mean of the lognormal distribution	2			–2.01	
Log-likelihood		113,980		113,976	
Implied valuation for $1 drop in fuel cost		$0.82		$1.00	
Implied undervaluation		18%			

4. Conclusion

Our analysis shows that, if not accounted for, unobserved consumer heterogeneity can significantly affect the estimated MWTP for discounted future fuel costs. We believe that this may partly explain consumer undervaluation of future fuel costs and the wide range of estimates found in the literature. To properly evaluate the existence and magnitude of the energy paradox, further econometric analysis that explicitly models consumer heterogeneity, such as random coefficient models in either a discrete choice or hedonic framework (e.g., Berry et al. 1995; Bajari and Benkard 2005), are needed.

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