How Gasoline Prices Impact Household Driving and Auto Purchasing Decisions

A Revealed Preference Approach

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October 2010

Research funded by Resources for the Future’s Joseph L. Fisher Doctoral Dissertation Fellowship
Policy Relevance

• Consumer response to changing gasoline prices
  o Climate change
  o Air pollution
  o Congestion
  o National security concerns
Elasticity of Demand for Gasoline

- Accurately measuring the elasticity of demand for gasoline
  - Importance in climate policy models
  - Economic incidence of gasoline tax - burden falls on consumers or producers
  - Optimal gasoline tax
- Prior studies range of elasticities: -0.02 to -1.59
  - Espey (1996): data, econometric technique, demand specification, assumptions
VMT Demand/Gasoline Prices

![Graph showing oil prices and vehicle miles driven over time](image)

- **Oil Prices**
  - Y/Y Change

- **Vehicle Miles Driven**
  - Y/Y Change

Data: Oil – Cushing, OK WTI Spot Price FOB(EIA); Vehicle Miles (Federal Highway Administration)
Gasoline Prices/Truck Demand

Figure 1: Change in Market Shares of U.S. Firms and SUVs and Gasoline Price, 2002-2007

Graph From Klier and Linn (2008)
Change in SUV/car sales

Taken from US DOE website, 2008
• Downward bias/Misspecification due to:
  o Assumptions
  o Research Methods
Incorporate the following into measurement of gasoline demand elasticity:

1. **Extensive and Intensive Margin (vehicle purchase decision and VMT)**
   - Type of vehicle ↔ Amount of driving
   - Estimate jointly:
     - Model choice
     - Fleet size
     - Driving demand
Model Objectives and Innovations

Incorporate the following into measurement of gasoline demand elasticity:

- **Extensive and Intensive Margin (vehicle purchase decision and VMT)**
  - Type of vehicle ↔ Amount of driving
  - Estimate jointly:
    - Model choice
    - Fleet size
    - Driving demand

- **Household fleet’s VMT decisions jointly determined**
  - Allocation of VMT between vehicles
  - Substitution as relative operating costs change
  - Hensher (1985), Berkowitz et.al. (1990): 2 and 3 car households more elastic
Model Objectives and Innovations

• *Vehicle Fixed Effects*
  - Unobserved vehicle attributes affect purchase decision
  - Berry, Levinsohn, and Pakes (1995): no fixed effects biases price coefficient
    - Unobserved attributes (style) make individuals appear less price sensitive
Model Objectives and Innovations

• **Vehicle Fixed Effects**
  
  o Unobserved vehicle attributes affect purchase decision
  
  o Berry, Levinsohn, and Pakes (1995): no fixed effects biases price coefficient
    
    ▶ Unobserved attributes (style) make individuals appear less price sensitive

• **Detailed choice set**
  
  o To capture subtle changes in vehicle purchase decision
    
    ▶ Aggregate choice set won’t capture movement within the aggregation (i.e. Ford Taurus -> Honda Civic)
Methodological Hurdle

- **High dimensionality** of choice set
- 3,751 types of vehicles (model-year) in dataset
  - If households can choose 2: 7,033,125 possible choices
  - If households can choose 3: 8,789,061,875 possible choices
- Typical logit, probit models do not allow for such high dimensionality
Proposed Method

• Revealed preference approach:
  o Observed household vehicle holdings is equilibrium, provides maximum utility
  o Any deviation from equilibrium results in lower utility
    ❖ Thus, can compare the utility levels:
      \[ \text{Utility(bundle choice)} > \text{Utility(deviation from choice)} \]

• Allows for unconstrained choice set and fixed effects
Outline

1. Literature Review
2. Model
3. Method
4. Unobserved Consumer Heterogeneity
5. Data
6. Results
7. Conclusion
Literature Review

- Extensive/intensive margins estimated independently

- Two-step sequential estimation of extensive/intensive margins

- One step approach
  - Berkowitz et al. (1990), Feng, Fullerton, and Gan (2005), Bento et al. (2008)

- Fleet model
  - Green and Hu (1985)
Model

Per-vehicle sub-utility (additively separable in total utility):

\[ u_{ij} = \alpha_{ij} VMT_{ij}^\rho + \gamma_i X_j + \xi_j + \varphi_{ij} \]

\( i \): household

\( j \): vehicle

\( VMT_{ij} \): Vehicle Miles Travelled per year

\( X_j \): observable attributes of vehicle \( j \)

\( \xi_j \): unobservable attributes of vehicle \( j \)

\( \varphi_{ij} \sim N(0, \sigma^2) \)
Marginal utility of driving:

\[ \alpha_{ij} = \exp\left(a_1 Z_{i1} X_1 + a_2 Z_{i2} X_2 + \ldots + a_t Z_{it} X_t\right) / n_i \]

- \( Z_i \): Household \( i \)'s attributes
- \( n_i \): Number of vehicles in household \( i \)'s garage
  - diminishing marginal returns of use as number of vehicles in garage increases

Fixed effects:

\[ \gamma_i = g_0 + g_1 Z_i \]
\[ \theta_j = g_0 X_j + \xi_j \]
Model

Marginal utility of driving:

$$\alpha_{ij} = \exp(a_1Z_{i1}X_1 + a_2Z_{i2}X_2 + ... a_tZ_{it}X_t)/n_i$$

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  - diminishing marginal returns of use as number of vehicles in garage increases

Fixed effects:

$$\gamma_i = g_0 + g_1Z_i$$
$$\theta_j = g_0X_j + \xi_j$$

Thus:

$$u_{ij} = \frac{\exp(\bar{Z}_iA\bar{X}_j)}{n_j}VMT_{ij}^\rho + g_1Z_iX_j + \theta_j + \varepsilon_{ij}$$
Model: Utility Maximization

\[
\max_{VMT,c} U_i = \sum_j u_{ij} + c_i^p
\]

\[
s.t. \quad y_i = \sum_j P_j + \sum_j P_{ij}^d \text{VMT}_{ij} + P^c c_i
\]

\(y_i\) : household income

\(P_j\) : vehicle \(j\)'s used price (opportunity cost of not selling)

\(P_{ij}^d\) : operating cost ($/mile)

\(P^c\) : price of consumption = 1
Interdependence of vehicles in fleet:

\[ VMT_{ij}^* = \left( \frac{P^d_{ij}}{\alpha_{ij}} \right)^{\frac{1}{\rho-1}} \left( y_i - \sum_k P^u_{ik} \right) \left( 1 + \sum_k \left( P^d_{ik} \left( \frac{\rho}{\rho-1} \right) \left( \frac{1}{\alpha_{ik}} \right)^{\frac{1}{\rho-1}} \right) \right) \]

\[ \rightarrow \text{Indirect Utility} \]

\[ V_i^* = U_i \left( VMT_{ij}^*, c_i^* \right) \]
Two steps:

1. Difference out fixed effects, estimate $\alpha_{ij}, g_1, \rho$
2. Recapture fixed effects, estimate $g_0$
First Stage Estimation: Swapping

• **Assumption 1:** Household in equilibrium with vehicle purchase and \( VMT \) decision

\[
V_{iF_i^*} \geq V_{iF_i} \quad \forall F_i \neq F_i^*
\]

\( F_i^* \): Fleet chosen by household \( i \)
First Stage Estimation: Swapping

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• Two households, 1 and 2, have vehicles \( A, B \) respectively:

\[
\tilde{V}_{1A} + \theta_A \geq \tilde{V}_{1B} + \theta_B \quad \text{For Household 1}
\]

\[
\tilde{V}_{2B} + \theta_B \geq \tilde{V}_{2A} + \theta_A \quad \text{For Household 2}
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\[
\tilde{V}_{2B} + \theta_B \geq \tilde{V}_{2A} + \theta_A \quad \text{For Household 2}
\]

Thus:

\[
\tilde{V}_{1A} - \tilde{V}_{1B} + \theta_A - \theta_B + \tilde{V}_{2B} - \tilde{V}_{2A} + \theta_B - \theta_A \geq 0
\]

\[
\tilde{V}_{1A} - \tilde{V}_{1B} + \tilde{V}_{2B} - \tilde{V}_{2A} \geq 0
\]
First Stage Estimation

\[
\Pr(\tilde{V}_{1A} - \tilde{V}_{1B} + \tilde{V}_{2B} - \tilde{V}_{2A} \geq 0) = \Pr(\varepsilon_{12,AB} \leq \tilde{V}_{1A} - \tilde{V}_{1B} + \tilde{V}_{2B} - \tilde{V}_{2A})
\]

\[
= \Phi\left(\frac{\tilde{V}_{1A} - \tilde{V}_{1B} + \tilde{V}_{2B} - \tilde{V}_{2A}}{\sigma_{\varepsilon}}\right)
\]

Maximum Likelihood:

\[
LL(\beta) = \sum_{\text{swaps} (i_1, i_2), (j_1, j_2)} \log \Phi\left(\frac{\tilde{V}_{i_1j_1} - \tilde{V}_{i_1j_2} + \tilde{V}_{i_2j_2} - \tilde{V}_{i_2j_1}}{\sigma_{\varepsilon}}\right)
\]

Normalization:

\[
\beta_c = 1
\]
First Stage Estimation: Overview

- Guess at parameter vector $\beta = (\alpha, g_1, \rho)$
First Stage Estimation: Overview

- Guess at parameter vector \( \beta = (\alpha, g_1, \rho) \)

- For each vehicle in dataset:
  - Step 1: Randomly choose a vehicle from another household
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- For each vehicle in dataset:
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  - Step 2: Swap chosen vehicles between households
  - Step 3: Calculate optimal VMT for observed fleet and proposed deviation (given current $\beta$)
  - Step 4: Calculate indirect utility under each scenario (observed and proposed)
  - Step 5: Difference indirect utilities
  - Calculate objective function (summed log of differences)
  - Find $\beta$ that increases objective function
  - Repeat until convergence

$\rho$, $\alpha$, $g_1$, $\beta$
First Stage Estimation: Overview

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- Calculate objective function (summed log of differences)

- Find $\beta'$ that increases objective function

- Repeat until convergence
Unobserved Consumer Heterogeneity

- Incorporate observed driving behavior into estimation

\[ \alpha_{ij} = \exp\left( a_1 Z_{i1}X_1 + a_2 Z_{i2}X_2 + \ldots + a_t Z_{it}X_t \right) / n_i + \mu_i \]

- Contraction mapping: at each stage of iteration, solve

\[
\left( \frac{1}{j} \sum_j VMT_{ij}^* - \frac{1}{j} \sum_j \overline{VMT}_{ij} \right)^2 = 0
\]
1. Guess at parameter vector $\beta = (\alpha, g_1, \rho)$
Unobserved Consumer Heterogeneity

1. Guess at parameter vector $\beta = (\alpha, g_1, \rho)$
2. Find $\mu_i$ that minimizes distance between observed and optimal $VMT_{ij}$
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3. Calculate $VMT_{ij}^*$ given $\mu_i, \beta$
1. Guess at parameter vector $\beta = (\alpha, g_1, \rho)$

2. Find $\mu_i$ that minimizes distance between observed and optimal $VMT_{ij}$

3. Calculate $VMT_{ij}^*$ given $\mu_i, \beta$

4. Find new parameter vector that maximizes objective function.
1. Guess at parameter vector $\beta = (\alpha, g_1, \rho)$
2. Find $\mu_i$ that minimizes distance between observed and optimal $VMT_{ij}^*$
3. Calculate $VMT_{ij}^*$ given $\mu_i, \beta$
4. Find new parameter vector that maximizes objective function.
5. Repeat steps 2-4 until convergence.
Second Stage Estimation

- **Assumption 2**: Net sub-utility of $j^{th}$ vehicle > 0
- **Assumption 3**: $j^{th} + 1$ vehicle decreases total utility
Second Stage Estimation

- **Assumption 2**: Net sub-utility of $j^{th}$ vehicle $> 0$
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- Thus:

  \[ V_{1A} \geq V_1^0 \quad \text{For Household 1} \]

  \[ V_{2B} \geq V_{2B,A} \quad \text{For Household 2} \]
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- **Assumption 2**: Net sub-utility of $j^{th}$ vehicle $> 0$
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- Rewriting:
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  \]
  \[
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  \]
Second Stage Estimation

• For Household 1:

\[ P(\varepsilon_{1A} \leq \bar{V}_{1A} + \theta_A) = \Phi \left( \frac{\bar{V}_{1A} + \theta_A}{\sigma_{\varepsilon_A}} \right) \]

• For Household 2:

\[ P(\varepsilon_{2A} \leq \bar{V}_{2B} - \bar{V}_{2A} - \theta_A) = \Phi \left( \frac{\Delta \bar{V}_2 - \theta_A}{\sigma_{\varepsilon_A}} \right) \]
Second Stage Estimation

- Maximum Likelihood:

\[
LL(\theta_j) = \sum_i y_{ij} \ln \Phi\left(\frac{\Delta V_i + \theta_j}{\sigma_{\epsilon_j}}\right) + (1 - y_{ij}) \ln \left(1 - \Phi\left(\frac{\Delta V_i - \theta_j}{\sigma_{\epsilon_j}}\right)\right)
\]
Second Stage Estimation

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\]

- **OLS:**

\[
\theta_j = g_0 X_j + \xi_j
\]
Second Stage Estimation: Overview

• For each type of vehicle:
  1) Find all households who own it: positive sub-utility from owning it.
  2) Find all households who don’t own it: adding this vehicle decreases utility.
  3) Form maximum likelihood over (1) and (2)
  4) Estimate fixed effect for this vehicle

• Run OLS of all FE on vehicle characteristics
### Data

- **Household level data: National Household Transportation Survey 2001 and 2009**

<table>
<thead>
<tr>
<th></th>
<th>NHTS 2001</th>
<th>NHTS 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Sample</td>
<td>26,038 households</td>
<td>143,084 households</td>
</tr>
<tr>
<td></td>
<td>53,275 observations</td>
<td>309,163 observations</td>
</tr>
<tr>
<td>Final Sample</td>
<td>11,354 households</td>
<td>11,366 households</td>
</tr>
<tr>
<td></td>
<td>18,166 observations</td>
<td>18,305 observations</td>
</tr>
</tbody>
</table>

- NHTS 2001: National Sample 26,038 households, 53,275 observations
  - Final Sample: 11,354 households, 18,166 observations
- NHTS 2009: Full Sample 143,084 households, 309,163 observations
  - Final Sample: 11,366 households, 18,305 observations
## Data: NHTS Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Final Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>% White</td>
<td>87%</td>
<td>85%</td>
</tr>
<tr>
<td>% Urban</td>
<td>70%</td>
<td>79%</td>
</tr>
<tr>
<td>Average Family Income</td>
<td>$55,832</td>
<td>$56,338</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>2.82</td>
<td>2.66</td>
</tr>
<tr>
<td>Average Workers to Vehicles</td>
<td>0.65</td>
<td>0.72</td>
</tr>
<tr>
<td>Average Fleet Size</td>
<td>2.69</td>
<td>2.04</td>
</tr>
<tr>
<td>Average MPG</td>
<td>25.72</td>
<td>25.87</td>
</tr>
<tr>
<td>Average Vehicle Age (years)</td>
<td>8.49</td>
<td>7.21</td>
</tr>
<tr>
<td>Average Yearly VMT</td>
<td>10,995</td>
<td>11,594</td>
</tr>
</tbody>
</table>
Data: Vehicles

• Vehicle characteristic data: Polk, Ward’s Automotive Yearbook
  o Provides detailed information on 6,594 vehicles 1971-2009

• Used vehicle prices: NADA
Data: Gasoline Prices

- American Chamber of Commerce Research Association (ACCRA) 2001, 2009 data
  - provides gas prices at the city level
  - yearly averages
  - aggregate to MSA

<table>
<thead>
<tr>
<th>MSA</th>
<th>Gas Prices 2001</th>
<th>Gas Prices 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oklahoma City, OK</td>
<td>1.23</td>
<td>2.07</td>
</tr>
<tr>
<td>Houston, TX</td>
<td>1.34</td>
<td>2.34</td>
</tr>
<tr>
<td>Raleigh, NC</td>
<td>1.39</td>
<td>2.47</td>
</tr>
<tr>
<td>Chicago, IL</td>
<td>1.50</td>
<td>2.73</td>
</tr>
<tr>
<td>Philadelphia, PA</td>
<td>1.56</td>
<td>2.53</td>
</tr>
<tr>
<td>San Francisco, CA</td>
<td>1.92</td>
<td>2.80</td>
</tr>
</tbody>
</table>
Data: Gasoline Prices

2009 Gasoline Prices
2001 Gasoline Prices
### Results: First Stage

<table>
<thead>
<tr>
<th>Marginal Utility of Driving Parameters</th>
<th>Interaction Term</th>
<th>Parameter Value (Std. Err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(HP/weight) * urban</td>
<td>2.341*** (0.055)</td>
</tr>
<tr>
<td></td>
<td>Vehicle Size * household size</td>
<td>-0.252* (0.147)</td>
</tr>
<tr>
<td></td>
<td>Wheelbase* urban</td>
<td>0.051 (1.531)</td>
</tr>
<tr>
<td></td>
<td>Household size/# vehicles</td>
<td>-0.166 (0.353)</td>
</tr>
</tbody>
</table>

***: significant at 99% level, *: significant at 90%
## Results: First Stage

<table>
<thead>
<tr>
<th>Indirect Utility of Driving Parameters</th>
<th>Interaction Term</th>
<th>Parameter Value (Std. Err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Green* income</td>
<td>-0.063 (0.268)</td>
</tr>
<tr>
<td></td>
<td>Green* Pacific</td>
<td>0.124 (1.147)</td>
</tr>
<tr>
<td></td>
<td>Green* New England</td>
<td>0.731** (0.347)</td>
</tr>
<tr>
<td></td>
<td>Size* Income</td>
<td>0.547*** (0.146)</td>
</tr>
<tr>
<td></td>
<td>Size* Pacific</td>
<td>-1.703*** (0.220)</td>
</tr>
<tr>
<td></td>
<td>Size* Mountain</td>
<td>2.085*** (0.204)</td>
</tr>
<tr>
<td></td>
<td>Domestic* Income</td>
<td>0.101 (0.439)</td>
</tr>
<tr>
<td></td>
<td>Domestic* Midwest (WNC)</td>
<td>2.147*** (0.142)</td>
</tr>
<tr>
<td></td>
<td>Domestic* Midwest (ENC)</td>
<td>1.118*** (0.168)</td>
</tr>
<tr>
<td></td>
<td>European* Income</td>
<td>0.989*** (0.137)</td>
</tr>
<tr>
<td></td>
<td>Japanese* Income</td>
<td>0.495*** (0.149)</td>
</tr>
<tr>
<td></td>
<td>Japanese* Pacific</td>
<td>1.170*** (0.161)</td>
</tr>
<tr>
<td></td>
<td>Vehicle Age* Income</td>
<td>-0.037 (0.144)</td>
</tr>
<tr>
<td></td>
<td>Size* Urban</td>
<td>-2.021*** (0.154)</td>
</tr>
</tbody>
</table>

(***: statistically significant at 99%, **: statistically significant at 95%, *: statistically significant at 90%)
### Results: First Stage

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Parameter Value (Std. Err.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CES Parameter</td>
<td>$\rho$</td>
</tr>
<tr>
<td>Std. Dev. Of Error Term</td>
<td>$\sigma_{\bar{\varepsilon}}$</td>
</tr>
<tr>
<td>Elasticity of Demand for Gasoline, $\Delta Price = 1%$</td>
<td></td>
</tr>
</tbody>
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(***: statistically significant at 99%)
Results: Second Stage Estimation

- **OLS Regression**

\[ \theta_j = g_0 X_j + \xi_j \]

<table>
<thead>
<tr>
<th>Parameter</th>
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</tr>
</thead>
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<tr>
<td>Constant</td>
<td>16.086*** (1.231)</td>
</tr>
<tr>
<td>Green</td>
<td>0.869** (0.321)</td>
</tr>
<tr>
<td>Vehicle Size</td>
<td>1.081*** (0.435)</td>
</tr>
<tr>
<td>Domestic</td>
<td>2.941*** (1.012)</td>
</tr>
<tr>
<td>European</td>
<td>1.181* (0.876)</td>
</tr>
<tr>
<td>Japanese</td>
<td>7.777*** (1.452)</td>
</tr>
<tr>
<td>Vehicle Age</td>
<td>-0.512*** (0.035)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.675</td>
</tr>
</tbody>
</table>

(***: statistically significant at 99%, **: statistically significant at 95%, *: statistically significant at 90%)
Measuring the Bias

• Unobserved heterogeneity:
  o Elasticity = -1.108, 15.3% bias (+)

• Independence assumption:
  o Elasticity = -1.123, 12.1% bias (-)

• Aggregation assumption:
  o Elasticity = -1.003, 21.5% bias (-)

• Independence and aggregation:
  o Elasticity = -0.992, 22.3% bias. (-)
Conclusion

• Demand for gasoline is elastic
• Bias due to assuming independence and aggregating the choice set
• Household choices are better represented
  o Discrete-continuous household portfolio model
  o Estimation method does not artificially restrict choice set
Thank you!

Any Questions?
Starting Values for First Stage

1. Minimize distance given observed and optimal VMT, calculate $\hat{\alpha}_{ij}$ that solves:

$$\left( \frac{1}{j} \sum_j VMT_{ij} - \frac{1}{j} \sum_j \overline{VMT}_{ij} \right)^2 = 0$$

2. Hold $\hat{\alpha}_{ij}$ fixed, calculate $\hat{g}_1$ to solve likelihood function

3. Use $\hat{\alpha}_{ij}$ and $\hat{g}_1$ as the full set of starting values.
Indirect Utility Function

• Assumptions:
  - Constant MRS between vehicles =1 due to static nature of model
  - Additive separability in $\theta_j$ and $\varepsilon_{ij}$
  - Non-linear in $VMT_{ij}^*$
  - Non-separable in $VMT_{ij}^*$
  - Composite error term $\tilde{\varepsilon}_{ij} = \sum_j \varepsilon_{ij} \sim N(0, \sigma_{\tilde{\varepsilon}}^2)$
Mcfadden et.al. (1978)

• Subsampling of Alternatives
  o IIA property -> parameter estimates off random sample of choices statistically equal to whole choice set estimates
  o Red bus/blue bus problem in logit errors/IIA
  o In bundle application: errors are bundle specific

• Swapping: prior to swaps, errors are iid.
  o Han (1987) : cross sectional error terms iid, then consistency in pair-wise estimation