The Economics of Gasoline Market
Supply, Demand, Tax, Pricing

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Hastings “Vertical Relationships and Competition in Retail Gasoline Markets” AER(2004) & Houde “Spatial differentiation, vertical mergers in retail markets for gasoline” AER(2012)

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Bento, Goulder, Jaconsen, Haefen “Distributional and efficiency impacts of increased US gasoline taxes.” AER (2009)

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Introduction

- CA prices higher + greatly higher variation between its cities. Why?
    1. Vertical contracts between refiners and their retail stations
    2. Decrease in the number of independent unbranded (unbranded+lowest price)
- "quasiexperiment": conversion of approximately 260 independent Thrifty gasoline stations to ARCO (Atlantic Richfield Company)
- Identification: conversions differentially affected local markets, allowing for a prepost comparison between affected and unaffected markets.

Introduction

- The independent Thrifty stations were converted to both company-op and dealer-run ARCO stations
- Compares price changes in markets with a new company-op ARCO versus price changes in those with a new dealer-run ARCO
- Results indicate that stations competing with a Thrifty station had a significant increase in price
- Results support a model of price competition with differentiated products and consumer brand loyalty.

Industry Background

- Gasoline is produced by a refiner and then transported to a main distribution center called a “distribution rack”
- Branded gasoline has an additive that is mixed into the gasoline just before it is taken for delivery to a retail station.
- Branded station: three vertical contract
  1. company operated station (company-op): refiner owns & manages station
  2. lessee dealer: refiner owns & leases it. lessee set the retail price, buy gas by wholesale prices
  3. dealer-owned station: retailer owns & signs a contract with a branded refiner to sell & display its brand
- dealer own must buy brand gasoline either from refinery or an intermediate called “jobber”
- Jobber buys gas at distribution rack, pays rack price

Industry Background

- Unbranded gasoline buy from lowest price rack and compete in prices
- Independents offering no brand differentiation, and few of the amenities (car washes or fast-food chains)
- What does economic theory predict by loss of independents?
- depends on the assumptions placed on consumer preferences
- Literature on contract form, and trade-off between double marginalization and principal-agent problems

Details of the Thrifty Purchase

- In March of 1997, ARCO long-term lease of independent Thrifty gasoline stations
- Thrifty had 260 stations while the next largest independent had 32
- All three types of conversions took place (chose by ARCO)
- Treatment: whether competitor is an independent
- Compare independent in affected and unaffected pre-post change
- A station competes with any station within one mile along a surface street or freeway

Description and Summary Statistics

Panel A

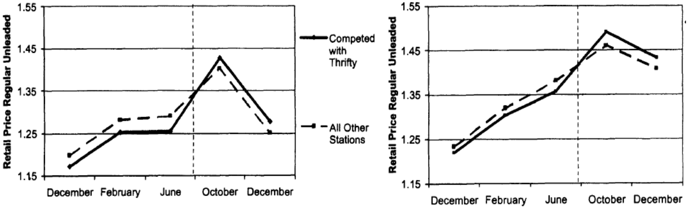
Percent of stations in sample	Los Angeles	San Diego
ARCO	19.41	13.21
Chevron	17.84	17.61
Mobil	15.88	13.21
Shell	14.12	17.61
Texaco	8.43	12.58
Unocal	12.55	11.95
Minor brands	5.25	8.18
Independents	6.52	5.66
Number of observations	$N = 510$	$N = 159$

Panel B

Average price (Standard deviation)	Los Angeles	San Diego
February, 1997	1.273	1.320
	(0.060)	(0.035)
June, 1997	1.285	1.375
	(0.068)	(0.049)
October, 1997	1.405	1.468
	(0.070)	(0.056)
December, 1997	1.266	1.414
	(0.073)	(0.0610)

Graphical Analysis

- Impact on competitors' prices

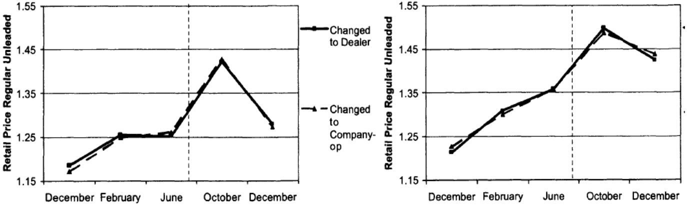


(a) Los Angeles (b) San Diego

- Before, competing stations with a Thrifty station (treatment) had lower prices than averages of others (the control group).
- After the conversion period, the stations in the treatment group had a higher price than the average price of stations in the control group

Graphical Analysis-impact of an increase in company-ops

- Divide treatment into company-op & dealer



(a) LOS ANGELES (b) SAN DIEGO

- increase in company-ops does not have a significant effect on local retail prices.

Fixed-Effects Estimation

- Fixed effects:
  - station-level fixed effects
  - city-time effects.
- The fixed-effect estimator is the only consistent estimator when the locations of independent stations are correlated with an unobservable local market characteristic that also influences price.
- Unidentifiable time-city invariant variables.

Specification

- Station-level fixed effects with city-time dummies:

$$p_{it} = \mu + \alpha_i + \delta\gamma.t + \phi c_{it} + \theta z_{it} + \varepsilon_{it}$$

  - α_i = station-specific deviation from the mean μ
  - γ = city dummy
  - t = quarterly dummy
  - z_{it} = indicator if the station competes with an independent station
  - c_{it} = indicator for if a competitor becomes a company operated station
  - ε_{it} = error term.

Results-Dependent: Retail Price for Regular Unleaded

Variable	(1)	(2)	(3)
Intercept	1.3465	1.3465	1.3617
	(0.0421)	(0.0415)	(0.0287)
Company operated	0.1080	−0.0033	−0.0033
	(0.0107)	(0.0178)	(0.0122)
Independent	—	−0.1013	−0.0500
		(0.0143)	(0.0101)
LA∗February	—	—	0.0180
			(0.0065)
LA∗June	—	—	0.0243
			(0.0065)
LA∗October	—	—	0.1390
			(0.0064)
SD∗February	—	—	−0.0851
			(0.0036)
SD∗June	—	—	−0.0304
			(0.0036)
SD∗October	—	—	0.0545
			(0.0036)
Adjusted R^2	0.3772	0.3953	0.7181
F-test for no fixed effects:			
Numerator DF: 668			
Denominator DF: 1,999			

Results Interpretation

- The coefficient measures the effect of the presence of an independent, indicating that prices were 5 cents lower at stations competing with a Thrifty before the conversion than they were after the conversion
- Changing a station to a company-op station does not have a significant positive impact on local competitors' prices.
- because ARCO assigned the new contract type, there is a potential for endogeneity bias
- A probit model of the choice of contract type at the new ARCO's was run on station characteristics, census-tract-level demographic data, and local market characteristics.

Results Interpretation

- The significant detenminants of the dealer-run contract choice were
  1. there was another ARCO dealer within a mile
  2. the existing Thrifty dealer accepted credit cards.

Testing Potential Causes for Price Increase

- The Thrifty station conversions essentially change the identity of a competitor along a single dimension, holding all other characteristics constant.
- Prices can go up or down depending on consumer preferences and substitution patterns.
- For example, suppose that all consumers have a preference for quality over brands.
- After conversion of an unbranded, the station has now become a closer substitute to other branded stations.
- Competition will intensity, causing prices to fall.

Testing Potential Causes for Price Increase

- Alternatively, prices could rise if preference is brand loyalty.
- Then under price competition, each firm's optimal price is increasing in the share of its brand-loyal customers, and its competitor's share of brand-loyal customers, and decreasing in the share of non-brand-loyal consumers.
- After conversion, price will increase most at stations that were close competitors to the independent, and least at stations that were further substitutes to the independent

Testing Potential Causes for Price Increase

- Define categories
  1. High-share brand: Chevron, Shell, or Unocal station.
  2. Mid-share brand: Exxon, Mobil, or Texaco station.
  3. Low-share brand:Beacon, Circle K, Citgo, Conoco, or Ultramar

Variable	(1) Parameter estimate	(2) Paramete estimate
Intercept	1.3622	1.3620
	(0.0287)	(0.0287)
Company operated	−0.0018	−0.0008
	(0.0124)	(0.0124)
Independent · High-share brands	−0.0273	−0.0362
	(0.0125)	(0.0156)
Independent · Middle-share brands	−0.0530	−0.0617
	(0.0154)	(0.0179)
Independent · Low-share brands	−0.0700	−0.0741
	(0.0185)	(0.0190)
Independent · ARCO	−0.0731	−0.0741
	(0.0149)	(0.0149)
Independent · *N*-decreased	—	0.0130
		(0.0136)
City-time effects	Yes	Yes
Adjusted R^2	0.7183	0.7187

Results Interpretation

- Consistent with the hypothesis that stations with low market share compete more intensely with unbranded stations for non-loyal customers than do stations with high market share and high brand loyalty
- Independent. N-decreased tests if a decrease in the number of competitors, N, contributed to an additional increase in price after controlling for the station's brand.

Second paper

Houde "Spatial differentiation, vertical mergers in retail markets for gasoline" AER(2012)

Introduction

- Regulator concerns b/c of major retail chains in gasoline markets
- Regulation: price floors, banning vertical integration
- Two methods for merger evaluation:
  1. retrospective analysis of consummated mergers-Hasting (unable to generalize)
  2. structural + merger simulation methodology- hard for spatial (counterfactuals)
- This paper combines structural & reduced-form approaches
- Incorporate mobility of consumers in product space into a discrete-choice model of demand along their route

Introduction

- Advantage: consumer can substitute along road network
- Competition is not solely localized
- Could be more competitive than previously assumed.
- PBL extended to evaluate market responses to policy changes
- Estimated markups (in commuting model) are small, similar to observed margins

Stations Characteristics

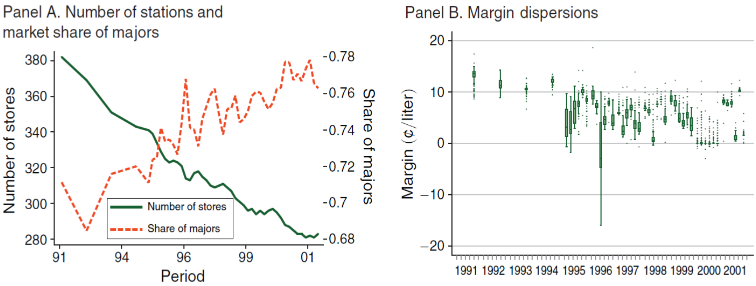
- Survey (14,263 observations for 429 stations) with characteristics:

	Fall 1991		Fall 2001		Full sample	
	Avg.	SD	Avg.	SD	Avg.	SD
Volume (liter/day)	3,949	2,415	6,271	3,812	4,934	3,289
Price (cpl)	65.13	1.24	62.07	0.22	63.83	1.78
Absolute price deviation (cpl)	0.90	0.85	0.13	0.17	0.57	0.73
Number of pumps	7.77	5.40	11.37	8.12	9.29	6.92
Number of islands	2.07	1.26	2.46	1.43	2.24	1.35
Large convenience store	0.23	0.42	0.34	0.47	0.27	0.45
Full service	0.54	0.50	0.28	0.45	0.43	0.50
Open 24 hours	0.34	0.47	0.42	0.49	0.37	0.48
Car wash	0.18	0.39	0.18	0.38	0.18	0.38
Repair shop	0.25	0.43	0.14	0.35	0.20	0.40
Major brands	0.68	0.47	0.66	0.47	0.67	0.47

- Large amount of heterogeneity across stations
- price dispersion decreased over time
- Dramatic change: self-service stations increased by ten 10%
- Branded (i.e., major) remained constant over time

Stations Characteristics

- Major innovations: automatization of the service, better inventory control systems+ environmental regulations
- $\Rightarrow$ Stations gets larger, automatized + decline in # stations



- (i) small cross-sectional dispersion in prices (ii) low level of markups (=ratio of rack price over retail price)

Empirical Distribution of Commuters

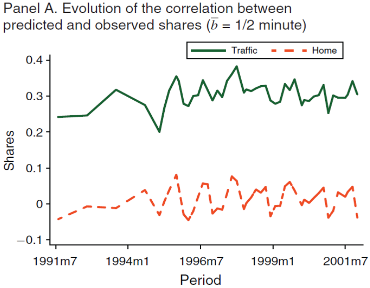
- Geography: L residence location, street intersections, road segments
- Two types of consumers: local and outside commuters
- local: centroid of residence, occupation by (s, d)
  - choose shortest travel root $r(s, d)$, time $t(s, d)$,distance $m(s, d)$
- Outside: travel along main highways

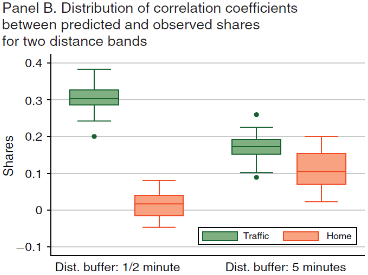
Distribution of Origin/Destination Locations

- Distribution of consumers T^t_{sd}
- Four components: # workers, full-time students, unemployed, # outside commuters
- Workers & students, commute between (s, d) w. prob. $L \times L$ matrices
- Outside commuters: beginning and end points of each highway segment
- # of outside commuters= # of occupied hotel rooms
- Commuting probabilities & distributions: surveys in 1991, 1996, 2001 & census

Correlation of Commuting/Home with Gas Sales

- Consumers select at random a store in (i) commuting path (ii)their home





- Correlation from commuting buffer is larger than home buffer

Demand Model

- Discrete choice problem over J + 1 options.
- 0 an alternative mode of transportation

$$u_{ij} = \begin{cases} X_j\beta + g_i(p_j) + \lambda_1 D(r(s_i, d_i), l_j) + \xi_j + \varepsilon_{ij} & if j \neq 0 \\ -\lambda_0 c(s_i, d_i) + \varepsilon_{i0} & otherwise \end{cases}$$

- $D(r(s_i, d_i), l_j)$ is distance between path $r(s_i, d_i)$ and location of station l_j (measure deviation to gas)

$$D(r(s,d), l) = t(s,l) + t(l,d) - t(s,d)$$

- $C(s, d)$ if home & work different zones (long r can use car)
- ε_{ij} type-1 extreme value distribution

Demand Model

- Consumers have inelastic & heterogenous demand for gasoline $\Rightarrow$ vary across income groups $g_i(p_j) = p_j(\bar{\alpha} + \alpha y_i)$ (y_i wage)
- Function of length $\bar{q}(r(s,d)) = c_0 + c_1 m(s,d)$ (c_0 fixed demand i.e. leisure, $c_1 = 0.1 liters/km$ for work and average cars)
- Size of market: $M = \sum_s \sum_d \bar{q}(s,d) T_{s,d}$
- Inclusion of utility shockε_{ij} $\Rightarrow$ unrealistic substitution patterns across products due to the embedded independence of irrelevant alternatives assumption (IIA)
- Willing to substitute toward "close"

Demand Model

- Conditional probability of buying from store j

$$P_j(r(s_i, d_i), y_i|\delta, p) = \frac{exp(\delta_j + \alpha p_j + \mu_{ij})}{1 + \sum_k exp(\delta_j + \bar{\alpha} p_k + \mu_{ik})}$$

- Mean value $\delta_j = X_j \beta + \xi_j$
- Heterogeneous $\mu_{ij} = \alpha p_j y_i + \lambda_0 C(s_i, d_i) + \lambda_1 D(r(s_i, d_i), l_j)$
- Aggregate

$$Q_j(P) = \sum_s \sum_d \int \bar{q}(s, d) P_j(r(s, sd), y|\delta, P) dF(y|s) T_{s,d}$$

Estimation Methodology

- Parameters $\Theta = \{c_0, \lambda_0, \lambda_1, \alpha, \bar{\alpha}, \beta\}$
- GMM estimator: Berry, Levinsohn, and Pakes (1995) to
  - correcting for a simultaneity problem of ξ_{jt} & prices
  - identify nonlinear preference parameters $(c_0, \lambda_0, \lambda_1, \alpha)$
- Two sets of moments: (Nevo 2001)
  1. IV interactions with fixed effects
     $\bar{g}^1_n(\Theta) = \frac{1}{n}\sum_{j,t} g^1_{jt}(\Theta) = \frac{1}{n}\sum_{j,t}\tilde{\xi}_{j,t}(\Theta)\tilde{W}^1_{jt}$ where $\tilde{\omega}_{jt} = \omega_{jt} - \frac{1}{n_j}\sum_t \omega_{jt}$ and $\tilde{W}^1_{jt}$ vector of X_{jt}, Z_{jt} (IV), period dummies
  2. Share of car users :$U_{sd}(\Theta), \hat{U}_{sd}$ predicted and actual:
     $\bar{g}^2_{n_2}(\Theta) = \frac{1}{n_2}\sum_{s,d\in Workers}(U_{sd}(\Theta) - \hat{U}_{sd})W^2_{sd}$ where W^2_{sd} dummy for long commutes, income,n_2 number of traffic zones.

Identification

- Challenge: identifying α, λ_1 linked to own and cross elasticities using market-level data
- Simultaneity of $p_{jt} \& \xi_{jt}$, worst for λ_1 b/c of non-linearity
  1. Prices adjust daily, affect position of j in price distribution
  2. $Firm_j$ & consumers observe ξ_{jt} so affect price choices
- Idea and assumption for identification:
  - unobserved location attributes are independent of neighboring station characteristics
  - entry independent of ξ_{jt} but correlated with the observed distribution of consumers
-

Demand Estimates from Multi Address Model

- Very high price elasticity

Variables	(1)	(2)	(3)	(4)
Min. consumption (c_0)	4.5746	4.5290	4.5582	4.5035
	(0.0334)	(0.0442)	(0.0299)	(0.0242)
Commuting distance (c_1)	0.2	0.2	0.2	0.2
	—	—	—	—
Income (α – log($/hour)/100)	0.0396	0.1082	0.0474	0.1677
	(0.0307)	(0.0809)	(0.0327)	(0.0482)
Long commuters (λ_0)	1.4972	1.4356	1.4768	1.3891
	(0.0326)	(0.0683)	(0.0299)	(0.0432)
Transportation cost (λ_1)	−1.2777	−0.5642	−1.0004	−0.3961
	(0.537)	(0.29)	(0.291)	(0.0909)
Price ($\overline{\alpha}$)	−0.2181	−0.1687	−0.1974	−0.1490
	(0.0767)	(0.033)	(0.0378)	(0.0233)
Travel cost – cpl/min.				
α_{25}/λ	5.880	3.387	5.091	2.717
α_{50}/λ	5.886	3.398	5.098	2.733
α_{75}/λ	5.890	3.407	5.103	2.746
Observations	14,263	14,263	14,263	14,263
Number of stores	429	429	429	429
Objective (J-stat)	3.07	1.22	6.06	40.5

Analysis of Cross-Price Elasticities

- Reg. cross-price elasticities on four measures of distance
  - elasticity of substitution decreases in distance between stations
  - increases in proportion of common traffic
  - larger elasticities for stations with common streets

Variables	(1)	(2)	(3)
Common street	0.182	0.0567	0.0611
	(0.0112)	(0.00779)	(0.00812)
Driving time	−0.00478	−0.00150	−0.00105
	(0.000104)	(7.16e-05)	(7.16e-05)
Share of common traffic		0.449	0.449
		(0.0173)	(0.0178)
Quality index ($\delta_{jt} \times \delta_{kt}$)	0.0411	0.0409	
	(0.00158)	(0.00111)	
Constant	−0.0977	−0.154	0.0186
	(0.00599)	(0.00511)	(0.00123)
Observations	428,636	428,636	428,636
R^2	0.225	0.472	0.453

Analysis of a Vertical Merger: Ultramar and Sunoco

- Canadian Competition Bureau (Dec 95): "deemed unlikely to result in a substantial prevention or lessening of competition.

	Jan. 1997	Jan. 1998	Jan. 1999	Jan. 2000
Distribution of Sunocos				
Number Sunoco brand	12	6	3	0
Number Ultramar brand	0	5	8	10
Fraction in ½ minute	0.053	0.052	0.053	0.051
Fraction in 1 minute	0.063	0.061	0.063	0.061
Fraction in 1.5 minutes	0.101	0.100	0.103	0.101
Fraction common street	0.314	0.306	0.309	0.307
Total number of stations	313	309	296	296

- Merger Simulation Analysis: estimate marginal cost, then counterfactual

Supply-Side Model and Estimation of Marginal Cost

- Upstream (U)/downstream (D): three types of vertical agreements
  1. company-owned stores (U sets price)
  2. commission (U sets price)
  3. lessee contracts (D sets price)
- But actually lessee negotiate wholesale prices based on station levels.
- Assumed U perfect resale price maintenance

Supply-Side Model and Estimation of Marginal Cost

- Vertically integrated:

$$max_{p_f} \sum_{j \in \zeta_f} (p_j - c_j) Q_j(p_f, p_{-f})$$

- ζ_f stores selling gasoline of brand f
- Ownership structure Ω, Betrand-Nash equilibrium:

$$Q(P) + (\Omega. \times \Delta(P))(P - c) = 0$$

- $\Delta(p)$ is a Jacobian matrix.
- Inverting to estimate c

Supply-Side Model and Estimation of Marginal Cost

- Estimate of c

Model	Store	Owner	RPM	Collusion	Observed MK
Multi-address	0.09703	0.101	0.1036	0.2684	0.0898
	(0.0106)	(0.0117)	(0.012)	(0.0799)	(0.0551)
Single-address	0.1414	0.1504	0.1576	0.858	0.0898
	(0.0123)	(0.0168)	(0.0163)	(0.0934)	(0.0551)

  - store = stations set price independently
  - owner = store-owners set prices jointly
  - RPM = brand suppliers set prices jointly
  - collusion = joint-profit maximization.

- At RPM $c =$ upstream marginal cost ω_f + downstream cost (function of observed Z_{jt}, unobserved η_{jt})

$$c_{jt} = p^0_{jt} + (\Omega^0_t . \times \Delta(p^0_t))^{-1} Q(p^0_t)_{jt} = Z_{jt}\gamma + \omega_{f_j,t} + \eta_{jt}$$

- OLS estimates

Merger Simulation Results

- Average predicted price differences:
- Treatment: competitive neighborhoods around Sunoco stations
- Control: outside of these neighborhoods

		Competitive neighborhoods			
		½ Minute	1 Minute	1.5 Minutes	Common street
Aggregate effects	Treatment	0.406	0.343	0.219	0.101
		(0.236)	(0.261)	(0.260)	(0.186)
	Control	0.019	0.019	0.019	0.011
		(0.056)	(0.056)	(0.056)	(0.034)
	Difference	0.388	0.325	0.200	0.090

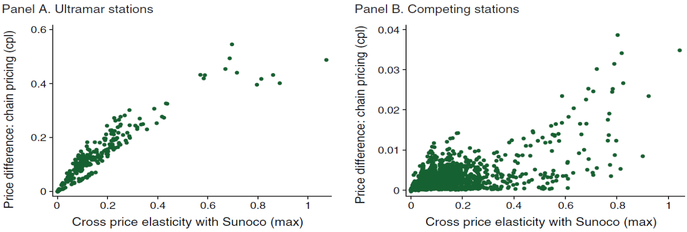
Merger Simulation Results

- The merger generates two effects (not adjust for cost efficiency)
  - direct: Sunoco & Ultramar increase price
  - indirect: competitors increase price

		Chain		Owner	Restricted choice set	
		Status quo	Cost adj.	Status quo	Chain	Owner
Sunoco price changes		0.526	0.486	0.607	0.452	0.516
		(0.173)	(0.351)	(0.202)	(0.219)	(0.234)
Direct effect	In ½ m.	0.460	0.429	0.523	0.409	0.459
		(0.200)	(0.331)	(0.243)	(0.212)	(0.237)
	Out ½ m.	0.102	0.103	0.101	0.087	0.086
		(0.105)	(0.107)	(0.104)	(0.132)	(0.131)
	Difference	0.357	0.326	0.422	0.323	0.373
Indirect effect	In ½ m.	0.026	0.025	0.026	0.064	0.066
		(0.105)	(0.107)	(0.104)	(0.132)	(0.131)
	Out ½ m.	0.002	0.002	0.000	0.002	0.001
		(0.003)	(0.003)	(0.009)	(0.004)	(0.008)
	Difference	0.023	0.022	0.025	0.062	0.066

Merger Simulation Results

- Direct and indirect effects of the merger as a function of the proximity to Sunoco (measured by the maximum elasticity of substitution with a Sunoco station)



Retrospective Analysis

- Similar to Hastings (2004) do a DiD
- In contrast to Hastings, (re-branding) loss of Sunoco took place over two-year period
- Immediate change: vertically (Ultramar became sole supplier of all Sunoco stations)
- If this new upstream supplier was able to fully or partially control the retail price (by price discrimination or resale-price maintenance)
  - post merger prices at Sunoco stations should be set less competitively than before.
  - could be efficiency gain due to lower cost for Ultramar (closer refinery)

DiD regressions

- Control: stations outside of these neighborhoods

$$p_{jt} = \gamma N_j^d \times T_t + Z_{jt}\beta + \mu_j + \tau_t + u_{jt}$$

$$p_{jt} = \gamma_0 N_j^d \times T_t \times S_{jt} + \gamma_1 N_j^d \times T_t \times (1 - S_{jt}) + \\ Z_{jt}\beta + \mu_j + \tau_t + u_{jt}$$

- S_{jt}indicator variable for stations that are supplied by Ultramar after the merger
- γ average effect of the merger
- γ_0, γ_1 direct and competitive effects

DiD regressions

- columns 3-6 excluding the 1996 price war

Variables	95/97 (1)	95/97 (2)	95/97 (3)	95/97 (4)	95/98 (5)	95/98 (6)
Merger ½ m. × Direct		0.501***		0.202**		0.211***
		(0.121)		(0.077)		(0.079)
Merger ½ m. × Competitive		0.0384		−0.106		0.325*
		(0.178)		(0.164)		(0.169)
Merger ½ m.	0.433***		0.156**		0.229***	
	(0.119)		(0.079)		(0.074)	
Constant	63.40***	63.41***	62.42***	62.43***	54.91***	54.90***
	(1.414)	(1.415)	(1.293)	(1.294)	(1.248)	(1.248)
Observations	5,778	5,778	5,457	5,457	7,287	7,287
R^2	0.785	0.785	0.840	0.840	0.917	0.917

- Prices higher after merger in treated neighborhoods,
  - anti-competitive dominated any efficiency gains
- Most of this due to Sunoco and Ultramar posting higher prices after the merger
  - direct effect 0.2 cpl and 0.5 cpl

Table of Content

Hastings “Vertical Relationships and Competition in Retail Gasoline Markets” AER(2004) & Houde “Spatial differentiation, vertical mergers in retail markets for gasoline” AER(2012)

Levin, Lewis, Wolak. ”High Frequency Evidence on the Demand For Gasoline”, Working Paper

Bento, Goulder, Jaconsen, Haefen “Distributional and efficiency impacts of increased US gasoline taxes.” AER (2009)

Gicheva, et al. “Investigating Income Effects in Scanner Data” AER(2010) & Anderson, et al. “Forecasting gasoline prices using consumer surveys” AER. (2011), Allcott “Consumers’ perceptions and misperceptions of energy costs” AER (2011)

Motivation

- Goal: estimate the gasoline demand responsiveness (shortrun elasticity of gasoline demand)
  - used in macroeconomic analysis
  - estimating the value of policy measures intended to limit the associated price volatility
- Literature: gasoline demand is fairly inelastic and perhaps even more inelastic in the short run.
- Contrubution: the study uses daily gasoline prices and citywide gasoline expenditures from 243 U.S. cities

Short Run Elasticity-Aggregate Data

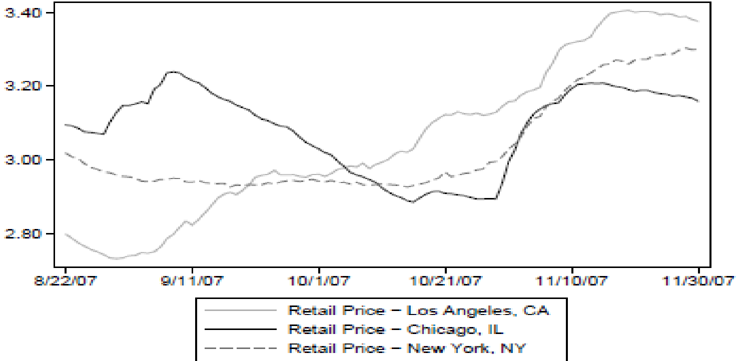
- Dahl and Sterner (1991) and Espey (1998) = -0.26.
  - data from 1970, 1980
- Hughes, Knittel and Sperling (2008)
  - =-0.024 to -0.34 for 1975-1980
  - = -0.034 to -0.077 for 2001-2006.
  - montly national data
  - Reduced form estimation
- Small and Van Dender (2007)
  - =-0.066 for 1997-02001.
  - annual state level data
  - structural model of demand for vehicle fuel efficiency and miles traveled from 19662001

Data

- daily gasoline price and expenditure data for 243 metropolitan areas, from February 1, 2006 to December 31, 2009
- Price: American Automobile Associations (AAA), the city average prices using prices collected from fleet credit card transactions and direct feeds from gas stations.
- expenditure: Vis, total dollar amount of purchases by all Visa debit and credit card users at gas stations within a city on a given day
  - include data from non-fuels (i.e. shopping)
  - try to fixed it by fixed effects.

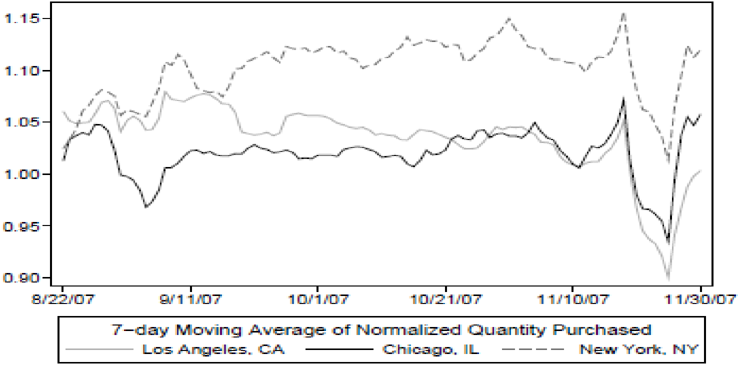
Daily Average Retail Gasoline Prices

- significant idiosyncratic fluctuation across cities (transitory differences in daily prices+richer price variation than monthly data)



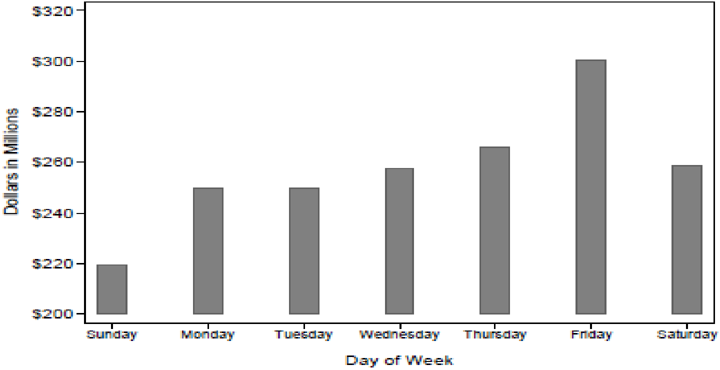
Seven Day Moving Average of Total Quantity Purchased

- expenditures also follow different patterns across MSAs (normalized by the average quantity purchased in that MSA)



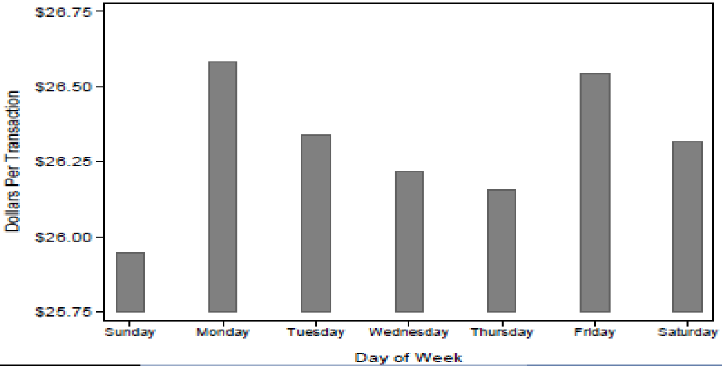
Day-of-Week Averages of Gasoline Expenditures

- very strong within-week pattern in gasoline purchasing behavior.



Day-of-Week Averages of Expenditures per Transaction

- within-week pattern observed in total expenditures results largely from fluctuations in the number of transactions occurring in each day.



Traditional Estimation

- Regressing a measure of gasoline consumption on gasoline prices (usually a constant-elasticity or log-log form)
- Including other variables to control for shifts in demand
- Time-series studies rely on observable proxies (income) to control for demand shifts
- Dependent variable: per capita gasoline quantity= gasoline expenditure/ gasoline price /number of consumers used their Visa card for any type of transaction within that city

$$ln(q_{jd}) = \alpha_j + \lambda_d + \beta ln(p_{jd}) + \varepsilon_{jd}$$

- Standard error estimates are clustered at the city level to allow for arbitrary serial correlation within each city.

Traditional Model of Gasoline Demand

- elasticities = -0.36. With month × city = -0.62 (compared with Hughes et al. (2008) in the range of -0.034 to -0.077)
- important to control for city specific fluctuations in demand.

Table 1: Traditional Model of Gasoline Demand

Dependent Variable:	$\ln(q_{jd})$ (1)	q_{jd} (2)	$\ln(q_{jd})$ (3)	q_{jd} (4)
$\ln(\text{price}_{jd})$	−0.358		−0.614	
	(0.027)		(0.034)	
price_{jd}		−0.069		−0.114
		(0.005)		(0.007)
Fixed Effects:				
Day of Sample	X	X	X	X
City	X	X	X	X
Month of Sample × City			X	X
Implied Elasticity of Demand	−0.358	−0.373	−0.614	−0.623

Note: q_{jt} represents the per-capita amount of gasoline purchased in city j on day d. Standard errors are robust and clustered to allow arbitrary serial correlation within a city. The implied elasticity of demand for linear specifications is calculated at mean levels of price and per-capita consumption.

Potential Biases from Non-gasoline Purchases

- Limitation: only observe total number and dollar amount of transactions at gasoline stations (include non-gasoline purchases)
- Higher elastic estimation of gasoline price. (demand non-gasoline uncorrelated to gasoline price, so dividing by gasoline purchase produce mechanically elasticity -1)
- Average gasoline station in the U.S. receives 21% of its total revenues from non-fuel sales.
- They also have pay-at-pump purchases (76% of total expenditures and over 64% of all transactions), these exclude those paid their gas in stores, but they are potential buyers of gas. (sample selection)

Traditional Model, only those paid at pumps

- elasticities = -0.29. With month × city = -0.56 (earlier method elasticities = -0.36. With month × city = -0.62)
- comparable to results from total expenditures

Dependent Variable:	$\ln(q_{jd})$ (1)	q_{jd} (2)	$\ln(q_{jd})$ (3)	q_{jd} (4)
$\ln(\text{price}_{jd})$	−0.288		−0.561	
	(0.026)		(0.039)	
price_{jd}		−0.043		−0.076
		(0.003)		(0.005)
Fixed Effects:				
Day of Sample	X	X	X	X
City	X	X	X	X
Month of Sample × City			X	X
Implied Elasticity of Demand	−0.288	−0.316	−0.561	−0.559

Note: q_{jt} represents the per-capita amount of gasoline purchased at the pump in city j on day d. Standard errors are robust and clustered to allow arbitrary serial correlation within a city. The implied elasticity of demand for linear specifications is calculated at mean levels of price and per-capita consumption.

Examining the Divergence from Previous Findings

- Others used a highly aggregated level
- Problem: aggregate data constructed from surveys of refineries by EIA.
- Distribution lags and storage capabilities, the amount of product flowing from secondary distributors to retailers differby consumption.
- Include gasoline exported for use in other countries.

Estimating Demand Elasticity Using Aggregated Data

- Let $D_{jd}(p_{jd}; X_{jd})$=daily demand for gasoline in MSA j during day d (X_{jd} is the vector of characteristics)

$$Q_m = \sum_{d \in S(m)} \sum_{j=1}^{J} D_{jd}(p_{jd}, X_{jd})$$

- In aggregate you are assuming: consumers' daily demand for gasoline in each city responds only to the average gasoline price for that month in the state rather than the actual price of gasoline in that city on that particular day.
- Thus yield a substantially smaller (in absolute) estimated monthly demand response to changes in the monthly average price.

Estimating Demand Elasticity Using Aggregated Data

- Aggregate per-capita quantities = sum of the daily quantity purchased divided by the total number of Visa customers in the combined area.
- Quantity weighted average price. (constant by using the GDP implicit price deflator)
- Use a complete set of time period and cross-sectional fixed effects

Regressions Using Aggregated Data

- Less elastic than disaggregated regression
- close to those of Hughes et al. (2008)

Dependent Variable = ln(quantity per capita)

Geography: Periodicity:	city daily (1)	city monthly (2)	state daily (3)	state monthly (4)	national daily (5)	national monthly (6)
All Purchases:						
$\ln(\text{price}_{it})$	−0.358	−0.290	−0.297	−0.270	−0.143	−0.127
	(0.027)	(0.015)	(0.007)	(0.025)	(0.065)	(0.024)
$\ln(\text{income}_{it})$						−0.244
						(0.440)
Pay-at-Pump Purchases Only:						
$\ln(\text{price}_{it})$	−0.288	−0.214	−0.206	−0.176	−0.020	0.002
	(0.026)	(0.017)	(0.008)	(0.028)	(0.069)	(0.024)
$\ln(\text{income}_{it})$						−0.734
						(0.333)
Fixed Effects:						
Day of Sample	X		X			
Day of Week					X	
Month of Sample		X		X	X	
Month of Year						X
City	X	X				
State			X	X		

Note: Standard errors for panel specifications are robust and clustered at the level of the cross-sectional unit.

Controlling for Demand Shocks

- Disaggregated panel data= control for demand differences across days and cities by fixed effects.
- Using per-capita income to account for changes in demand is not enough
- With panel data we observe many different locations experiencing the same macroeconomic demand shocks so it is possible to identify demand response by observing how idiosyncratic price deviations between cities result in corresponding quantity changes.
- Elasticity estimates are likely to be biased downward if there are demand shocks that are not controlled for by the day-of-week and month-of-sample fixed effects

Controlling for Demand Shocks

- The difference between estimates could stem from day-fixed effcts. We can not have day-fixed effect in aggregate data.
- In order to examine this, estimate similar specifications (i.e., with incomplete time fixed effects) using our fully disaggregated data.
- Incomplete time fixed effects: Month of Sample, Month of Year, Day of Week
- Complete time fixed effects: day-of-sample

Regressions Using Different Time Fixed Effects

- Elasticity drop to -0.25 all purchases, -0.16 pay-at-pump.
- Effective control for demand is a major reason for differences

Dependent Variable = ln(quantity per capita)

Geography:	city	city	city
Periodicity:	daily	daily	daily
	(1)	(2)	(3)
All Purchases:			
$\ln(\text{price}_{it})$	−0.358	−0.252	−0.158
	(0.027)	(0.014)	(0.005)
$\ln(\text{income}_{it})$			−0.323
			(0.136)
Pay-at-Pump Purchases Only:			
$\ln(\text{price}_{it})$	−0.288	−0.159	−0.039
	(0.026)	(0.014)	(0.004)
$\ln(\text{income}_{it})$			−0.444
			(0.165)
Fixed Effects:			
Day of Sample	X		
Month of Sample		X	
Month of Year			X
Day of Week		X	X
City	X	X	X

Note: Standard errors are robust and clustered by city to allow for arbitrary serial correlation.

Short Run vs Longer Run Demand Elasticity

- Alternative explanation that both estimates are correct
- Daily data is elastic because it captures consumers initial response
- Demand curves more elastic in the short run than in the long run.
- Why? consumers hold inventories, so demand is a function of previous prices. (withdraw or save)
- Traditional demand specification doesnt allow for this behavior.

Traditional Demand Model with Lagged Prices

- Even 20 days elasticity is very elastic

Dependent Variable = ln(quantity per capita)

	All Purchases (1)	Pay at Pump (2)
$\ln(\text{price}_{jd})$	−0.824	−0.853
	(0.073)	(0.079)
$\ln(\text{price}_{j,d-1})$	−0.513	−0.610
	(0.084)	(0.100)
$\ln(\text{price}_{j,d-2})$	0.545	0.661
	(0.078)	(0.092)
$\ln(\text{price}_{j,d-3})$	0.323	0.403
	(0.041)	(0.046)
$\ln(\text{price}_{j,d-4})$	0.146	0.183
	(0.042)	(0.047)
$\ln(\text{price}_{j,d-5})$	0.080	0.067
	(0.036)	(0.041)
$\ln(\text{price}_{j,d-10})$	−0.068	−0.085
	(0.018)	(0.022)
$\ln(\text{price}_{j,d-20})$	−0.025	−0.034
	(0.018)	(0.018)
Fixed Effects:		
Day of Sample	X	X
City	X	X
Total Implied Elasticity 20 Days After a Price Change	−0.338	−0.267

Note: Standard errors are robust and clustered to allow arbitrary serial correlation within a city. The implied elasticity of demand for linear specifications is calculated at mean levels of price and per-capita consumption.

Traditional Demand Model with Lagged Prices

- Consumers purchase more gasoline sooner when prices fall and they reduce their purchases for several days after prices rise, perhaps waiting to see if prices will fall again before they have to buy.
- Impossible to determine whether consumers alter their driving intensity or whether they simply delay or expedite purchases
- This is one of the main goals of the consumer purchase model described in the next section
- Attempting to separate consumers demand (or usage) decision

Model of Consumer Demand and Purchase Behavior

- Storing: daily demand for gasoline differ from the consumers expenditures on gasoline. demand:

$$d_{jd} = exp(\alpha_j + \lambda_d + \beta ln(p_{jd}) + \varepsilon_{jd})$$

- Probability a consumer in MSA j purchases gasoline on a day d

$$\rho_{jd} = \gamma_j + \delta_d$$

- Assume expenditure on gasoline during day d by each customer in MSA j

$$e_{jd} = \frac{p_{jd} d_{jd}}{\rho_{jd}}$$

Model of Consumer Demand and Purchase Behavior

- Total gasoline expenditures during day d for MSA j:

$$E_{jd} = e_{jd} n_{jd} = \frac{p_{jd} d(p_{jd}, \varepsilon_{jd}) n_{jd}}{\rho_{jd}}$$

- $n_{jd} =$ number of customers in MSA j during day d making a gasoline purchase
- $\frac{n_{jd}}{N_{jd}}$ unbiased estimate of ρ_{jd}, thus run ($N_{jd} =$total number of active Visa cards)

$$\frac{n_{jd}}{N_{jd}} = \gamma_j + \delta_d + \nu_{jd}$$

Model of Consumer Demand and Purchase Behavior

- Econometric model of gasoline expenditures:

$$ln(E_{jd}) = \alpha_j + \lambda_d + (\beta + 1)ln(p_{jd}) + ln(n_{jd}) - ln(\hat{\rho_{jd}}) + \varepsilon_{jd}$$

- in terms of the quantity purchased

$$ln(Q_{jd}) = \alpha_j + \lambda_{jd} + \beta ln(p_{jd}) + ln(n_{jd}) - ln(\hat{\rho_{jd}}) + \varepsilon_{jd}$$

- Standard error estimates are generated using a nonparametric bootstrap to account for the fact that the predicted probability of purchase is estimated in a first-stage regression.
- Theory: coeff. of $ln(n_{jd}), ln(\hat{\rho_{jd}})$ are 1, -1

Estimation of the Frequency of Purchase Model

- Elasticity around -0.4

Dependent Variable = $ln(quantity_{jd})$

	All Purchases			Pay-at-Pump Only		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\text{price}_{jd})$	−0.448	−0.396	−0.480	−0.341	−0.288	−0.351
	(0.019)	(0.009)	(0.005)	(0.020)	(0.006)	(0.002)
$\ln(\#\text{ of transactions}_{jd})$	1	0.999	1.025	1	0.997	0.993
		(0.005)	(0.003)		(0.002)	(0.001)
ln(predicted probability	−1	0.007	0.008	−1	−0.003	−0.007
of purchase_{jd})		(0.002)	(0.002)		(0.001)	(0.001)
Fixed Effects:						
Day of Sample	X	X	X	X	X	X
City	X	X	X	X	X	X
Month of Sample × City			X			X

Note: Standard errors are generated using a nonparametric bootstrap that allows errors to be arbitrary serial correlated within a city and jointly distributed with the error term in the first-stage regression.

Estimation of the Frequency of Purchase Model

- As theory predicted $ln(n_{jd})$ is 1
- Why coeff. $ln(\hat{\rho_{jd}})$ is close to zero rather than -1?
- This may be because the fixed effects absorb most of the variation in the probability of purchase (given the functional form specified), and any variation left may be measured with error.

Purchase Model with Lagged Prices

- Are consumers altering gasoline usage or simply shifting when they make purchases in the days following a price change?
- If consumers are substituting driving intertemporally in response to price changes then their daily demand may be influenced by past prices.
- If consumers are using their inventories of gasoline strategically, both current and past prices may influence a consumers probability of purchase.

$$d_{jd} = exp(\alpha_j + \lambda_d + \beta ln(p_{jd}) + \sum_{l \in L} \zeta ln(p_{j,d-l}) + \varepsilon_{jd})$$

$$\rho_{jd} = \gamma_j + \delta_d + \psi ln(p_{jd}) + \sum_{l \in L} \eta ln(p_{j,d-l})$$

Purchase Model with Lagged Prices

- Aggregate demand:

$$\begin{aligned} ln(Q_{jd}) = \quad & \alpha_j + \lambda_d + \beta ln(p_{jd}) + \sum_{l \in L} \zeta ln(p_{j,d-l}) \\ & + ln(n_{jd}) - ln(\hat{\rho_{jd}}) + \varepsilon_{jd} \end{aligned}$$

- predicted purchase probability can be estimated from an OLS regression

$$\frac{n_{jd}}{N_{jd}} = \gamma_j + \delta_d + \psi ln(p_{jd}) + \sum_{l \in L} \eta ln(p_{j,d-1}) + \nu_{jd}$$

- Lags: previous 5 days,10 and 20 days previous.
- Also included in the purchase probability equation

Purchase Model with Lagged Pricesl

- Purchase: share of Visa customers purchasing; deman: log of average quantity purchased per capita by Visa customers

	All Purchases		Pay at Pump	
	Purchase Equation (1)	Demand Equation (2)	Purchase Equation (3)	Demand Equation (4)
$\ln(\text{price}_{jd})$	−0.007	−0.579	−0.009	−0.449
	(0.004)	(0.022)	(0.003)	(0.015)
$\ln(\text{price}_{j,d-1})$	−0.032	0.001	−0.028	0.092
	(0.004)	(0.020)	(0.004)	(0.012)
$\ln(\text{price}_{j,d-2})$	0.024	0.090	0.023	0.0002
	(0.004)	(0.018)	(0.003)	(0.001)
$\ln(\text{price}_{j,d-3})$	0.016	0.058	0.014	0.054
	(0.002)	(0.013)	(0.001)	(0.008)
$\ln(\text{price}_{j,d-4})$	0.001	0.039	0.003	0.021
	(0.002)	(0.013)	(0.002)	(0.008)
$\ln(\text{price}_{j,d-5})$	0.007	0.001	0.003	−0.012
	(0.002)	(0.011)	(0.002)	(0.008)
$\ln(\text{price}_{j,d-10})$	−0.004	−0.005	−0.003	0.0003
	(0.001)	(0.006)	(0.001)	(0.003)
$\ln(\text{price}_{j,d-20})$	−0.0001	−0.025	−0.001	0.013
	(0.001)	(0.007)	(0.001)	(0.005)
$\ln(\#\text{ of transactions}_{jd})$		0.998		0.996
		(0.007)		(0.004)
$\ln(\text{predicted probability of purchase}_{jd})$		0.025		−0.008
		(0.007)		(0.003)
Fixed Effects:				
Day of Sample	X	X	X	X
City	X	X	X	X
Total Implied Elasticity 20 Days After a Price Change	0.096	−0.420	0.061	−0.281

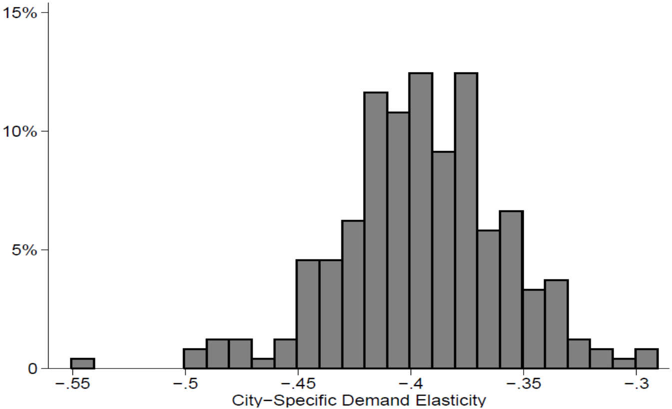
Purchase Model with Lagged Prices

- Demand is identical as before.
- The probability of purchase falls significantly on the day of and on the day following a price increase.
- Probability one day after a price change exhibits an elasticity w.r.t price=-0.76
- But, overal purchase elasticity $= 0.09$
- Much of the temporary portion of the very large response in expenditures is due to consumers delaying purchases while the fraction of the response in expenditures that persists is largely due to changes in underlying gasoline usage.

Geographic Variation in Demand Elasticity

- Allows the elasticity of demand to vary across cities.
- Include interactions between the city fixed effects and the $ln(p_{jd})$ term.
- Significant variation across cities, $\in (-0.35, -0.45)$
- Individual city elasticity estimates are fairly precise, with most having standard errors of 0.005 or less

Histogram of Demand Elasticity Estimates Across Sample Citiesl



Geographic Variation in Demand Elasticity

- Variation in demand elasticity results from differences in the way consumers use gasoline
- Difficult to identify how differences in consumer behavior or budget translate into price sensitivity.
- Lets, examine how city level demographic relates to elasticity estimates.

Summary Statistics for City Characteristics

	Mean	S.D.	Median	Min	Max
persons per square mile	1771	932	932	535	6313
ln(persons per square mile)	7.35	0.494	7.32	6.28	8.75
population share over twice the poverty level	0.704	0.071	0.712	0.483	0.898
share commuting by:					
car (alone)	0.823	0.044	0.831	0.518	0.889
subway or rail	0.003	0.012	0.0002	0	0.088
bus	0.016	0.018	0.010	0.001	0.178
carpool	0.125	0.025	0.124	0.082	0.203
walking or bicycle	0.034	0.019	0.029	0.010	0.103

Geographic Variation in Demand Elasticity

- Theory: gasoline demand is more elastic in areas where there are more modes of transportation
- No data, but we can see their choice of transportation for early years.
- Estimate demand by the assumption

$$\beta_{jd} = \gamma_0 + Z'_{jd}\gamma$$

- So:

$$\begin{aligned} ln(Q_{jd}) = \quad & \alpha_j + \lambda_d + \gamma_0 ln(p_{jd}) + ln(p_{j,d}) Z'_{jd}\gamma \\ & + ln(n_{jd}) - ln(\hat{\rho_{jd}}) + \varepsilon_{jd} \end{aligned}$$

Summary Statistics for City Characteristics

	(all purchases) (1)	(pay-at-pump) (2)
ln(p) = logarithm of price of gasoline	−0.551 (0.047)	−0.420 (0.033)
ln(p)*ln(persons per square mile)	−0.010 (0.005)	−0.007 (0.004)
ln(p)*population share over twice the poverty level	0.214 (0.040)	0.207 (0.029)
ln(p)*share commuting by subway or rail	−0.302 (0.237)	−0.382 (0.153)
ln(p)*share commuting by bus	0.034 (0.171)	0.009 (0.113)
ln(p)*share commuting by carpool	0.492 (0.120)	0.178 (0.076)
ln(p)*share commuting by walking or bicycle	0.475 (0.152)	0.472 (0.103)
ln(number of transactions)	0.997 (0.005)	0.996 (0.002)
ln(predicted probability of purchase)	0.006 (0.003)	−0.003 (0.001)
MSAs Fixed Effects	X	X
Day-of-Sample Fixed Effects	X	X

Geographic Variation in Demand Elasticity

- More densely populated MSAs and those with more low income households have more elastic demand for gasoline.
- MSAs with more workers commuting by carpool or by walking or biking have slightly less elastic demand,
- MSAs with more workers commute by subway or rail have slightly more elastic demand.
- Results are only suggestive

Literature

- Wolak et al. show that consumers shift their consumption and not that much their usage.
- It could be because of cars (technologies) they use to drive.
- Are they rational in their car purchase?
- No, Allcott, Hunt, and Nathan Wozny. "Gasoline prices, fuel economy, and the energy paradox." Review of Economics and Statistics 96.5 (2014): 779-795.

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Importance

- Major US public policy: reducing automobile-based gasoline
  - environmental s: 22 % of US emissions of carbon dioxide
  - oil : gasoline accounts for 44 % of US demand for crude oil
- The US Senate recently passed a bill that would raise corporate average fuel economy (CAFE) standards from the current 27.5 mpg to 35 mpg by 2020.
- The 2005 Energy Bill includes tax credits for households purchasing relatively fuel-efficient vehicles such as hybrid cars.
- The California State Assembly mandates carbon dioxide emissions in automobile fuel economy.
- Other proposals: subsidies to retirements of older vehicles + federal gasoline tax.

This Paper

- Question: examine the gas tax option, employing an econometrically based multimarket simulation model to evaluate the policys efficiency and distributional implications.
- Impacts of increased US gasoline taxes on fuel consumption, relating these impacts to changes in fleet composition (shifts to higher mileage automobiles) and vehicle miles traveled (VMT).
- Evaluate the economy-wide costs of higher gasoline taxes, and explore how the costs are distributed across households that differ by income, region of residence, race, and other characteristics.

Literature

1. Estimating the demand for gasoline as a function of gasoline price and household income.
   - Hausman & Newey (1995) household-level data on gasoline consumption, estimate deadweight loss from gasoline taxes
   - West & Williams (2004, 2005) same data to assess the distributional impacts of gasoline taxes and the optimal gasoline tax.
2. Infer the demand for gasoline from automobile choice and utilization models.
   - Berkovec (1985), Train (1986), West (2004) estimate the households discrete automobile purchase decision and its continuous choice of VMT

Literature

3 Supply-side: impacts of policies on new car production and the composition of the automobile fleet (contribution: model imperfectly competitive nature of the new car market and the pricing behavior) BLP (1995)

- Goldberg (1998) analyze tighter CAFE standards
- Austin and Dinan (2005) examine CAFE standards and a gasoline tax increase.

Contribution of This Paper

1. Considers supply and equilibrium not only in the new car market, but in the used car and scrap markets as well.
   - capture important dynamic effects
   - imperfectly competitive nature of the new car market. (BLP)
   - connect this market to the used and scrap markets.

2 Address distributional effects.
   - considers over 20,000 households that differ in income, family size, employment status (working or retired), region of residence, and ethnic background.
   - capture distributional impacts in several dimensions (not just income)
   - consider the ways that the government's disposition of gas tax revenue influences distribution

Contribution of This Paper

3 Econometric approach

- West (2004) account for connections between the automobile purchase and use (VMT) decisions by employing sequential, two-step estimators.
- it ignores the cross-equation restrictions implied by a unified behavior model
- paper adopts a full-information, one step structural approach that simultaneously estimates these choice dimensions within a utility theoretic framework that permits recovering sound welfare estimates.
- Random coefficients allow for correlations in the unobservable factors

Model Overview

- Economic agents
  - households
  - producers of new cars
  - used car suppliers
  - scrap firms
- Control: car-ownership and VMT decisions (simultaneously)
- States: cars (age, class, and manufacturer)

Classes	Age categories	Manufacturers
Compact	New cars	Ford
Luxury compact	1–2 years old	Chrysler
Midsize	3–6 years old	General Motors
Fullsize	7–11 years old	Honda
Luxury mid/fullsize	12–18 years old	Toyota
Small SUV		Other Asian
Large SUV		European
Small truck		
Large truck		
Minivan		

Model Overview

- Supply of used cars remaining after scrapping
- Supply new cars with Bertrand (price) competition (consider demand & CAFE standards)
- The model solves for a sequence of market equilibria at one-year intervals
- Car vintages are updated each year, so that last year's new cars become one-year-old cars
- Producers change the fuel economy of new models in a manner consistent with profit maximization.

Household Demands

- Households (i) obtain utility from car (j) ownership, its use, other goods (x_i)

$$U_{ij} = U_{ij}(z_j, M_i, x_i)$$

- Use utility depends on characteristics of the automobile (z_j) + VMT (miles i traveled M_i)
- Exogenous income+ car endowment
- If own a car: hold or relinquish (sell or scrap)
- If relinquish: whether purchase a different car (new or used)
- If no car: whether to purchase a car.

Household Demands

- Utility conditional on car j

$$V_{ij} = V'_{ij} = \mu_i \varepsilon_{ij}$$

$$V'_{ij} = V'_{ij}(y_i - r_{ij}, p^M_{ij}, p_{ix}, z_j, z_i, z_{ij})$$

- y_i: income
- r_{ij}:rental price of car j to household i
- p^M_{ij}:per-mile operating cost
- p_{ix}: price of the outside good, x
- z_i: vector of characteristics of household i
- $z_i j$:vector of characteristics of household i, interacted with characteristics of car j.

Household Demands

- Treat car purchases as rentals,payments over years:

$$y_i = r_{ij} + p_{ij}^M M_i + p_{ix} x_i$$

- Operating cost $p_{ij}^M =$ fuel cost (including gasoline taxes)$+$ maintenance $+$ variable insurance costs
- r_{ij} accounts for depreciation, registration fees, insurance costs
- Indirect utility includes random component $\mu_i \varepsilon_{ij}$ (ε: type I extreme-value distribution,μ scale)
- Probability car j maximizes utility i: $exp(\frac{V'_{ij}}{\mu_i})/\sum_k exp(\frac{V'_{ik}}{\mu_i})$

Supply of New Car

- Bertrand pricing (vector P for all), elasticity for brand
- Producer (k) problem accounts for CAFE standards
  - each manufacturer's fleet-wide average fuel economy be above a certain level in "light trucks" (set T) and "passenger cars" (set C), with efficiency requirement e_T, e_C

$$\max_{p_k, e_k} \sum_k (p_k - c_k(e_k))q_k(P, e)$$

$$\text{s.t. } \frac{\sum_{k\in C} q_k}{\sum_{k\in C} \frac{q_k}{e_k}} \geq \bar{e_C} \text{ and } \frac{\sum_{k\in T} q_k}{\sum_{k\in T} \frac{q_k}{e_k}} \geq \bar{e_T}$$

- To identify the cost function parameters: data on markups, prices, quantities ,+ estimated demand
- All firms simultaneously solve since the residual demand curve faced by a given firm depends on the prices set by the others

Used Car and Scrap Markets

- Used car: stock of operating in previous year less those scrapped
- manufacturer-class (l) , θ_l probability that l scrapped

$$q^U_{l,t+1} = (1-\theta_l)q^U_{l,t} + q^N_{l,t}$$

- Rental prices clear markets, solved simultaneously.
- Scarp: when scrap value $>$ resale value (with price p_j)
- Not an age-manufacturer-class scrap same time, so put a probability:

$$\theta_j = b_j(p_j)^{\eta_j}$$

- Change by standards through the p_j
- b_j, η_j adjusted by age and class to get observed scarp rate

Solution Method

- Solution is a vector of all prices such that
  1. every available (not scrapped) used car has a buyer (or retainer)
  2. for every new car producer, the first-order conditions for constrained profit maximization are satisfied.

- Solution steps:

  (i) given new car prices, solve for the used car prices satisfy (1)
  (ii) adjust new car prices to meet (2)
  (iii) solve again for used car prices to meet (1) given adjusted new car prices
  (iv) repeat this procedure until (1), (2), are met

Used Car and Scrap Markets

- Revenue from gasoline taxes is returned to households
- Government revenues and transfers are mutually dependent
- The overall solution is
  - a set of prices for each car that simultaneously clears all markets
  - an aggregate transfer level that equals the government's revenues from the gasoline tax
- Broydens method (a derivative-based quasi-Newton search algorithm)

Data: Household

- 2001 National Household Travel Survey (NHTS): 26,038 households

Variable	Mean (SD)
Household size	2.490 (1.34)
Number of adults $\geq$ 18 years old	1.861 (0.69)
Number of adults $\geq$ 65 years old	0.380 (0.67)
Number of children $\leq$ 2 years old	0.096 (0.32)
Number of children 3–6 years old	0.136 (0.41)
Number of children 7–11 years old	0.185 (0.49)
Number of children 12–17 years old	0.211 (0.54)
Number of workers	1.272 (0.95)
Number of females	1.033 (0.52)
Average age among adults ($\geq$ 18)	49.560 (16.8)
Household income (2001 $s)	56,621 (43,276)

Data: Household

Household breakdown	Percentage
1 male adult, no children, not retired	5.71
1 female adult, no children, not retired	7.88
1 adult, no children, retired	10.30
2+ adults w/ average age $\leq$ 35, no children, not retired	7.10
2+ adults w/ average age $>$ 35 and $\leq$ 50, no children, not retired	8.43
2+ adults w/ average age $>$ 50, no children, not retired	9.04
2+ adults w/ average age $\leq$ 67, no children, retired	9.29
2+ adults w/ average age $>$ 67, no children, retired	8.47
1+ adults w/ youngest child $<$ 3 years old	8.69
1+ adults w/ youngest child 3–6 years old	7.65
1+ adults w/ youngest child 7–11 years old	8.64
1+ adults w/ youngest child 12–17 years old	8.85
White household respondent[a]	85.60
Black household respondent	7.62
Hispanic household respondent	6.25
Asian household respondent	2.17
Adults with high school diplomas	89.40
Adults with four-year college degrees	30.50
Resident of MSA $<$ 250k	7.62
Resident of MSA 250–500k	8.22
Resident of MSA 500k–1m	8.30
Resident of MSA 1–3m	22.20
Resident of MSA $>$ 3m	32.50
Nonresident of MSA	21.10
Household income $<$ \$25,000	22.80

The Automobile Sample

Characteristic	Compact	Luxury compact	Midsize	Fullsize	Luxury mid/full	Small SUV	Large SUV/van	Trucks and minivans	Total
Miles per gallon[a]									
All car ages	29.73	24.18	27.16	25.57	23.65	23.75	20.04	22.19	24.39
	(27.8, 35.6)	(22.2, 26.9)	(24.2, 31.0)	(22.6, 30.5)	(21.3, 25.0)	(17.8, 27.0)	(16.6, 26.8)	(16.8, 27.7)	(16.6, 35.6)
Model years									
2001–2002	30.29	24.47	26.90	25.61	23.70	24.17	19.08	21.51	24.15
	(28.0, 32.8)	(22.9, 26.9)	(24.2, 30.5)	(23.0, 28.0)	(23.0, 24.2)	(21.9, 26.4)	(17.2, 22.5)	(16.8, 25.9)	(16.8, 32.8)
1999–2000	30.32	24.45	27.29	25.79	23.86	23.80	18.21	22.07	24.18
	(28.1, 35.6)	(23.1, 26.8)	(25.1, 29.7)	(22.6, 28.0)	(23.0, 24.4)	(19.8, 27.0)	(16.7, 19.6)	(18.8, 26.3)	(16.7, 35.6)
1995–1998	30.02	24.24	27.50	25.51	24.29	23.44	19.60	22.01	24.44
	(28.4, 32.1)	(22.3, 26.4)	(25.4, 29.8)	(23.0, 27.8)	(23.3, 25.0)	(19.6, 26.3)	(16.6, 23.7)	(17.7, 27.2)	(16.6, 32.1)
1990–1994	29.21	23.81	26.74	25.37	22.91	22.67	20.90	21.80	24.08
	(27.8, 30.4)	(22.2, 26.3)	(25.2, 30.0)	(23.5, 28.8)	(21.3, 24.0)	(17.8, 24.9)	(17.2, 26.0)	(17.6, 26.0)	(17.2, 30.4)
1983–1989	28.82	23.94	27.38	25.56	23.23	24.84	22.88	23.75	25.14
	(28.2, 29.4)	(22.6, 26.1)	(24.3, 31.0)	(23.8, 30.5)	(22.1, 24.3)	(23.3, 26.3)	(18.1, 26.8)	(20.0, 27.7)	(18.1, 31.0)
Horsepower/100									
All car ages	1.286	2.275	1.530	1.726	2.177	1.531	1.909	1.665	1.719
	(0.88, 1.78)	(1.56, 3.63)	(0.98, 1.96)	(0.86, 2.21)	(1.42, 2.81)	(1.02, 1.95)	(0.88, 2.59)	(0.94, 2.79)	(0.86, 3.63)
Model years									
2001–2002	1.526	2.621	1.787	2.123	2.463	1.763	2.391	2.023	2.036
	(1.34, 1.78)	(1.64, 3.63)	(1.65, 1.96)	(1.97, 2.21)	(2.13, 2.81)	(1.65, 1.95)	(2.15, 2.59)	(1.40, 2.79)	(1.34, 3.63)
1999–2000	1.454	2.488	1.682	1.917	2.376	1.648	2.271	1.920	1.932
	(1.23, 1.68)	(1.70, 3.45)	(1.58, 1.80)	(1.50, 2.07)	(2.10)	(1.45, 1.88)	(2.12, 2.52)	(1.34, 2.63)	(1.23, 3.45)
1995–1998	1.342	2.414	1.597	1.835	2.237	1.554	2.024	1.633	1.773
	(1.09, 1.47)	(1.75, 3.38)	(1.47, 1.72)	(1.41, 2.07)	(2.01, 2.53)	(1.35, 1.83)	(1.86, 2.17)	(1.09, 2.06)	(1.09, 3.38)
1990–1994	1.152	2.075	1.418	1.469	1.952	1.467	1.476	1.430	1.516
	(1.05, 1.24)	(1.60, 2.54)	(1.28, 1.54)	(0.90, 1.74)	(1.83, 2.11)	(1.29, 1.59)	(0.90, 1.77)	(1.07, 1.78)	(0.90, 2.54)
1983–1989	0.955	1.777	1.166	1.212	1.637	1.164	1.244	1.243	1.270
	(0.88, 1.03)	(1.56, 2.15)	(0.98, 1.41)	(0.86, 1.36)	(1.42, 2.01)	(1.02, 1.27)	(0.88, 1.46)	(0.94, 1.51)	(0.86, 2.15)
Rental price/1000									
All car ages	2.570	5.959	2.749	3.029	5.680	3.141	4.289	3.149	3.681
	(0.38, 6.84)	(0.55, 26.6)	(0.38, 8.55)	(0.39, 8.67)	(0.45, 21.4)	(0.42, 7.81)	(0.43, 14.4)	(0.26, 8.32)	(0.26, 26.6)
Model years									
2001–2002	5.798	15.94	6.528	7.463	14.45	6.823	10.27	6.750	8.792
	(5.14, 6.84)	(7.23, 26.6)	(5.65, 8.55)	(6.84, 8.67)	(11.8, 21.4)	(6.12, 7.81)	(7.92, 14.4)	(4.78, 8.32)	(4.78, 26.6)
1999–2000	3.258	6.819	3.274	3.628	5.712	3.724	4.566	3.850	4.237
	(2.14, 4.24)	(3.74, 12.6)	(2.10, 4.72)	(3.13, 4.52)	(3.99, 8.69)	(3.11, 4.35)	(2.20, 7.69)	(2.91, 5.24)	(2.10, 12.6)

Rental Prices

- For household i owning car$j$:

$$r_{ij} = D_j + 0.85 I_{ij}^A + F_{ij} + Rp_j$$

- D_j: depreciation in the real value of car j
- I_{ij}^A:household i's annual insurance costs for car j
- F_{ij}: household i's annual insurance costs for car j
- R: real interest rate

- Rental prices are included in utility relative to price of outside good (cost of living) faced by each household

- 363 cost of living indices for regions + insurance + registration.

Per-Mile Operating Costs

- Per-Mile Operating Costs

$$p_{ij}^{M} = (p_i^{gas}/MPG_J^{*}) + N_j + 0.15 I_{ij}^{M}$$

- p_i^{gas}: household i's per gallon price of gasoline,
- MPG_j: miles per gallon for car j
- N_j: per-mile maintenance and repair costs for car j
- I_{ij}^{M}: household i's per-mile insurance costs for car j

Econometric Model

- Challenge 1: integrate automobile ownership and utilization decisions
  - estimates simultaneously the decisions on both margins
- Challenge 2: households frequently own more than one car (too many potential bundles)
  - solved by repeated discrete-continuous framework
  - separable choice occasions
  - first a discrete choice of whether to own one of J automobiles
  - conditionally, how much to drive it
  - households have multiple choice occasions on which different automobile to buy
  - assume their number depends on the number of adults in a given household.

Econometric Model

- repeated discrete-continuous model of automobile demand
  - HH i, fixed number of choice occasions T_i ($\#$ adults $+1$)
  - Pref for car j:$V_{itj} = V'_{ij} + \mu_i \varepsilon_{itj}$

$$V'_{ij} = \frac{-1}{\lambda_i} exp\left(-\lambda_i \left(\frac{y_i/T_i - r_{ij}}{p_{ix}}\right)\right) - \frac{1}{\beta_{ij}} exp\left(\alpha_{ij} + \beta_{ij}\frac{p^M_{ij}}{p_{ix}}\right) + \tau_{ij}$$

$$\begin{aligned} \alpha_{ij} &= \tilde{\alpha}_i^T z_{ij}^{\alpha} \\ \beta_{ij} &= -exp(\tilde{\beta}_i^T z_{ij}^{\beta}) \\ \lambda_i &= exp(\tilde{\lambda}_i^T z_i^{\lambda}) \\ \tau_{ij} &= \tilde{\tau}_i^T z_{ij}^{\tau} \\ \mu_i &= exp(\mu_i^*) \end{aligned}$$

  - $(y_i, r_{ij}, p^M_{ij}, p_{ix})$:income, rental price, utilization price,Hicksian composite commodity price

Econometric Model

- The rest of utility:
  - $(z_{ij}^{\alpha}, z_{ij}^{beta}, z_{ij}^{\tau})$ alternative automobile characteristics (including make, age, class dummies)
  - z_{ij}^{λ} just household characteristics
  - $(\tilde{\alpha}_i^T, \tilde{\beta}_i^T, \tilde{\lambda}_i^T, \tilde{\tau}_i^T, \mu_i^*)$ vary randomly across households
  - ε_{itj} additional unobserved heterogeneity that varies randomly across households, automobiles, and choice occasions
  - If decide not to buy

$$V_{it0} = \frac{-1}{\lambda_i} exp\left(-\lambda_i\left(\frac{y_i/T_i}{p_{ix}}\right)\right) + \phi_i^T z_i^{\phi} + \mu_i \varepsilon_{it0}$$

  - ε_{itj} independent draws from the normalized type I extreme value distribution,

$$Pr_{it}(j) = \frac{exp(V'_{ij}/\mu_i)}{\sum_k exp(V'_{ik}/\mu_i)}$$

Econometric Model

- The rest of utility:
  - if chooses j, Roy's identity : household's conditional VMT demand is

$$M_{itj} = exp\left(\alpha_{ij} + \beta_{ij}\left(\frac{p_{ij}^{M}}{p_{ix}}\right) + \lambda_i\left(\frac{y_i/T_i - r(ij)}{p_{ix}}\right)\right)$$

  - Analyst observe: $\tilde{M}_{itj} = M_{itj} + \eta_{itj}$ (η_{itj} normal draw from mean zero and $\sigma_i = exp(\sigma_i^*)$)
  - Likelihood observing $\tilde{M}_{itj}$

$$l(\tilde{M}_{itj}|j \quad chosen, j \neq 0) = \frac{1}{(2\pi)^{1/2}\sigma_i} exp\left(-\frac{1}{2}\left(\frac{\tilde{M}_{itj} - M_{itj}}{\sigma_i}\right)\right)$$

Econometric Model

- Full likelihood for i condition on $\delta = (\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\lambda}_i, \tilde{\tau}_i, \phi_i, \mu_i^*, \sigma_i^*)$

$$L_i = \Pi_{t=1}^{T_i} \left[\Pi_{j=0}^{J} Pr_{it}(j)^{1_{itj}} \Pi_{j=1}^{J} l(\tilde{M}_{itj} | j \quad chosen)^{1_{itj}} \right]$$

- 1_{itj} indicator function equal to one if car j is chosen

Estimation Strategy

- Past econometric: sequential estimation strategy for the induced selectivity bias in derived VMT demand with a Heckman-like (1979) correction factor.
- This paper: full-information estimation, accounts for correlations in unobserved determinants using random parameters (McFadden and Train 2000).
- Random parameters: allow variation in unobserved variables.
- $\delta = (\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\lambda}_i, \tilde{\tau}_i, \phi_i, \mu_i^*, \sigma_i^*)$ distributed multivariate normal with mean $\overline{\delta}$ and variance-covariance matrix Σ_δ

What is Heckman Models

- We only observe VMT for those bought a car (self-selection)

$$\begin{aligned} M^*_{itj} &= X\Omega + u \\ E\left[M_{itj}|X, j \neq 0\right] &= X\Omega + E\left[u|X, j \neq 0\right] \\ E\left[M_{itj}|X, j \neq 0\right] &= X\Omega + \rho\sigma_u\lambda(Z\gamma) \end{aligned}$$

  - ρ correlation between unobserved determinants of propensity to buy a car (error to $Prob(j \neq 0|Z) = \Phi(Z\gamma)$) and unobserved determinants of VTM (u)
  - σ_u standard deviation of u
  - λ is the inverse Mills ratio function evaluated at $Z\gamma$
  - Z has at least one (selection) variable compare to X
- Two step estimation: 1)estimate γ in a Probit regression of car purchase 2) regress Heckman model
- Test for sample selectivity by coefficient of λ

Estimation Strategy

- Standard MLE is computational burdensome.
- Adopt a Bayesian statistical perspective (Gibbs sampler estimation procedure)
  - initial beliefs $(\bar{\delta}, \Sigma_\delta)$ with probability distribution $f(\bar{\delta}, \Sigma_\delta)$
  - observe x update to $f(\bar{\delta}, \Sigma_\delta | x)$ a posterior distribution
  - Bayes's rule $f(\bar{\delta}, \Sigma_\delta | x) = f(\bar{\delta}, \Sigma_\delta) L(x | \bar{\delta}, \Sigma_\delta)/D$ (D constant
  - using f difficult to draw inference
  - simulate random samples from $f(\bar{\delta}, \Sigma_\delta | x)$ draw inference (Markov Chain Monte Carlo (MCMC))
- Number of household (N=20,429), stratify to 12 groups and 12 separate estimation.

Empirical Results

	Elasticity of gasoline use wrt price[a]	Elasticity of gasoline use wrt income[a]	Car ownership elasticity wrt rental price	VMT elasticity wrt operating cost[a]
All	−0.35	0.76	−0.82	−0.74
By household				
Retired	−0.32	0.61	−0.93	−0.69
Not retired, no children	−0.32	0.68	−0.72	−0.69
Not retired, with children	−0.39	0.96	−0.85	−0.83
By auto				
By class				
All cars				
Compact	−0.27	0.83	−0.65	−0.59
Luxury compact	−0.30	0.78	−1.25	−0.64
Midsize	−0.28	0.74	−0.67	−0.60
Fullsize	−0.29	0.75	−0.73	−0.63
Luxury midsize/fullsize	−0.30	0.79	−1.25	−0.63
Small SUV	−0.29	0.93	−0.73	−0.63
Large SUV/van	−0.32	0.88	−0.98	−0.69
Small truck	−0.34	0.78	−0.62	−0.72
Large truck	−0.31	0.79	−0.85	−0.66
Minivan	−0.31	0.85	−0.77	−0.65
New cars				
Compact	−0.28	1.14	−1.44	−0.60
Luxury compact	−0.27	0.76	−3.14	−0.46
Midsize	−0.29	0.95	−1.58	−0.60
Fullsize	−0.29	1.04	−1.77	−0.61
Luxury midsize/fullsize	−0.28	0.83	−3.04	−0.47
Small SUV	−0.26	1.86	−1.58	−0.55
Large SUV/van	−0.34	1.06	−2.30	−0.69

Empirical Results

- Elasticity of gasoline use with respect to gasoline price
  - across all households and cars: -0.35
  - larger for families with children and owners of trucks and SUVs
- Elasticity of gasoline use with respect to income
  - average: 0.76
  - highest for families with children and owners of new vehicles
- Car ownership elasticities with respect to the own rental price
  - mean rental price elasticities of 0.88
  - new vehicles only: -1.97
  - luxury cars, SUVs, trucks: highest rental price elasticities
- Household level data produces smaller elasticities.
- Long-run VMT elasticities with respect to operating costs
  - average elasticity is 0.74
  - lower for new cars

Simulation Results

- Alternative ways of recycling the additional revenues from the tax increase
  - "Flat" recycling: revenues are returned in equal amounts to every household.
  - "Income-based" recycling: revenues are allocated to households according to each households share of aggregate income.
  - "VMT-based" recycling: revenues are allocated as a lump sum according to each household's share of aggregate vehicle miles traveled in the baseline.

Simulation Results-Gasoline Consumption

- 25 cents tax increase
- Change in gasoline consumption

	Flat		Income-based		VMT-based	
Recycling method	Year 1	Year 10	Year 1	Year 10	Year 1	Year 10
Baseline gasoline use per household (gallons)	775.18	828.89	775.18	828.89	775.18	828.89
Percentage change in gasoline use	−5.09	−4.99	−5.06	−5.07	−4.51	−4.40
Percentage change in VMT	−5.01	−4.84	−4.98	−4.93	−4.43	−4.21
Percentage change in VMT per car	−4.62	−4.37	−4.56	−4.38	−4.01	−3.69
Percentage change in cars in operation	−0.41	−0.49	−0.44	−0.57	−0.44	−0.54
Percentage change in overall MPG	0.08	0.16	0.08	0.15	0.09	0.20

- The percentage change in gasoline = % change in miles traveled (VMT) minus % improvement in fuel economy (miles per gallon).

Simulation Results-Gasoline Consumption

- Most of the reduction in gasoline use comes from the reduction in VMT
- short run:an increase in the scrapping rate for vehicles with unusually low fuel economy
  - First year: additional 160,000 used large trucks and large SUVs are scrapped

Simulation Results-Fleet Composition

- Fleet size and composition

	Baseline[a]		25-cent gasoline tax increase[b]					
			Flat recycling		Income-based recycling		VMT-based recycling	
	Year 1	Year 10	Year 1	Year 10	Year 1	Year 10	Year 1	Year 10
Cars in operation								
All	188.3	191.0	−0.41	−0.49	−0.44	−0.57	−0.44	−0.54
New	16.7	18.2	−1.00	−0.08	−1.12	−0.38	−0.93	−0.07
Used	171.6	172.8	−0.35	−0.53	−0.37	−0.59	−0.39	−0.59
Low MPG	75.9	78.9	−0.47	−0.81	−0.50	−0.82	−0.49	−0.77
High MPG	112.4	112.1	−0.37	−0.26	−0.40	−0.39	−0.40	−0.38

- shift away from cars
- shift toward used cars (those more fuel economy)
- long-run reduction is smaller than the short-run reduction

Simulation Results-Efficiency Costs

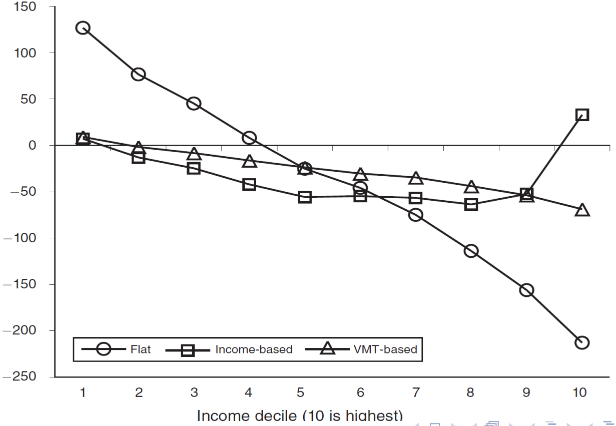
- Weighted sum of the negative of each household's equivalent variation

Revenue recycling	Flat			Income-based			VMT-based		
Tax increase (cents)	10	25	75	10	25	75	10	25	75
Net tax revenue ($billion)	7.43	17.96	48.46	7.43	17.97	48.43	7.52	18.29	49.91
Efficiency cost[a]									
Total ($billion)	1.23	3.24	11.43	1.25	3.28	11.72	1.11	2.89	10.38
Per dollar of additional revenue	0.16	0.18	0.24	0.17	0.18	0.24	0.15	0.16	0.21
Per avoided gallon of gasoline consumed ($)	0.71	0.76	0.96	0.73	0.78	0.98	0.72	0.77	0.97

- The costs under the alternative recycling cases are not much different from those in the flat recycling case
- The nature of recycling, important distributionally (as indicated below), no affect aggregate costs.

Distributional Impacts

- Welfare impacts are in average price-adjusted 2001 dollars per household



Distributional Impacts

- changes in the gasoline price and the transfer are by far the most important sources of the household welfare impact
- Decomposition of welfare impact

	Gasoline price	Transfer	Car prices	Producer profits	EV	EV as a percent of income
Flat recycling						
Income						
<25	−84.36	157.58	2.62	−3.12	74.96	0.45
25–50	−196.36	160.22	−0.43	−7.19	−51.87	−0.14
50–75	−284.09	158.88	−3.16	−11.88	−154.50	−0.24
>75	−334.45	160.29	−4.62	−19.11	−213.94	−0.21
All	−176.02	159.04	0.04	−7.22	−29.73	−0.08
Income-based recycling						
Income						
<25	−83.90	68.33	2.90	−3.42	−13.75	−0.08
25–50	−196.40	157.21	−0.40	−7.86	−55.45	−0.15
50–75	−284.65	259.81	−3.40	−13.00	−55.33	−0.09
>75	−336.04	417.87	−5.07	−20.90	39.99	0.04
All	−176.06	157.83	0.10	−7.90	−31.48	−0.08
VMT-based recycling						
Income						
<25	−84.26	79.40	2.86	−2.80	−2.01	−0.01
25–50	−197.37	181.56	−0.38	−6.44	−30.56	−0.08
50–75	−285.89	261.01	−3.31	−10.64	−52.80	−0.08
>75	−340.00	307.48	−4.92	−17.12	−69.87	−0.07
All	−177.08	162.93	0.11	−6.46	−25.70	−0.07

Sensitivity Analysis

- Faster technological improvement in fuel economy
  - gasoline tax increase induces a smaller long-run effect
- Double the scrap elasticity η_j to 6.0
  - Gasoline tax causes a somewhat larger reduction in the short run
- No binding CAFE standard
  - Gasoline tax causes a somewhat larger reduction in the short run
- Increase in gasoline taxes yields a significantly larger short- and long-run improvement in fuel economy

Sensitivity Analysis

- Percent change relative to the baseline under the same parameter assumptions

	Year 1		Year 10	
	Baseline	25-cent tax increase[a] (percent)	Baseline	25-cent tax increase[a] (percent)
Central case				
Gasoline consumption (gallons/household)	775.18	−5.09	828.89	−4.99
Aggregate VMT (000's miles/household)	18.80	−5.01	21.23	−4.84
Average MPG (miles weighted)	24.26	0.082	25.62	0.155
Average EV (price-adjusted dollars)	—	−30.13	—	−31.28
Faster fuel-economy improvements[b]				
Gasoline consumption	773.66	−5.07	751.56	−4.48
Aggregate VMT	18.83	−4.99	22.25	−4.23
Average MPG	24.34	0.080	29.60	0.263
Average EV	—	−29.67	—	−24.23
High scrap elasticity				
Gasoline consumption	775.18	−5.16	828.89	−5.00
Aggregate VMT	18.80	−5.08	21.23	−4.86
Average MPG	24.26	0.088	25.62	0.154
Average EV	—	−29.75	—	−30.93
No CAFE standard				
Gasoline consumption	775.18	−5.25	828.89	−6.21
Aggregate VMT	18.80	−4.93	21.23	−4.90
Average MPG	24.26	0.339	25.62	1.401
Average EV	—	−29.28	—	−30.11
Gasoline tax revenue not recycled[c]				
Gasoline consumption	775.18	−5.49	828.89	−5.62
Aggregate VMT	18.80	−5.41	21.23	−5.50
Average MPG	24.26	0.084	25.62	0.122
Average EV	—	−218.07	—	−231.32

Table of Content

Hastings "Vertical Relationships and Competition in Retail Gasoline Markets" AER(2004) & Houde "Spatial differentiation, vertical mergers in retail markets for gasoline" AER(2012)

Levin, Lewis, Wolak. "High Frequency Evidence on the Demand For Gasoline", Working Paper

Bento, Goulder, Jaconsen, Haefen "Distributional and efficiency impacts of increased US gasoline taxes." AER (2009)

Gicheva, et al. "Investigating Income Effects in Scanner Data" AER(2010) & Anderson, et al. "Forecasting gasoline prices using consumer surveys" AER. (2011), Allcott "Consumers' perceptions and misperceptions of energy costs" AER (2011)

Introduction

- Gicheva, Dora, Justine Hastings, and Sofia Villas-Boas. "Investigating Income Effects in Scanner Data: Do Gasoline Prices Affect Grocery Purchases?." AER (2010)
- Question: how consumers adjust their purchase in meals of rising fuel prices.
- Could be both intertemporal income effects (this paper) and exogenous shifters of production costs (literature)
- This paper: uses sharp changes in gasoline prices to estimate the impact that short run changes in disposable income have on measures of consumer price sensitivity at the grocery store.

Introduction

- Weekly store level scanner data from 180 West Coast grocery stores for products (UPCs) in frequently purchased food categories.
- Results: when gasoline prices rising
  - substitute to sales items
  - stronger at stores serving lower income
  - quantity weighted price paid for products decreases
- Thus, in addition to increasing production costs, rising fuel prices lower profit margins by increasing competitive pressure on retail firms as consumers become more price sensitive to compensate for lost income devoted to increased fuel expenditures.

Data

- Gasoline prices have increased dramatically, particularly in California
- Average Californian spent about five percent of income on gasoline in 2002
- Weekly store level data: Family Cold Cereal, Family Yogurt, Fresh Chicken, and Refrigerated Orange Juice
  - quantity of each product sold
  - gross revenue
  - revenue net promotional discounts
  - weight sold where needed (i.e. pounds of meat)
  - membership card data with customer income

Regressions

- If income effects are important: (null hypotheses) when gasoline prices are high:
  - consumers purchase a higher fraction of products on sale
  - quantity weighted net price paid per unit falls

$$ln(y_{jt}) = \alpha_j + \beta ln(gasprice_t) + \gamma' X_{jt} + \varepsilon_{jt}$$

- y_{jt}
  - fraction of sales in a category at store j in week t that come from promotional items
  - quantity weighted price paid
- store fixed effects, regional time trend, regional monthly dummies, holiday fixed effects, the fraction of UPCs in each category that are on sale in week t at store j, and its square.
- Allow first-order autocorrelation in the error terms, ε_{jt}

Results-share promotion sold

Dependent variable: ln(percent of sales from promotional items)	All stores (1)	Stores in income quartile 1 (2)	Stores in income quartile 2 (3)	Stores in income quartile 3 (4)	Stores in income quartile 4 (5)
Adult cereal: ln(gas price)	0.190	0.269	0.170	0.179	0.154
	(0.012)**	(0.029)**	(0.021)**	(0.023)**	(0.025)**
Dep. variable mean	0.65	0.66	0.66	0.64	0.62
Yogurt: ln(gas price)	0.252	0.360	0.234	0.283	0.164
	(0.040)**	(0.085)**	(0.076)**	(0.079)**	(0.078)*
Dep. variable mean	0.50	0.53	0.51	0.51	0.47
Chicken: ln(gas price)	0.491	0.548	0.522	0.475	0.445
	(0.055)**	(0.129)**	(0.110)**	(0.111)**	(0.091)**
Dep. variable mean	0.60	0.63	0.61	0.59	0.58
Fresh orange juice: ln(gas price)	0.103	0.075	0.103	0.103	0.131
	(0.007)**	(0.016)**	(0.013)**	(0.014)**	(0.014)**
Dep. mean	0.83	0.84	0.83	0.83	0.82
Observations	27,540	6,426	7,344	6,885	6,885
Number of stores	180	42	48	45	45

Results

- (cereal) a 100 % increase in gasoline prices results in a 19 % increase in the fraction of cereal purchases coming from promotional items.
- Largest for stores serving patrons in the lowest quartile of the income distribution
- Yogurt & chicken similar pattern
- But, smallest effect for fresh orange juice + no income effect
  - May be because an easy substitute for this category is frozen or shelf-stable juices

Results-quantity weighted grocery price

Dependent variable: ln(percent of quantity-weighted price paid)	All stores (1)	Stores in income quartile 1 (2)	Stores in income quartile 2 (3)	Stores in income quartile 3 (4)	Stores in income quartile 4 (5)
Adult Cereal: Coef. on ln(gas price)	−0.049	−0.066	−0.036	−0.058	−0.038
	(0.007)**	(0.016)**	(0.013)**	(0.013)**	(0.013)**
Dep. mean	3.10	3.03	3.06	3.11	3.20
Yogurt: Coef. on ln(gas price)	−0.072	−0.084	−0.085	−0.051	−0.075
	(0.010)**	(0.021)**	(0.019)**	(0.020)**	(0.020)**
Dep. mean	0.73	0.71	0.72	0.74	0.76
Chicken: Coef. on ln(gas price)	−0.103	−0.075	−0.095	−0.153	−0.09
	(0.022)**	(0.046)	(0.044)*	(0.044)**	(0.041)*
Dep. mean	2.37	2.05	2.32	2.39	2.70
Fresh orange juice: Coef. on ln(gas price)	−0.109	−0.101	−0.116	−0.106	−0.11
	(0.008)**	(0.018)**	(0.016)**	(0.016)**	(0.016)**
Dep. mean	3.10	3.03	3.08	3.12	3.17
Observations	27,540	6,426	7,344	6,885	6,885
Number of stores	180	42	48	45	45

Results

- quantity weighted net price falls significantly when gasoline prices increase
- Average quantity weighted price paid per box of cereal is $3, $\Rightarrow$ consumers decrease their overall cereal expenditures by 15 cents per box (5% decline)

Introduction

- Anderson,& Kellogg, & Sallee & Curtin, “Forecasting gasoline prices using consumer surveys”, AER, 2011
- Investment on energy sector depends on quality of future energy price predictions
- Biased predictions may explain the so-called “energy paradox”
  - failure of market participants to make seemingly cost-effective investments in energy efficiency
- Contribution:This paper introduces a new dataset on consumers retail gasoline price forecasts obtained from the nationally representative Michigan Survey of Consumers (MSC).

Question-Data

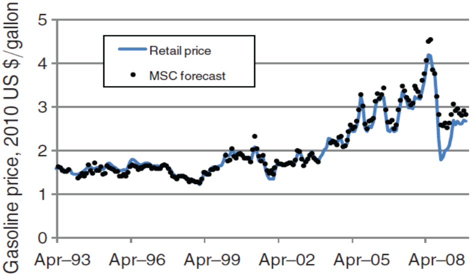
- MSC survey data on consumers' beliefs about future inflation: outperform time-series and macroeconomic models
- Anderson, Kellogg, Sallee (2011): what do consumers believe about real future gasoline prices?
  - average consumer's belief (over a five-year horizon) is statistically indistinguishable from a real no-change forecast
- This paper: how well do consumers predict future prices?
- Consumers hold reasonable beliefs about future prices $\Rightarrow$ unlikely to be the source of the energy paradox.

The Michigan Survey of Consumers (MSC) Data

- Every month, 500 respondents to report their beliefs
- Since April 1993, asked gasoline prices will be higher or lower (or the same) in five years + forecast exact price change
- Since late 2005, asked gasoline prices in one year
- Deflate her nominal gasoline price forecast by her own forecast for inflation rate

MSC Five-year Forcast of the Real Price of Gasoline

- Monthly time series of real US average gasoline prices and mean inflation- adjusted MSC forecasts



- Overlap closely ⇒ average consumer forecasts the future real price of gasoline to equal the current price.

MSC Five-year Forcast of the Real Price of Gasoline

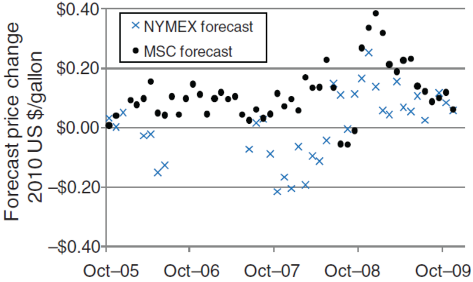
- Forecast error that results from using the current gasoline price and the mean MSC forecast to predict the real price of gasoline five years ahead.
- Root mean squared prediction error (RMSE) for the no-change forecast is \$0.803, while that of the MSC forecast is \$0.800.
- There is no future price for retail gasoline to compare it with MSC.
- MSC better for gasoline than the prediction of long-term crude future market at predicting future oil prices.

Forecast in Crisis

- Economic crisis in late 2008
- Consumers consistently forecasted that gasoline prices would increase in real terms.
- Given the rapid rebound in gasoline prices in 2009, these consumer forecasts were substantially more accurate than a no-change forecast.

New York Mercantile Exchange (NYMEX)

- NYMEX wholesale gasoline futures market, for one year ahead



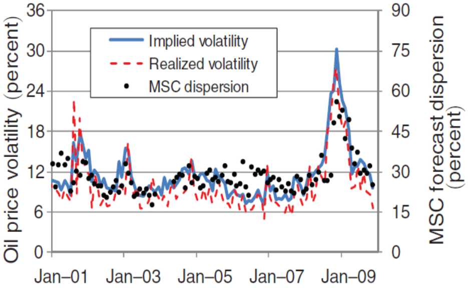
- The increase in the MSCs forecasted price change in late 2008 coincides by the NYMEX futures market predictions

Dispersion in MSC Forecasts and Price Volatility

- Dispersion of gasoline price forecasts across MSC respondents each month as a proxy for price volatility
- Dispersion often around 30% but rose to 60% in recent crisis
- Measures of oil price volatility from Alquist, Kilian, and Vigfusson (2010):
  - implied price volatility from NYMEX oil futures options (markets forecast of volatility over the upcoming month)
  - realized volatility, which the authors calculate as the within-month standard deviation of the daily percentage return on the spot price of oil

Dispersion in MSC Forecasts and Price Volatility

- Comparison of MSC Forecast Dispersion to Oil Price Volatility



- All three are correlated duting the crisis.
- Greater dispersion in survey forecasts may proxy for greater uncertainty during extreme events, dispersion is otherwise a noisy measure of volatility or simply reflects disagreement in forecasts due to staggered

Third Paper

- Allcott, “Consumers Perceptions and Misperceptions of Energy Costs”, AER, 2011
- Economic decisions depend on preferences over outcomes and beliefs about how each possible choice maps into these outcomes.
- Typically assume beliefs as rational expectations, perfect information, and unbounded computational capacity.
- Seems not true:
    - biased beliefs about food calorie (Bollinger, et al.2011)
    - returns to schooling (Jensen 2010)
    - potential earnings in other countries (McKenzie et al. 2007)
    - own likelihood of gym attendance (DellaVigna, Malmendier 2006)

Energy Belief

- Belief in energy when buying durable goods:
  - expectations of future energy prices
  - forecast their usage
  - know each product's energy efficiency rating
  - combine this information to compute a total energy cost.
- MPG Illusion: which one has bigger difference in fuel cost?
  - paid 1: two cars with MPG 11 and 13
  - paid 1: two cars with MPG 29 and 49
- The fuel cost differences are almost exactly the same: the difference between each pair of vehicles in gallons of gasoline consumed per mile driven is 0.014.
- Policy aspect: cognitive errors reduce demand for energy efficient autos
- But there are almost no empirical papers to quantify it.

Introduction

- The Vehicle Ownership and Alternatives Survey (VOAS)
- 2,100-person nationally representative survey
  - demographic
  - vehicle ownership
  - expectations of future fuel prices
- Stylized facts
  1. Little cognitive attention to fuel costs when purchase autos
  2. MPG Illusion: underestimate energy cost differences between low-MPG vehicles and overestimate the cost differences between high-MPG vehicles
  3. Knowledgeable about current gas prices, predict unchanged

Introduction

- challenge for
  - unbounded computational capacity
  - rational expectations
  - equal attention to prices versus other product costs.
- Cause consumers to underinvest or overinvest in energy efficiency
- No clear welfare costs of these mistakes are large

Data

- Participants selected by Random Digit Dialing and Address-Based Sampling (include unlisted phone numbers)
- Unselected volunteers are not allowed to join.
- Computer-assisted self-interview, and households with no computer are given one
- Unrepresentative on unobservables related to value of time and willingness to participate in surveys
- Weighted to be nationally representative on a set of observed characteristics.

Data

- Four main sets of questions:
  1. "current vehicle": make,model, model year, engine size, automatic, fourwheel
  2. beliefs about current and future gasoline prices + total costs to fuel their vehicles.
  3. "second choice vehicle" if the model they actually did buy did not exist, and elicited perceived fuel cost differences between the current and second-choice vehicles
  4. "replacement vehicle" with a randomly selected difference in MPG and elicited perceived cost differences
- Accurate questions: if drive the same amount what would be the cost (only effect of MPG) or ask to ignore inflation then predict prices (make them real)

Result-Cognitive Effort

- Final question:

  In this survey, we asked you to calculate fuel costs fairly mathematically and precisely. Think back to the time when you were deciding whether to purchase your vehicle. At that time, how precisely did you calculate the potential fuel costs for your vehicle and other vehicles you could have bought?

1. I did not think about fuel costs at all when making my decision	40%
2. I did think some about fuel costs when making my decision, but I did not do any calculations at all.	35%
3. I calculated some, but not as precisely as I did just now in this survey.	13%
4. I calculated about the same as I did just now in this survey.	8%
5. I calculated more precisely than I did just now during this survey.	3%

Result-Cognitive Effort

- Calculation variable: codes the five possible responses 1 to 5, standardizes the values to mean 0 and standard deviation 1.

Dependent variable:	Calculation	Calculation	MPG
Regression:	Pairwise correlation	Conditional correlation	Conditional correlation
	(1)	(2)	(3)
Calculation			0.90
			0.19***
Income ($000's)	0.0019	0.00001	−0.0076
	0.00065***	0.0007	0.0038**
Education (years)	0.059	0.055	0.42
	0.012***	0.013***	0.072***
Age (years)	−0.0051	−0.0037	−0.00093
	0.0018***	0.0018**	0.011
1(male)	0.190	0.18	−1.04
	0.06***	0.06***	0.30***
1(rural)	−0.20	−0.15	−0.89
	0.068***	0.070**	0.40**
Liberal	0.056	0.038	0.22
	0.031*	0.031	0.17
Gas price ($/gal)	0.15	0.14	0.54
	0.045***	0.045***	0.30*
Constant		−1.00	16
		0.24***	1.50***
Observations		1,953	1,953

Result-Cognitive Effort

- Interpretation:
  - one additional year of education is correlated with a 0.059 standard deviation increase in Calculation
  - one standard deviation more cognitive attention to calculating fuel costs purchased vehicles with 0.90 higher MPG
- Is consistent with "rational computation"?
  1. May be not a lot of money is at stake: not true
     - trade off of a minute calculation with fuel costs
     - buy 20-MPG instead 21-MPG then save $82 annually
     - with 9% discount rate, buying 19 MPG instead 24 MPG
     - present value costs $3,000
     - consumers appear to calculate more when higher gas prices magnify these cost differences
     - estimates: one dollar increase in gasoline prices is correlated with a 0.15 standard deviation increase in Calculation

Result-Cognitive Effort

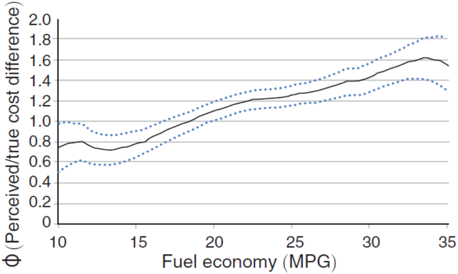
2. Initial perceptions could already be quite precise.
   - although consumers may not be aware of their imprecision, substantial noise (Allcott 2010).
3. Many consumers have sufficiently strong preferences for a particular vehicle that additional calculation would be unlikely to affect their decisions.
4. Costs of calculation are high.
   - heterogeneity in costs could generate heterogeneity in cognitive effort
   - more highly educated people can presumably calculate more easily and thus should calculate more

Result-Systematically Biased Beliefs

- Consumers underestimate the energy cost differences between low-MPG vehicles and overestimate cost differences between high-MPG vehicles.
- Total fuel costs scale linearly in a vehicle's gallons per mile.
- Respondent reports perceived fuel cost differences current, second, replacement
- $\phi =$ perceived cost differences divided by true differences

Result-Systematically Biased Beliefs

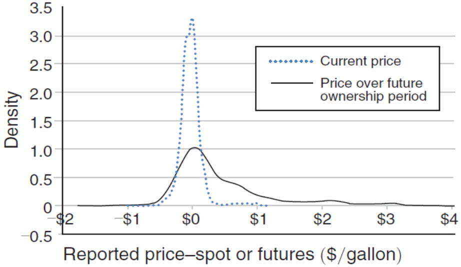
- ϕ versus current vehicle fuel economy (MPG)



- Underestimate financial value of fuel economy: below one
- Consumers evaluating low-MPG: underestimate, consumers evaluating high-MPG: overestimate (MPG Illusion)
- MPG illusion $\Rightarrow$ high-MPG hybrids and low-MPG trucks and purchase more medium MPG vehicles

Result-Gasoline Price Expectations

- Know current fuel prices, expect real prices to rise in the future
- reported current price minus spot, estimated future price minus NYMAX future oil price (extract regional variation)



- Wrongly belief the future gas prices, would be higher
- Even when exclude outliers.

How to resolve last two papers?

- The MSC is a survey of selected groups.
- The VOAS is sample of car owners (by phone)
- So, there may be a bias in beliefs of average customers