Fueling Alternatives: Evidence From Real-World Driving Data

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Typical American family will spend \$1,991 on gas in 2019

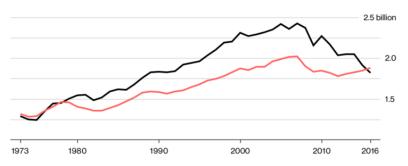


Projection - Gas Buddy, Image - Track Gabe Blog

America's New Pollution King

Transportation emissions have surpassed electricity emissions for the first time since 1978





U.S. Energy Information Administration

Bloomberg

Gasoline, economics, and policy

- Gasoline remains a dominant transportation fuel and transportation now # 1 source of CO₂
 - Policy and technology driven changes to the industry
 - Fuel economy standards, gas taxes, rise of EVs/hybrids
- Therefore, researchers and policymakers interested in understanding consumer behavior in this market
 - Many theoretical and empirical works on demand/search
 - Due to data limitations, most of the literature has had to rely on aggregate data or strong modeling assumptions

This paper

- Driver's choice about where/when to buy gas is complex
 - We use a unique data set to better understand how drivers decision of where/when to purchase gas
- First paper to use high-frequency micro data on drivers' geographic locations and gasoline purchase behavior
 - We observe 600+ variables including:
 - the last station each driver refueled, stations recently passed, drivers' current tank level, distance out of the way to each potential station
- We model drivers' decision as a combination of:
 - 1. A choice of which stations to consider
 - 2. Which station to purchase from conditional on the consideration set

This paper

- We then use our empirical model of driver behavior to evaluate:
 - Drivers' implied value of time
 - Crucial for knowing the required density an alternative fuel network
 - Driver's demand elasticity w.r.t. current prices vs. average prices
 - Key to understanding implications of fuel taxes and fuel economy standards
 - The value of full information in gasoline markets
 - How much are drivers leaving on the table? This also provides an estimate of the cost of search in this mkt.

Literature - choice with imperfect information

- Search Literature
 - Online markets, where actual search behavior is observed (De los Santos, Hortacsu, and Wildenbeest, 2012). But, these are often not products that are purchased frequently or in such national volumes.
 - Other empirical search models: Hortacsu, Syverson (2004), Honka (2014), Salz (2017), and more
- Choice Set Formation
 - Sovinsky Goeree (2008), Abaluck and Adams (2018)
- Hybrids: papers that combine search, rational inattention, and choice set formation
 - Masatlioglu, Nakajima, Ozbay (2012), Matejka and McKay (2015), Hortacsu, Madanizadeh, Puller (2017), Caplin, Dean, Leahy (2018)...

Literature - gasoline demand

- Estimating elasticity of demand for gasoline using aggregate data
 - Houthakker, Verleger, Sheehan (1974), Ramsey, Rasche, Allen (1975), Hughes, Knittel, Sperling (2008), Levin, Lewis, Wolak (2017) and others
- Discrete choice with aggregate data
 - Houde (2012) estimates a model of station-level demand based on distribution of commute patterns.
- Search in gasoline markets
 - Focused on search and consumer price expectations as generating price dispersion and "rockets and feathers" price movements.
 - Yang and Ye (2007), Lewis (2008), Tappata (2009), Chandra and Tappata (2011), and many others.

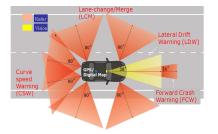
The IVBSS Experiment

- IVBSS (Integrated Vehicle-Based Safety System) was a \$32 million field test of advanced crash-warning technology by the USDOT, industry partners, and the UM Transportation Research Institute (UMTRI)
- Sixteen identical passenger cars were fitted with the technology
- 108 drivers from southeast Michigan were given the vehicles to use for approximately six weeks



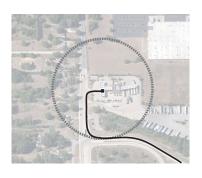
What data was collected during the experiments?

- Each car had a computer installed that recorded 600 variables at a rate of 10 times per second
 - Vehicle location, speed, acceleration, fuel use, etc
 - Detailed data from the crash warning systems



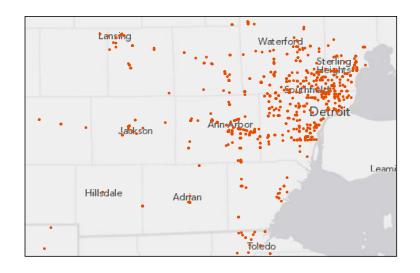
■ Each car included five cameras (two in-car, three exterior)

Gas pump stops identified using combination of GPS tracks and in-car cameras

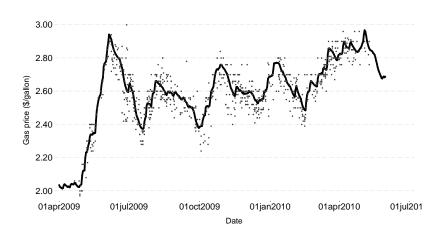




We identified over 700 vehicle stops at gas pumps

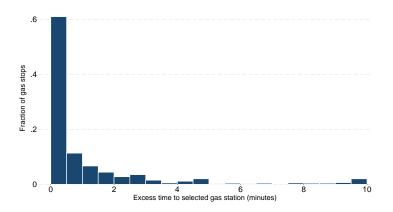


Pump stops matched to daily station-level price data to obtain gas price paid



People don't drive out of their way to buy gas

We use this data to calculate the excess distance that driver i would need to travel to get to station j on trip t and how long this would take.



Model of station choice

- On each trip, t, driver i can stop at a set, C, of potential stations
 - ullet C includes all station within 3 min. of driver's route
 - ▶ 99.2% of stops are < 3 min. away
 - Drivers may not consider all of these stations
- We model the purchase decision in two stages:
 - 1. Drivers consider a subset $S \subseteq C$ of stations
 - ▶ Whether a driver considers a station j can depend on vector Z_{ijt} (i.e. has driver passed stn. recently)
 - 2. Drivers select a station *j* from S, or the "outside option" of not stopping to maximize utility
 - ► A driver's utility from choosing station *j* depends on a vector *X*_{ijt} (i.e. current station price)

Probability driver *i* chooses *j* on trip *t*:

$$Prob_{itj} = \sum_{\mathcal{S} \in \mathcal{C}_j} \underbrace{Prob. \ considers \ the \ subset \mathcal{S}}_{Pr(\mathcal{S}|Z_{itj}, \theta)} * \underbrace{Pr(j|X_{itj}, \mathcal{S}, \beta)}_{Prob. \ chooses \ j \ from \ \mathcal{S}}$$
Sum over all choice sets that contain j

■ The probability that driver considers *j*:

$$\phi_{itj}(\theta) = \frac{exp(Z_{itj}\theta)}{1 + exp(Z_{itj}\theta)}$$

■ The probability of consideration set S occurring:

$$Pr(S|Z_{itj}, \theta) = \prod_{l \in S} \phi_{itl} \prod_{k \notin S} (1 - \phi_{itk})$$

 $lue{}$ Given \mathcal{S} , the choice rule follows a standard logit form

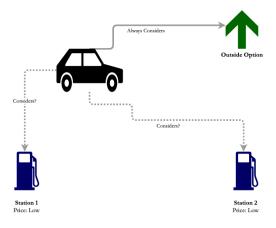
Estimation

- We estimate the parameters via simulated maximum likelihood
 - We find utility parameters, β , and consideration parameters, θ , that best fit the observed station choices
 - Large number of potential consideration sets for each trip
 - Avg. trip has 16 stations nearby, so $2^{16} = 65,536$ possible choice sets
 - Therefore, we approximate the probability of a choice at each parameter by averaging over 100 "simulated choice sets"

How can we identify the probability that drivers consider each station?

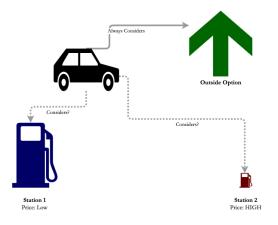
- Suppose there are 2 stations and "outside option" of not stopping
 - Each station either sets a "high price" or "low price"
 - We see a panel of market shares for each station and the "outside option"
- There are 3 parameters to estimate:
 - β_0 the "constant" utility obtained from stopping at either of the stations
 - $-\beta_1$ distaste from stopping at a "high price" station
 - ullet heta The probability of considering each station
- Identifying Assumption: The "outside option" is considered with probability 1

Observation 1: low prices



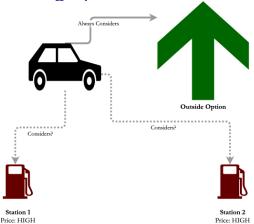
■ These mkt. shares provide information about drivers' utility from stopping (β_0) and how likely they are to consider each station (θ)

Observation 2: differential prices



■ These mkt. shares provide information about drivers' sensitivity to price (β_1) and how likely they are to consider each station (θ)

Observation 3: high prices



■ This pins down consideration, θ , given β_1 , β_0 . Intuition: If fewer drivers substitute to the "outside option" than we would have predicted from observation 2, we infer that many drivers weren't considering both stations

Empirical Implementations

- Variables that influence consideration
 - All specifications: constant, tank level, (tank level)²
 - Specification 1: excess distance to station
 - Specification 2: time since driver last passed station, last station chosen
- Variables that influence choice
 - All specifications: constant, current price, station avg. price, excess dist., right-side arrival

Results: consideration probabilities

Consideration probabilities fall with distance



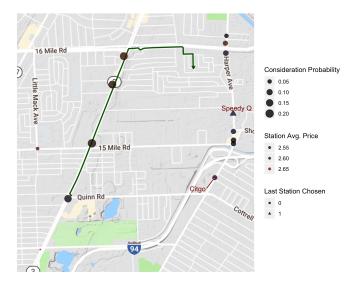
Driver 65, Trip 228, Tank level=72%

Results: choice probabilities



Driver 65, Trip 228, Tank level=72%

Consideration probabilities rise as tank level declines



Driver 6, Trip 74, Tank level=42% ▶ Graph ▶ Graph2

Drivers more likely to consider recently passed stations MUCH more likely to consider last chosen station



Driver 47, Trip 386, Tank level=35% Choice Probs.

Avg. marginal effects of determinants of consideration

	(1)	(2)
Tank Level (L/10)	-0.093	0.004
$(Tank Level)^2 (L/10)^2$	0.004	-0.012
Excess Distance (min)	-0.033	
Passed Last 7 Days $(0/1)$		0.014
Last Station Chosen $(0/1)$		0.102
E[Stations Considered] E[Stations Considered Purchase]	1.09 6.74	0.76 4.52
Num. of Trips Observations	22,360 352,449	22,360 352,449

In a third specification, we also find that drivers consider more stations when wholesale prices are higher • Additional Specs.

Choice parameter estimates

	(1)	(2)
Choice of Station		
"Inside" good	-3.532***	-3.406***
	(0.096)	(0.089)
Current Station Price (\$/gal)	-0.360	-0.081
, , <u>-</u> ,	(0.322)	(0.347)
Average Station Price (\$/gal)	-7.150***	-6.773***
(,,,,,	(0.936)	(1.031)
Excess Distance (min)	-0.414^{***}	-0.898***
,	(0.081))	(0.059)
Right-Side Arrival $(0/1)$	0.268***	0.266***
- (, ,	(0.091)	(0.097)
O o Florible on Commun Disc	0.012	0.202
Own Elasticity w.r.t. Current Price	-0.913	-0.203
Own Elasticity w.r.t. Avg. Price	-18.985	-17.153

Drivers very sensitive to avg. prices, but not to current station station prices

Value of time and information

	(1)	(2)	Logit
Implied Value of Time (\$/hr)	10.459	24.825	20.8699
Annual Value of Full Info (\$/driver)	229.435	338.146	-
Δ CS from Full Info $/$ Gas Expenditures	0.242	0.357	-

- These values of time are substantially smaller than existing estimates
 - \$54 per hour (Houde, 2012)
- Getting consideration sets right is crucial for value of time estimate

Value of time and information

	(1)	(2)	Logit
Implied Value of Time (\$/hr)	10.459	24.825	20.8699
Annual Value of Full Info (\$/driver)	229.435	338.146	-
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- Driver welfare would be substantially improved by better information about stations available
 - Lower prices, more convenient stops
 - 2nd col. likely an overestimate of information value if consideration correlated with unobserved quality (more work here)



Chargefox continues expansion of ultra-rapid electric car charging network

APRIL 15, 2019 - 3 MINUTE READ - BRIDIE SCHMIDT



Chargefox continues expansion of ultra-rapid electric car charging network World's fastest EV charger gives drivers 120 miles in 8 minutes

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Loz Blain | April 26th, 2018

ny ABB has released a DC fast charger capable of recharging an EV nearly three

han Tesla's Supercharger... if only there was a car that could handle that kind of

EVgo Goes Plaid With New Ultra-Fast Charging Station In Baker, California

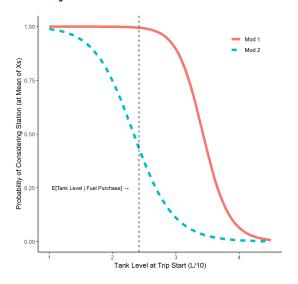
- Alternative fueling stations may not need to be as dense as existing stations to be competitive
 - Clear prices would provide a competitive advantage by reducing search costs.
 - Lower value of time than previous estimates reinforces this result (more work to do here).
 - Density can be even lower if alternative fuel is cheaper per mile.
- Information is critically valuable in improving drivers' welfare.
 - Some of this will come by reducing stations' profits.
 - Misallocation of drivers across stations causes a pure welfare loss.
 - Not clear how much this has been improved by "Gas Buddy" and the like.

Next steps

- Refine and better understand our estimates.
 - Allow station average price to influence consideration.
 - Improved modeling of unobservable station quality (e.g. last stop, brand, etc).
 - Improved modeling of quantity purchased at each stop: fillers vs. non-fillers.
 - Understand what affects the implied value of time and value of information.
- Potential other counterfactuals? Ideas?

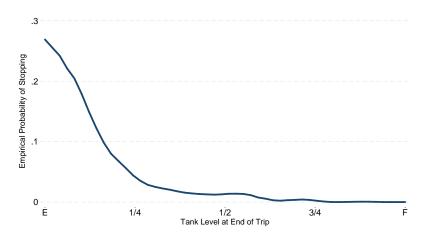
Additional tables and figures

Consideration by tank level





Drivers are more likely to stop as their tank gets closer to empty





Choice probabilities



Avg. marginal effects of determinants of consideration

	(1)	(2)	(3)	(4)
Initial Tank Level (L/10)	-0.310	-0.093	-0.531	0.004
Initial Tank Level Squared $(L/10)^2$	0.025	0.004	0.048	-0.012
Wholesale Price Rising $(0/1)$			-0.021	
Wholesale Price (\$/gal)			0.104	
Excess Distance (min)		-0.033	0.125	
Ever Passed				-0.001
Passed Last 7 Days				0.014
Passed Last 3 Days				0.015
Last Station Chosen $(0/1)$				0.102
E[Stations Considered] E[Stations Considered Purchase]	3.05 17.85	1.09 6.74	5.6 24.28	0.76 4.52
Num. of Trips Observations	22,360 352,449	22,360 352,449	22,360 352,449	22,360 352,449

Value of time and information

	(1)	(2)	(3)	(4)	Logit
Own Elasticity w.r.t. Current Price	-1.015	-0.913	-2.344	-0.203	-0.759
Own Elasticity w.r.t. Avg. Price	-19.772	-18.985	-19.882	-17.153	-18.9666
Implied Value of Time (\$/hr)	26.856	10.459	40.921	24.825	20.8699
Annual Value of Full Info (\$/driver)	109.146	229.435	107.127	338.146	-
Δ CS from Full Info $/$ Gas Expenditures	0.115	0.242	0.113	0.357	-

→ Back