Fueling Alternatives: Evidence From Real-World Driving Data

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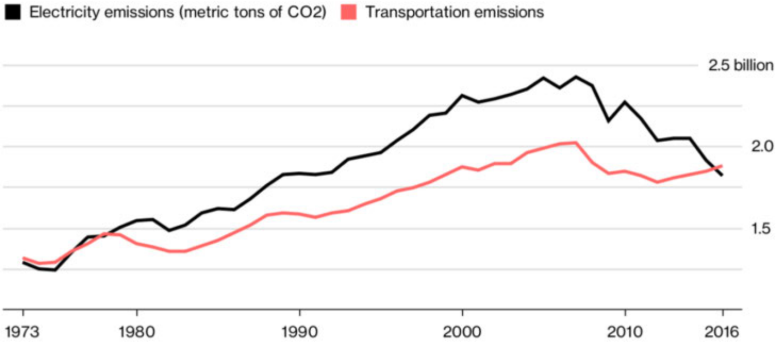
Typical American family will spend $1,991 on gas in 2019

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 CO_2
  - 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

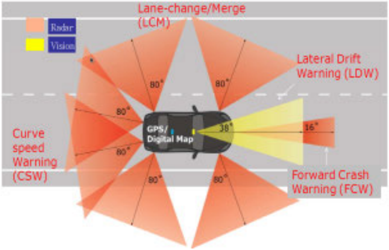
- Estimating elasticity of demand for gasoline using aggregate data
  - Houthakker, Verleger, Sheehan (1974), Ramsey, Rasche, Allen (1975), Hughes, Knittel, Sperling (2008), Levin, Lewis, Wolak (2017) and others
- Discrete choice with aggregate data
  - Houde (2012) estimates a model of station-level 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

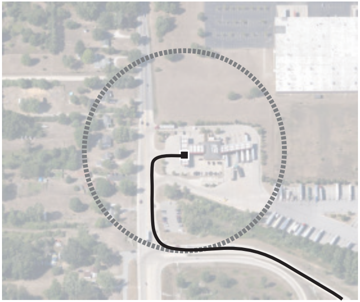
What data was collected during the experiments?

- 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

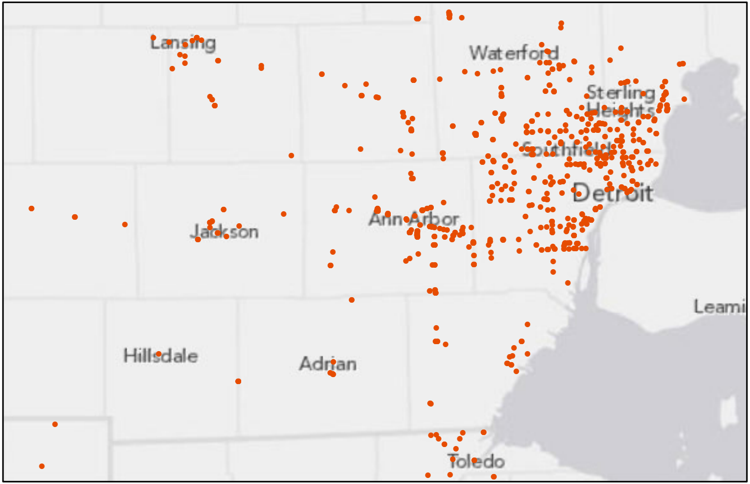


- Each car included five cameras (two in-car, three exterior)

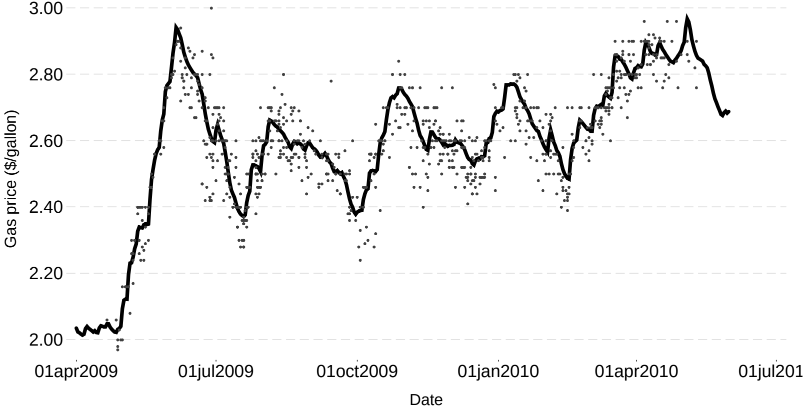
Gas pump stops identified using combination of GPS tracks and in-car cameras



We identified over 700 vehicle stops at gas pumps

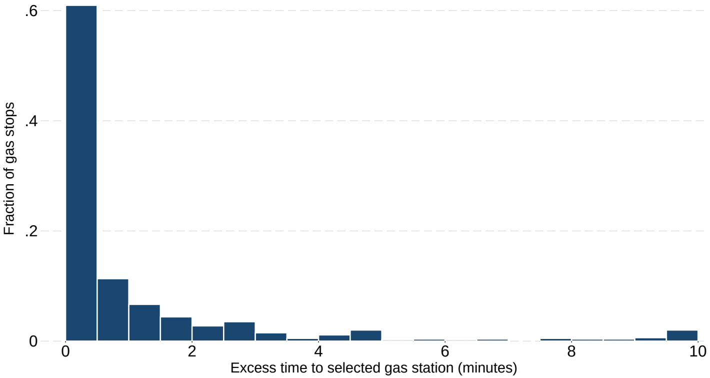


Pump stops matched to daily station-level price data to obtain gas price paid



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, $\mathcal{C}$, of potential stations
  - $\mathcal{C}$ 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 $\mathcal{S} \subseteq \mathcal{C}$ 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 $\mathcal{S}$, 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:

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

- The probability that driver considers j:

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

- The probability of consideration set $\mathcal{S}$ occurring:

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

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

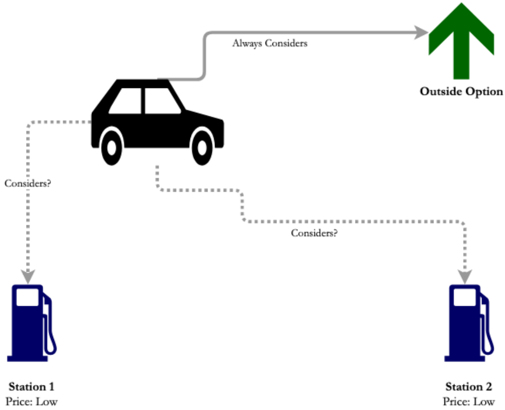
Estimation

- 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?

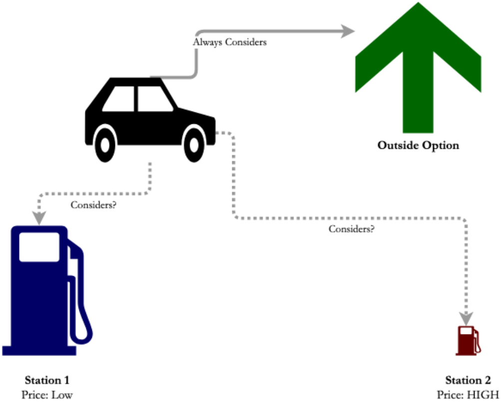
- *Identifying Assumption*: The "outside option" is considered with probability 1
- Suppose there are 2 stations and "outside option" of not stopping
  - Each station either sets a "high price" or "low price"
  - We see a panel of market shares for each station and the "outside option"
- There are 3 parameters to estimate:
  - β_0 - the "constant" utility obtained from stopping at either of the stations
  - -β_1 - distaste from stopping at a "high price" station
  - θ - The probability of considering each station

Observation 1: low prices



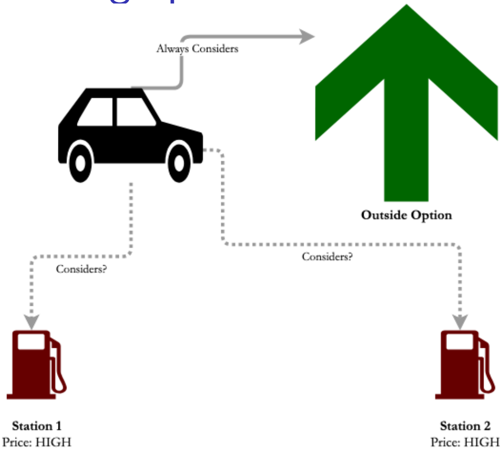
- These mkt. shares provide information about drivers' utility from stopping (β_0) and how likely they are to consider each station (θ)

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

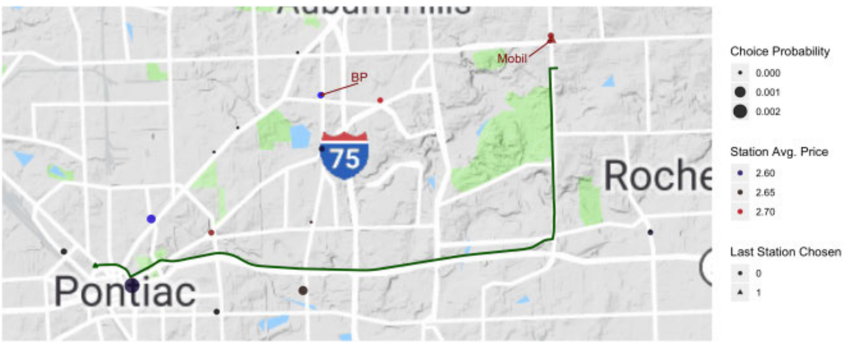
- Variables that influence consideration
  - All specifications: constant, tank level, $(\text{tank level})^2$
  - Specification 1: excess distance to station
  - Specification 2: time since driver last passed station, last station chosen
- Variables that influence choice
  - All specifications: constant,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

Results: consideration probabilities

- Consideration probabilities fall with distance

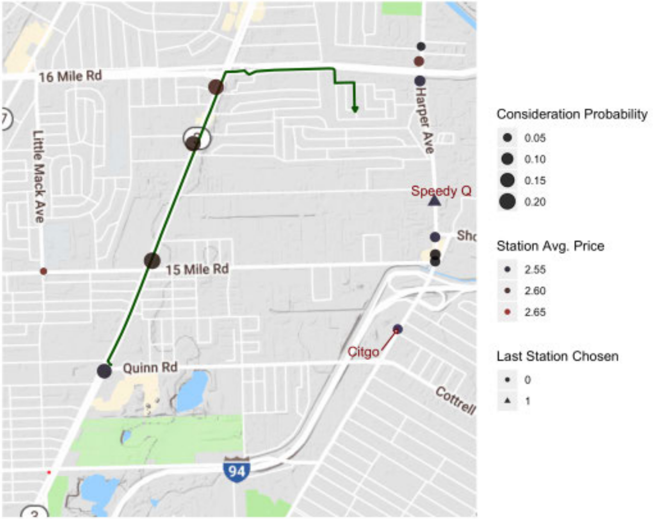
Driver 65, Trip 228, Tank level=72%

Results: choice probabilities



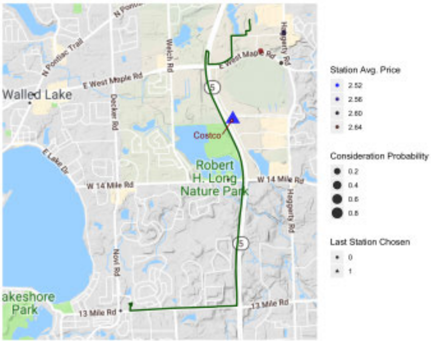
Driver 65, Trip 228, Tank level=72%

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
$(\text{Tank Level})^2$ $(L/10)^2$	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]	1.09	0.76
E[Stations Considered | Purchase]	6.74	4.52
Num. of Trips	22,360	22,360
Observations	352,449	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 ($/gal)	-0.360	-0.081
	(0.322)	(0.347)
Average Station Price ($/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)
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	-
Δ CS from Full Info / Gas Expenditures	0.242	0.357	-

- 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)

More Specs.

Policy implications

Chargefox continues expansion of ultra-rapid electric car charging network

APRIL 15, 2019 · 3 MINUTE READ · BRIDIE SCHMIDT

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World's fastest EV charger gives drivers 120 miles in 8 minutes

Loz Blain | April 26th, 2018

Swiss company ABB has released a DC fast charger capable of recharging an EV nearly three times faster than Tesla's Supercharger... If only there was a car that could handle that kind of electron flow (Credit: ABB)

Policy implications

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han Tesla's Supercharger... If only there was a car that could handle that kind of
(Credit: ABB)

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

Policy implications

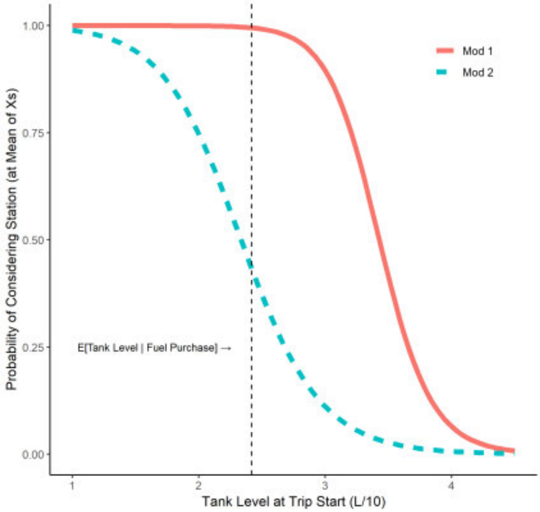
- Alternative fueling stations may not need to be as dense as existing stations to be competitive
    - Clear prices would provide a competitive advantage by reducing search costs.
    - Lower value of time than previous estimates reinforces this result (more work to do here).
    - Density can be even 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?

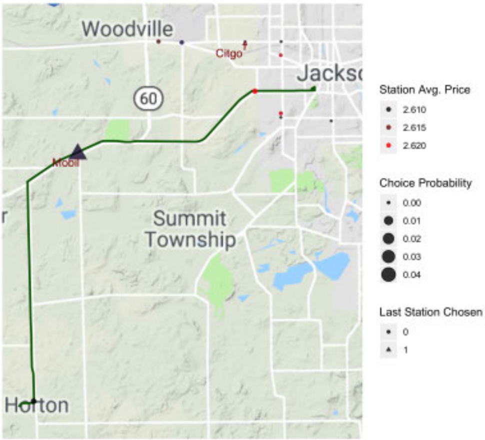
Additional tables and figures

Consideration by tank level



▸ Back

Choice probabilities



Driver 47, Trip 386, Tank level=35% Back

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]	3.05	1.09	5.6	0.76
E[Stations Considered | Purchase]	17.85	6.74	24.28	4.52
Num. of Trips	22,360	22,360	22,360	22,360
Observations	352,449	352,449	352,449	352,449

Back

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