The Power to Choose

Summary

Based on Ali Hortaçsu, Seyed Ali Madanizadeh, and Steven L. Puller (2017) "Power to Choose? An Analysis of Consumer Inertia in the Residential Electricity Market"

- Important because argument for efficient merchant generation requires retail access.
- Inertial in choice, not changing vendors when you should, can hamper this. This looks like brand loyalty.
- Inattention, not looking for alternatives, can also mean that a low cost vendor can't get customers.

The Setting

- Texas has more retail competition, power but not distribution and transmission from alternative providers, than any state, rivaled only by the New England states.
- They set up a website that made it easy to search.
  - They can observe who switched. (Micro data)
  - They can see people switching multiple times.
- Model in two steps
  - Do you change? (Logit)
  - Who do you change to? (Multinomial Logit)
  - More common to just do one step, who do you choose, but this is better.

The common approach

- The usual approach to this kind of choice problem is multinomial logit.
- Multinomial logit builds a choice model by
  - Creating a latent variable, thing how much you like something, based on characteristics of the good.
  - Determine the odds of each choice based the relative merit of each.

Odd example

This is not exactly right but gives the flavor

- Three choices with how much you like them:
  - A: 10
  - B: 7
  - C: 3
- You would choose
  - A $10/20 = 50\%$
  - B $7/20 = 35\%$
  - C $3/20 = 15\%$

You never know for sure what people will choose but you can tell the probabilities (Technical: we see odds)

There is a technical assumption, independence of irrelevant alternatives

IIA Example

It means that if you add a new choice that is, from the decision makers point of view, just like one another, it should not change the odds of the remaining choices.

- Three choices with how much you like them:
  - A: 10
  - B: 7
  - Blue C: 3
  - Red C: 3
- You would choose
  - A $10/23 = 43.48\%$ was 50%
  - B $7/23 = 30.43\%$ was 35%
  - Blue C $3/23 = 13.0434783\%$
  - Red C $3/23 = 13.0434783\%$
- Red C and Blue C should be together 15%

See the problem? Keep this in mind.

Logit

Logit is used for yes/no or true false and does the same thing.

- Parameters give the change in odds
- Note this paper uses a linear probability model to show some results.

Sample Prices

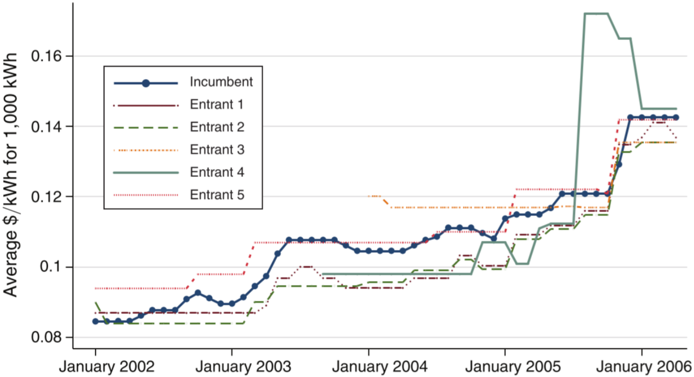

FIGURE 1. PRICES CHARGED BY INCUMBENT AND NEW ENTRANT RETAILERS IN FIRST FOUR YEARS OF MARKET

Figure 1

Price Comments

- Incumbent, LDC, prices were rigged to be a little high because they are still recovering capital costs.
- Most of the time alternative prices are higher.
- No idea if some of these are 'green' That may be why sometimes these are higher.
- TX has a bunch of wind and solar.

Market Shares

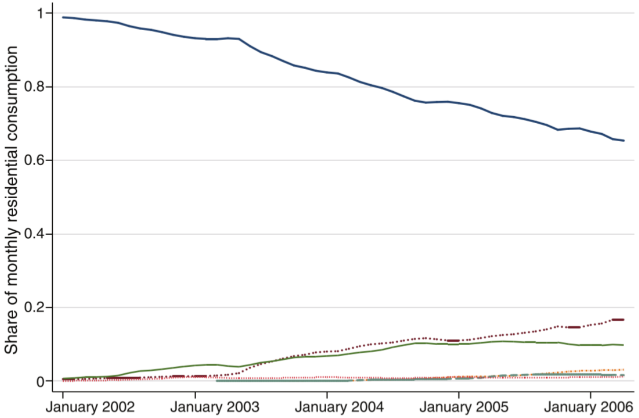

FIGURE 2. MARKET SHARES OF INCUMBENT AND NEW ENTRANT RETAILERS IN FIRST FOUR YEARS OF MARKET

Figure 2

Comments on Market Shares

- Wish I could connect prices to shares graphically.
- Wish I knew marketing expenditures.
- Makes sense that the incumbent shrinks
- Notice that one rival takes off.
- Notice that most new rivals enter and then hit a plateau
- Notice that change starts in 2003

Switching -

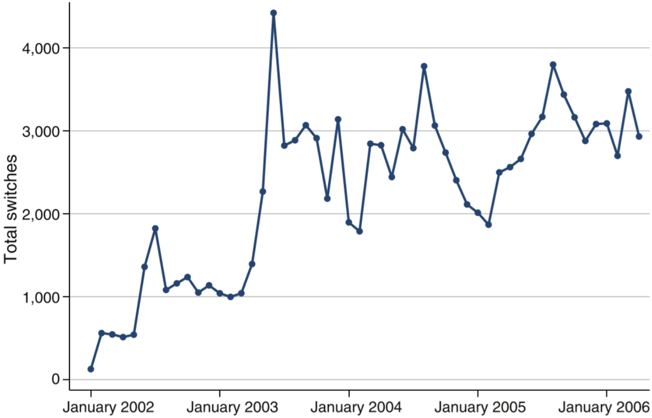

FIGURE 3. TOTAL NUMBER OF SWITCHES OF RETAILER BY MONTH

Figure 3

Comments on Switches

- Should notice a pre-2003 vs post-2003 pattern.
- See the spike in 2003?
- Authors made the smart choice of not using the data before the spike.
- Can't be sure that the world was the same before the spike and can't be sure that just a dummy variable would fix it.

Basics of Switching

TABLE 1—DESCRIPTIVE ANALYSIS OF SWITCHING AWAY FROM INCUMBENT

	Dependent variable: Indicator of switching from incumbent		
	(1)	(2)	(3)
Number of cheaper entrant retailers	0.0015 (0.0001)	0.0016 (0.0001)	0.0020 (0.0001)
log of last monthly bill received		0.0027 (0.0001)	0.0010 (0.0001)
Calendar quarter 2			0.0038 (0.0001)
Calendar quarter 3			0.0069 (0.0001)
Calendar quarter 4			0.0070 (0.0001)
Constant	0.0047 (0.0002)	−0.0081 (0.0005)	−0.0056 (0.0005)
Household fixed effects	Yes	Yes	Yes
Observations	3,729,919	3,729,919	3,729,919

Notes: This table reports factors that are associated with switching away from the incumbent. An observation is a household-month when the household was served by the incumbent in the previous month. The dependent variable is an indicator of whether the household switched away from the incumbent to an entrant retailer in that month; the mean switch rate is 1 percent. We estimate the correlations with a linear probability model using household fixed effects.

Figure 4

Comments on Switching

- This is an LP model, which you tend to avoid when probabilities are not near 50%, but this is descriptive.
- 3.7M observations so everything will be significant.
- Look at the constant. Probability of switching in any month is less than 1%
    - In model 3 the constant is quarter 1.
- Not sure how I feel about number of cheaper entrants.
    - Wouldn't I only need one?
    - What if too many choices paralyzed me. BTW well known behavioral econ effect.

What is a Markov Model?

Probability of switching from one ‘state’ to another. Example sick vs not sick.

- Given sick:
  - P staying sick .2
  - P healthy .8
- Given healthy
  - P stay healthy .95
  - P sick .05

Often shown as matrix

Row is current state and column is the next potential.

	Sick	Healthy
Sick	.2	.8
Healthy	.05	.95

Note that the paper goes other way. You can use them to find long-run probabilities

Paper's Markov Model

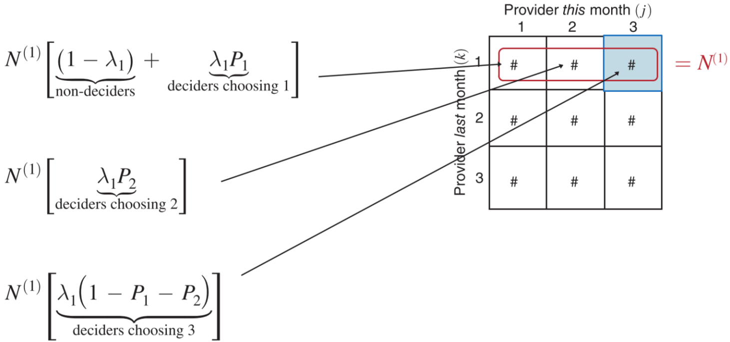

FIGURE 4. ILLUSTRATION OF IDENTIFICATION STRATEGY

Figure 5

Comments on Paper's Markov Model

- Every change is given you went to the website, did you stay or switch to others.
- If you didn't visit, you didn't change.
- Note probability of visiting the website is different depending on your ESP.
- This is the second stage.

Main Results

TABLE 2—PRIMARY MODEL RESULTS

	Benchmark (1)	Seasonality in search (2)	Large bill affects search (3)	All (4)
Stage one: Decision to choose				
Parameters (γ)				
Constant	−3.363	−3.720	−3.468	−3.643
	(0.045)	(0.123)	(0.048)	(0.149)
Incumbent	−0.643	−0.647	−0.589	−0.626
	(0.064)	(0.062)	(0.068)	(0.064)
January		0.222		0.038
February		0.375		0.315
March		0.266		0.043
April		0.041		−0.125
May		0.210		0.176
June		0.228		0.170
July		0.638		0.364
August		0.635		0.474
September		0.541		0.424
October		0.547		0.429
November		0.383		0.365
Large bill ($ change in two most recent bills)			0.007	0.003
			(0.002)	(0.003)
Estimated effects				
Pr(monthly search) incumbent customer (λ)	0.018	0.018	0.018	0.017
Pr(monthly search) entrant customer (λ)	0.033	0.033	0.032	0.032
Stage two: Choice of retailer				
Parameters (θ)				
Price (cents/kWh)	−0.435	−0.464	−0.462	−0.445
	(0.091)	(0.083)	(0.096)	(0.085)
Incumbent brand dummy	2.764	2.946	2.789	2.834
	(0.256)	(0.269)	(0.294)	(0.293)
Incumbent month-of-sample counter	−0.076	−0.086	−0.075	−0.080
	(0.014)	(0.015)	(0.016)	(0.016)
Estimated effects				
Incumbent price elasticity	−2.52	−2.61	−2.67	−2.55
Average entrant price elasticity	−4.51	−4.82	−4.80	−4.62
Incumbent brand effect ($/mo) in January 2004	$61.86	$61.61	$58.72	$61.85
Incumbent brand effect ($/mo) in April 2006	$14.87	$11.67	$14.66	$13.50

Figure 6

Comments on the Main Results

- See no SD for months. Common for nuisance parameters.
- Large bill is probability correlated with month, why the effect goes down and is not significant in model 4.
- Incumbent (LDC) parameter is stable.
- Once you start switching, you are more likely to switch again.
- Brand effect gets smaller
  - Slightly larger potential savings later.
  - Unbelievably huge earlier
- See different price elasticities.

People that Move are different?

TABLE 3—ILLUSTRATING IMPLICATIONS OF OUR MODELING FRAMEWORK

	Benchmark (1)	Include movers (2)	No decision stage (3)
Stage one: Decision to choose			
Parameters (γ)			$\lambda_{it}^{k} == 1$
Constant	−3.363	−3.363	
	(0.045)	(0.045)	
Incumbent	−0.643	−0.643	
	(0.064)	(0.064)	
Estimated effects			
Pr(monthly search) incumbent customer (λ)	0.018	0.018	== 1
Pr(monthly search) entrant customer (λ)	0.033	0.033	== 1
Stage two: Choice of retailer			
Parameters (θ)			
Price (cents/kWh)	−0.435	−0.435	−0.008
	(0.091)	(0.091)	(0.002)
Incumbent brand dummy	2.764	2.764	0.132
	(0.256)	(0.256)	(0.024)
Incumbent × month–of–sample counter	−0.076	−0.076	−0.004
	(0.014)	(0.014)	(0.001)
Mover × price		−0.090	
		(0.118)	
Mover × incumbent		1.231	
		(0.276)	
Mover × incumbent × month–of–sample counter		0.030	
		(0.015)	
Estimated effects			
Incumbent price elasticity	−2.52	−2.51	−0.08
Average entrant price elasticity	−4.51	−4.46	−0.08
Incumbent brand effect ($/mo) in January 2004	$61.86	$61.86	$163.51
Incumbent brand effect ($/mo) in April 2006	$14.87	$14.87	$30.80
Movers incumbent brand effect ($/mo) in January 2004		$75.25	
Movers incumbent brand effect ($/mo) in April 2006		$51.58	

Figure 7

Comments on the movers.

Basically, people that moved had less information and focused on the LDC

Robustness Check

TABLE 4—BENCHMARK MODEL BY NEIGHBORHOOD DEMOGRAPHICS

	Income		Education		% senior citizens	
	Below median	Above median	Below median	Above median	Below median	Above median
Stage one: Decision to choose						
Parameters (γ)						
Constant	−3.298	−3.385	−3.300	−3.437	−3.426	−3.292
	(0.100)	(0.048)	(0.104)	(0.039)	(0.047)	(0.093)
Incumbent	−1.019	−0.350	−1.284	−0.197	−0.291	−1.021
	(0.151)	(0.066)	(0.155)	(0.055)	(0.071)	(0.148)
Estimated effects						
Pr(search) if incumbent customer (λ)	0.013	0.023	0.010	0.026	0.024	0.013
Pr(search) if new retailer customer (λ)	0.036	0.033	0.036	0.031	0.031	0.036
Stage two: Choice of retailer						
Parameters (θ)						
Price (cents/kWh)	−0.275	−0.499	−0.134	−0.456	−0.497	−0.406
	(0.146)	(0.104)	(0.111)	(0.095)	(0.093)	(0.235)
Incumbent	3.204	2.641	3.707	2.194	2.327	3.616
	(0.538)	(0.275)	(0.602)	(0.173)	(0.225)	(0.507)
Incumbent × month-of-sample counter	−0.091	−0.071	−0.124	−0.046	−0.055	−0.104
	(0.030)	(0.015)	(0.032)	(0.009)	(0.012)	(0.028)
Estimated effects						
Incumbent price elasticity	−1.35	−3.04	−0.59	−2.98	−3.23	−1.81
Avg. entrant price elasticity	−2.93	−5.13	−1.46	−4.67	−5.08	−4.36
Incumbent brand effect ($/mo) in January 2004	$113.31	$51.51	$266.78	$47.10	$45.70	$86.41
Incumbent brand effect ($/mo) in April 2006	$23.47	$13.13	$17.08	$19.89	$16.04	$17.05

Notes: This table reports results of estimating the benchmark model (column 1 of Table 2) split by the demographic characteristics of the household's census block group. A household is classified by whether its census block group is above or below the median among all census block groups. Education is defined by the fraction of the population with a bachelor's degree or above.

Source: Authors' calculations

Figure 8

Comments on Robustness

- This adds new variables, could be robustness or just different ways of adding the variables.
  - The divisions are neighborhood effects.
  - They can't observe who you are.
- Rich, Educated and not seniors have smaller brand effects.
  - Differences compress over time.
  - Poor and elderly can be very risk averse.

Two Potential Treatments

Thought experiment on why there is a brand effect. These are two potential bill stuffers.

- "The State of Texas has created a website www.powertochoose.com where you can see all the options available to you. It's quick. It's easy to use. And you can switch your retailer at no cost to you in 15 minutes or less."
- "*It's all the same power*—the quality of electrical service will not change because $\ll$Firm X$\gg$ controls your powerlines rather than $\ll$The Incumbent$\gg$ or any other retailer."

Figure 9

The stuffers.

- Low cost to switch.
- Same produce, only the price is different.

A Few Small Flaws

- No real analysis for risk attitudes. Low income and elderly face more risks to change.
- Why has no expert middleman arisen to handle switching?
- IAA? What if the alternatives had the same price or prices that were 'similar enough'?