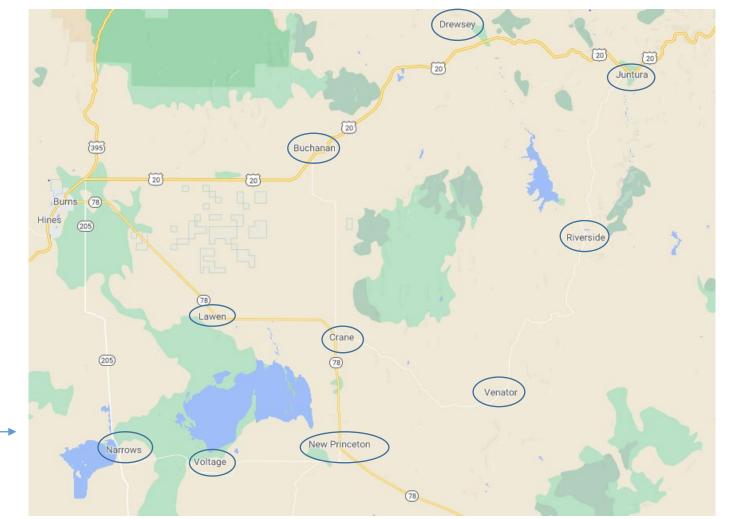


Bresnahan and Reiss: "Entry and Competition in Concentrated Markets," JPE 1991

The research question here is how competition changes with entry.

We have noted that reliable data on markups can be difficult to come by. What if, instead, we look at the number of firms in a series of markets. What can observing these numbers tell us about competition?

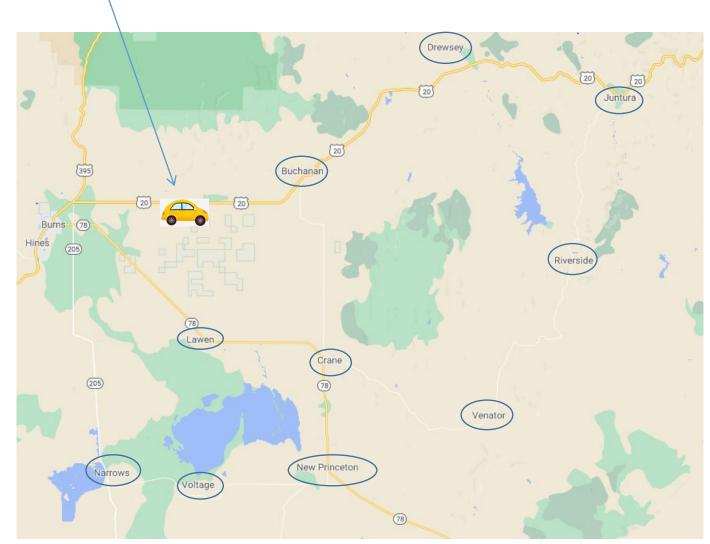
A market could be a particular good or service in a geographically isolated town. These are towns in the western VS.



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Bresnahan and Reiss: "Entry and Competition in Concentrated Markets," JPE 1991 Tim and Peter

B-R did a few things to collect data for this project. They consulted phone books and business directories to find the number of various types of business in about 200 isolated towns in the western US. (Think doctors, dentists, plumbers, etc.) They also collected population and demographic data on each town. Finally, they drove to visit them, to make sure that the data on firms they had collected was accurate and to verify that they were isolated markets.



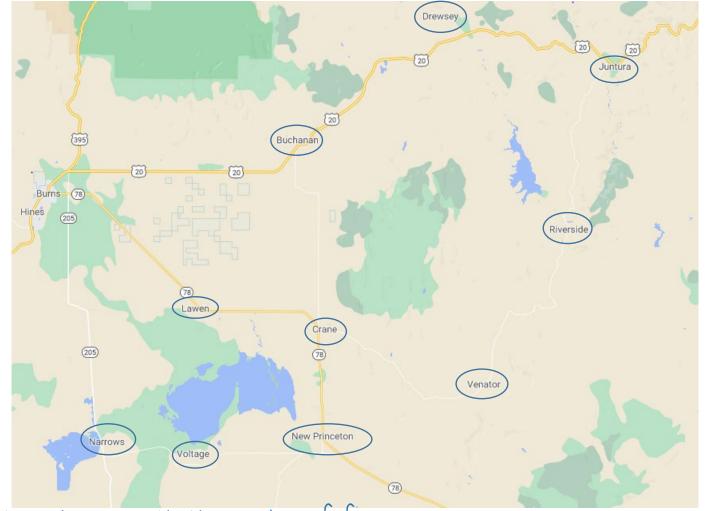
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Bresnahan and Reiss: "Entry and Competition in Concentrated Markets," JPE 1991

Note that this paper does not observe entry or exit of firms in these markets. They, instead, have a snapshot of existing firms.

So why is "entry" in the paper title? Because they are interpreting the number of firms as the equilibrium outcome of a free-entry game in each town.

We can, then, infer something about that game if we know (or can estimate) the market size and we observe the number of firms. © Google. All rights reserved. This content is excluded from our Creative Commons license. For more information, see https://ocw.mit.edu/help/faq-fair-use/



like how competition changes with the number of firm

- Basic idea
 - Consider entry decision of a firm with fixed costs F under symmetric competition with per-firm profits $\pi(S, N) = \frac{S}{N}(p_N c)D(p_N) \equiv \frac{S}{N}\pi_N$
 - We will have N firms in equilibrium if $\frac{S}{N}\pi_N > F > \frac{S}{N+1}\pi_{N+1}$
 - Let S_N be the minimum size at which a market has N firms.
 - We assumed F does not vary with N so $\frac{S_N}{N}\pi_N = F = \frac{S_{N+1}}{N+1}\pi_{N+1}$ gives

$$\frac{\pi_{N+1}}{\pi_N} = \frac{N+1}{N} \frac{S_N}{S_{N+1}}$$

• If entry increases competition (i.e., if more firms means lower markups) then we would expect this ratio to be less than 1. We can estimate how N affects per-customer profits by estimating the thresholds S_N.

This is a really powerful idea: no data on markups, costs, prices, or quantities! And yet we can infer something about the nature of competition among these firms. 5

The previous slide suggests just directly estimating thresholds. B-R do something a little more complicated because they want to allow covariates to affect various model elements.
Effective population S₁ = Rep. 1, V 2

- Effective population $S_i = Pop_i + X_i \lambda$ growin rates, etc. per capita variable profit fn of # firms, per
- Per consumer profits $\pi_{iN} = \alpha_N + X_i\beta$ capita income, age distribution, etc.
- Per firm profits with N firms $\pi_i = \frac{S_i}{N} \pi_{iN} F_i + \varepsilon_i \longrightarrow N(0,1)$ market-specific shock

This is an "ordered probit" model, which one typically estimates by MLE:

$$L(N_i|X_i;\alpha,\beta,\gamma,\delta,\lambda) = Prob\left\{-\left(\frac{S_i}{N}\pi_{iN} - F_i\right) \le \varepsilon_i < -\left(\frac{S_i}{N+1}\pi_{iN+1} - F_i\right)\right\}$$

This directly estimates the α_N , but the presentation then goes back to implied S_i .

- Data
 - Gathered data on the number of dentists, druggists, plumbers, tire dealers, etc. in 202 small towns in the Western US.
 - The mean population of their small towns is 3,740.
 - All are at least 100 miles from any city of 100,000 people and at least 20 miles from any town of 1,000 people.

TABLE 2

Industry	NUMBER OF FIRMS								
	N = 0	N = 1	N = 2	N = 3	N = 4	N = 5	N = 6	$N \ge 7$	
Druggists	28	62	68	23	8	6	3	4	
Doctors	37	61	36	16	11	7	6	28	
Dentists	32	67	39	15	12	12	4	21	
Plumbers	71	47	26	21	10	4	6	17	
Tire dealers	45	39	39	24	13	15	6	21	
Barbers	95	66	23	9	3	6	0	0	
Opticians	173	19	5	1	4	0	0	0	
Beauticians	10	26	19	24	26	19	11	67	
Optometrists	68	85	36	7	3	3	0	0	
Electricians	60	54	32	17	10	5	7	17	
Veterinarians	53	80	41	21	5	0	1	1	
Movie theaters	90	72	25	10	5	0	0	0	
Automobile dealers	38	44	54	35	25	2	1	3	
Heating contractors	117	40	19	8	4	8	3	3	
Cooling contractors	153	30	13	5	1	0	0	0	
Farm equipment dealers	90	39	23	19	17	9	1	4	

MARKET COUNTS BY INDUSTRY AND NUMBER OF INCUMBENTS

SOURCE .- Authors' tabulations from American Business Lists, Inc.

Here are some descriptive statistics. Lots of variation across towns and firm type in # of firms.

TABLE 5

Per-firm entry

threshold ratio is an

estimate of π_N/π_{N+1}

A. ENTRY THRESHOLD ESTIMATES

Profession	ENTRY THRESHOLDS (000's)					PER FIRM ENTRY THRESHOLD RATIOS			
	S_1	S_2	S_3	S_4	S_5	s_2/s_1	s ₅ /s ₂	s_4/s_3	s_{5}/s_{4}
Doctors	.88	3.49	5.78	7.72	9.14	1.98	1.10	1.00	.95
Dentists	.71	2.54	4.18	5.43	6.41	1.78	.79	.97	.94
Druggists	.53	2.12	5.04	7.67	9.39	1.99	1.58	1.14	.98
Plumbers	1.43	3.02	4.53	6.20	7.47	1.06	1.00	1.02	.96
Tire dealers	.49	1.78	3.41	4.74	6.10	1.81	1.28	1.04	1.03

B. LIKELIHOOD RATIO TESTS FOR THRESHOLD PROPORTIONALITY

Profession	Test for $s_4 = s_5$	Test for $s_3 = s_4 = s_5$	Test for $s_2 = s_3 = s_4 = s_5$	Test for $s_1 = s_2 = s_3 = s_4 = s_5$
Doctors	1.12 (1)	6.20 (3)	8.33 (4)	45.06* (6)
Dentists	1.59 (1)	12.30* (2)	19.13* (4)	36.67* (5)
Druggists	.43 (2)	7.13 (4)	65.28* (6)	113.92* (8)
Plumbers	1.99 (2)	4.01 (4)	12.07 (6)	15.62* (7)
Tire dealers	3.59 (2)	4.24 (3)	14.52* (5)	20.89* (7)

NOTE.—Estimates are based on the coefficient estimates in table 4. Numbers in parentheses in pt. B are degrees of freedom. * Significant at the 5 percent level.

In all businesses except for plumbers per-consumer profits drop by 40-50% when a second firm enters.
Most businesses have further increase in competition with 3rd firm. Magnitudes vary.
All businesses seem to have reached competitive limit by the time N=4.

Comments:

- The model interprets the number of observed firms as the equilibrium number that would enter given the market size and effect of competition on profits. Many towns are declining. If firms pay a sunk cost to enter, there could be a discrepancy between whether it's profitable to stay and whether firms would not enter.
- Counting firms can be more difficult in their application than in businesses with more substantial fixed assets. How do we count a minister/handyman who does some plumbing? A store clerk who cuts hair on the side? Data on opticians, doctors, dentists is better in this regard.
- The basic idea of inferring profits from entry has been tremendously influential. The strategy of using isolated markets as independent observations is also widespread.

Berry and Waldfogel: "Free Entry and Social Inefficiency in Radio Broadcasting," *RAND* 1999

We saw that, in theory, entry can be higher (due to business stealing) or lower (due to firms not considering consumer surplus) than is socially optimal.

In this paper, Berry and Waldfogel aim to quantify the sign and magnitude of the difference between actual and socially optimal entry and to estimate welfare losses from free entry in the radio industry.



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Before we cover this paper, it's useful to point out that broadcast radio can be thought of as a platform, matching listeners and advertisers.

Advertisers pay the platform for "ears." Listeners care about the content and may just put up with the advertising.

The standard way that US antitrust authorities treat media markets is to focus on the side of the business that involves stations producing ears and selling them to advertisers. With this perspective, actions that limit the number of commercials per hour will be thought of as restricting output and creating DWL.

BW mostly focus on this side too, ignoring the welfare of listeners, but they are well aware of the issue and discuss it when presenting results.

The basic idea of B-W is to estimate how the actual number of radio stations in 135 US markets compares with what would be "socially efficient" and to estimate welfare losses.

They primarily follow the FTC approach of considering only station profits and advertiser surplus, and also assume that "ears" are a homogeneous good.

With this approach the welfare function is a simplified version of the homogenous good entry model from last class (with purely fixed costs).

$$W(N) = \int_0^{NL^*(N)} P(x) dx - NF$$

Elements to be estimated are the per-firm listening function $L^*(N)$, advertiser inverse demand P(L), and fixed costs F.

Listening $L^*(N)$ is is derived from nested logit preferences for consumer utility. Utility for i from listening to station j is $\ln \alpha$ symmetric model $NL^*(N) = \frac{N^{1-\sigma}}{\sigma^{-\delta} + N^{1-\sigma}}$

$$u_{ij} = \delta_j + \nu_i(\sigma) + (1 - \sigma)\varepsilon_{ij}.$$

The parameter σ gives the model flexibility in estimating business stealing: when $\sigma = 1$ a new firm's demand is entirely business stealing; when $\sigma = 0$ we have logit demand. In the data listening varies across markets. IV estimates use population as an instrument for the number of firms.

Advertising inverse demand is assumed to depend on the share S_k listening in market k. Estimate

 $\ln(p_k) = x_k \delta + \eta \ln(S_k) + \omega_k$

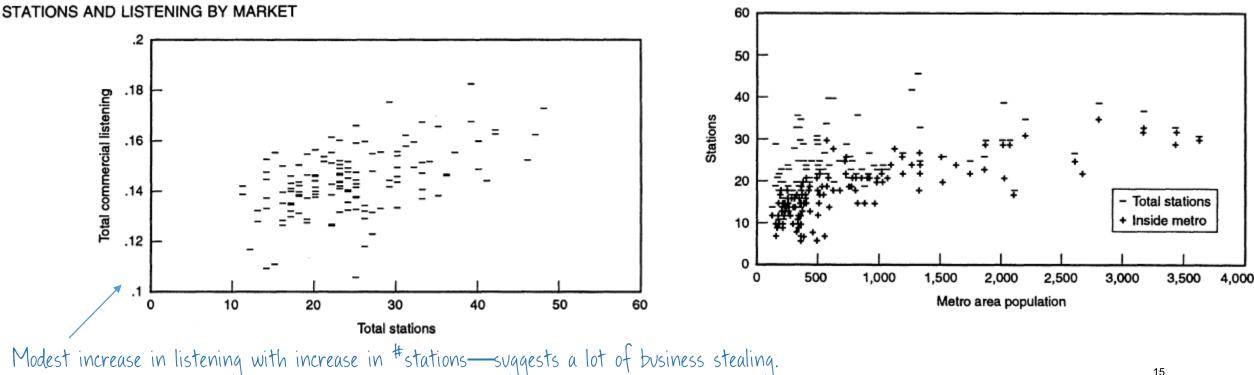
using market-level data on advertising revenues.

Fixed costs are estimated via an ordered probit-like approach similar to that in Bresnahan-Reiss. Fixed costs are assumed to be drawn from a log-normal distribution with a mean and standard distribution to be estimated.

Data contain information on 3,285 stations in 135 markets.

Listening

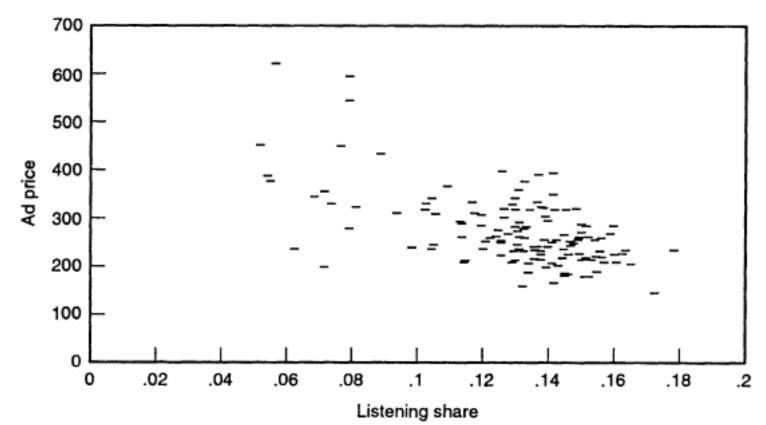
The raw data underlying the demand estimates is shown below.



POPULATION AND STATIONS BY MARKET

Advertising prices (per listener-hour) do decline in the listening share.

IN-METRO LISTENING SHARE AND AD PRICE



Results:

- 1. They estimate σ close to 1, which implies that entry results mostly in business stealing, as opposed to market expansion.
- 2. They estimate that welfare under free entry is \$5.3 billion, with \$7.6 billion under a social planner, and \$7.4 billion if a monopolist (!) was allowed to choose the number of stations in each market.
- 3. There are 2509 within-metro stations in the dataset. They estimate that 649 stations would be socially optimal.

Advertising price: $277 \rightarrow 326$

Listening share: $12.9\% \rightarrow 9.3\%$

Fixed costs: $\$5.0B \rightarrow \$1.1B$

4. To make the current number of stations optimal, we would need listener surplus of about 13.5 cents/listener hour. (Advertising revenues are about 4.2 cents.)

	Free Entry	Optimal	Monopoly
In-metro entry	2,509	649	341
-		(46)	(55)
Aggregate costs (\$ millions)	5,007	1,144	602
	(3)	(92)	(101)
Aggregate revenue (\$ millions)	5,100	4,334	3,959
		(204)	(173)
Welfare (\$ millions)	5,331	7,640	7,422
	(3,064)	(3,037)	(2,878)
Ad price	277	326	375
		(11)	(48)
Listening share (%)	12.91	9.28	7.53
		(.19)	(.50)

TABLE 4Comparison of Free Entry, Optimality, and Monopoly

The free-entry numbers without standard errors are calculated directly from data. The difference between free entry and optimal welfare has a standard error of 167.

The approach has several limitations (many noted in section 7):

- 1. Modeling "ears" as a homogeneous good sold to advertisers implies that entry is excessive, so they are just estimating how excessive.
- 2. Ears produced by different stations, e.g. classical vs. top 40, are presumably differentiated from the advertiser perspective and match-quality surplus from this is not estimated.
- 3. Given that all stations are free, the paper can't directly estimate listener surplus.
- 4. It would be nice to allow firm quality and fixed costs to vary across stations. Listenership is very different across stations.
- 5. It would be nice to estimate the effect of the number of minutes of advertising per hour on station-level listening and make advertising minutes a choice variable.

Bronnenberg, Dhar, and Dubé: "Brand History, Geography, and the Persistence of Brand Shares," JPE 2009

Much of the theory literature treats all entrants as competing on level terms.

The empirical literature has long noted that this seems far from accurate even on many products that seem undifferentiated.



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Kraft high in Denver, low in LA; Bronnenberg, Dhar, and Dubé: "Persistence of Brand Shares"

Golder and Tellis (JMR 1993) noted that many leading brands have been leaders for a very long time.

BDD argue against persistent quality differences by noting that leaders differ across cities.

- The graph at right shows market 1. shares for two mayonnaise brands in Denver and Los Angeles.
- 2. Ground coffee is another example. Folger's share ranges from 16% in NYC to 59% in Des Moines. Maxwell House's share is 4% in Seattle and 46% in Pittsburgh.

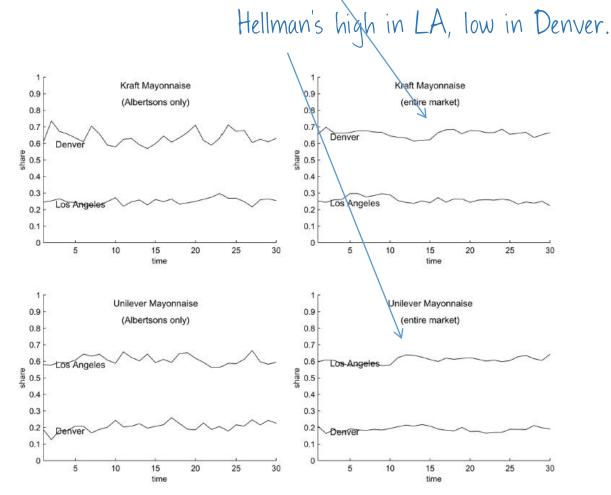


FIG. 1.—Brand shares in the mayonnaise industry with retailers and in markets (time is measured in 4-week intervals). And they're persistent.

21

Bronnenberg, Dhar, and Dubé: "Persistence of Brand Shares"

BDD present two analyses connecting market share variation and entry.

1. They found the city of origin for 40 brands. (The median entry date is about 100 years ago.)

They regress each brand's city-specific market shares on the distance to origin.

Share_{*icm*} =
$$\alpha_i + \sum_{k=0}^{11} \delta_k \text{Dist}_{icm}^k + \epsilon_{im}$$

2. In six product categories they were able to identify the order in which the two leading products entered each city.

They regress city-specific market shares on brand fixed effects and entry order dummies.

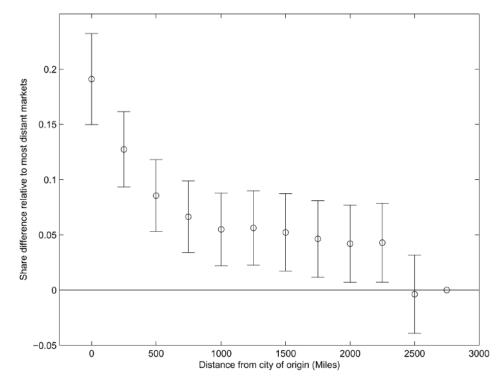
Bronnenberg, Dhar, and Dubé: "Persistence of Brand Shares"

Industry	Brand	City of Origin	Year of Launch	
Bagels	Lender's	New Haven, CT	1927	
Bagels	Sara Lee	Greenville, SC	1985	
Beer	Budweiser	St. Louis	1876	
Beer	Miller	Milwaukee	1855	
Bread	Wonder	Indianapolis	1921	
Bread	Sunbeam	Philadelphia	1942	
Breakfast sausage	Jimmy Dean	Plainview, TX	1969	
Breakfast sausage	Bob Evans Farm	Gallipolis, OH	1948	
Butter	Land o'Lakes	Saint Paul, MN	1924	
Butter	Challenge	Los Angeles	1911	
Cereal	Kellogg's	Battlecreek, MI	1906	
Cereal	General Mills	Minneapolis	1924	
Chunk cheese	Kraft	Chicago	1903	
Coffee	Folgers	San Francisco	1872	
Coffee	Maxwell House	Nashville	1892	
Cottage cheese	Knudsen	San Diego	1919	
Cream cheese	Philadelphia	Chester, NY	1880	
Cream cheese	Temptee	Louisville	1927	
Dinner sausage	Thorn Apple Valley	Detroit	1969	
Dinner sausage	Eckrich	Fort Wayne, IN	1894	
Dried rice	Uncle Ben's	Beaumont, TX	1943	
Dried rice	Mahatma	Abbeville, LA	1911	
Frozen topping	Cool Whip	Avon, NY	1967	
Frozen topping	ReddiWip	St. Louis	1948	
Fruit spreads	Smucker's	Orrville, OH	1897	
Fruit spreads	Welch's	Concord, MA	1869	
Hot dogs	Oscar Mayer	Chicago	1900	
Hot dogs	Hygrade	Southfield, MI	1957	
Ketchup	Heinz	Pittsburgh	1876	
Ketchup	Hunts	Santa Rosa Valley, CA	1890	
Marshmallows	Campfire	Elk Grove Village, IL	1917	
Mayonnaise	Kraft	Salem, IL	1931	
Mayonnaise	Unilever	New York City	1905	

Bronnenberg, Dhar, and Dubé: "Persistence of Brand Shares"

Estimates:

- 1. The distance-to-origin analysis finds that current market shares are 18 percentage points higher in the closest cities than in the most distant cities. (The mean share is 22%.)
- 2. The order of entry analysis finds that the first-entrant advantage ranges from 1.3 points (Budweiser vs. Miller beer) to 6.3 points (Kraft vs. Unilever mayonnaise).



Bronnenberg, Dubé, Gentzkow: "The Evolution of Brand Preferences: Evidence from Consumer Migration," AER 2012

Persistent brand advantages could have diverse causes:

- 1. Demand side. Consumers could develop tastes for products they consumed growing up.
- 2. Supply side. Economies of scale in advertising, allocation of shelf space, etc. may help leading brands invest in maintaining their dominant position.

BDG investigate this by examining the purchase patterns of people who move.

The dataset highlights the benefits of being well funded and well connected: they got Nielsen to survey the members of its Homescan panel to learn their state of birth, date moved, time in current location, gender, education, etc. With a 65% response rate, they have information on 80,000 individuals in 49,000 households.

Quite a contrast with Bresnahan-Reiss.

Members of the Homescan panel scan items they purchase from any store.

Nielsen classifies UPC codes by both product category ("module") and brand. BDG focus on the **top two brands** in the 238 modules for which they observe at least 5000 purchasing households and the top two brands have different owners.

Current market share data is supplemented with historical data at the state level from 1948-1968 obtained from published surveys.

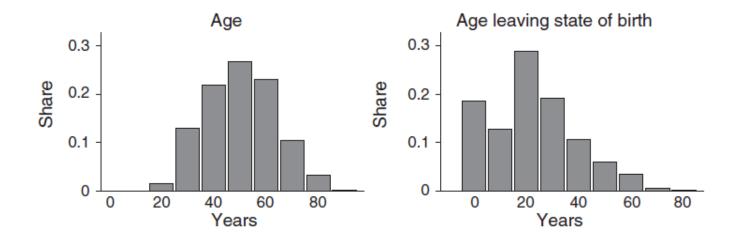
Here's part of the product list. "Aggregate purchase share" is share of brand 1 among purchases of brand 1 or brand 2. In mayo, Hellmann's vs. Kraft is 0.55 SD 0.25.

Module	Brand 1	Brand 2	Aggregate purchase share	Cross-state SD	Ad intense	Socially visible
Abrasive clnsr-liq	Soft Scrub	Comet	0.90	0.07	0	0
Abrasive clnsr-pwdr	Comet	Ajax	0.78	0.08	0	0
Adult incont. prod	Poise	Tena Serenity	0.68	0.15	0	0
Analgesic/chest rubs	Icy Hot	Vicks Vaporub	0.55	0.12	0	0
Antacids	Prilosec	Rolaids	0.71	0.08	1	0
Anti-gas products	Beano	Gas-X	0.52	0.13	0	0
Auto. dishwshr cmpnd	Cascade	Electrasol Jet-Dry	0.73	0.08	0	0
Baby food-strained	Gerber	Beechnut Stages	0.70	0.17	0	0
Bakery bagels	Thomas'	Sara Lee	0.74	0.29	0	0
Bakery bfast rolls	Little Debbie	Entenmann's	0.64	0.24	0	0
Bakery bread	Nature's Own	Sara Lee Soft and Smth	0.50	0.32	0	0
Bakery buns	Sara Lee	Wonder	0.61	0.32	0	0
Bakery cakes	Little Debbie	Hostess	0.91	0.07	0	0
Bakery cheesecake	The Father's Table	Cheesecake Factory	0.59	0.24	0	0
Bakery doughnuts	Hostess	Entenmann's	0.52	0.27	0	0
Bakery misc.	Homestyle	Flatout	0.51	0.26	0	0
Bakery pies	Little Debbie	JJ's	0.52	0.29	0	0
Bakery rolls	King's Hawaiian	Martin's	0.51	0.36	0	0
Baking cups and liners	Reynolds	Wilton	0.78	0.07	0	0
Bath additive-liq	Lander	Mr. Bubble	0.73	0.20	0	0
Beer	Budweiser	Miller High Life	0.64	0.19	1	1
Bouillon	Wyler's	Knorr	0.61	0.25	0	0

About 27% of households are "migrants" (primary shopper born in a different state). About 16% were born in a different census region.

Region of birth	Region of residence				
	Northeast	Midwest	South	West	
Northeast	6,765	269	1,539	448	
Midwest	165	10,654	1,377	885	
South	193	435	9,725	292	
West	56	214	341	4,740	

TABLE 1—MIGRATION PATTERNS



For each migrant i and category j define β_{ij} to reflect the degree to which purchase shares resemble those of nonmigrants in their current state s' vs. birth location s.

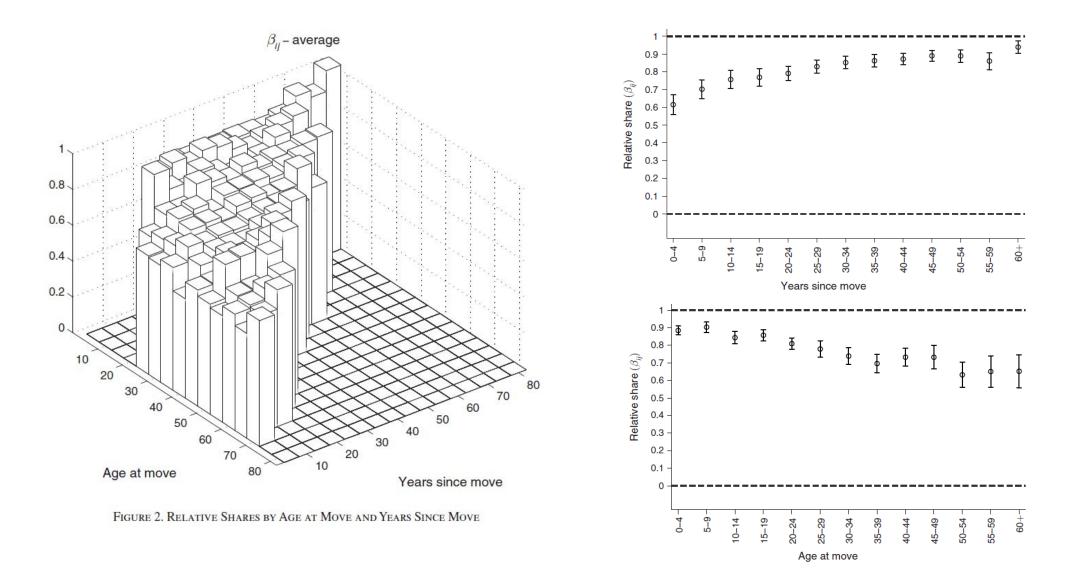
$$\beta_{ij} = rac{\hat{y}_{ij} - \hat{\mu}_{sj}}{\hat{\mu}_{s'j} - \hat{\mu}_{sj}}$$

They estimate how purchase patterns are related to the age a_i at which the individual moved and time t_i spent at their current location estimating

$$\beta_{ij} = f(a_i, t_i) + \varepsilon_{ij}$$

via weighted least squares, placing more weight on observations where the birth and current state patterns are more different.

Figures 2-4 present the estimated $f(a_i, t_i)$ and easier to read versions collapsed to a single dimension.



Results:

- 1. People instantly move 60% of the way toward the new location purchasing pattern upon moving. This suggests that the differences in BDD are not just due to endogenous tastes and must reflect also advantages due to shelf placement, advertising, etc.
- 2. Purchases become more similar to the new-location norm over time. By 20 years post-move consumers have shifted 80% of the way to the new-location norm.
- The β's are also related to the age at move. The age < 10 mean is 90%. The age 60+ mean is 65%.
- 4. Data on pre-move migrants indicates that result 1 is not about selection into moving.

Dependent variable:		(2)	(2)		1.5
Relative share (β_{ij})	(1)	(2)	(3)	(4)	(5)
Decades since move	0.098	0.079	0.075	18-10-	0.092
	(0.009)	(0.009)	(0.010)	3 <u>1</u>	(0.016)
Decades since move squared	-0.009	-0.008	-0.007		-0.010
	(0.001)	(0.001)	(0.001)		(0.004)
Age (in decades) when moved	<u>a-a</u>	-0.018		-0.019	-0.013
Na an		(0.005)		(0.005)	(0.008)
Constant	0.624	0.705	37-39	8	0.668
	(0.029)	(0.026)	<u> </u>	<u> 19 - 19 -</u>	(0.037)
Decades since move fixed effects	no	no	no	yes	no
Age when moved fixed effects	no	no	yes	no	no
Sample	all	all	all	all	age
-					moved ≥ 25
Number of modules	238	238	238	238	238
Number of HH-module observations	528,621	528,621	528,621	528,621	212,957

TABLE 3-THE EVOLUTION OF BRAND PREFERENCES FOR MIGRANTS

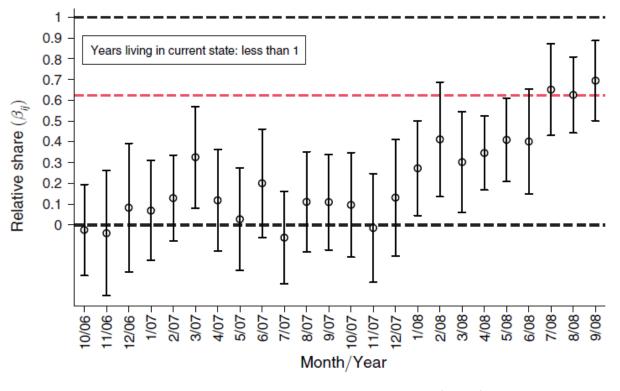


FIGURE 5. RELATIVE SHARES BY MONTH (MOVED 10/07-9/08)

Next week's topic is strategic investment.

Monday's lecture will be basic theory, much of it from Chapter 8 of Tirole.

See you then!

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14.271 Industrial Organization I Fall 2022

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