Price Discrimination

Glenn Ellison

Price Discrimination Empirics

Again, all of the models I discussed last class are mathematically correct. But empirical work could help us think about many questions. Some examples are:

1. Do firms price discriminate?
2. Is pricing consistent with what the models say about how prices would be related to elasticities, etc. if profit-maximizing? How does it differ?
3. How large are the potential/realized profits from discrimination?
4. What are the effects of discrimination on consumer surplus and social welfare?
5. What types of information are most valuable for discrimination?

Early NEIO Empirical Papers

An early empirical literature made the basic case that firms do engage in degree price discrimination. Two papers looked at gasoline prices, and reflect NEIO sensibilities in being cautious about cost data.

- Borenstein (*Rand* 1991) argued that leaded-unleaded gasoline price differences are an example of 3rd degree discrimination. He relied on cost data, accounting for differences in credit-card usage, average quantity, etc.
- Shepard (*JPE* 1991) argued that the gaps between self-serve and full-serve gas prices at dual-format stations are an example of 2nd degree discrimination. She argues that price data from single-product stations (just full-serve or just self-serve gasoline) can provide a control for costs of providing full service.

Race and Gender Discrimination in Retail Prices

There is substantial interest in whether (and why) firms discriminate by race and gender in pricing. Different papers have reported substantially different results.

- Ayres and Siegelman (*AER* 1995). Sent identically trained white/black buyers to car dealerships. Report that black males were charged $1100 more than white males and black females were charged $410 more than white females.
- Goldberg (*JPE* 1996). Used data on car purchases from the Consumer Expenditure Survey. Found no significant differences in prices paid by whites and blacks.
- Graddy (*RAND* 1995). Collected data on purchases of whiting at New York's Fulton Street Fish Market. Found that Asians paid 7% less than whites on average.

The data available limit what the papers can do.

“Consumer Information and Discrimination: Does the Internet Affect the Pricing of New Cars to Women and Minorities”, Scott Morton, Zettelmeyer, Silva-Risso, *QME* 2003

The paper has multiple motivations:

- Reexamine earlier findings on car prices exploiting much richer data now available to them
- Examine whether profit-maximizing price discrimination models explain price differences
- Examine whether shift to online sales affects discrimination

"Consumer Information and Discrimination," Scott Morton, Zettelmeyer, Silva-Risso

The paper is from early in the e-retail era. The online data come from from a firm that pioneered car sales over the internet, Autobytel. The offline data come from a firm, JD Power, that gathers data from and provides data to car dealers.

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The dataset for the paper is remarkable and highlights the value of seeking out and gaining access to new data sources.

- Transaction-level data on 671,468 purchases at 3562 US dealerships from January 1, 1999 to February 28, 2000.
  - Detailed model information including engine, transmission, trim level, and the dealer cost of additional accessories
  - Transaction price together with the dealer's estimate of any trade-in overallowance
  - Buyer's home address and a name-based guess of gender and Latinx/Asian ethnicity
- Transaction-level data on each of the 2,000,000 requests for price quotes submitted in 1999 by users of Autobytel.com. Requests are passed on to a single dealer who is encouraged to have a dedicated salesperson contact the consumer and offer a no-haggle price.
  - Requests matched to the auto purchase database

“Consumer Information and Discrimination”

Estimates of Price Differences

The initial analysis of whether firms discriminate by race/gender is a simple regression of log price on consumer and neighborhood demographics D_i and controls X_i:

$$\log(P_i) = D_i\Upsilon + X_i\beta + \varepsilon_i$$

The vector X_i of controls includes car fixed effects, costs of accessories, month, region, weekend, and end-of month dummies, and a measure of the number of nearby dealers.

“Consumer Information and Discrimination”

Estimates of Price Differences

The analysis provides precise estimates of a number of ways in which prices paid covary with individual and census block group demographics:

- Those in more black areas pay more (1.5%)
- Those in more Hispanic areas pay more (1.1%)
- Those in more Asian areas pay less (0.4%)
- Hispanic and Asian effects visible in buyer characteristics
- Women pay more (0.2%)

There are also many systematic differences in addition to those for race, gender, and ethnicity.

- Those in more college educated areas pay less (0.3%)
- Those in areas with more homeowners pay less (0.3%)

Table 2. Effect of demographics on car prices.†

Dep. variable ln (price)	(1) Full sample	(2) Full sample	(3) > 75% or < 2%Black
%Black	0.015	0.015	
	(0.00054)**	(0.00054)**	
%Hispanic	0.011	0.0067	0.0029
	(0.001)**	(0.001)**	(0.0014)*
%Asian	− 0.0039	− 0.00096	− 0.00031
	(0.00096)**	(0.00098)	(0.0014)
Hispanic		0.51	0.54
		(0.03)**	(0.038)**
Asian		− 0.97	− 0.85
		(0.043)**	(0.058)**
%Black > 75			1.37
			(0.062)**
Female	0.21	0.21	0.19
	(0.01)**	(0.01)**	(0.018)**
Customer Age	0.0045	0.0047	0.003
	(0.00063)**	(0.00063)**	(0.00081)**
Age > 64	− 0.17	− 0.17	− 0.15
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MedianHHIncome	− 0.00002	− 0.00002	− 0.00002
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%CollegeGrad	− 0.0031	− 0.0033	− 0.0011
	(0.00095)**	(0.00095)**	(0.0012)
% < High School	0.0039	0.0031	0.0033
	(0.0013)**	(0.0013)*	(0.0017)*
%HouseOwn.	− 0.0027	− 0.0027	− 0.0024
	(0.00045)**	(0.00045)**	(0.00062)**
%Professional	0.0046	0.0047	0.0016
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	(0.0015)	(0.0015)	(0.0018)
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“Consumer Information and Discrimination”

Causes of Price Differences

Why do prices differ across groups? Many factors could be involved:

- Cost differences
- Demand elasticity differences (due to differences in preferences, search costs, competition, etc.)
- Differences in bargaining skills/costs
- Racial/gender biases

The dataset does not allow them to directly assess these possibilities, e.g. they lack data on post-sale profits, cannot estimate elasticities, don’t observe the bargaining process, etc.

Instead they rely on a set of auxiliary regressions to try to gain insights on these issues.

"Consumer Information and Discrimination"

Causes of Price Differences

Additional specifications provide some evidence.

- Omitting controls only make effects somewhat larger (2.0% Black and 2.5% Hispanic). Suggests some of what remains could be unobserved differences in car costs/search costs.
- Results similar with dealer fixed effects. Goes against competition explanation.
- Race and gender effects only a little smaller in subsample not requiring dealer financing. Suggests time costs of failed purchases not so relevant.
- Race premium smaller (0.8% Black and 0.6% Hispanic) for those trading in cars. If search cost differences are smaller for these buyers, suggests search cost differences could be part of explanation

Table 5. Regressions for explanations section.†

Dep. variable ln(price)	(1) Full sample	(2) Franchise fixed effects	(3) Full sample	(4) Full sample	(5) Full sample	(6) No financing
%Black	0.02	0.013	0.013	0.013	0.019	0.012
	(0.00051)**	(0.00054)**	(0.00089)**	(0.00070)**	(0.00065)**	(0.001)**
%Hispanic	0.023	0.01	0.0006	0.0077	0.014	0.007
	(0.00081)**	(0.0011)**	(0.0014)	(0.0012)**	(0.0011)**	(0.002)**
%Asian	−0.0096	0.00023	−0.0017	−0.0012	−0.0039	−0.002
	(0.00093)**	(0.00098)	(0.0016)	(0.0012)	(0.00096)**	(0.002)
Hispanic		0.49				0.32
		(0.026)**				(0.061)**
Asian		−0.76				−0.69
		(0.042)**				(0.068)**
Female	0.21	0.19	0.23	0.21	0.21	0.29
	(0.014)**	(0.013)**	(0.022)**	(0.014)**	(0.014)**	(0.025)**
AnyTrade	0.34	0.25	0.31	0.31	0.43	0.81
	(0.014)**	(0.013)**	(0.014)**	(0.014)**	(0.018)**	(0.024)**
— * %Black					−0.011	
					(0.001)**	
— * %Hispanic					−0.0072	
					(0.0014)**	

"Consumer Information and Discrimination"
Effects of Online Purchasing

To examine whether patterns differ for customers who use Autobytel.com they include dummies for whether a consumer had searched for the car model they eventually bought on Autobytel.com, regardless of whether they eventually purchased from that dealer or another dealer.

- Customers who use Autobytel pay about 0.9% less on average
- Interactions indicate that race and gender price differences are much smaller in the Autobytel sample.

Dep. variable ln(price)	(1) Full sample	(2) Full sample	(3) Full sample	(4) Franchise fixed effects
Autobytel	– 0.88	– 0.59	– 0.63	– 0.0061
	(0.028)**	(0.045)**	(0.045)**	(0.044)**
Autobytel Franchise	– 0.46	– 0.46	– 0.49	0.17
	(0.015)**	(0.015)**	(0.015)**	(0.069)*
%Black	0.015	0.015	0.02	0.013
	(0.00053)**	(0.00054)**	(0.00051)**	(0.00054)**
%Hispanic	0.0071	0.0075	0.019	0.011
	(0.001)**	(0.001)**	(0.00084)**	(0.0011)**
%Asian	– 0.00066	– 0.00033	– 0.0054	0.00003
	(0.00095)	(0.00097)	(0.00094)**	–(0.00097)
Hispanic	0.51	0.51	0.53	0.49
	(0.027)**	(0.028)**	(0.028)**	(0.026)**
Asian	– 0.95	– 0.96	– 0.98	– 0.76
	(0.042)**	(0.043)**	(0.043)**	(0.042)**
Female	0.21	0.21	0.21	0.19
	(0.014)**	(0.014)**	(0.014)**	(0.013)**
%Black > 75				
Autobytel * %Black		– 0.012	– 0.011	– 0.012
		(0.0028)**	(0.0028)**	(0.0027)**
— * %Hispanic		– 0.02	– 0.02	– 0.012
		(0.0038)**	(0.0038)**	(0.0037)**
— * %Asian		– 0.007	– 0.007	0.00075
		(0.0033)*	(0.0033)*	–(0.0032)
— * Hispanic		– 0.57	– 0.57	– 0.53
		(0.15)**	(0.15)**	(0.14)**
— * Asian		0.143	0.14	0.089
		(0.16)	(0.16)	–(0.16)
— * Female		– 0.12	– 0.12	– 0.01
		(0.058)*	(0.058)*	–(0.056)

“Consumer Information and Discrimination”

Conclusions

The papers cleanest results are those estimating the magnitudes of racial and gender price differences. They exist, but are smaller than some had suggested.

The authors stress most that much of the differences attributable to race and gender are eliminated when purchases are initiated online.

They do not attribute this result to race and gender being unknown for online customers. Rather, they argue that consumers who initiate online have credibly signaled that they have better information and so are in a better position to bargain.

They also argue that racial and gender premia for in-person sales are mostly due to “disparate impact,” not “disparate treatment,” of sellers inferring price elasticities.

Comment: Given that $\frac{d\pi}{dp}(p^m) = 0$, firm profits from the mean demographic differences must be very small.

Effects of 3rd Degree Price Discrimination

In monopoly models 3rd degree price discrimination increases firm profits, but can raise or lower consumer surplus or welfare.

The lack of privacy and the lower cost of customizing prices may create substantially greater scope for price discrimination in online markets.

Two recent papers have explored the magnitude of profit effects and the direction of welfare effects in online markets:

- Shiller (*IER* 2020) explores how Netflix could have discriminated with demographic data and data on consumers' full browsing histories.
- Dubé and Misra (*JPE* 2022) explores how Ziprecruiter could have discriminated across small firms signing up for its service for the first time using a set of firm/job characteristics that firms must report to get a price quote.

"Approximating Purchase Propensities and Reservation Prices From Broad Consumer Tracking," Shiller

Shiller has information on the web browsing activities of 61,312 users in 2006.

- The ComScore data are not full browsing logs, but provide a time-stamped list of top-level domain visits including the referring domain, the number of pages viewed, and information on transactions.
- Data also include user demographics.

He focuses on the demand for Netflix (which mailed DVDs). Motivations include:

- One can infer whether users are subscribers from browsing histories.
- Netflix could reasonably be treated as a monopolist.
- Netflix's substantial market share (~16%) helps in estimating demand.
- The simplicity of the business lets him treat costs as known from accounting data.

A substantial data limitation is that there is no price variation. One usually regards such variation as necessary to estimate demand elasticities.

"Approximating Purchase Propensities and Reservation Prices From Broad Consumer Tracking," Shiller

Tobias will lecture on demand estimation a couple weeks from now.

A basic insight is that we can estimate demand elasticities if we have exogenous variation in prices, and we can estimate costs if we also assume observed prices are profit maximizing.

Shiller takes a nonstandard approach, noting that if we are willing to assume that costs are known and Netflix is profit-maximizing, then we can estimate the market-wide demand elasticity without any price variation.

- Assume that consumer i's utility from choosing package j is

$$u_{ij} = v_i - \alpha P_j + \xi_j + \sigma \varepsilon_{ij}$$

- Assume that $v_i = X_i \beta$ where X_i contains 4633 explanatory variables: 18 demographic variables, 15 relating to the quantity/timing of browsing, and 4600 related to how much time they spend on the 4600 most popular websites.
- Elasticities can differ to the extent that the v_i differ across consumers.
- The β parameters are estimated via a Lasso-like modified MLE estimation.

“Approximating Purchase Propensities and Reservation Prices From Broad Consumer Tracking,” Shiller

Here’s what the demographic and relevant browsing variables look like.

Household Demographics	
I(Children)	
Yes	59.5%
Age (Eldest)	
Group 1 (18–20)	0.3%
Group 2 (21–24)	2.0%
Group 3 (25–29)	4.1%
Group 4 (30–34)	14.9%
Group 5 (35–39)	9.1%
Group 6 (40–44)	19.7%
Group 7 (45–49)	12.1%
Group 8 (50–54)	12.1%
Group 9 (55–59)	8.7%
Group 10 (60–54)	6.8%
Group 11 (65+)	10.4%
Race	
Caucasian	94.5%
Black	4.0 %
Asian	1.1%
Other	0.4%
I(Hispanic)	
Yes	20.3%
Income (in Thousands)	
Group 1 (<15)	9.8%
Group 2 (15–24.9)	6.5%
Group 3 (25–34.9)	10.9%
Group 4 (35–49.9)	20.3%
Group 5 (50–74.9)	26.0%
Group 6 (75–99.9)	12.2%
Group 7 (>100)	14.3%

Household Demographics		
Number of Residents		
One Resident	13.4%	
Two	32.9%	
Three	21.2%	
Four	18.2%	
Five	9.8%	
Six or More	4.6%	
Zipcode	Mean	St dev
Area (Square Miles)	70.4	162.3
Population Density	3,161.4	7,995.5
Browsing Habits		
I(Broadband)		
Yes	78.5%	
Timing of Internet Use	Mean	StDev
Early Morning (Midnight to 6 a.m.)	8.7%	14.4
Mid Morning (6 a.m. to 9 a.m.)	11.7%	13.5
Late Morning (9 a.m. to Noon)	21.1%	13.9
Afternoon (Noon to 5 p.m.)	34.9%	16.1
Evening (6 p.m. to Midnight)	23.6%	26.5
Monday	15%	4.0
Tuesday	15.6%	4.8
Wednesday	15.6%	4.6
Thursday	15.2%	4.7
Friday	14.6%	4.4
Saturday	11.9%	7.0
Sunday	12.1%	7.2

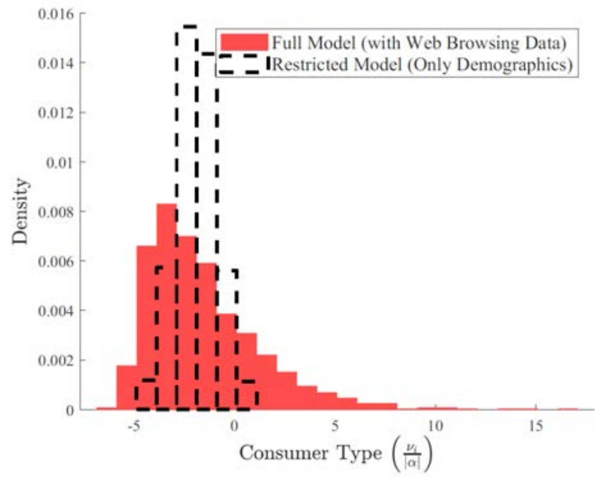
Order	Visits to:	Coef. Value	Δ Pr(Subscribe) (w. One Standard Deviation Increase in Visits)
1	gamefly.com	0.78	11.78
2	ameblo.jp	−0.48	−5.03
3	slysoft.com	0.36	4.80
4	audible.com	0.33	4.40
5	dvdfab.com	0.30	4.01
6	sutterhealth.org	0.30	3.96
7	4chan.org	0.29	3.84
8	jambase.com	0.29	3.83
9	imdb.com	0.28	3.72
10	houstonpress.com	0.27	3.49
11	kw.com	−0.26	−2.90
12	somethingawful.com	−0.25	−2.83
13	jacksonville.com	−0.24	−2.72
14	lacity.org	−0.24	−2.65
15	jalopyjournal.com	0.23	3.03
16	uhaul.com	0.23	2.99
17	smackjeeves.com	0.23	2.98
18	dailypress.com	−0.23	−2.58
19	sonlight-email.com	−0.22	−2.54
20	fairfaxcounty.gov	0.22	2.89
21	ganeshaspeaks.com	0.22	2.89
22	onstation.com	−0.22	−2.49
23	whig.com	0.21	2.74
24	techdirt.com	0.21	2.68
25	zylom.com	−0.21	−2.36
26	npr.org	0.20	2.64
27	baseballamerica.com	0.20	2.63
28	apunkachoice.com	0.20	2.63
29	elpais.com	0.20	2.61
30	amazon.com	0.20	2.56

“Approximating Purchase Propensities and Reservation Prices From Broad Consumer Tracking,” Shiller

Estimates include:

- Tailoring profits to the demographic variables only lets us increase Netflix’s profits by 0.3%.
- Tailoring profits to the web browsing variables lets us increase Netflix’s profits by 13%.
- Consumer surplus increases by 0.05% with demographic targeting and decreases by 0.5% with browsing-based targeting.
- Social welfare is higher with discrimination in both cases.
- If Netflix starts to use 2nd degree discrimination – the base estimates assume markups do not differ by tier – profits could be increased by 22.5% without using any customer-specific information.

The figure at right shows the distribution of the signal that Netflix receives when it has access to demographic and web browsing data.



“Approximating Purchase Propensities and Reservation Prices From Broad Consumer Tracking,” Shiller

Comments:

- It took several nice observations to make it feasible to address effects of price discrimination with an off-the-shelf dataset: identification strategy; Netflix; demographics vs. browsing
- Some of the observations could be practically important:
  - Demographics are of little value for discrimination.
  - Web browsing can reveal much more information.
  - It would be difficult for consumers to distort their browsing to avoid getting charged high prices.
- The assumptions needed to make the model work are strong. This may be the best you can do with the limited data, but they’re still strong and make it hard to be confident in the results.
- We’d really like to separately estimate heterogeneity in utility levels and price-sensitivity.
- What are the properties of the assumed distribution of utility?
- Theory teaches us that welfare effects depend on DWL and misallocation. These in turn can depend on shapes of signal distributions and whether they lead the monopolist to sell to many or few in each group. It would be nice to have a model that takes aim at the components and estimates them flexibly.

“Personalized Pricing and Consumer Welfare,” Dubé and Misra, *JPE* forthcoming

Dubé and Misra estimate the profit and welfare changes that would result from Ziprecruiter practicing price discrimination when new small firms sign up for accounts. (Formerly it charged such employers $99/month.)

- The paper exploits data from two pricing experiments run by Ziprecruiter.
- It considers discrimination on the basis of answers to questions employers must answer before being given a price quote. It’s a small number of seemingly minor questions, but generates 133 “features” that can be used.

	Monthly Price
Control	99
Test 1	19
Test 2	39
Test 3	59
Test 4	79
Test 5	159
Test 6	199
Test 7	249
Test 8	299
Test 9	399

Feature Name
job state
company type
commissions offered
Number of job slots needed
total benefits
employment type
resume required
medical benefit
dental benefit
vision benefit
life insurance benefit
job category

"Personalized Pricing and Consumer Welfare," Dubé and Misra

The experiment from which they estimate demand had 7867 customers.

The utility model is similar to that of the prior paper, but also allows covariates to affect the price sensitivity parameter:

- Assume that consumer i's utility from purchasing is

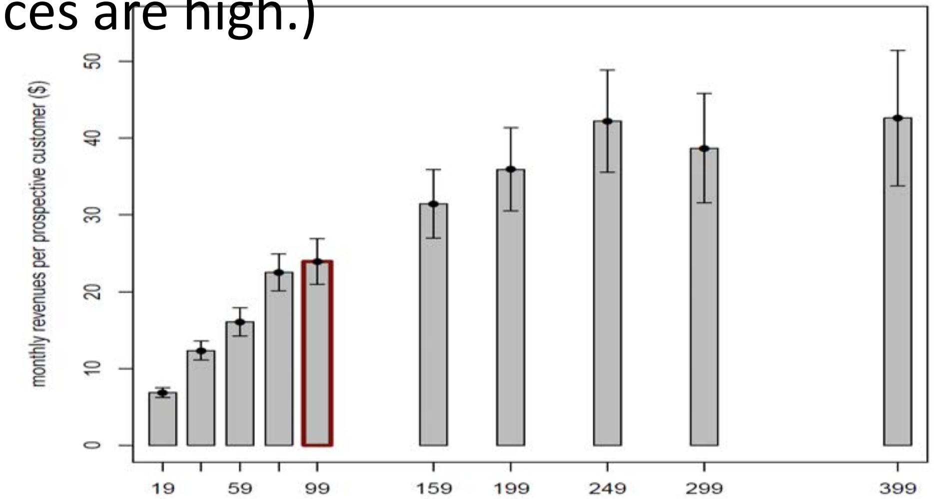
$$u_i = X_i\beta - (X_i\theta_\alpha)P + \varepsilon_i$$

- Estimate the parameters via three different procedures, MLE, LASSO, and a Weighted Likelihood Bootstrap Lasso (WLB) estimator that estimates uncertainty both over the set of features with nonzero coefficients and the coefficient values.
- Validations on a held out sample suggest the WLB estimates are best.

“Personalized Pricing and Consumer Welfare,” Dubé and Misra

Estimates include:

- Summary statistics show clearly that prices are below short-run profit-maximizing. The $249 arm had the highest profit. The optimal uniform price is estimated to be $327.
- There is substantial heterogeneity both in price sensitivity and in CS from purchasing at $99.
- Optimal personalized prices would range from $126 to $6292 with a mean of $277. Capping prices at $499, personalized pricing is estimated to increase profits by 8.2% relative to optimal uniform pricing.
- Optimal personalized prices are predicted to reduce expected consumer surplus by about 25% and to reduce social welfare relative to optimal uniform pricing. (Total output does not increase and many prices are high.)



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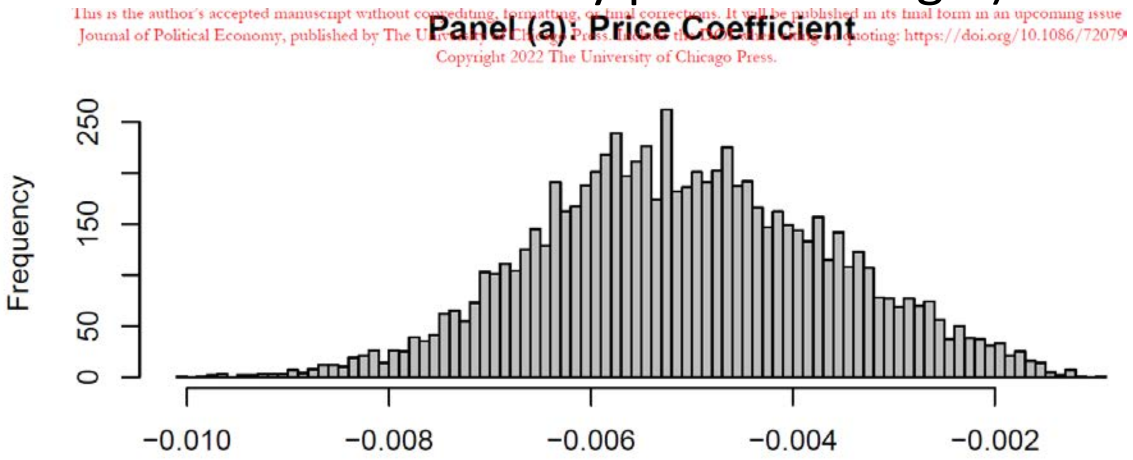

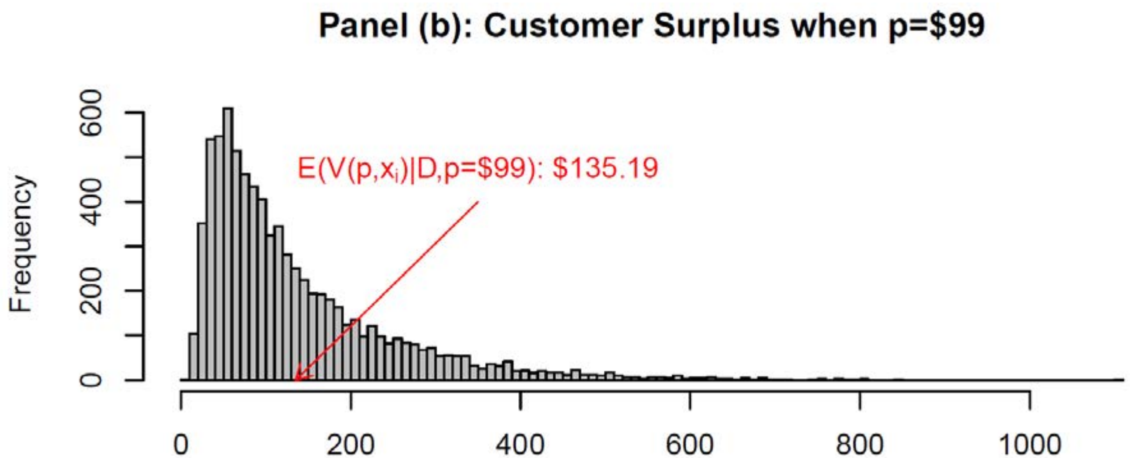

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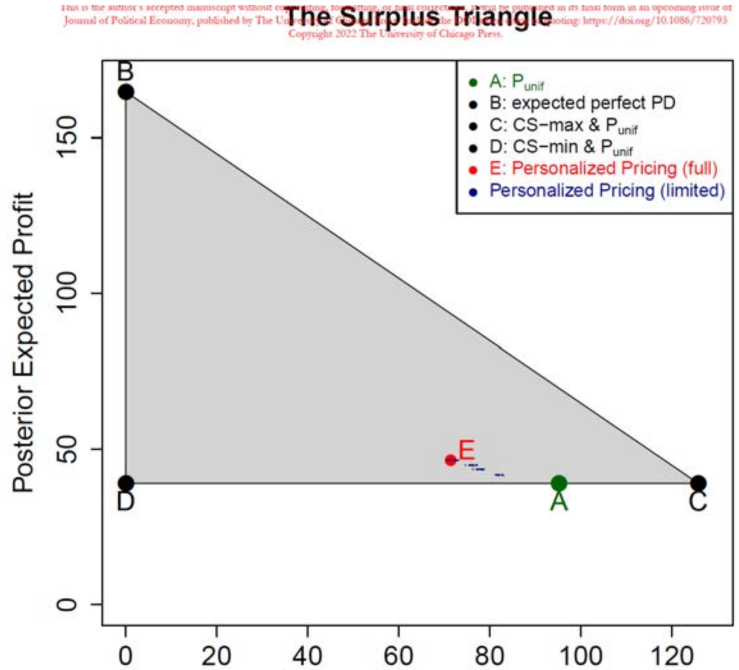

“Personalized Pricing and Consumer Welfare,” Dubé and Misra

A very nice feature of the paper is that they also conducted a second validation experiment.

Influenced by the first experiment, Ziprecruiter switched to a $249 uniform price for small new customers.

- The validation experiment compares $99, $249, and personalized pricing with a $499 cap. It has 5315 observations.
- Experimental outcomes are very close to predictions based on the estimates from the first experiment.

	control ($99)	test ($249)	test (personalized pricing)
Sample Size	1,360	1,430	2,485
mean conversion	0.23	0.15	0.15
	(0.21,0.25)	(0.13,0.17)	(0.13,0.16)
mean revenue per consumer	$22.57	$37.79	$41.59
	(20.36,24.77)	(33.15,42.42)	(37.49,45.7)
posterior mean conversion	0.26	0.15	0.14
	(0.23,0.29)	(0.13,0.18)	(0.12,0.17)
posterior mean revenue per consumer	$25.5	$38.37	$41.05
	(23.26,28.31)	(32.04,44.9)	(33.78,48.78)

Table 7: Predicted versus Realized Outcomes in November 2015 Experiment (Below each realized outcome, we report in brackets the 95% confidence intervals. Below each posterior predicted outcome, we report in brackets the 95% credibility interval.)

“Personalized Pricing and Consumer Welfare,” Dubé and Misra

Comments:

- The paper highlights the benefits of working collaboratively with firms to obtain rich data with experimental variation.
- The segmentation analysis is also very well done and could be a model for future studies.
- The applied results are consistent with Shiller’s demographic results: price discrimination may not have enough of an effect on profits to make firms want to do it.
- To assess the welfare findings it would again be nice to know more about segmented logit-based demand systems. Welfare and CS reductions are implied by the finding that output won’t increase.
- A potential applied concern is that the experiments only identify short-run individual effects. Follow up studies could look at effects on customer retention. But they won’t tell us about word-of-mouth customer acquisition, effects on expert reviews, and the possibility that price discrimination will lead to popular outrage.
- Reductions in employer signups could also affect signups of job-seekers, with feedback effects on the value to employers. We’ll talk about two-sided markets later in the term.

Incident from several years ago---it appeared that Amazon was engaging in personalized pricing, there was an uproar, they denied it but vowed to never do it again.

Amazon Apologizes for Pricing Blunder

By Lori Enos
E-Commerce Times
09/28/00 12:00 AM PT

Print Version
E-Mail Article
Reprints

Amazon CEO Jeff Bezos said his company will never test prices based on customer demographics.

E-tail giant Amazon.com (Nasdaq: AMZN) issued a formal apology Wednesday for price testing it conducted earlier in the month that caused customers to be quoted different prices for the same DVD.

Although several news reports indicated that Amazon was altering the prices based on demographics, the Seattle, Washington-based e-tailer denied those claims, saying, "These reports were incorrect and were not based on the facts." The company added that it was simply trying to determine how much sales are affected by lower prices.

"We've never tested and we never will test prices based on customer demographics," said Amazon founder and CEO Jeff Bezos. "What we did was a random price test, and even that was a mistake because it created uncertainty for customers rather than simplifying their lives."

On Wednesday I'll discuss models of oligopoly competition. It will probably be mostly textbook material apart from Zhou's paper.

See you then!