MKT927: INTRO TO QUANTITATIVE MARKETING

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Lecture 6: Pricing

MBA LEVEL PRICING

OVERVIEW

- Key components of pricing strategy:
  - Value creation
  - Value communication
  - Value capture
- Common pricing mistakes:
  - Cost-plus pricing without considering value
  - Ignoring competitive dynamics
  - Not segmenting customers effectively

VALUE-BASED PRICING FRAMEWORK

- Understanding customer willingness to pay (WTP)
- Economic Value to Customer (EVC):
  - Reference value (next best alternative)
  - Differentiation value (additional benefits)
- Price positioning:
  - Premium
  - Value
  - Economy

PRICE DISCRIMINATION STRATEGIES

- First-degree: Individual-level pricing
  - Example: Negotiated B2B contracts
- Second-degree: Quantity discounts
  - Example: Package sizing
- Third-degree: Segment-based pricing
  - Example: Student discounts
- Requirements for effective price discrimination:
  - Market segmentation
  - Prevention of arbitrage

DYNAMIC PRICING

- Adjusting prices based on:
  - Demand fluctuations
  - Inventory levels
  - Competitive actions
  - Time sensitivity
- Common applications:
  - Airlines
  - Hotels
  - Ride-sharing

OTHER PRICING STRATEGIES

- Price presentation strategies:
  - ‘Charm’ pricing (e.g., $9.99 vs $10.00)
  - Price anchoring
  - Decoy pricing
- Bundle pricing:
  - Pure bundling
  - Mixed bundling
  - Component pricing
- Proactive churn management
- Discounting

DIGITAL PRICING CHALLENGES

- Price transparency
- Real-time competitive monitoring
- Algorithmic pricing
- Subscription models:
  - Freemium strategies
  - Tiered pricing
  - Usage-based pricing
- Platform pricing:
  - Network effects
  - Multi-sided markets
  - Customer acquisition vs. monetization

CLASSIC PRICING MODELS

MUSSA-ROSEN MODEL (1978)

- The Mussa-Rosen model (1978) explains how a monopolist optimally differentiates product quality
- Key insight: Price discrimination through quality differentiation
- Applications: Consumer electronics, software versions, airline seats

MODEL SETUP

- Monopolist can produce goods of different quality levels s
- Production cost $c(s)$ is increasing and convex in quality
- Consumers have different valuations θ for quality
- Consumer utility: $U(\theta) = \theta s - p$
- Consumers buy at most one unit

CONSUMER HETEROGENEITY

- Consumer types θ distributed uniformly on $[\underline{\theta}, \overline{\theta}]$
- Higher θ indicates higher willingness to pay for quality
- Each consumer chooses whether to buy and which quality to select
- Individual Rationality (IR): $U(\theta) \geq 0$
- Incentive Compatibility (IC): Consumer selects preferred quality level

MONOPOLIST'S PROBLEM

$$\max_{s(\theta),p(\theta)} \int_{\underline{\theta}}^{\overline{\theta}} [p(\theta) - c(s(\theta))] f(\theta) d\theta$$

$$\text{s.t. } \theta s(\theta) - p(\theta) \geq 0 \text{ (IR)}$$

$$\theta s(\theta) - p(\theta) \geq \theta s(\theta') - p(\theta') \text{ (IC)}$$

OPTIMAL SOLUTION

- Quality distortion at the bottom, efficiency at the top
- Lower quality products are intentionally degraded
- Optimal quality schedule:

$$c'(s(\theta)) = \theta - \frac{F(\theta)}{f(\theta)}$$

- Quality increases with consumer type θ

KEY IMPLICATIONS

- Pricing and product line decisions are intimately linked
- Price-quality schedule creates self-selection and serves as screening mechanism
- Theory that can guide empirical analysis: For example Substack subscription tiers, b2b saas bundles, etc...

BUNDLE PRICING

- Similar intuition as in the Mussa-Rosen model, can use product design to screen consumers.
- When consumers have negatively correlated valuations, bundling can increase profits.
- With digital goods, large bundles are attractive since marginal cost is close to zero and goods are non-rival.

PRACTICAL CHALLENGES

PRICING EXPERIMENTS ARE HARD TO RUN

- Price is often viewed as a commitment to future behavior.
- For example, Netflix’s price change in 2011 was very controversial.
- Firms compete, so a price change can lead to a price war.
- Role for observational causal inference.

COSTS ARE HARD TO ESTIMATE

- Underappreciated challenge in pricing.
- Suppose you are running a warehouse, and you offer a contract to a customer. To price it correctly, you need to estimate the labor and energy costs of running the warehouse, capacity utilitization, and demand from other customers.
- Different product types have different costs of shipping, storage, and handling.

PRICING MAY BE HARD TO CONTROL

- If the firm is selling to other businesses, prices may be negotiated.
- Salespeople may have misaligned incentives and may also have private information about the customer.
- Long-lived contracts may make it hard to change prices.

EMPIRICAL PRICING RESEARCH

THEMES IN EMPIRICAL PRICING RESEARCH

- Explaining price patterns. (Pink-tax papers, supermarket pricing patterns)
- Quantifying the loss due to incorrect pricing. (Hortacsu et al. on airline pricing).
- Designing pricing mechanisms and testing them (Dube and Misra's Ziprecruiter paper).
- Pricing algorithms (will return to this in the algorithms part of the course).
- Pricing when consumers are not fully rational (Stubhub paper Blake et al.).

PERSONALIZED PRICING AND CONSUMER WELFARE.

WHY THIS PAPER?

- It’s a great paper!
- One of the few papers that uses one experiment to design a policy and then another to validate it.
- Classic question about price discrimination and consumer welfare.
- Raises interesting policy questions about the use of consumer data.

RESEARCH BACKGROUND

- Extensive literature on price discrimination, yet large-scale personalized pricing is emerging.
- Prior work focuses on consumer purchase histories; this paper uses observable features.
- Field experiments at ZipRecruiter provide a natural laboratory.

RESEARCH QUESTIONS

- What are the profit implications of personalized pricing relative to uniform pricing?
- How does personalization affect aggregate consumer surplus?
- How do data granularity and segmentation schemes influence welfare outcomes?

THEORETICAL FRAMEWORK

- **Decision-Theoretic Pricing:**
  - Firm maximizes posterior expected profit by setting consumer-specific prices.
  - Uses Bayesian updating to incorporate demand uncertainty.
- Key condition (simplified):

$$p_i^* = \arg\max_p \, (p - c) \cdot \mathbb{E}\left[q(p; \Psi_i)\right]$$

DEMAND ESTIMATION AND DATA

- Field experiment conducted at ZipRecruiter with over 7,800 prospective consumers.
- Demand modeled via a binary logit specification:

$$P(y_i = 1 \mid p, \Psi_i) = \frac{\exp\{(1-p)(a(x_i) + b(x_i)p)\}}{1 + \exp\{(1-p)(a(x_i) + b(x_i)p)\}}$$

- High-dimensional consumer features (over 130 dummies) used to capture heterogeneity.

EXPERIMENTAL DESIGN: STAGE 1

- Randomized pricing cells ranging from $19 to $399.
- Measured conversion rates and revenue per consumer.
- Evidence of inelastic demand and substantial unexercised market power.

EXPERIMENTAL RESULTS: PRICE

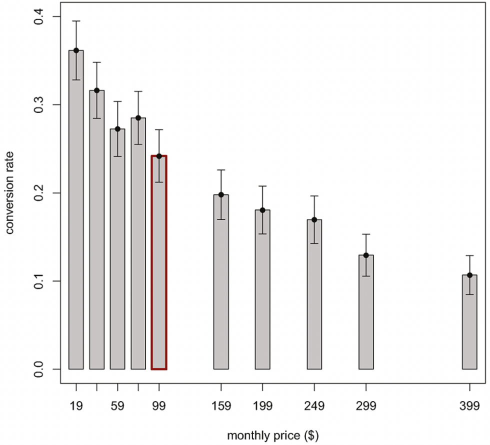

FIG. 1.—Stage 1 experimental conversion rates. Each bar corresponds to one of our 10 experimental price cells. The height of the bar corresponds to the average conversion rate within the cell. Error bars indicate the 95% confidence interval for the conversion rate.

EXPERIMENTAL RESULTS: REVENUE

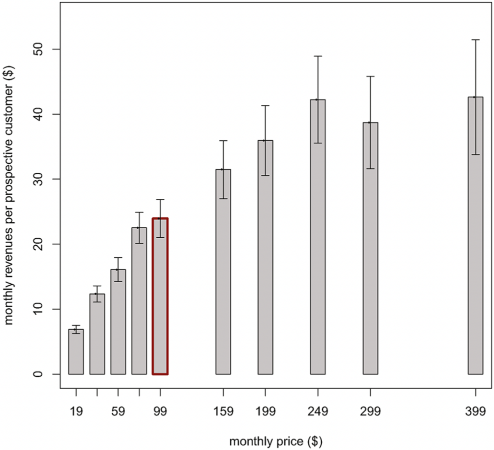

FIG. 2.—Stage 1 experimental revenues per customer. Each bar corresponds to one of our 10 experimental price cells. The height of the bar corresponds to the average revenue per prospective consumer within the cell. Error bars indicate the 95% confidence interval for the revenues per consumer.

EXPERIMENTAL RESULTS: RETENTION

TABLE 4
Acquisition and Retention Rates (September 2015)

Price ($)	Acquisition	At Least 1 Month	At Least 2 Months	At Least 3 Months	At Least 4 Months
19	.36	.8	.77	.61	.56
39	.32	.75	.73	.52	.47
59	.27	.65	.63	.49	.4
79	.29	.69	.64	.5	.39
99	.24	.69	.66	.48	.38
159	.2	.63	.61	.43	.34
199	.18	.56	.5	.31	.19
249	.17	.63	.59	.39	.27
299	.13	.58	.53	.35	.29
399	.11	.54	.52	.37	.25

UNIFORM VS. PERSONALIZED PRICING

- Uniform optimal pricing: Derived via inverse elasticity rule (e.g., $327 in experiment). Company chose $249.
- Personalized pricing: Decision-theoretic approach adjusts prices based on individual features.

EXPERIMENT 2

TABLE 7
PREDICTED VERSUS REALIZED OUTCOMES IN NOVEMBER 2015 EXPERIMENT

	Control ($99)	Test ($249)	Test (Personalized Pricing)
Sample size	1,360	1,430	2,485
Mean conversion	.23	.15	.15
	(.21, .25)	(.13, .17)	(.13, .16)
Mean revenue per consumer ($)	22.57	37.79	41.59
	(20.36, 24.77)	(33.15, 42.42)	(37.49, 45.7)
Posterior mean conversion	.26	.15	.14
	(.23, .29)	(.13, .18)	(.12, .17)
Posterior mean revenue per consumer ($)	25.5	38.37	41.05
	(23.26, 28.31)	(32.04, 44.9)	(33.78, 48.78)

NOTE.—Below each realized outcome, we report the 95% confidence intervals in parentheses. Below each posterior predicted outcome, we report the 95% credibility interval in parentheses.

CONSUMER WELFARE ANALYSIS

- Consumer surplus evaluated using alternative welfare functions:

$$S_r(p) = \left(\frac{1}{N} \sum_{i=1}^{N} V_i(p)^r \right)^{1/r}, \quad r \in \{1, 0, -1\}$$

- Total surplus declines under personalization, but majority of consumers benefit.
- Redistribution effects: Smaller, disadvantaged firms receive lower prices.

ROLE OF DATA GRANULARITY

- Analysis of different segmentation schemes (using subsets of consumer features).
- Findings indicate a non-monotonic relationship:
  - Some restrictions may exacerbate consumer welfare loss.
  - More granular data can improve allocative efficiency.

ROBUSTNESS CHECKS: MACHINE LEARNING METHODS

- Comparison of LASSO-based estimation versus deep learning architectures.
- Deep learning models (2-layer, 3-layer) yield similar uniform and personalized prices.
- Welfare implications remain robust across estimation methods.

KEY EMPIRICAL FINDINGS

- **Firm Side:** Personalized pricing increases profits significantly.
- **Consumer Side:** Total consumer surplus declines, yet majority benefit.
- **Policy Relevance:** Restrictions on data use (e.g., via GDPR) may have unintended welfare effects.

POLICY IMPLICATIONS AND DISCUSSION

- Trade-off between efficiency gains for firms and redistribution effects for consumers.
- Consideration of inequality-aversion in welfare analysis.
- Implications for regulation: Over-regulation may reduce allocative benefits.

ORGANIZATIONAL STRUCTURE AND PRICING: EVIDENCE FROM A LARGE U.S. AIRLINE? HORTAÇSU, NATAN, PARSLEY, SCHWIEG, AND WILLIAMS (2024)

MOTIVATION: BEYOND THE UNITARY FIRM

- **Standard Economic Assumption:** Firms act as a *unitary, rational decision-maker* to maximize profits.
- **But...** Real-world firms are complex organizations.
- **Organizational Decomposition:** Large firms often decompose complex decisions, delegating parts to distinct sub-units (departments).
- **Consequences?**
  - Potential for coordination failures.
  - Reliance on heuristics within sub-units.
  - Deviations from "optimal" pricing and firm behavior.
- **This Paper:** Investigates the impact of organizational structure and heuristics on pricing in a major U.S. Airline.

RESEARCH QUESTION

Central Question

Pitch: How does organizational structure and the use of heuristics within departments influence pricing decisions in a complex firm, and what are the welfare implications?

But really, can we explain airline pricing?

GRANULAR DATA FROM A LARGE U.S. AIRLINE

- Daily prices and quantities.
- Department decisions: Capacity choices, fare decisions, internal demand model, demand estimates, flight-level forecasts.
- **Crucially:** Exact design (code) of the pricing heuristic.
- Consumer interactions (clicks) on the airline's website.
- 300,000 flights and 470 domestic routes over two years.

FACT 1: PRICING RULES DEVIATE FROM OPTIMAL DYNAMIC PRICING

- Observed pricing rules differ from predictions of optimal dynamic unitary decision-making.
- Firm uses a myopic heuristic (EMSRb) that solves a static allocation problem daily.
- Heuristic abstracts from: product substitution, cross-cabin, competitor options, full dynamic programming.
- *See Figure 3 in the paper for evidence on opportunity costs and price responses.*

FACT 2: BIASED AND MISCOORDINATED DEPARTMENT INPUT DECISIONS

- Revenue Management (RM) department uses a simplified single-product demand model across all routes.
- Departments do not fully internalize decisions of other departments, leading to "incompatible" inputs.
- Pricing department frequently sets fares on the inelastic side of the RM department’s demand model.
- *See Figure 4 in the paper for evidence on price adjustments and opportunity cost changes.*

FACT 3: DEPARTMENTS MANIPULATE INPUTS (BIASED FORECASTS)

- RM analysts inflate demand forecasts, leading to systematic overprediction.
- 93% of flights are over-forecasted when supplied to the heuristic.
- Consistent with behavioral explanations (overconfidence, mis-reaction) or a "kludge" to address heuristic limitations.
- *See Figure 5 in the paper for forecast bias by week before departure.*

COUNTERFACTUAL ANALYSIS: DEPARTMENTAL DEVIATIONS

- **Pricing Department Deviations (Coordination Focus):**
  - Counterfactual: Pricing department removes fares that lead to "inelastic prices" according to RM department's model
  - Attempt to align pricing with RM department's demand estimates
- **Result:**
  - No revenue improvement
  - Actually leads to slight revenue decrease (0.9%)
- **Implication:** Observed "miscoordination" may be optimal given current organizational structure

COUNTERFACTUAL: RM DEPARTMENT DEVIATIONS

- **Focus:** Addressing forecast bias
- **Counterfactual Change:**
  - Reduce upward bias in demand forecasts
  - Scale down the demand model to be more "realistic"
- **Result:**
  - Unilateral bias reduction reduces revenues
  - More accurate forecasts lead to worse outcomes
- **Implication:** Upward forecasting bias, while seemingly a "mistake," might be revenue maximizing

KEY INSIGHTS FROM DEPARTMENTAL COUNTERFACTUALS

- Seemingly suboptimal behaviors may be optimal within constraints:
  - Pricing-RM misalignment
  - Systematic forecast bias
- Organizational structure matters:
  - Departmental "mistakes" can offset other constraints
  - Fixing one issue in isolation may backfire
- Implications for firm design:
  - Major changes require coordinated reform
  - Current practices may be "locally optimal"

COUNTERFACTUAL ANALYSIS: COMPARISON TO UNITARY DECISION-MAKER

- **Dynamic Programming (DP) Counterfactual:**
  - Simulate prices if the firm were a unitary, rational decision-maker solving a dynamic program.
  - Limited to routes with at most twice daily service due to computational constraints.
- **Welfare and Revenue Comparison:**
  - DP pricing results in **lower welfare** (by 9%) compared to observed practices.
  - Leisure consumers benefit (lower prices early on), business consumers worse off (increased price targeting).
  - DP results in **higher revenues** (by 14%) than observed.

DISCUSSION AND BROADER IMPLICATIONS

- **Key Takeaway:** Treating firms as unitary, rational decision-makers can lead to misinterpretations of firm behavior and biased welfare estimates.
- **Organizational Structure Matters:** Decomposition and heuristics significantly impact pricing outcomes.
- **Heuristic Rationality:** Departmental decisions, even seemingly biased ones, can be rational within the organizational context and given the heuristic.
- **Welfare and Market Power:** Ignoring organizational structure can bias counterfactual welfare and market power measurements.

DISCUSSION POINTS:

- To what extent do you think these findings generalize to other complex industries beyond airlines?
- What are the most promising avenues for future research building on this paper?

GENDER-BASED PRICING IN CONSUMER PACKAGED GOODS: A PINK TAX?

MOSHARY, TUCHMAN, AND VARJRAVELU (2023)

INTRODUCTION AND MOTIVATION

- **Pink Tax Debate:** Popular press and some policymakers suggest women's personal care products are priced higher.
- **Research Question:** Does gender-based price discrimination (the "pink tax") exist in personal care products?
- **Key Insight:** The paper differentiates between second-degree (via product differentiation) and third-degree price discrimination.

BACKGROUND ON GENDER-BASED PRICING

- **Gender Segmentation:** Over 80% of products in the sample are gendered.
- **Differentiation:** Manufacturers often vary product attributes (ingredients, packaging, size) between men's and women's products.
- **Legislative Context:** Recent bills (e.g., Pink Tax Repeal Act) target price parity for "substantially similar" products.

DATA SOURCES

- **Nielsen Retail Scanner Data:** Prices and sales across thousands of US outlets (2015–2018).
- **Syndigo Data:** Detailed product ingredient information.
- **Additional Sources:** Walgreens.com, Label Insight, and Consumer Panel data for gender targeting.

EMPIRICAL STRATEGY

- **Price Specification:**

$$p_{jst} = \beta \cdot \text{women}_j + \gamma_m + \gamma_t + \gamma_s + \varepsilon_{jst}$$

  - women_j: Indicator for women-targeted product.
  - Fixed effects for manufacturer (γ_m), year (γ_t), and store (γ_s).

- **Two Sets of Comparisons:**
  1. **Unconditional Analysis:** Comparing overall prices.
  2. **Conditional Analysis:** Controlling for product formulation (leading ingredients) to assess "substantially similar" products.

MAIN EMPIRICAL RESULTS

- **Unconditional Pink Gap:** On average, women's products are about 10.6% more expensive (unit price basis).
- **Conditional on Formulation:** When comparing products with similar ingredients, the price gap shrinks to nearly 0% (even slightly negative in some categories).
- **Interpretation:** Price differences largely reflect second-degree discrimination—price variation driven by product differentiation.

PRODUCT DIFFERENTIATION

- **Ingredient Analysis:** Very little overlap in leading ingredients between men's and women's products within the same category.
- **Implication:** The differentiation (in attributes like ingredients, package size) supports segmentation and reduces incentives for arbitrage.

POLICY IMPLICATIONS AND DISCUSSION

- **Legislative Considerations:** The Pink Tax Repeal Act focuses on “substantially similar” products.
- **Findings Suggest:** Most products are differentiated; hence, enforcing price parity on these may have limited impact.
- **Consumer Welfare:** Substitution effects and consumer preferences may mean that average consumer surplus is not significantly harmed.

NEXT TIME

- Assignment is due, we will discuss.
- Start platforms (will give an overview of theory, and the literature in general).
- Please read:
  - The welfare effects of peer entry: the case of Airbnb and the accommodation industry
  - Tipping and concentration in markets with indirect network effects.
  - Intro and experimental design of “Sources of Market Power.” Chloe to discuss.