Pricing

UCSD MGT 100 Week 6

Kenneth C. Wilbur and Dan Yavorsky

FTC Surveillance Pricing Study Indicates Wide Range of Personal Data Used to Set Individualized Consumer Prices

The agency details interim insights from staff perspective examining how companies track consumer behaviors to inform surveillance pricing

January 17, 2025

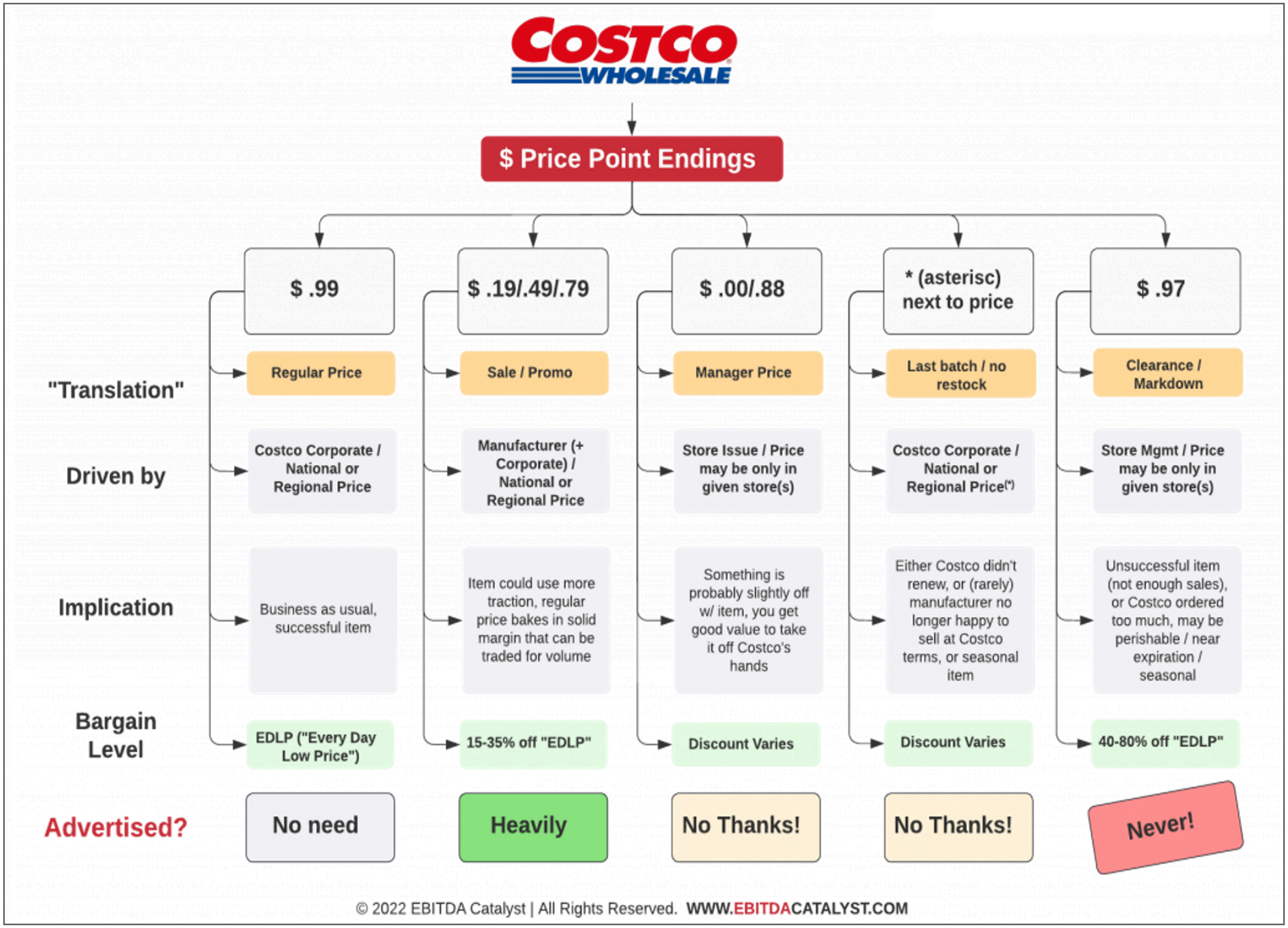
The staff perspective is based on an examination of documents obtained by FTC staff's 6(b) orders sent to several companies in July aiming to better understand the shadowy market that third-party intermediaries use to set individualized prices for products and services based on consumers' characteristics and behaviors, like location, demographics, browsing patterns and shopping history.

Staff found that consumer behaviors ranging from mouse movements on a webpage to the type of products that consumers leave unpurchased in an online shopping cart can be tracked and used by retailers to tailor consumer pricing.

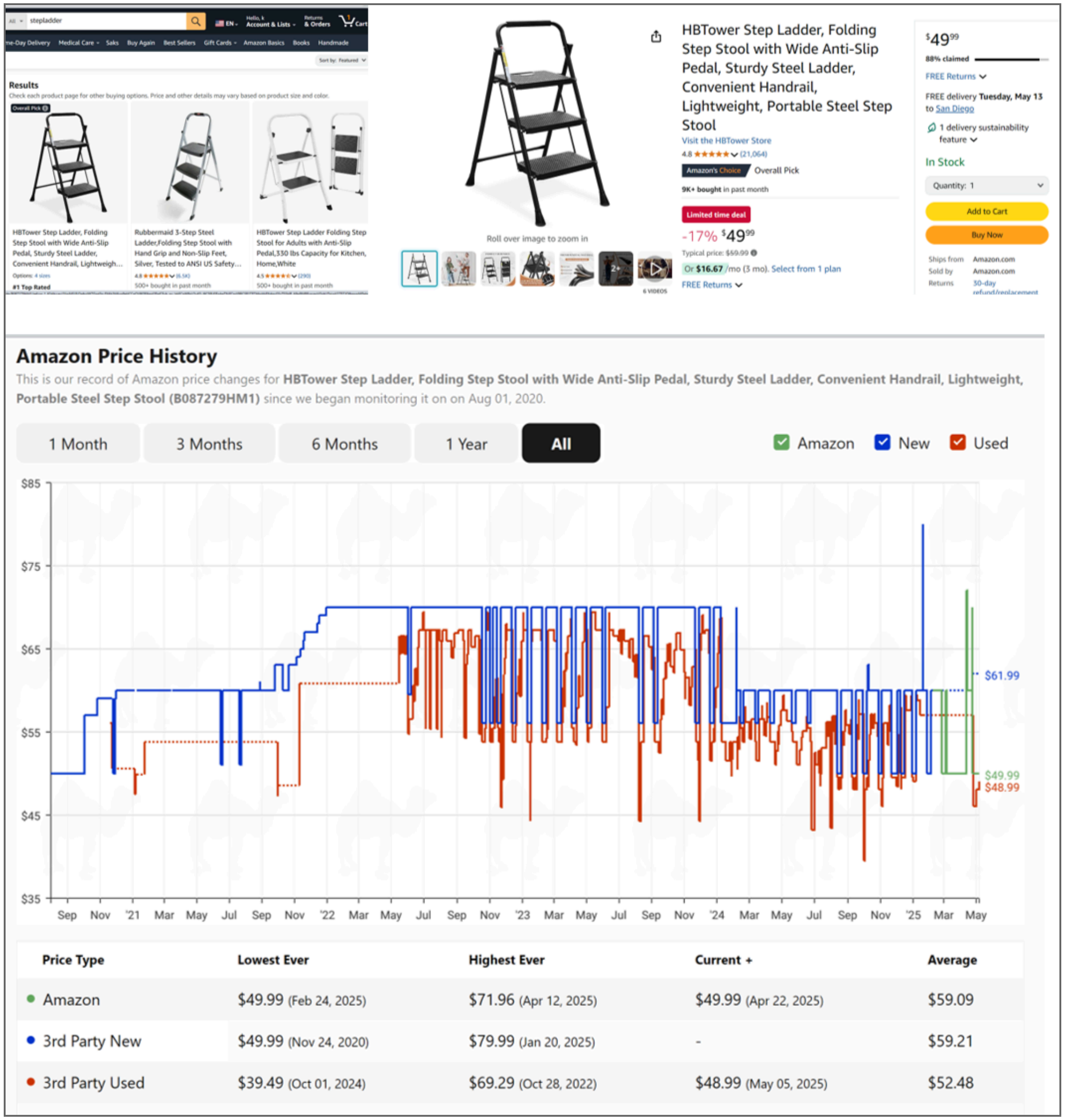
"Initial staff findings show that retailers frequently use people's personal information to set targeted, tailored prices for goods and services—from a person's location and demographics, down to their mouse movements on a webpage," said FTC Chair Lina M. Khan. "The FTC should continue to investigate surveillance pricing practices because Americans deserve to know how their private data is being used to set the prices they pay and whether firms are charging different people different prices for the same good or service."

The FTC's study of the 6(b) documents is still ongoing. The staff perspective is based on an initial analysis of documents provided by Mastercard, Accenture, PROS, Bloomreach, Revionics and McKinsey & Co.

orig



source “Bargains on bargains”… Why not use signs?



source. See also PriceSpy, SmartScout; but not Honey or Keepa

How firms set prices

- Importance and challenge
- Common approaches
- Economic Value to the Customer
- Human factors
- Using Demand Model to Price

Pricing importance

- #2 topic after two-sided value creation
- Average US net margin is 8% (**Damodaran Online**)
- Widely cited research by McKinsey

```
- 1% price increase can lead to 11% profit increase
- 1% price decrease can lead to 8% profit decrease
- Logic assumes no decrease in quantity
- Correlations, but widely misinterpreted as causal
```

- Consultants say most companies price too low; price is low-hanging fruit
- “Your margin is my opportunity”

Price changes are risky & scary

Harvard Business School

Note on Behavioral Pricing

Unfortunately, it appears that many firms lack the necessary understanding of a consumer's "willingness to pay" to optimally set product prices. When asked whether they were "well-informed" on six of the potential inputs to the product pricing decision, managers at one well-respected U.S.-based multinational responded as follows:[2]

- 84% were well-informed on the variable cost of providing their product.
- 81% were well-informed on the fixed cost of providing their product.
- 75% were well-informed on the price of competitors' products.
- 61% were well-informed on the value of their product to the customer.
- 34% were well-informed on how consumers would respond to price changes.
- 21% were well-informed on consumers' willingness to pay at various price levels.

These managers were well-informed on the costs of providing its products and on the price of competitor's products. They were also well-informed on the value its products delivered to consumers. However, when it came to a consumer's willingness to pay or to a consumer's response to potential price changes, these managers were lacking the insight needed to optimally set prices. Experience suggests that this company is not unique in this regard.

How firms set prices

Limited-data analyses

- EVC / Value pricing
- Competitor price benchmarking
- Cost-based pricing

Stated-Preference Data

- Open-ended: How much are you wtp? $___
- Prompted: Would you buy (product) at ($price)?
- Interviews, Focus Groups, Von Westendorp surveys
- Conjoint Analysis: Designs can be incentivized or not

Revealed-Preference Data

- Simulated purchase environments, Test markets
- Algorithms (bandits, rev mgmt), Experiments (**Amazon pricing labs**)
- Demand estimation

```
- Requires data, exogneous price variation, human attention/expertise
```

Customer co-determination

- Monopsony, auctions, negotiation, pay-what-you-want

None

- Seller takes market price

Pricing strategies are secret

- What not announce your pricing strategy?
- We can survey pricing managers anonymously, but (i) nonrandom selection, (ii) survey design inconsistencies, and (iii) self-reporting biases
- Salt taken, let’s look at pricing manager surveys

Table 3: How is the Price of Your Main Product Set
Firm Size and Sector

Firm size	Micro 5-9	Small 10-49	Medium, 50-249	Large 250+
No autonomous price setting	8.6	15.9	14.1	25.9
Price set by customer(s)	6.0	4.2	4.3	9.4
Price set following main competitors	34.0	32.3	30.7	30.9
Price based on costs and self-determined profit margin	45.6	41.3	42.6	30.1
Other	5.8	6.3	8.3	3.7
Sector	**Manufacturing**	**Construction**	**Trade & Distribution**	**Other services**
No autonomous price setting	9.7	4.5	18.3	7.6
Price set by customer(s)	9.8	7.3	3.9	5.1
Price set following main competitors	22.5	27.9	32.7	37.6
Price based on costs and self-determined profit margin	57.6	56.2	39.9	41.6
Other	0.4	4.1	5.2	8.1

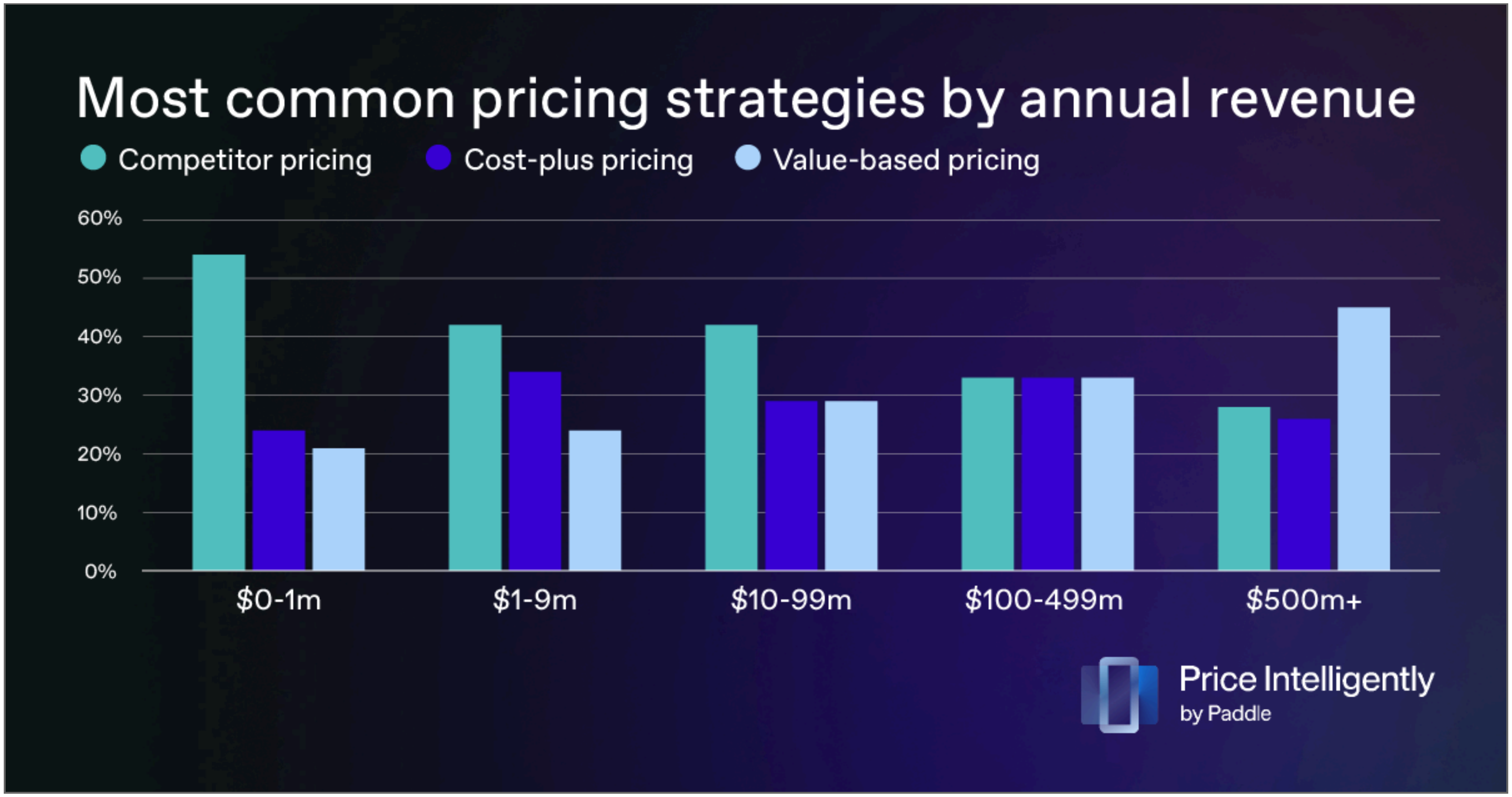

Most common pricing strategies by annual revenue
Competitor pricing
Cost-plus pricing
Value-based pricing
60%
50%
40%
30%
20%
10%
0%
$0-1m
$1-9m
$10-99m
$100-499m
$500m+
Price Intelligently
by Paddle

Table A1: Pricing practices by firms with and without pricing algorithms (Survey)

	Pricing Algorithms used	
How often does your firm change prices?	No	Yes
1= continuous	0.037	0.130
2 = hourly		
3 = daily	0.074	0.148
4 = weekly	0.074	0.074
5 = monthly	0.000	0.148
6 = quarterly	0.296	0.222
7 = yearly	0.333	0.167
8 = less than yearly	0.111	0.074
Customize		
Individualized to each customer	0.316	0.243
Customized geographically and each consumer segment	0.368	0.432
Customized for different segments	0.105	0.054
Customized for different regions	0.211	0.162
Uniform across segments and geographic regions	0.000	0.108
varies prices across customers and geographies		
Individual to each consumer;	0.259	0.167
Geographically and each consumer segment	0.333	0.352
Customized for different segments	0.111	0.130
Customized for different regions	0.111	0.167
Uniform across segments and geographic regions	0.000	0.111
Different parts of the company use different price variations	0.185	0.074

Table A2: Data and type of method used for pricing algorithm (Survey)

Data used for Pricing Algorithm (most familiar product)	**Proportion**
Your firm's costs	0.757
Your firm's past revenue or profit data	0.730
Competing firm's prices	0.568
Past consumer behavior	0.541
Demographics and Geographics	0.595
External info	0.405
Type of Pricing Algorithm (method or rules used)	**Proportion**
"Win-Continue Lose-Reverse" rule	0.297
Q-Learning	0.135
Artificial neural networks	0.054
Deep learning	0.135
Adaptive machine learning	0.270
Unsupervised or reinforcement learning	0.108

Value Pricing: Price in (cost, wtp)

- But… how do you learn wtp? Esp. if you have not sold before?
  - For large time/budget: Conjoint, simulated purchase environments, test markets, …
  - For small time/budget: Economic Value to the Customer (EVC)
- EVC: estimates customer benefit from a product, relative to the next best alternative
- EVC & VP are often used by new firms, highly differentiated products, firms lacking credible market research and related expertise
- Steps: 1. Calculate EVC, 2. Choose a price in (Cost, EVC)

How to calculate EVC(x | y)

1. Select the best available alternative y and find its price

```
- Interview target customers to learn how they solve the core need (y)
- If wrong y, EVC estimate will be too high
```

2. Determine non-price costs of using y and x

```
- Include start-up costs and/or post-purchase costs
- Make sure NonPriceCosts(x) exclude the price of x (why?)
```

3. Determine the incremental economic value of x over y

```
- Usually, functional benefits or non-price cost savings
```

4. EVC(x | y) = Price(y) + (NonPriceCosts(x) - NonPriceCosts(y)) + IncrementalValue(x | y)

```
- In practice, 99% of effort is getting the assumptions right
```

EVC tips

- y might not be a commercial product.
- EVC and y often vary across customer segments

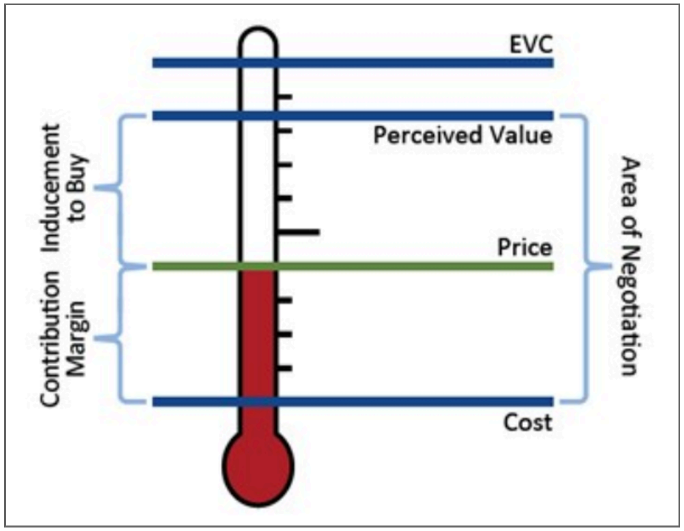
```
- Calculate heterogeneous EVC(x|y) for multiple y
```

- Unquantifiable factors influence price selection in (cost,EVC)
- If EVC(x | y)<0, reconsider product or target customer

Example: What is EVC(Batteriser | y)?

- The Batteriser is a durable metal sleeve that increases disposable battery life by 800%. With a thickness of just 0.1 millimetres, the sleeve can be fitted over any size battery, in any size compartment
- Assume the typical battery costs $0.50

“Pricing Thermometer”



- How much inducement do you give your customer?
- How will customers, competitors, suppliers react?

```
- SR vs. LR? More judgment than math. "Your margin is my opportunity"
```

Choosing p in (cost, EVC)

- Some advise: $\boxed{\text{Price} = \text{Cost} + (\text{EVC} - \text{Cost})^* \{z\%\}}$

```
- I've heard z = 25%, 33%, 50%, and 70%
- Do you want profits or growth? What's your exit?
```

- Human factors to consider when making your judgment:

```
- Perceived benefit - actual benefit
- Perceived costs - actual costs
- Consumer price sensitivity, reference price of y
- Established pricing benchmarks
- Fairness, signaling
- Customer risk of adoption, skepticism; brand credibility
```

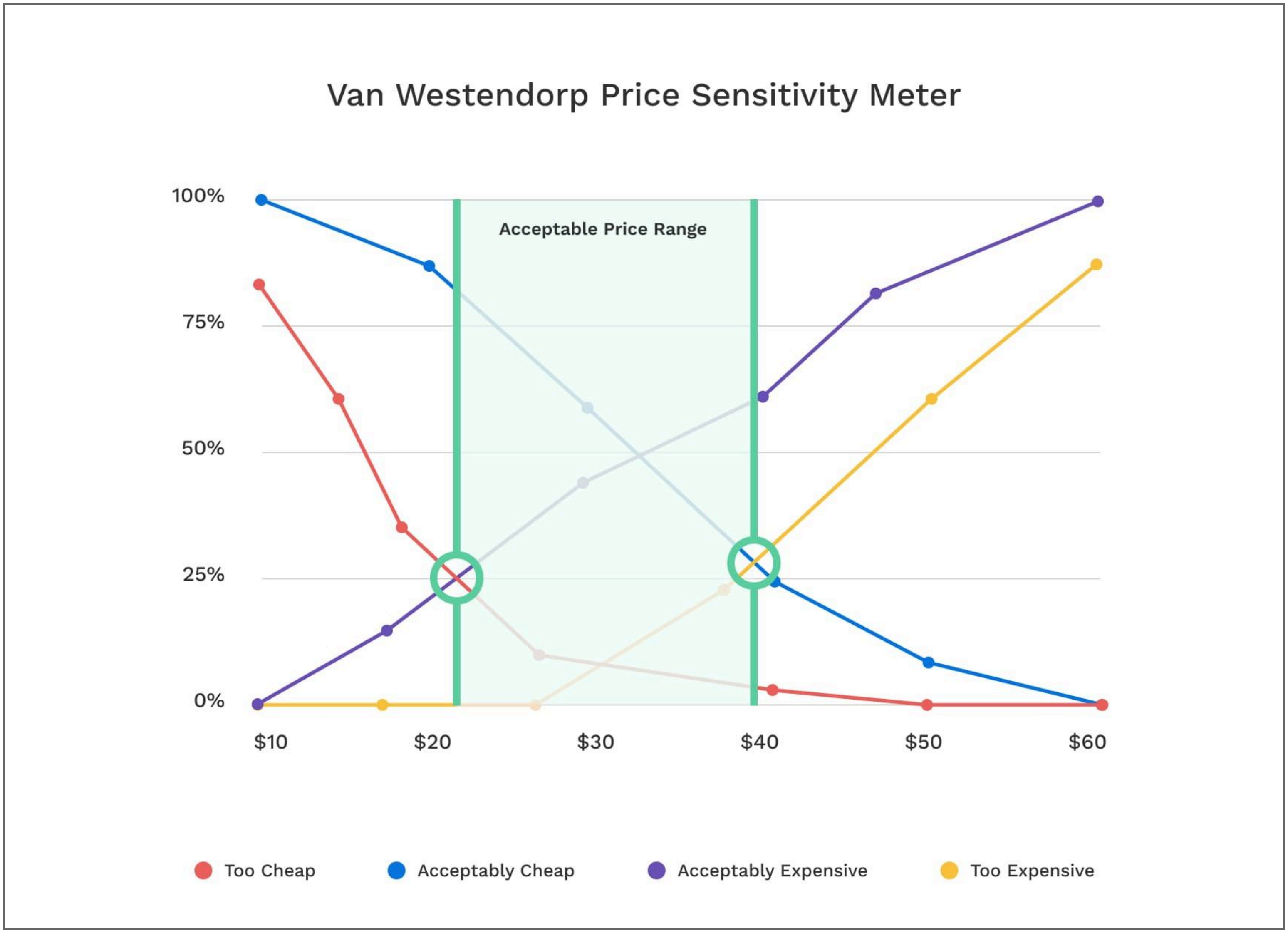
Van Westendorp Pricing Model

- Goal: Estimate stated WTP *range* for each customer
- Survey target customers: At price $X is (product)…

```
- Too Cheap? I.e., that you would question its quality
- Acceptably Cheap?
- Acceptably Expensive?
- Too Expensive? I.e., that you would not consider buying
```

- Ask for my values of $X, then plot 4 CDFs

```
- Too Cheap and Acceptably Cheap decrease with price
- Acceptably Expensive and Too Expensive increase with price
- Crossing points bound the Acceptable Price Range
```



- “Too cheap” meets “Acceptably Expensive”: “Point of Marginal Cheapness”

```
- VW says: Price<PMC signals poor quality
```

- “Acceptably Cheap” meets “Too Expensive”: “Point of Marginal Expensiveness”

```
    - VW says: Price>PME prices out most of your market
```

- “Too Cheap” meets “Too Expensive”: Min. # of price-refusers
- “Good Value” meets “Expensive”: Possibly max. # of price-accepters
- Strengths

```
    - Estimable with survey data only; Estimates distributions of consumer heterogeneity;
Incorporates reference prices and price-quality signals
    - Extensible to incorporate stated purchase intentions at each price. Add cost data, you can
then max. profits
```

- Limitations

```
    - Identifies a price range, not a price
    - Thinking about 4 CDFs is difficult, easy to misinterpret
    - Stated-preference data only; disregards competitors & marginal costs, hence don't use
standalone
    - Limited field evidence that it works well
```

Conjoint works for pricing too

Pricing with Conjoint

First, calculate price per util

(70 – 30) / (17.5 + 18) = 1.127

Next, pick target and reference values of a feature, and calculate change in utility

Target: 1 GB data

Reference: 500 MB data

Change in utility: (-25) – (-10) = 15

Calculate dollar value of that change in utility

(Change in utility) * (Price per Util)

15 * 1.127 = 16.9

This is like the EVC of moving from 500MG to 1GB of data

Attribute / Level	MNL Coefficient
Price	
$70	-18
$50	0.5
$30	17.5
Data	
500 MB	-25
1 GB	-10
10 GB	12
Unlimited	23
Int'l Minutes	
0 min	-2
90 min	-1
300 min	3
SMS Texts	
300	-7
Unlimited	7

Signals and *Perceived Quality*

- Signals of high quality

```
- High prices, Brand names, Warranties, Return policies, Ad spending
- Costly signals when the firm doesn't deliver
- Brand reputation can convey credibility
```

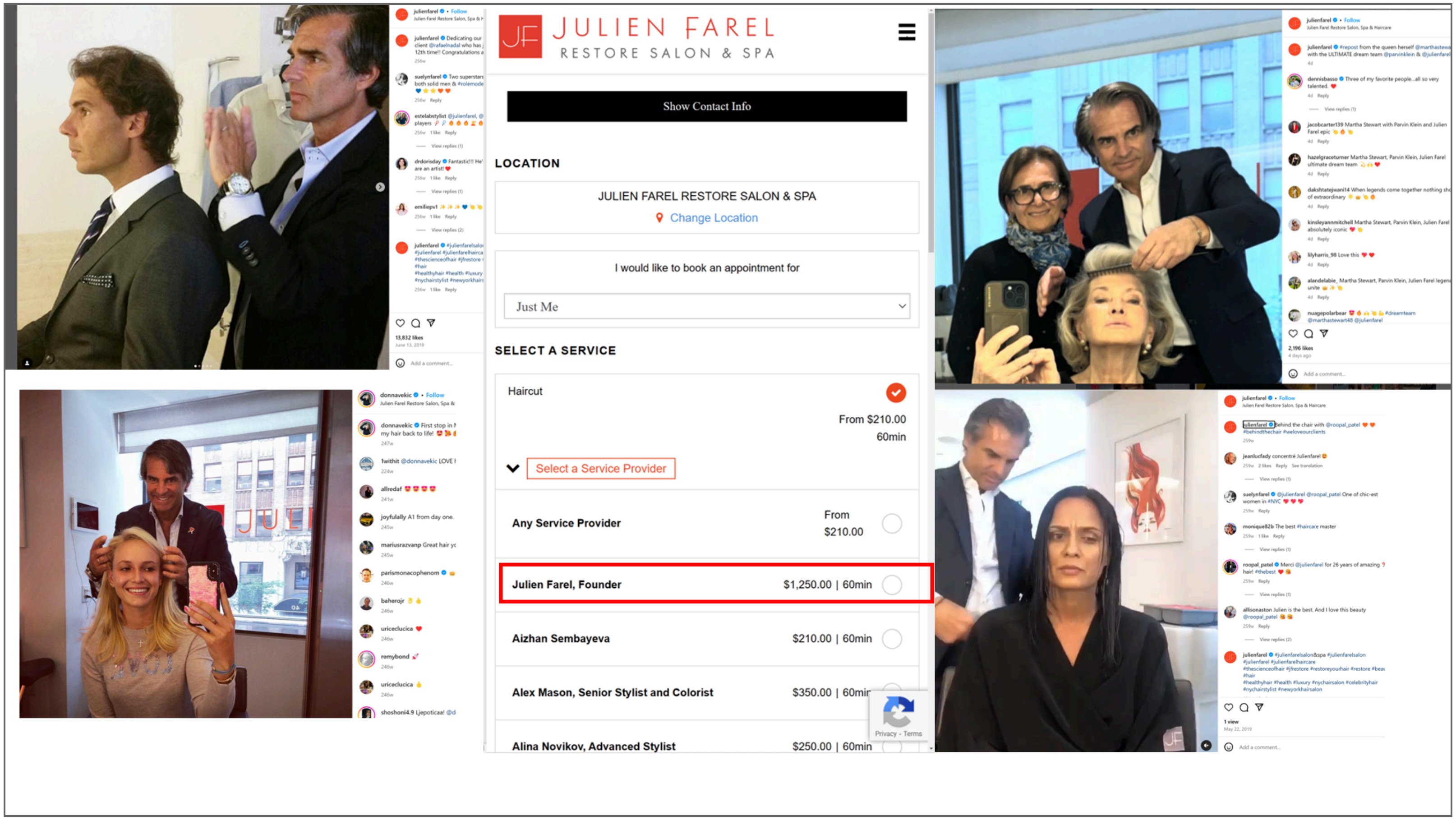
- Signals of low quality

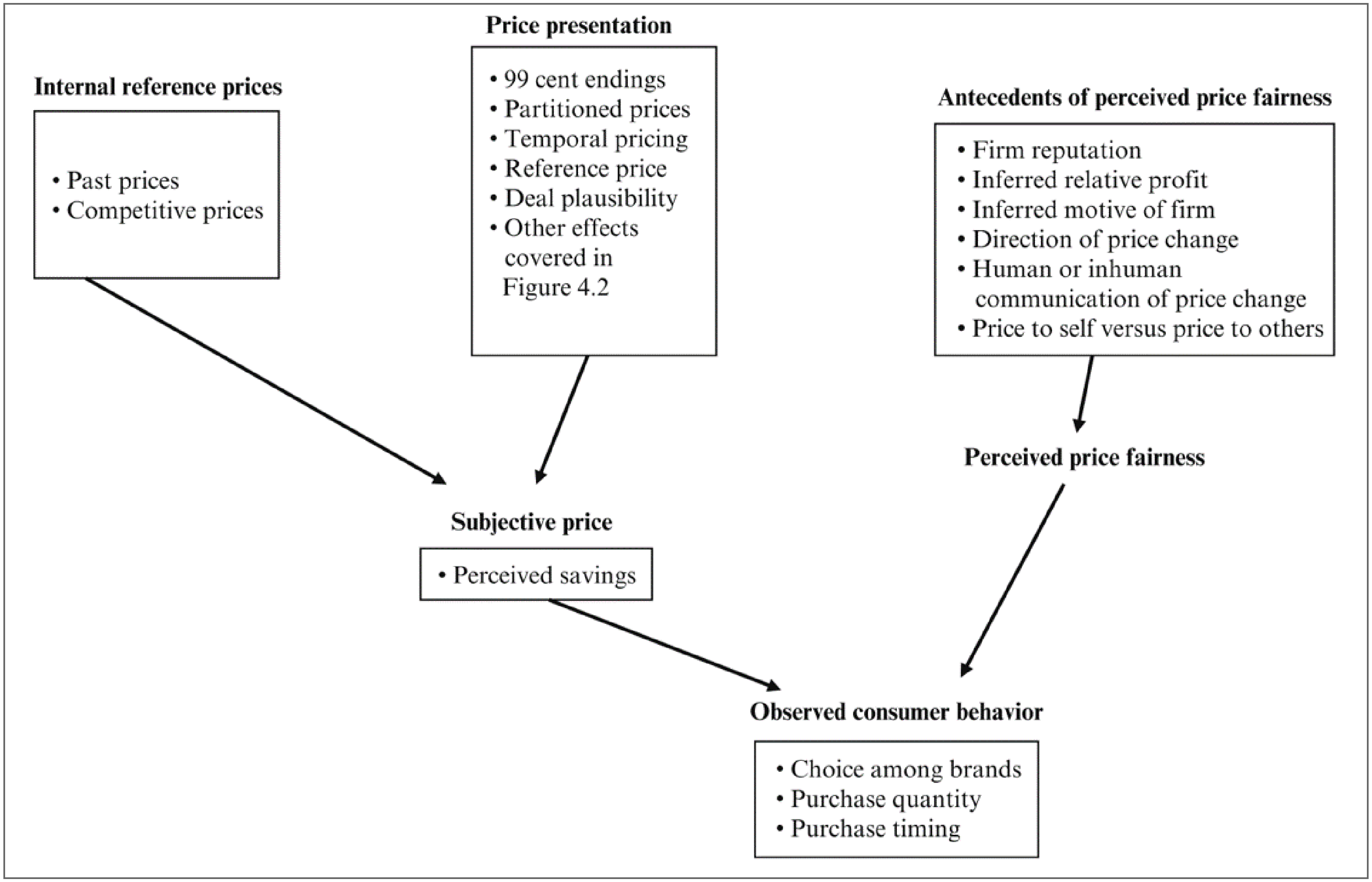
```
- Low prices, Price promotions, Price-matching guarantees
- Signals that look too good to be true
- "If it's so good, why is it so cheap?''
```

- Prescription: Price consistent with your quality position in the market

```
- Otherwise, you undercut your own message and leave money on the table
- Findings replicate in numerous contexts
```

Human factors: Price as a signal



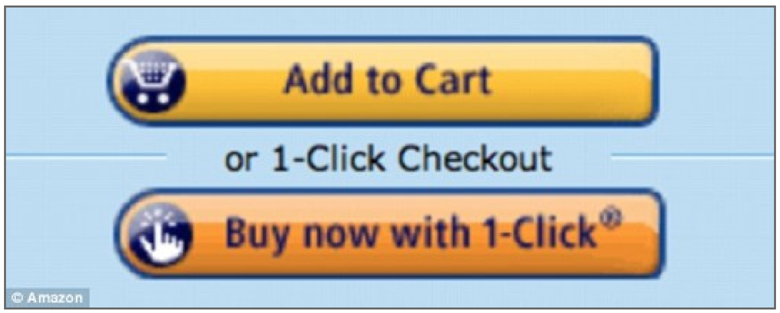

Internal reference prices
• Past prices
• Competitive prices
Price presentation
• 99 cent endings
• Partitioned prices
• Temporal pricing
• Reference price
• Deal plausibility
• Other effects covered in Figure 4.2
Antecedents of perceived price fairness
• Firm reputation
• Inferred relative profit
• Inferred motive of firm
• Direction of price change
• Human or inhuman communication of price change
• Price to self versus price to others
Perceived price fairness
Subjective price
• Perceived savings
Observed consumer behavior
• Choice among brands
• Purchase quantity
• Purchase timing

Human factors: Non-monetary costs

- Total customer cost is

```
Cognitive cost to decide the purchase
+ Physical cost to acquire the product
+ Financial payment
```

- Simplicity can increase sales. Remove frictions



Human factors: Perceived prices

- Which is the better bargain?
  - Regular price $0.89, sale price $0.75
  - Regular price $0.93, sale price $0.79

Left-digit bias: Demand Effects

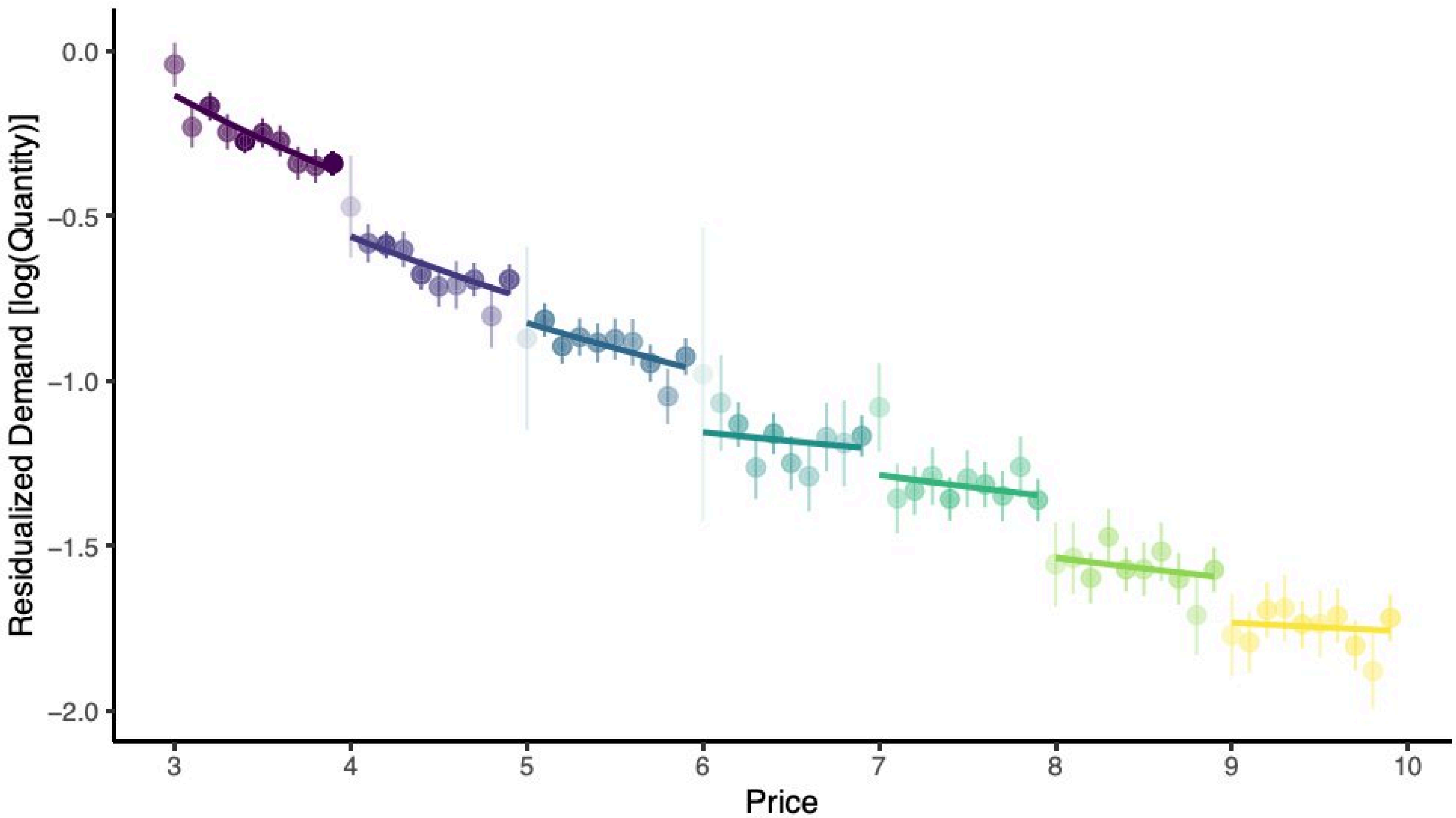
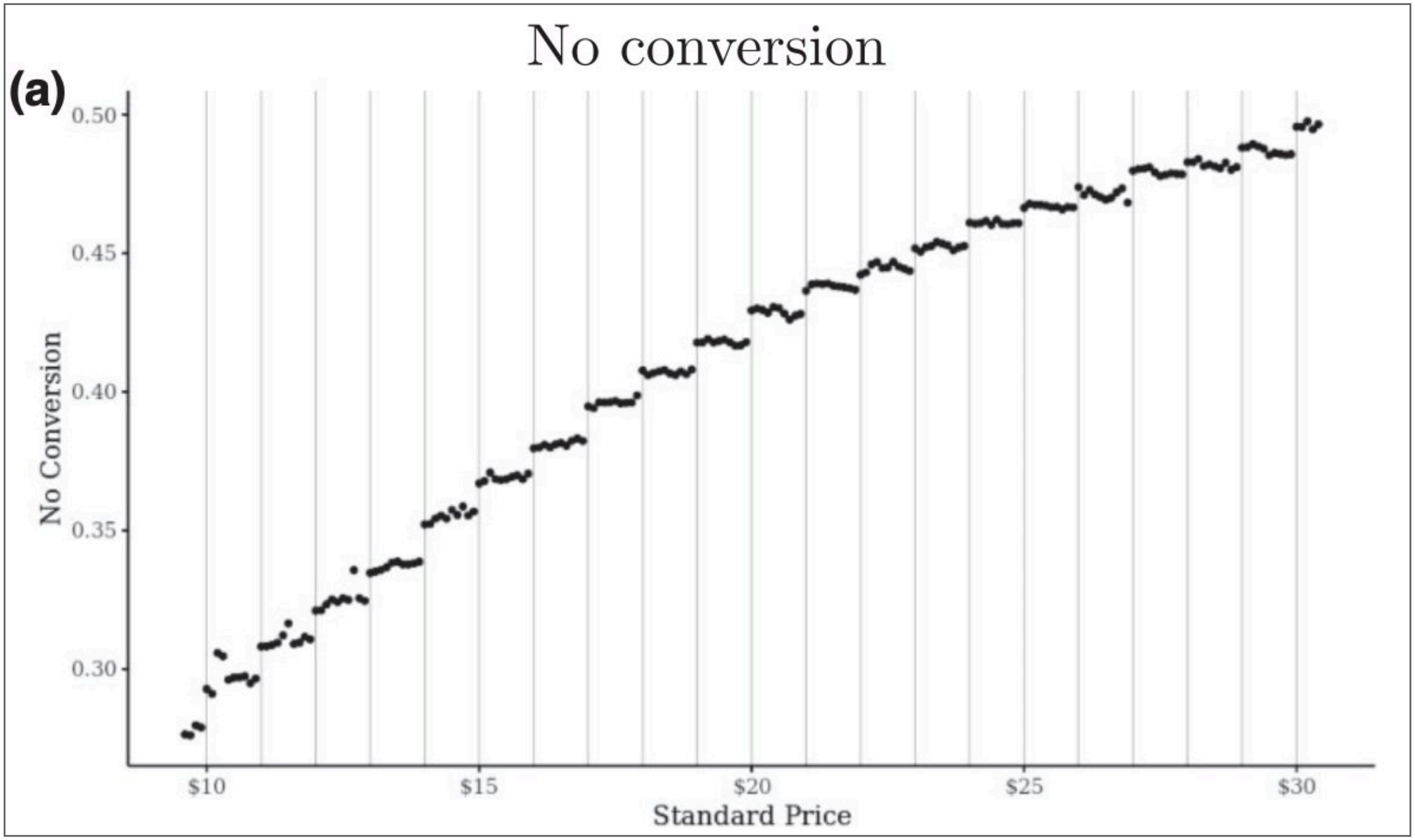
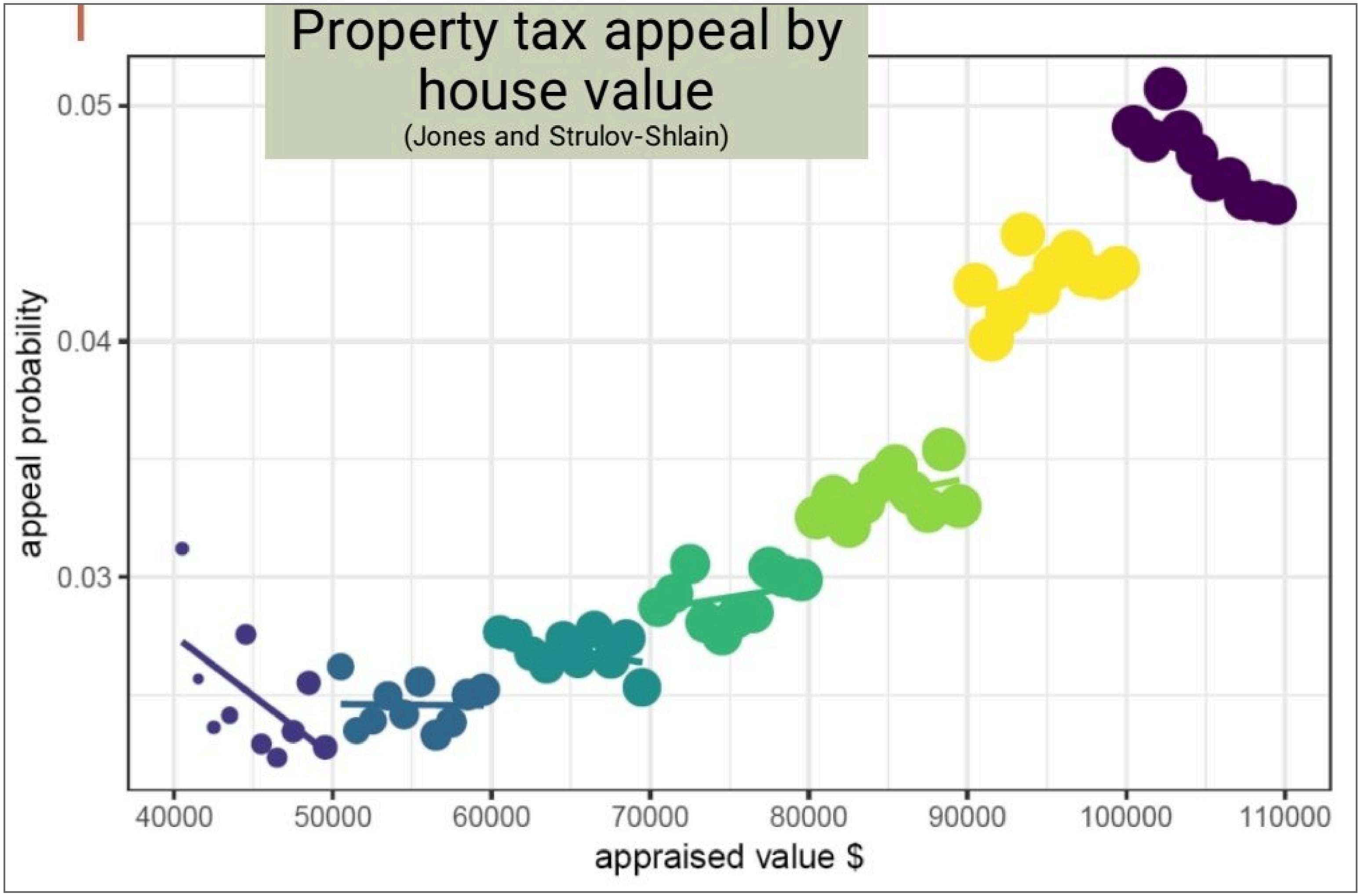


FIGURE 2
Demand curve of thirty-seven products, exhibiting drops at dollar digits

Left-digit bias: Lyft rides




Property tax appeal by house value
(Jones and Strulov-Shlain)
appeal probability
0.05
0.04
0.03
40000
50000
60000
70000
80000
90000
100000
110000
appraised value $

Human factors: Anchoring

- "You are lying on the beach on a hot lazy afternoon. For about an hour now, you have been thinking about an ice-cold bottle of your favorite beer. One of your friends gets up to make a phone call and offers to get you your favorite beer from a *small run-down grocery store* on the way back. Your friend says that the beer might be expensive and asks the maximum price that you are willing to pay. If the price is higher, your friend won't buy the beer. What is your maximum price?
- … *fancy resort hotel* …

Human factors: Price salience

- Show the price early, late or never?

```
- Drinks in a loud nightclub
- USPS "Forever Stamps"
- Price advertising, coupons
```

- Price salience emphasizes Savings or Exclusivity

Human factors: Decoy effects

- Choose 1:
  - Brand A: Rated 50/100, priced at 1.80
  - Brand B: Rated 70/100, priced at 2.60
- 33% chose A

Human factors: Decoy effects

- Choose 1:
  - Brand A: Rated 40/100, priced at 1.60
  - Brand B: Rated 50/100, priced at 1.80
  - Brand C: Rated 70/100, priced at 2.60
- 47% chose B (why?)

Field evidence in Diamonds

MARKETING SCIENCE

JOURNAL HOME ARTICLES IN ADVANCE CURRENT ISSUE ARCHIVES ABOUT SUBMIT SUBSCRIBE

View PDF

Tools Share

Home > Marketing Science > Vol. 39, No. 5 >

Profiting from the Decoy Effect: A Case Study of an Online Diamond Retailer

Chunhua Wu, Koray Cosguner

Published Online: 4 Aug 2020 | https://doi.org/10.1287/mksc.2020.1231

Go to Section

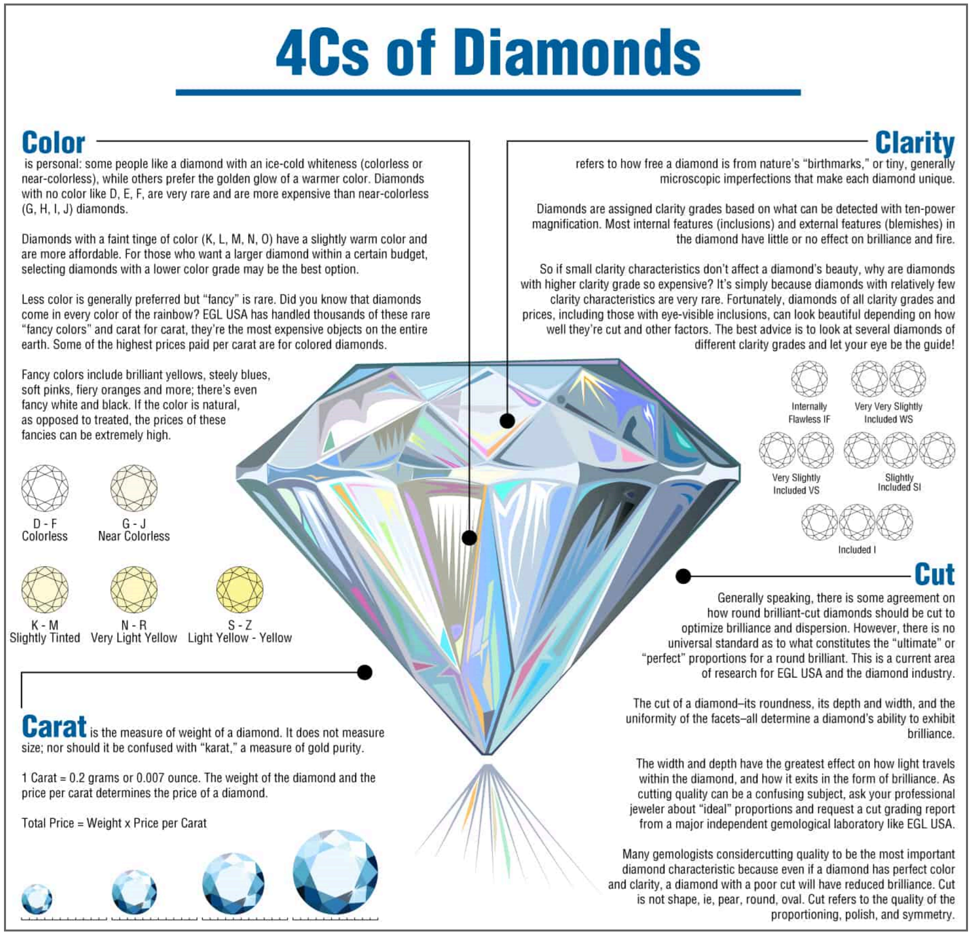
Abstract

Abstract

The decoy effect (DE) has been robustly documented across dozens of product categories and choice settings using laboratory experiments. However, it has never been verified in a real product market in the literature. In this paper, we empirically test and quantify the DE in the diamond sales of a leading online jewelry retailer. We develop a diamond-level proportional hazard framework by jointly modeling market-level decoy–dominant detection probabilities and the boost in sales upon detection of dominants. Results suggest that decoy–dominant detection probabilities are low (11%–25%) in the diamond market; however, upon detection, the DE increases dominant diamonds' sale hazards significantly (1.8–3.2 times). In terms of the managerial significance, we find that the DE substantially increases the diamond retailer's gross profit by 14.3%. We further conduct simulation studies to understand the DE's profit impact under various dominance scenarios.

‹ Previous Back to Top Next ›

4 vertical attributes



Estimating Decoy Effects

- Context: Online diamond sales

```
    - #1 online diamond retailer, 50% share, big US brand
    - Retailer used a drop shipping model and fixed 18-20% markup
    - Anonymous diamond suppliers create listings, set prices
    - Diamonds listed individually; listings disappear upon purchase
    - Consumers filter by attributes and price
    - Retailer orders filtered listings by ascending price
    - Great setting: Rare-purchase category, high-price, limited/no fit attributes, many
unknowledgeable consumers
```

- Wu & Cosguner

```
    - Scraped 7 months of 2.7 million daily diamond listings
    - Decoy-dominant relationships were frequent
    - Estimated decoy/dominant effect on time-to-sale
```

Dominant-Dominated Diamond Pair

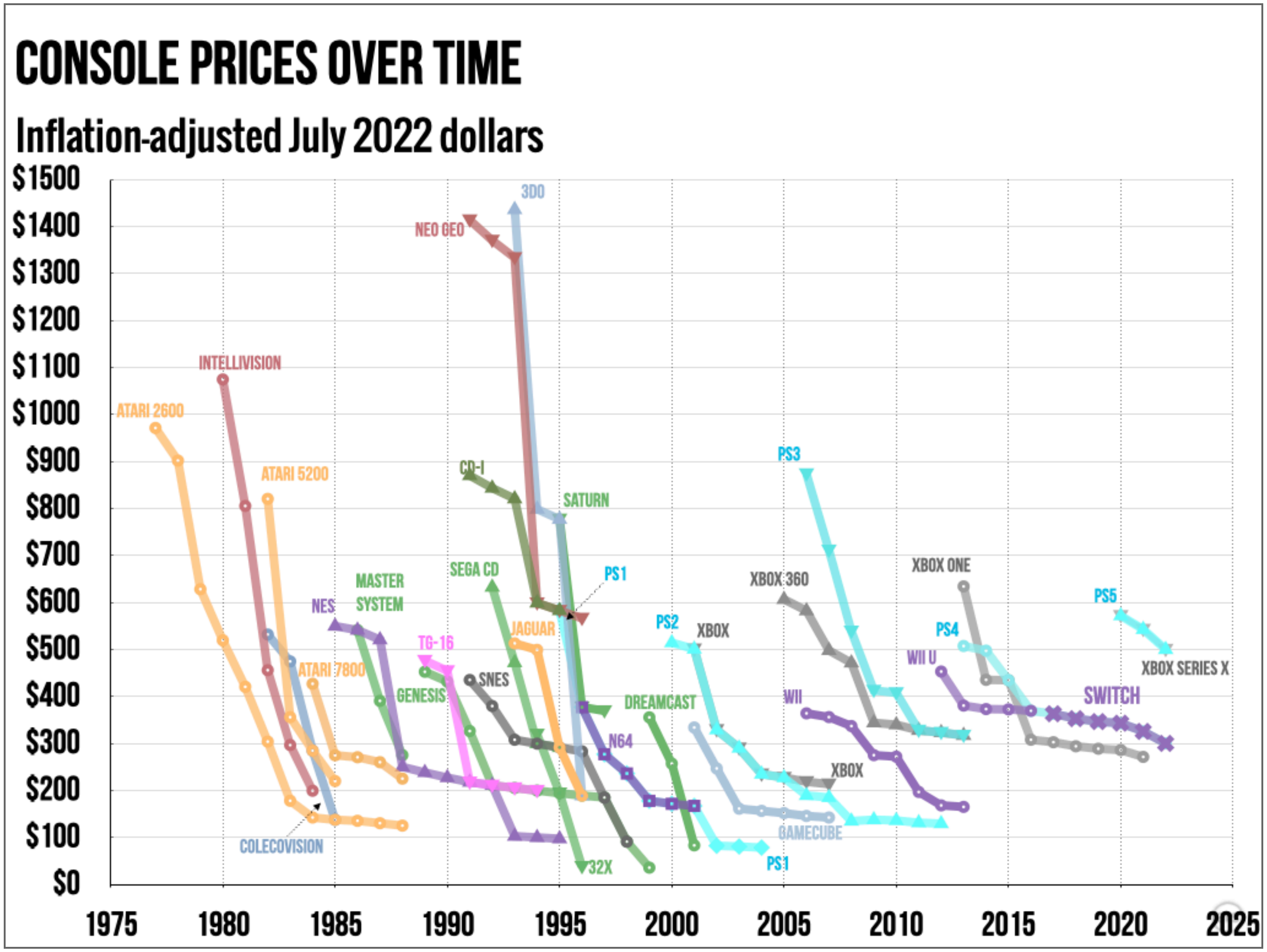
- Dominant/decoy pair defined as either:
  1. Same attributes, different prices
  2. Dominated attributes, same price
  3. Dominated attributes, disordered prices
- Example:
  - Dominant: 1-carat, Excellent cut, D color, VVS1 clarity, $3000 price
  - Decoy: 1-carat, Very Good cut, D color, VVS1 clarity, $3000 price
- Authors observe listings by date and can estimate the listing ordering algorithm
- However, authors do not observe individual user search results, so findings estimate a model of how search results appeared to customers

Model estimates indicate

- 11%-25% of diamond listings had a dominant or decoy listing
- Dominant diamonds sold 1.8-3.2x faster with decoy listings
- Simulations predict Decoy Effect increased retailer's gross profit by 14.3%

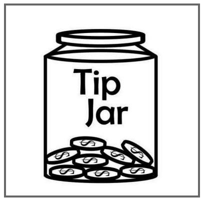
Economic factors: Price discrimination

- Amazon v. B&N
- Purchase time: Airline, Cruise tickets
- Needs: e.g. Business vs. Home segments
- Skimming by delivery time: Movie release windows
- Geography: Typically accounts for 20% of variation in online prices
- Quantity: Cups of coffee, Paper towels
- Reduce resentment via new/loyal customer, merit (veterans, seniors), ability to pay/sliding scale, value provided, cost of supply
- Always frame price differences as discounts


CONSOLE PRICES OVER TIME
Inflation-adjusted July 2022 dollars
$1500
$1400
$1300
$1200
$1100
$1000
$900
$800
$700
$600
$500
$400
$300
$200
$100
$0
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025
ATARI 2600
INTELLIVISION
ATARI 5200
COLECOVISION
ATARI 7800
NES
MASTER SYSTEM
GENESIS
TG-16
SEGA CD
SNES
CD-I
NEO GEO
3DO
JAGUAR
SATURN
PS1
N64
32X
DREAMCAST
PS2
XBOX
GAMECUBE
PS1
XBOX 360
XBOX
PS3
WII
WII U
PS4
XBOX ONE
SWITCH
PS5
XBOX SERIES X

Economic factors: Beware a price war!

- If you explicitly mention a competitor’s price
  - You make Customer aware of Competitor
  - Competitor will notice: You invite them to match or retaliate
- Better to price-compare vs. unnamed/generic competitor
- Who wins a price war?
  - Only one winner: Customer
  - All firms suffer, some die
  - Most likely to survive: Seller with lowest cost structure
  - Smart firms avoid price wars & keep costs secret



Price Elasticity of Demand

- $elas. = \frac{d(lnQ)}{d(lnP)} = \frac{P}{Q}\frac{dQ}{dP} \leq 0$
- For $-1 < elas. < 0$, we say demand is price-inelastic
- For $elas. < -1$, we say demand is price-elastic
- Elasticity is "scale-free" : % change response to % change
- We can calculate elasticity at a point, or on an interval
  Results depend on interval width and demand curvature
- Narrower intervals yield more precise elasticities

Price Elasticity of Demand

- $elas. = \frac{d(lnQ)}{d(lnP)} = \frac{P}{Q}\frac{dQ}{dP}$
- A special class of demand functions have constant elasticity
  $Q = e^a * P^b$ for $a > 0$ & $b > 0$, then $elast. = b$
  Implies $lnQ = \alpha + \beta lnP$, called "log-log"

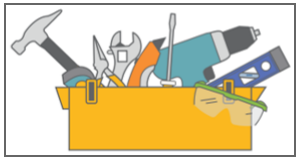
```
Still need exogenous price variation for to estimate a causal effect

Otherwise, beta should be interpreted as a correlation
```

- C.E. imposes a particular shape on demand & enables easy price optimization, given marginal cost data
- But, C.E. restricts demand -> can lead to suboptimal pricing

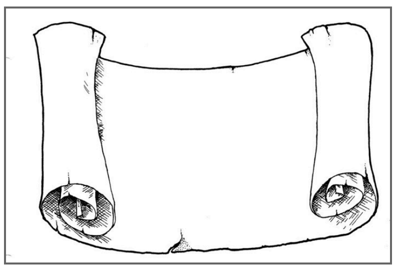
How to use demand model to set price

- $q_j(p_j) = N\hat{s}_j(p_j)$
- Total contribution = $\pi(p) = q_j(p_j)[p_j - c_j(q_j(p_j))]$
- Grid search:
  - Choose candidate prices $p_m = p_1, p_2, \ldots, p_M$
  - $p^* = argmax_{p_m} \pi(p_m)$
  - Optional: Repeat using a more refined grid around p^*
- We often assume $c_j(q_j(p_j)) = c$ for convenience
- Multiproduct line pricing requires sum over brand's owned products
- Can you predict competitor price reaction, or how your demand responds to new competitor price? How?



Class script

- Use demand model to trace out a demand curve
- Compare different arc elasticity results
- Conduct a grid search to find the profit-maximizing price, all else constant
- Compare the grid search result to the CE-demand price
- Consider multi-product price optimization

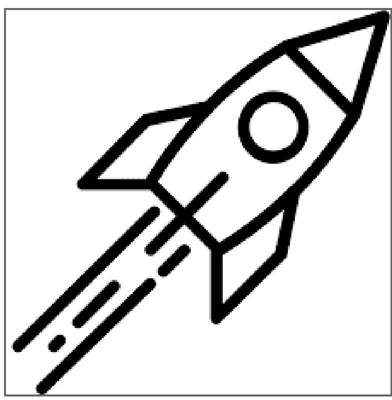


Recap

- The most common price setting methods are value pricing, competitor price matching, and cost-based pricing. All 3 are incomplete
- Consumers usually expect product prices to reflect quality positions in the marketplace
- Optimal pricing requires attention to both economic factors and human factors

Going further

- **Willingness to Pay Measurement Approaches**
- **Science of price experimentation at Amazon**
- **Behavioral Pricing**
- **More than a Penny's Worth: Left-Digit Bias and Firm Pricing**
- **Dynamic Online Pricing with Incomplete Information Using Multiarmed Bandit Experiments**
- **Universal Paperclips** : Fun price setting game



- Here is a snippet of the diamonds data, including prices and attributes