DEMAND CURVE ESTIMATION
Demand curve estimation

• Statistical methods
  – Problem: identification
  – Examples: NY Mets, gasoline

• Surveys

• Experimenting

• Qualitative educated guessing
Demand curve estimation

- Statistical methods
- Surveys
  - Eliciting truthful information
  - Example: BBC
- Experimenting
- Qualitative educated guessing
Demand curve estimation

- Statistical methods
- Surveys
- Experimenting
  - Can be very expensive (financially and reputationally)
  - Examples: Amazon, Netflix
- Qualitative educated guessing
Demand curve estimation

- Statistical methods
- Surveys
- Experimenting
- Qualitative educated guessing
  - See rules of thumb
Rules of thumb

• Rule of thumb 1: Demand for luxuries more sensitive to price changes than demand for necessities
  – Food vs Armani suits

• Rule of thumb 2: Demand for specific products more sensitive to price changes than demand for a category as a whole

• Rule of thumb 3: Long-run demand more sensitive to price changes than short-run demand
Rules of thumb

- Rule of thumb 1: Demand for luxuries more sensitive to price changes than demand for necessities

- Rule of thumb 2: Demand for specific products more sensitive to price changes than demand for a category as a whole
  - Mazda 323 vs cars overall

- Rule of thumb 3: Long-run demand more sensitive to price changes than short-run demand
• Rule of thumb 1: Demand for luxuries more sensitive to price changes than demand for necessities

• Rule of thumb 2: Demand for specific products more sensitive to price changes than demand for a category as a whole

• Rule of thumb 3: Long-run demand more sensitive to price changes than short-run demand
  — Gasoline
Statistical estimation

- From historical market data on quantity and price \((q, p)\), estimate demand as
  \[
  \ln q = \alpha + \beta \ln p + \gamma \ln x + \xi
  \]
  where \(x\) denotes demand shifters, \(\xi\) unobservables; parameters to estimate: \(\alpha, \gamma\) and \(\beta\) (demand elasticity)

- \(\hat{\beta} < 0\) for agricultural products, \(\hat{\beta} > 0\) for industrial products!
The identification problem
The identification problem

- If only demand shifts, data plots supply (e.g., ABC or DEF)
- If only supply shifts, data plots demand (e.g., AD, BE or CF)
- If both curves shift and if shocks are positively correlated (common occurrence) then data corresponds to DB or DC; connecting such points yields neither demand nor supply curve
- Key to identifying demand: find shocks that primarily shift supply curve, not demand curve; more on this later
The endogeneity problem

- Suppose that price-setters observe demand shocks that statistician does not; then $p$ is positively correlated with $\xi$:

$$\xi = \lambda \ln p + \epsilon$$

where $\epsilon$ is unobserved by price-setters and statistician

- Then elasticity estimate is biased

$$\ln q = \alpha + (\beta + \lambda) \ln p + \gamma \ln x + \epsilon$$

- If $\lambda \gg 0$, then will obtain positive estimate of demand elasticity even though (as theory predicts) $\beta < 0$
Example: U.S. gasoline demand
Example: gasoline demand

$p$ index (1983=100)

$q$ index (1983=100)
Example: gasoline demand

- Over time, increase in quantity and price
- Connecting dots implies positive “demand” elasticity!
- Possible solution: find controls $x$ that shift demand: income, population, price of cars
- Expanded equation yields negative coefficient on $\ln p$, but...
- Is this an unbiased estimate? Are there variables observable by market participants but not by me? Most likely
- Solution (as mentioned earlier): find shocks that primarily shift supply curve, not demand curve
US gasoline supply shocks and price

- Gasoline price
- US gasoline supply disruption

- Time
- Price
- Supply disruption (Katrina)
US gasoline supply shocks and price

- Hurricane Katrina (2005) affected US gasoline supply considerably
- Arguably, effect on demand was small (drivers in southern LA)
- Supply shock implied higher price
- Estimate demand elasticity as $\Delta \log q / \Delta \log p$ for this period
- General procedure more complicated but same basic principle
- Var. “supply disruption” is called an instrumental variable
Example: demand for NY Mets tickets
Stars indicate seasons when the Mets made it to post-season play. Source: mbl.com
NY Mets performance at the ticket office

Stars indicate seasons when the Mets made it to post-season play. A vertical dotted line indicates the introduction of variable pricing.

Sources: baseball-almanac.com and New York Mets.
Demand for Mets tickets

$p (\$)$

$q (\text{per game}(000))$

$D_{1998}$

$D_{2000}$

1998

2000

10 20 30 40

10 20 30 40
Variable pricing

• Until 2002 season, prices uniform across games (not across seats)
• From 2003 season, four pricing tiers: gold, silver, bronze, value; later platinum as well
• Before season starts, games are classified in each tier; prices vary by a factor of 3 (gold/value)
Estimating demand elasticity

• Within year (until 2002) there is no price variation (across games)
• From year to year, price varies but so do unobservable demand shifters (e.g., fan’s expectations)
• After 2003, prices vary within season, but clearly endogenously
• Additional problem: capacity constraints and censored data
Tickets sold per game: Mezanine Box

# tickets

Time

1997 2000 2003
Tickets sold per game: Loge Box

Time

# tickets
Tickets sold per game: Upper Reserved

# tickets

<table>
<thead>
<tr>
<th>Time</th>
<th># tickets</th>
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<tr>
<td>1997</td>
<td>5000</td>
</tr>
<tr>
<td>2000</td>
<td>10000</td>
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<tr>
<td>2003</td>
<td>15000</td>
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</table>

Time

0  1997  2000  2003
Demand estimation: Upper Reserved

• In what follows, focus on Upper Reserve ticket sales (no censuring concerns)

• For reasons described earlier, no scope for estimating price elasticity

• Estimate demand shifters (useful info)
# Upper Reserved ticket demand

<table>
<thead>
<tr>
<th>Dummy variable</th>
<th>Coefficient</th>
<th>St. Dev.</th>
<th>z</th>
<th>p</th>
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<tbody>
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<td>1078</td>
<td>402</td>
<td>2.68</td>
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<tr>
<td>Evening</td>
<td>-905</td>
<td>391</td>
<td>-2.31</td>
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<td>Season opener</td>
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<td>1373</td>
<td>5.97</td>
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<td>July</td>
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<td>5.86</td>
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<td>August</td>
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<td>415</td>
<td>3.43</td>
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<td>September</td>
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<td>Yankees</td>
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<td>1002</td>
<td>9.15</td>
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<tr>
<td>Constant</td>
<td>401</td>
<td>634</td>
<td>2.21</td>
<td>0.03</td>
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</table>
Estimating price elasticity

- Quasi-natural experiment: in 2004 all tickets remained constant except Value Games in cheaper seats
- Use relative demand to account for cross-season effects

\[ \epsilon = \frac{\log(r_2) - \log(r_1)}{\log(5) - \log(8)} \]

where \( r_i \) is attendance in cheap seats (price change) divided by attendance in more expensive seats (no price change)

- Based on this method (diff-diff), we obtain a demand elasticity estimate of approximately \(-.35\)
- What assumptions do we make to legitimize this approach?
Takeaways

- Empirically estimating consumer demand can be tricky