Panel: Learning about Substitution and Welfare from Data

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What can we learn from experiments?

What are experiments informative about? (for substitution and welfare)

Substitution / Diversion Ratios:

$$MTE_p = \frac{\frac{\partial s_k}{\partial p_j}}{\left|\frac{\partial s_j}{\partial p_j}\right|}, \quad MTE_q \quad = \frac{\frac{\partial s_k}{\partial \xi_j}}{\left|\frac{\partial s_j}{\partial \xi_j}\right|}, \quad ATE = \frac{s_k(\mathcal{J} \setminus j) - s_k(\mathcal{J})}{|s_j(\mathcal{J} \setminus j) - s_j(\mathcal{J})|}, \quad Logit = \frac{s_k(\mathcal{J})}{1 - s_j(\mathcal{J})}$$

What are experiments informative about? (for substitution and welfare)

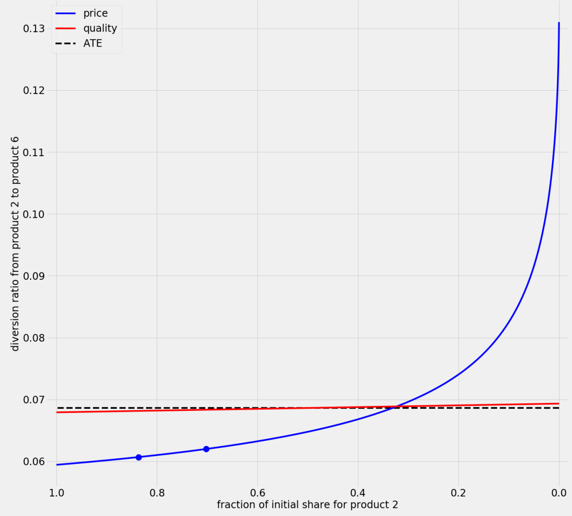
Consumer Welfare is largely about how outside good share responds

$$CS_i \propto \log \underbrace{\left(1 + \sum_{j \in \mathcal{J}} \exp[\tilde{v}_{ij} - \alpha_i p_j]\right)}_{s_{i0}^{-1}} + C_i$$

$$\text{price } \Delta = \frac{\partial \log s_{i0}}{\partial p_j}, \quad \text{quality } \Delta = \frac{\partial \log s_{i0}}{\partial \xi_j}, \quad \text{variety } \Delta = \frac{s_{i0}(\mathcal{J} \setminus j) - s_{i0}(\mathcal{J})}{s_{i0}(\mathcal{J})}$$

Caveat: outside good s_{i0t} unfortunately mostly about assumptions.

How do these objects look?



[Plot #2]

Examples of Experiments

1. Small price changes: "course of business" by firms, or by researchers
2. Second choice Surveys: "Where would you shop if we closed this Tesco?"
3. Product Removals: (easier online), stockouts as quasi-experiments

The hard part:

- Need to pay careful attention to which effect our experiments informs us about
  - Small price change? Change in assortment? Second choice data?
- Price effects of mergers (or UPP) are about small price changes
- WTP is concerned with second choice data or assortment.

Experiments: Complements or Substitutes?

Can we do antitrust with experiments only and without empirical models?

- Farrel Shapiro (2010) suggest maybe we can observe diversion in "course of business" or in discovery.
  - Is this measuring the right economic object?
  - Our experience suggests we need all substitutes (not merging parties) alone to measure diversion.
- Asking merging parties to submit to an experiment designed by a third party to measure substitution is unlikely to be feasible.
- Can use experiments as a source of exogenous variation to identify our parametric demand models
  - How to combine them?
  - How to balance experiments and observational data?

Notes on Best Practices

Best Practices

- Need (at minimum) heterogeneity in taste for constant and price.
- Instruments necessary for prices and random tastes:
  1. Start with differentiation IV of (Gandhi Houde, 2019)
  2. Construct Approximate IV (Chamberlain (1987), Raeynart Verboven (2014))
- Impose supply conditions when appropriate
- Add micro-moments (Covariance between price paid and income, Covariance between characteristics and demographics).

Shameless pyBLP plug

An Advertisement

- Available on `PyPI`

  `pip install pyblp`
- Extensive documentation: `https://pyblp.readthedocs.io/en/stable/`
- Long list of features

A Famous Example

```
blp_problem = pyblp.Problem(
    product_formulations=(
        pyblp.Formulation('1 + hpwt + air + mpd + space'),                      # Linear demand
        pyblp.Formulation('1 + prices + hpwt + air + mpd + space'),             # Nonlinear demand
        pyblp.Formulation('1 + log(hpwt) + air + log(mpg) + log(space) + trend')  # Supply
    ),
    agent_formulation=pyblp.Formulation('0 + I(1 / income)'),                   # Demographics
    product_data=pandas.read_csv(pyblp.data.BLP_PRODUCTS_LOCATION),
    agent_data=pandas.read_csv(pyblp.data.BLP_AGENTS_LOCATION)
)
```

```
Dimensions:
============================================
 N     T    K1    K2    K3    D    MD    MS
----  ---  ----  ----  ----  ---  ----  ----
2217  20    5     6     6     1    11    12
============================================


Formulations:
=====================================================================================
       Column Indices:           0          1        2       3         4         5
-----------------------------  --------  ---------  -----  --------  ----------  -----
 X1: Linear Characteristics      1        hpwt      air     mpd       space
X2: Nonlinear Characteristics    1        prices    hpwt    air       mpd        space
  X3: Cost Characteristics       1       log(hpwt)  air   log(mpg)  log(space)  trend
       d: Demographics         1/income
=====================================================================================
```

What can we do?

```
blp_results=blp_problem.solve()

blp_results.compute_elasticities()
blp_results.compute_diversion_ratios()
blp_results.compute_consumer_surpluses()


blp_results.compute_costs()
blp_results.compute_prices(ownership=post_merger)

opt_results = blp_results.compute_optimal_instruments().to_problem().solve()
```

And much more...