

How Do We Learn About Substitution Patterns from Data?

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Demand

Since Wright (1929), we understand that learning about demand requires **instruments** for price, like cost shifters.

But in differentiated products, how do we simultaneously learn about “substitution patterns”

- ▶ in the space of observed product characteristics, x_j
- ▶ in a vertical, partially unobserved, dimension (involving the product-specific demand error, ξ_j)

Many claim that you can read, say, BLP (1995) and still not be sure.

For a general overview of nonparametric arguments, see Berry and Haile (2016a).

More Instruments

A general intuition is that we need observed exogenous changes in the choice set.

In the case of **market level** data and nonparametric demand, Berry and Haile (2014) argue that we need:

- ▶ Cost instruments for price effects
- ▶ Exogenous shifters of own and rival-product demand (“BLP instruments”) to handle vertical substitution.

The latter “instrument for” the vector of market shares in inverse demand.

Approximations to the optimal instruments: Berry et al. (1999), Reynaert and Verboven (2014), Houde and Gandhi (2019), Conlon and Gortmaker (2019).

Not Enough/Not Strong Enough IVs

- ▶ Stronger **functional form**
- ▶ Adding a **cost side** adds many over-identifying restrictions
- ▶ **Micro data** that matches consumer attributes to product choices
- ▶ Ranked choices, panel data

Micro Data

Intuition: holding products fixed, “move consumers relative to the choices” via variations observable consumer attributes. Classic idea from McFadden et al. (1977) onwards, using product/consumer interactions in utility.

Berry and Haile (2016b): in a nonparametric context, micro data allows us to

- ▶ learn about substitution from the micro data alone
- ▶ do without the “BLP instruments”
- ▶ but still need instruments for price

How to Do It in Practice

Conlon and Gortmaker (2019), pyblp

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