Discussion of paper
"Scalable Nonparametric Price Elasticity Estimation"
by *Wang and Huang*

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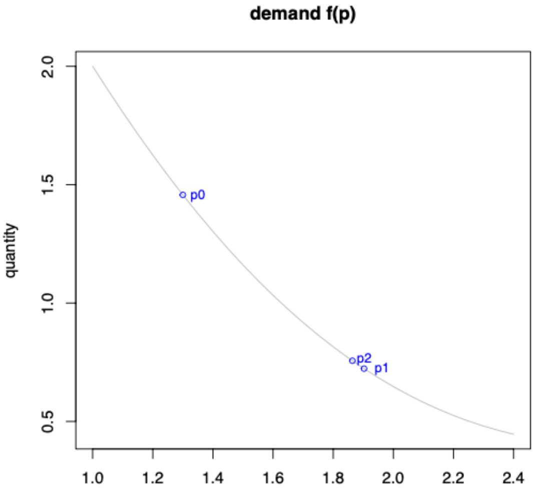
UTD FORMS

- Motivation: Obtain **price elasticities** from aggregate data.
- Our typical approach to demand models is parametric (e.g. logit)
- Want to do this using a nonparametric approach
    - Why?
- Use ML method, specifically bagged (bootstrap averaged) nearest neighbors
- Desiderata:
    - Minimal assumptions – nonparametric
    - No demand model required even
    - Closed form for function, conditional on function values at nearest neighbors
    - $\Longrightarrow$ Computationally light and scalable

How it works – with exogenous prices

- Consider simple case without endogeneity
- Model: $\boxed{s_{jt} = f_j(p_{jt}, x_{jt}) + \varepsilon_{jt}}$
- Elasticities: If you know function f, then we can easily obtain elasticities
  - Change price to $p + \Delta$, determine how sales change.
- How do you get f nonparametrically?
  - Use a ML method to obtain functional approximation
  - Universal function approximators for different classes of functions

Endogenous prices are a challenge



How it works – Dealing with endogeneity

- Control function approach is used to deal with endogeneity
- $\boxed{\mathbf{p} = \mathbf{g}(\mathbf{z}) + \mathbf{u}}$
- where z's are instruments
- Want to obtain price derivatives: $\partial_p f_j(p,x) = \partial_p \mathbf{E}[s_j|p,x] - \partial_p \mathbf{E}[\varepsilon_{jt}|p,x]$
- Newey, Powell and Vella (1999) provide a way to write the selection bias to get: $\partial_p \mathbf{E}[\varepsilon_{jt}|p,x] = (\partial_z g(z)' \partial_z g(z))^{-1} \partial_z g(z)' \partial_z \mathbf{E}[s_j|p,x]$
- All quantities can be easily obtained from data

What is the Role of ML here?

- One view of ML is that it is functional approximation
- If we have $\partial_p f_j(p,x)$ we can get elasticities
- Want to approximate

$$\partial_p f_j(p,x) = \partial_p \mathbf{E}[s_j|p,x] - \left(\partial_z g(z)' \partial_z g(z)\right)^{-1} \partial_z g(z)' \partial_z \mathbf{E}[s_j|p,x]$$

- Want a method that has "fast" asymptotic convergence (rate $\sqrt{m/T}$)
- Why the complexity:
    - Let's start with k-Nearest Neighbor (Bias-Variance Tradeoff)
    - Ensemble methods like Bagging can reduce variance (think of Random Forest)
    - ...But still biased.
    - use a jackknife to correct the bias (Biau, Cerou, and Guyader, 2010)
    - corrects first order bias.

Things to Like

- Paper is well written and motivated, which is not common in methodological papers
- Method is new and applicable to pretty much any demand setting.
- One of the biggest issues is endogeneity, which is accommodated here.
- Structural models can often take days, weeks or even months to estimate
- Anything that helps with obtaining realistic estimates of **economic quantities** like elasticity very useful
- Critical to have when **real-time** or timely decisions are required
- Scalable to lots of products, markets

Things to Like

- Nonparametric implies the model misspecification is not likely a huge issue
- Prove closed form for bagged nearest neighbors estimator
  - In parametric models, sometimes assumptions drive the result(rather than the data).
- Bagged Nearest Neighbor has attractive computational properties
- Not easy to obtain a method that has all the desirable properties
- Authors show monte carlos to show approximation quality
- Practical value in realistic applications...fast..

Thoughts – Model and Counterfactuals

- Let's start with profit-maximizing firm: $\pi(p) = f(x,p)(p-c)$
- In equilibrium, after solving FOC, Lerner index $\dfrac{p-c}{p} = -\dfrac{1}{\varepsilon(p)}$
- So, can use this to recover marginal costs if we know $\varepsilon(p)$.

Thoughts – Model and Counterfactuals

- Typically we start with a utility model $\boxed{u_{ijt} = \beta X_{jt} + \alpha p_{jt} + \xi_{jt} + +\omega_{ijt}}$
- We recover parameters $\theta = (\alpha, \beta)$.
- We might expect the sales to j to be impacted by all the unobservables ξ_{kt}. So we should have $f(x, p, \xi)$.
- What is the impact of extant price variation?
- Local versus Global: when are we likely to have local be a good approximation to global as in Compani (2022)?
  - What classes of demand and hence profit functions?
- Here the method cannot recover preference parameters
- However, the claim is we can still do counterfactuals. How?

Thoughts – Model and Counterfactuals

- **Key Restriction**: Demand $f(x, p)$ that is recovered through ML should not change in the counterfactual
  - Demand invariance
- What class of counterfactuals would work here?
  - An excise tax would be covered but a sales tax would not. Why?
- Excise tax $\implies$ cost increases $c \to c + \delta$ but does not impact demand directly in any way.
- $\implies$ elasticities are not affected.
- However, what happens when we have a sales tax increase?
  - The elasticity recovered from the data $\varepsilon(p)$ is different from counterfactual $\widetilde{\varepsilon}(p)$
- What about something like Petrin (2002), minivan?

Thoughts – ML

1. How are the hyperparameters (tuning parameters) of the ML algorithm set? No theoretical guidelines for this.
2. What about the g function (recall $p = g(z) + u$). This needs to be parametrically specified?
3. Can we use any other ML method in place of Bagged nearest neighbors?
   - Random Forest, Deep nets etc.
4. Boils down to what you need from a computational perspective as well as a

Conclusion

1. Very interesting and practically valuable contribution to estimate elasticities in the presence of price endogeneity
2. Authors show that method can satisfy a number of desirable properties both in theory and in practice
3. Need to have invariance of demand curve in the counterfactual