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

Discussion by Vineet Kumar (Yale School of Management)

March 2023
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
  - $\implies$ Computationally light and scalable

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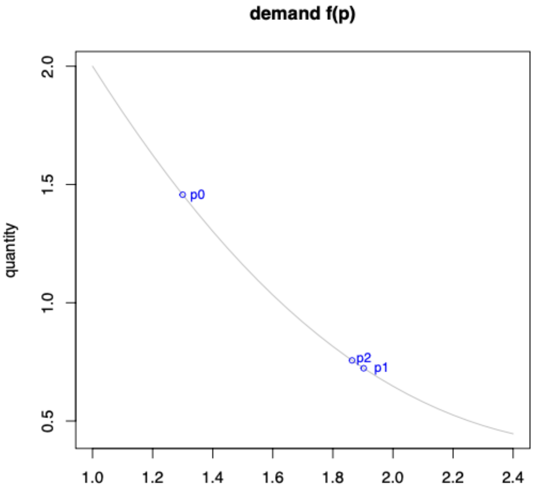
# How it works – with exogenous prices

- 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



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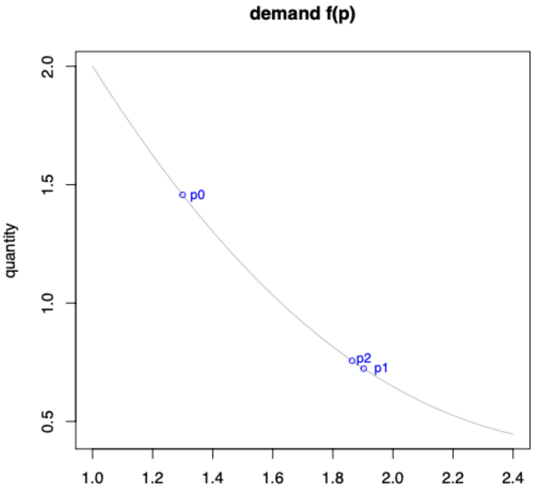

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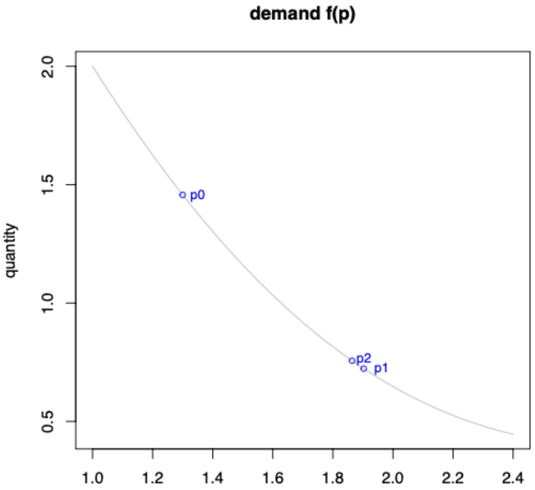

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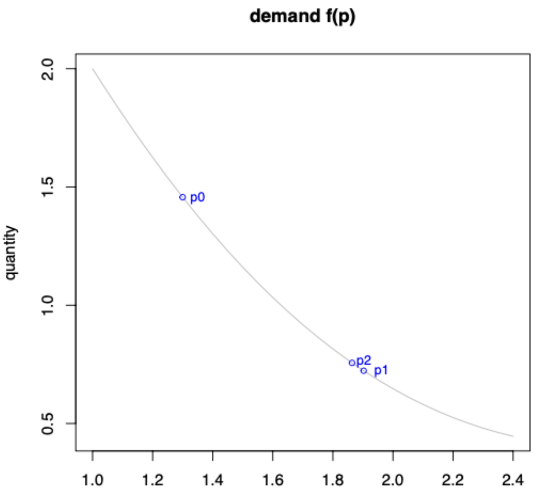

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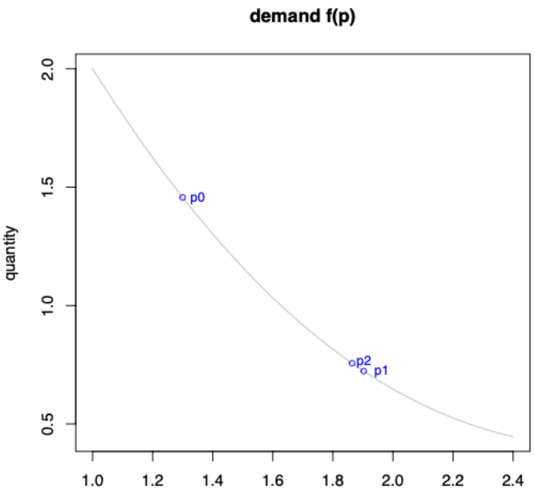

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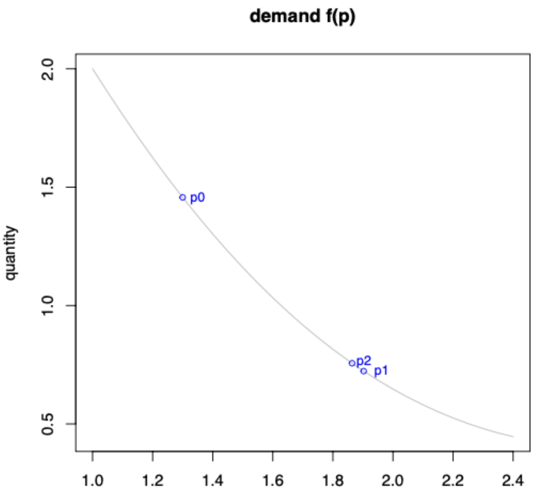

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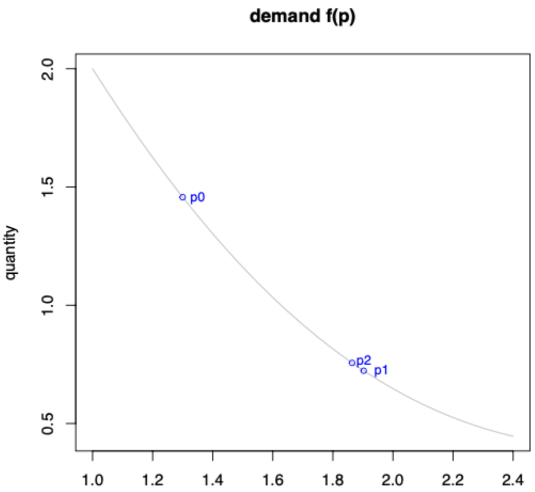

# How it works – Dealing with endogeneity

- 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: $\partial_p \mathbf{E}[\varepsilon_{jt}|p,x] = (\partial_z g(z)' \partial_z g(z))^{-1} \partial_z g(z)' \partial_z \mathbf{E}[s_j|p,x]$
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# 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

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- 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)
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- 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
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- Nonparametric implies the model misspecification is not likely a huge issue
  - 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 $\dfrac{p-c}{p} = -\dfrac{1}{\varepsilon(p)}$
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- We recover parameters $\theta = (\alpha, \beta)$.
- Here the method cannot recover preference parameters
- However, the claim is we can still do counterfactuals. How?
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