# Identification of Random Coefficient Latent Utility Models

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ASSA 2021

- Identifies distribution of random coefficients for large class of models.
- Covers discrete choice, bundles models, consideration set models, among others.
- Key feature: need to identify average demand function.
- Get traction by exploiting envelope theorem.

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Discrete choice with linear random coefficients

$$\mathbf{v}_k = \beta'_k \mathbf{x}_k + \varepsilon_k.$$

- $\beta$  and  $\varepsilon$  are random
- Special case is random coefficients logit, in which  $\varepsilon$  has a *known* distribution up to location.
  - Studied in Fox, il Kim, Ryan, Bajari (2012, JoE).
  - We differ by letting both  $\beta$  and  $\varepsilon$  have nonparametric distribution.
- Identify all moments of  $\beta = (\beta_1, \dots, \beta_K)$ .

These models (and others) can be written as perturbed utility models of the form

$$Y(X, \beta, \varepsilon) \in \operatorname*{argmax}_{y \in B} \sum_{k=1}^{K} (\beta'_k X_k) y_k + D(y, \varepsilon).$$

- Y is quantity vector for K goods.
- X collects regressors.
- $\varepsilon$  can be infinite dimensional.
- B is nonrandom however D(y, ε) can be −∞ for certain combinations.
  - Allows "consideration sets."

This paper starts with average structural function

$$\overline{Y}(x) = \int Y(x, \beta, \varepsilon) d\tau(\beta, \varepsilon)$$

and asks what we can learn about distribution of  $\beta$ .

• When X and  $(\beta, \varepsilon)$  are independent,

$$\overline{Y}(x) = \mathbb{E}[Y \mid X = x].$$

- Also identifiable with endogeneity.
  - We complement Berry and Haile (2014, ECTA), who identify  $\overline{Y}(x)$  in a demand setting with instruments.

#### Lemma

Let

$$V(\beta'_1x_1,\ldots,\beta'_Kx_K)=\int\left(\max_{y\in B}\sum_{k=1}^K y_k(\beta'_kx_k)+D(y,\varepsilon)\right)d\mu(\varepsilon).$$

Then

$$\int Y(x,\beta,\varepsilon)d\mu(\varepsilon) = \nabla V(\beta'_1x_1,\ldots,\beta'_Kx_K)$$

at any point of differentiability.

• Related to Williams-Daly-Zachary theorem of discrete choice.

#### Assumption

 $\beta$  and  $\varepsilon$  are independent so we can write

$$\overline{Y}(x) = \int \int Y(x,\beta,\varepsilon) d\mu(\varepsilon) d\nu(\beta).$$

Notation:

$$\overline{Y}(x,\beta) = \int Y(x,\beta,\varepsilon) d\mu(\varepsilon)$$
  
 $\overline{Y}(x) = \int \overline{Y}(x,\beta) d\nu(\beta).$ 

 Assume each  $x_k$  is scalar for simplicity.

Write envelope theorem as

$$\overline{Y}_k(x,\beta) = \partial_k V(\beta_1 x_1, \ldots, \beta_K x_K).$$

Differentiate envelope theorem further to get

$$\partial_{x_j}\overline{Y}_k(x,\beta) = \partial_{j,k}V(\beta_1x_1,\ldots,\beta_Kx_K)\beta_j$$

and

$$\partial_{x_{\ell}}\partial_{x_{j}}\overline{Y}_{k}(x,\beta)=\partial_{\ell,j,k}V(\beta_{1}x_{1},\ldots,\beta_{K}x_{K})\beta_{\ell}\beta_{j}.$$

 Take expectations over  $\beta$  and evaluate at x = 0 to get:

$$\partial_{x_{\ell}}\partial_{x_{j}}\overline{Y}_{k}(0) = \partial_{\ell,j,k}V(0)\int \beta_{\ell}\beta_{j}d\nu(\beta).$$

• Key feature:  $\partial_{\ell,j,k} V(0)$  does not depend on  $\beta$ .

### Example: Identification of Second Moments

$$\partial_{\mathbf{x}_{1}} \partial_{\mathbf{x}_{1}} \overline{Y}_{2}(0) = \partial_{\mathbf{1},\mathbf{1},2} V(0) \int \beta_{1}^{2} d\nu(\beta)$$
$$\partial_{\mathbf{x}_{1}} \partial_{\mathbf{x}_{2}} \overline{Y}_{2}(0) = \partial_{\mathbf{1},2,2} V(0) \int \beta_{2} \beta_{1} d\nu(\beta)$$
$$\partial_{\mathbf{x}_{2}} \partial_{\mathbf{x}_{1}} \overline{Y}_{1}(0) = \partial_{2,\mathbf{1},\mathbf{1}} V(0) \int \beta_{1} \beta_{2} d\nu(\beta)$$
$$\partial_{\mathbf{x}_{2}} \partial_{\mathbf{x}_{2}} \overline{Y}_{1}(0) = \partial_{2,2,\mathbf{1}} V(0) \int \beta_{2}^{2} d\nu(\beta)$$

### Example: Identification of Second Moments

$$\frac{\partial_{\mathbf{x}_{1}}\partial_{\mathbf{x}_{1}}\overline{Y}_{2}(0)}{\partial_{\mathbf{x}_{2}}\partial_{\mathbf{x}_{1}}\overline{Y}_{1}(0)} = \frac{\partial_{\mathbf{1},\mathbf{1},2}V(0)\int\beta_{1}^{2}d\nu(\beta)}{\partial_{2,\mathbf{1},1}V(0)\int\beta_{1}\beta_{2}d\nu(\beta)}$$
$$= \frac{\int\beta_{1}^{2}d\nu(\beta)}{\int\beta_{1}\beta_{2}d\nu(\beta)}$$

- Uses symmetry  $\partial_{1,1,2}V(0) = \partial_{2,1,1}V(0)$ .
- Symmetry has been used without random coefficients in Allen and Rehbeck (2019, ECTA).

## Example: Identification of Second Moments

Combining other equations identifies the ratio of any two second moments.

• Identification given a scale assumption  $\int \beta_1^2 d\nu(\beta) = 1$ .

#### Theorem

Assume  $\int \beta_{1,1}^M d\nu(\beta)$  is known. Under regularity conditions, each *M*-th order moment of the form

$$\int \beta_{k_1,\ell_1} \cdots \beta_{k_M,\ell_M} d\nu(\beta)$$

is identified. In addition, for each  $\gamma \in \{1, \dots, K\}^{M+1}$ ,

 $\partial_{\gamma}V(0)$ 

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is identified.

Can identify counterfactual/welfare objects under additional assumptions.

• Integrated indirect utility

$$V(\beta'_1x_1,\ldots,\beta'_Kx_K) = \int \left(\max_{y\in B}\sum_{k=1}^K y_k(\beta'_kx_k) + D(y,\varepsilon)\right) d\mu(\varepsilon).$$

How to identify V?

- Main result identified partial derivatives of V at 0.
- If V is real analytic we can identify the function globally from these derivatives.
- (Paper presents two other techniques.)

Once V is identified, counterfactuals can be identified from envelope theorem.

$$\overline{Y}_k(x,\beta) = \partial_k V(\beta'_1 x_1,\ldots,\beta'_K x_K).$$

- Identification of moments of linear random coefficient distribution in class of perturbed utility models.
- Covers several examples in a single framework.
- Requires only the average structural function.
- Exploits the envelope theorem.