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- Individual-specific elasticities

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- Behavioral types (e.g., price-sensitive vs quality-focused)

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Does the economic theory suggest continuous or discrete heterogeneity?

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Solutions:

- Multiple random starting values (minimum 50-100)
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Diagnostic: Compare final likelihood across different starts

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If estimates vary dramatically, increase number of starting values or simplify specification

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Warning Signs:

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- Nearly identical parameter vectors across types
- Unstable estimates across samples

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Start simple and build complexity gradually

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Statistical Approach:

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- Can you interpret and name each type?

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Practical constraint: Rarely use more than 4-5 types in practice

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$$\frac{\left|\mathcal{L}^{(t+1)} - \mathcal{L}^{(t)}\right|}{\left|\mathcal{L}^{(t)}\right|} < \text{tolerance}$$

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Be suspicious of "convergence" after very few iterations

Equilibrium Trade in Automobiles

Kenneth Gillingham

Yale University

Fedor Iskhakov

Australian National University

Anders Munk-Nielsen

University of Copenhagen

John Rust

Georgetown University

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University of Copenhagen

We introduce a computationally tractable dynamic equilibrium model of automobile markets with heterogeneous consumers, focused on stationary flow equilibria. We introduce a fast, robust algorithm for computing equilibria and use it to estimate a model using nearly 39 million observations on car ownership transitions from Denmark. The estimated model fits the data well, and counterfactual simulations show that Denmark could raise total tax revenue by reducing the new-car registration tax rate. We show that reducing this tax rate while raising the tax rate on fuel increases aggregate welfare, tax revenue, and car ownership, while reducing car ages, driving, and CO_2 emissions.

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Policy insight: Current registration tax above Laffer curve peak