Industrial Economics

A Short Introduction to Empirical Industrial Organization

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A Short Introduction to Empirical Industrial Organization

- For many policy decisions, we need to put a number on things
- The underlying parameters of a model need to be *structurally estimated* first, then *counterfactuals* can be simulated
- structural econometric models: models that combine explicit economic theories with statistical model
- structural estimation: analysis of data based on structural econometric model
- counterfactual: A hypothetical state of the world, used to assess the impact of an action.

Applications

- merger control
  - for example, in 2017 the PSA Group acquired Opel and Vauxhall
  - should competition authorities have cleared the acquisition?
  - counterfactual: what is the prediction on price changes for the acquisition?

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- environmental policy
  - for example, France introduced a feebate policy for cars in 2008
  - high CO2 emission cars get taxed, low CO2 emission cars get a rebate
  - the intention was to have a balanced budget

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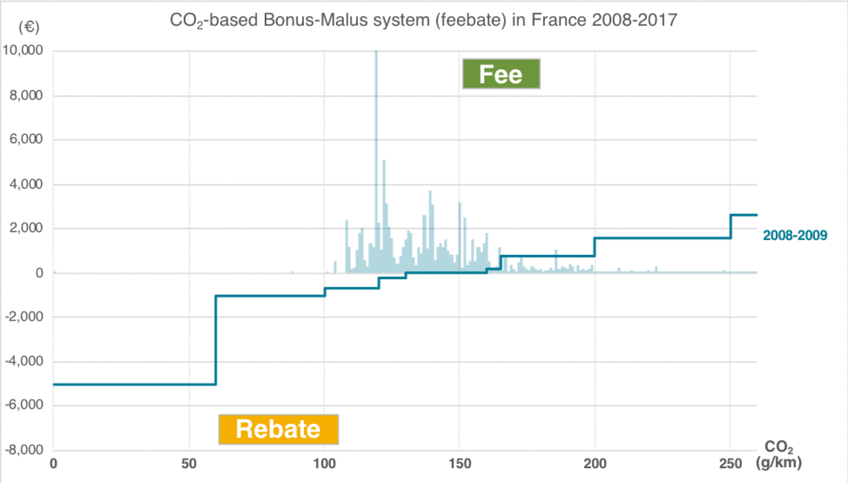

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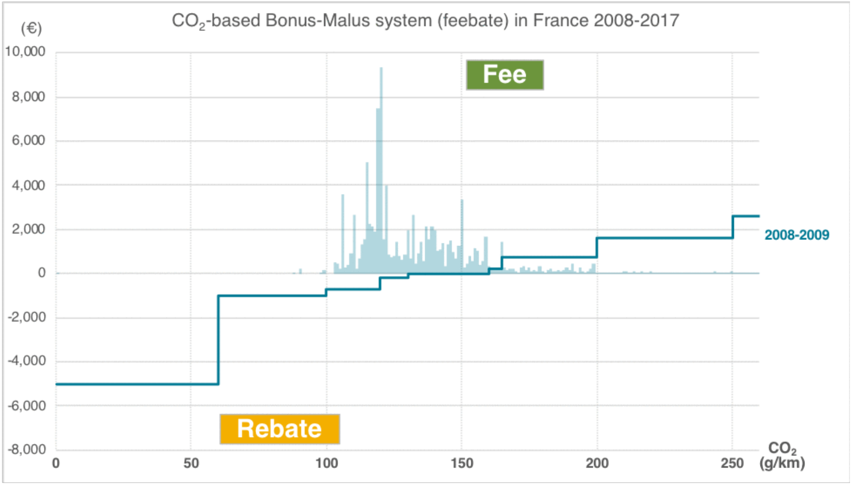

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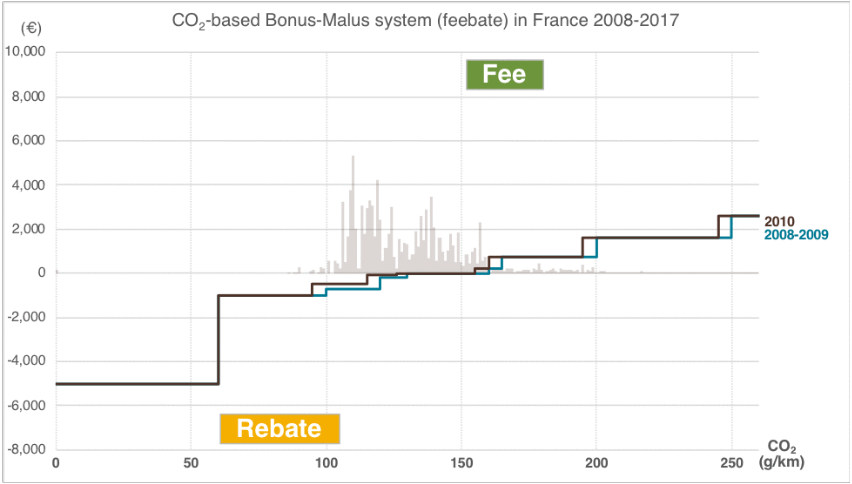

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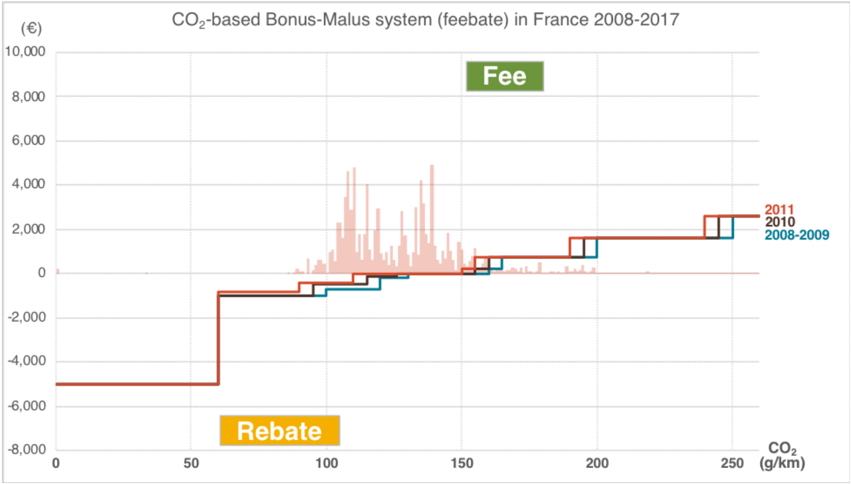

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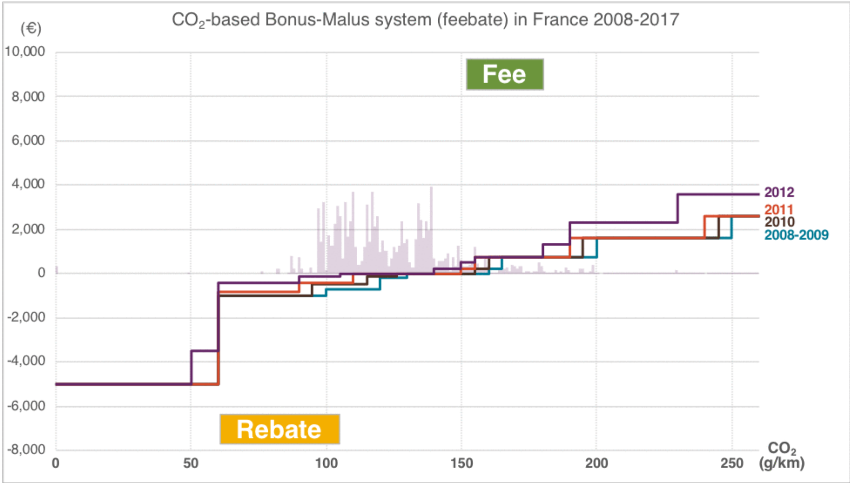

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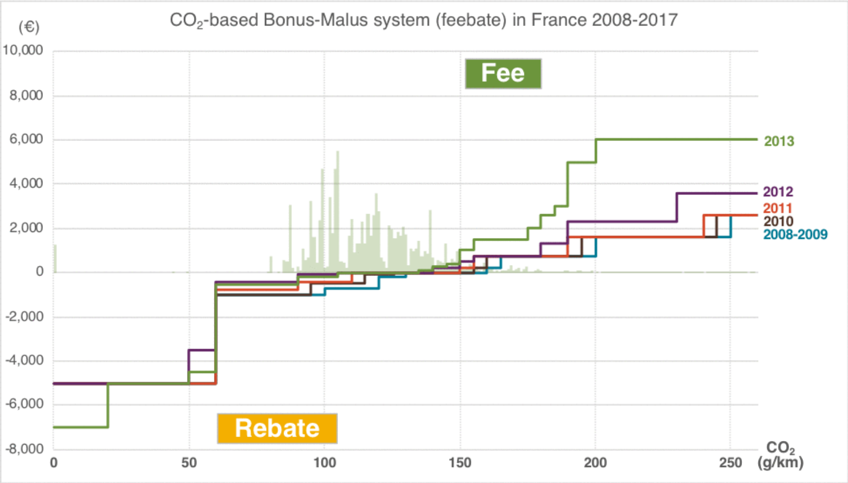

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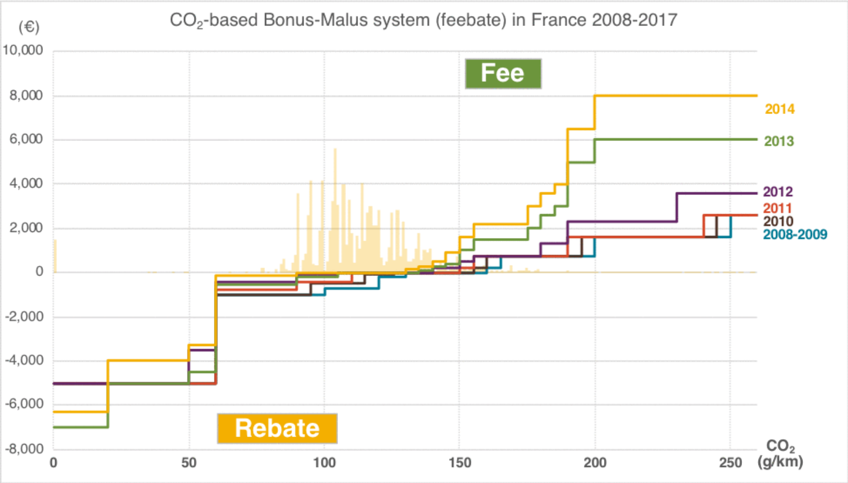

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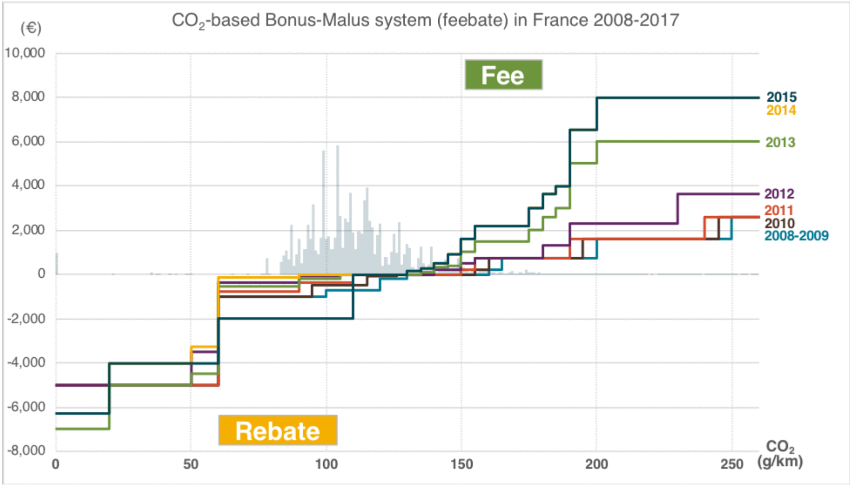

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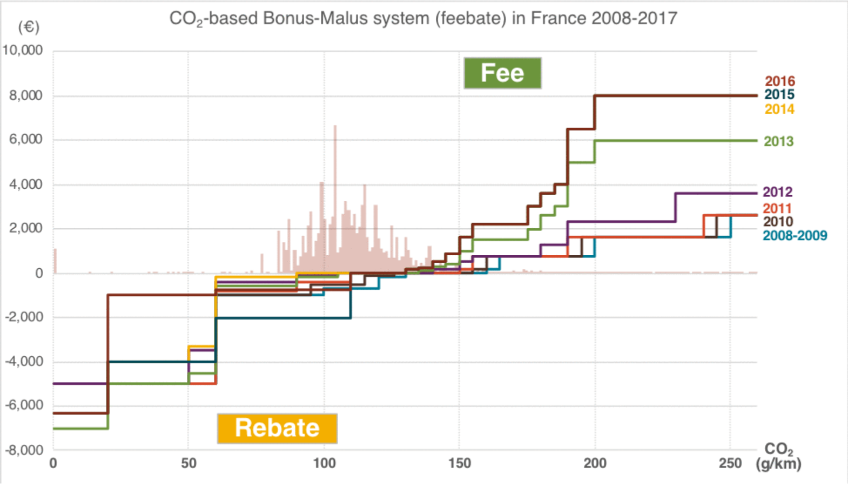

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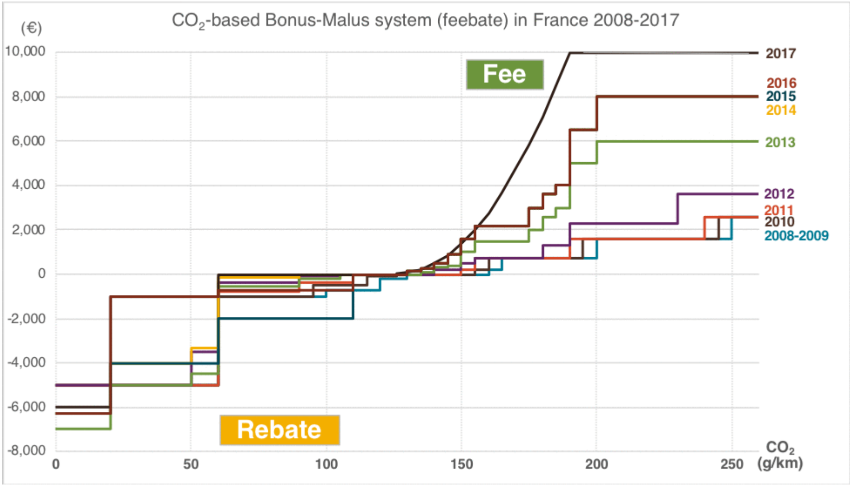

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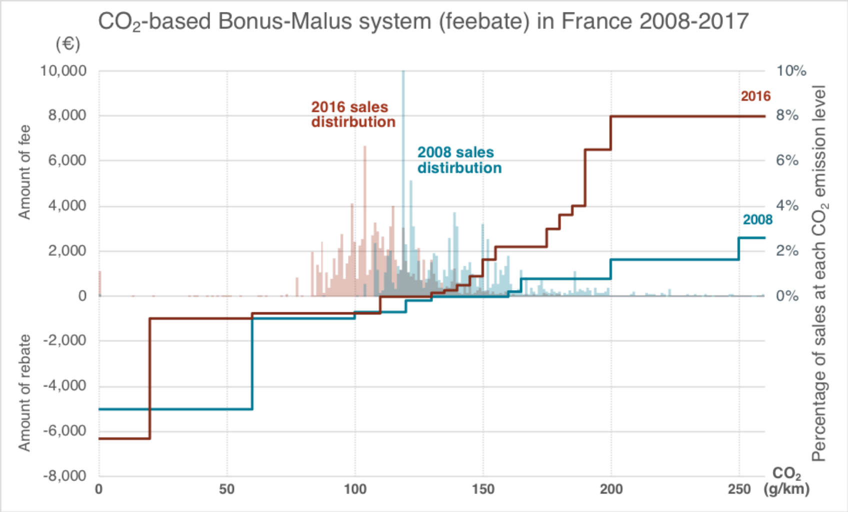
2008 vs 2016



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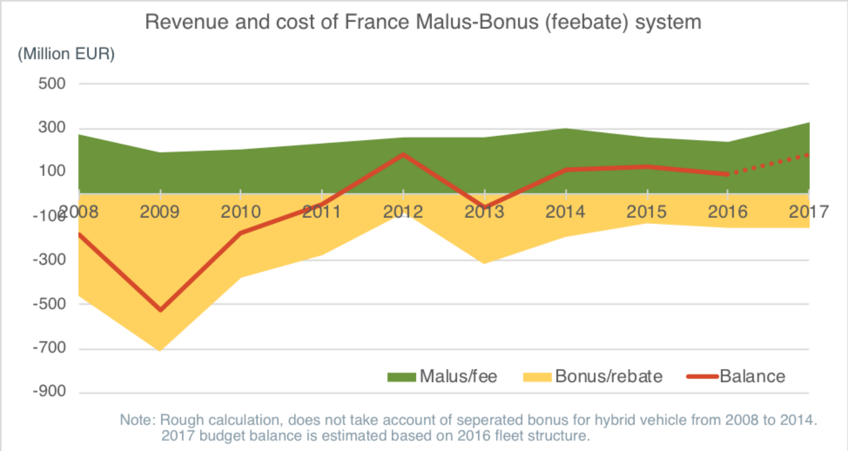
Budget



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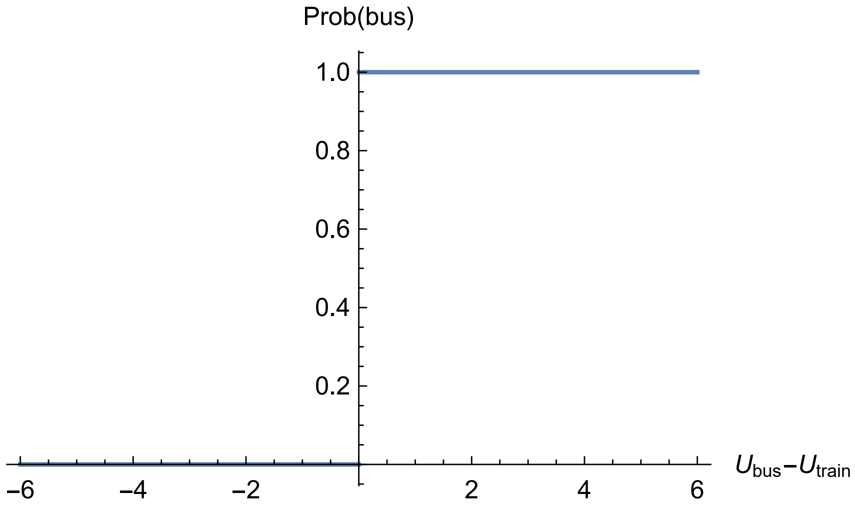
- auctions
  - for example, every year that Canadian government auctions off rights to log on government land
  - What is the optimal auction format?
  - Which minimal price should the goverment set?
- procurement auctions
  - (the government) buys from the lowest bidder on a project, e.g. the construction of roads
  - "Operation Hammer" in Quebec, started in 2009: uncovered widespread collusion in the bidding for government construction contracts
  - How do you detect collusion?
  - How do you compute damages from collusion?

Discrete Choice Models

- assume you have to choose whether you come to University by
  - train (choice 1)
  - bus (choice 2)
- utility from train: U_{train}
- utility from bus: U_{bus}
- choose
  - choose train if $U_{\text{train}} > U_{\text{bus}}$
  - choose bus if $U_{\text{train}} < U_{\text{bus}}$

Deterministic Binary Choice



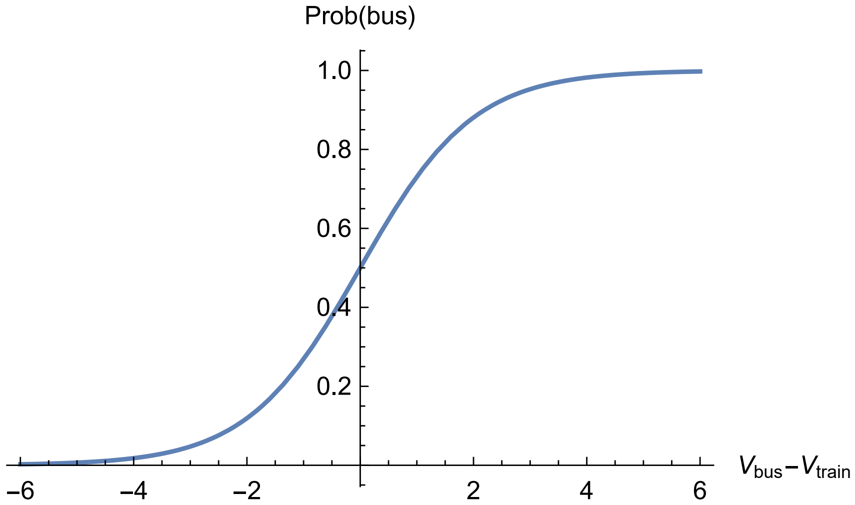
Probabilistic Binary Choice

- random utility for $j \in \{\text{train}, \text{bus}\}$:

$$U_j = V_j + \epsilon_j$$

- V_j: fixed utility for option j
- ϵ_j: random shock to utility of option j
  - location
  - unobserved taste variations
  - true randomness

Deterministic Binary Choice



Logit Model

- ϵ_1, ϵ_2 are extreme value distributed with cumulative distribution function $F(\epsilon_j) = \exp(-\exp(-\mu\epsilon_j))$ where μ is a scale variable
- the difference in random shocks $\Delta\epsilon = \epsilon_{\text{train}} - \epsilon_{\text{bus}}$ has a logistic distribution with cumulative distribution function

$$G(\Delta\epsilon) = \frac{1}{1 + \exp(-\mu\Delta\epsilon)}$$

- define fixed utility difference between bus and train as $\Delta V = V_{\text{bus}} - V_{\text{train}}$
- the probability of using the bus:

$$\begin{aligned}\text{Prob}(\text{bus}) &= \text{Prob}(U_{\text{bus}} > U_{\text{train}}) = \text{Prob}(V_{\text{bus}} + \epsilon_{\text{bus}} > V_{\text{train}} + \epsilon_{\text{train}}) \\ &= \text{Prob}(\Delta V > \Delta\epsilon) = G(\Delta V) = \frac{1}{1 + \exp(-\mu\Delta V)}\end{aligned}$$

Limits

- $\mu \to 0$: ΔV matters little
- draw graph here
- $\mu \to \infty$: ΔV matters a lot
- draw graph here

Extending Results to More Alternatives

- rewrite case with two choices as

$$\text{Prob}(\mathit{bus}) = \frac{1}{1 + \exp(-\mu \Delta V)} = \frac{\exp(\mu V_{\text{bus}})}{\exp(\mu V_{\text{bus}}) + \exp(\mu V_{\text{train}})}$$

- now consider three choices: {bus, train, stay home}
- probabilities turn out to be similar as two choice case
- for example for bus:

$$\text{Prob}(\mathit{bus}) = \frac{\exp(\mu V_{\text{bus}})}{\exp(\mu V_{\text{bus}}) + \exp(\mu V_{\text{train}}) + \exp(\mu V_{\text{stay home}})}$$

Basic Idea of Estimation

- We observe market shares s_j for option j
- With many consumers making the choice, the market share of option j is close to the probability that option j is chosen (law of large numbers)
- for example:

$$\text{Prob}(\text{bus}) = s_{\text{bus}}$$

- one utility can be normalized to 0, for example $V_{\text{stay home}} = 0$
- market share equation for product $j = \text{train}, \text{bus}$:

$$\ln \frac{s_j}{s_{\text{stay home}}} = \ln \frac{\exp(\mu V_j)}{\exp(\underbrace{\mu V_{\text{stay home}}}_{=0})} = \mu V_j$$

Independence of Irrelevant Alternatives

- basic idea: probability of choosing bus vs train does not depend on further alternatives (such as the possibility to stay home):

$$\frac{\text{Prob}(\text{bus}|\{\text{train}, \text{bus}\})}{\text{Prob}(\text{train}|\{\text{train}, \text{bus}\})} = \frac{\text{Prob}(\text{bus}|\{\text{train}, \text{bus}, \text{stay home}\})}{\text{Prob}(\text{train}|\{\text{train}, \text{bus}, \text{stay home}\})}$$

- this holds for logit specification, both left-hand-side and right-hand-side of the above equation are

$$\frac{\exp(\mu V_{\text{bus}})}{\exp(\mu V_{\text{train}})}$$

- V_j can be seen almost directly from market share
- some additional work has to be done to take care of μ

Implications

- assume consumer has first the choice set {train, bus} with $V_{\text{bus}} = V_{\text{train}}$

$$\text{Prob(bus)} = \frac{1}{2}$$
$$\text{Prob(train)} = \frac{1}{2}$$

- what happens if choice set expands to {train,bus,stay home} with $V_{\text{bus}} = V_{\text{train}} = V_{\text{stay home}}$?

$$\text{Prob(bus)} = \frac{1}{3}$$
$$\text{Prob(train)} = \frac{1}{3}$$
$$\text{Prob(stay home)} = \frac{1}{3}$$

- does this make sense? maybe

Blue Bus/Red Bus Problem

- but what if initial choice set is {train, blue bus} and new choice set is {train, blue bus, red bus}
- with initial choice set: Prob(blue bus) $= \frac{1}{2}$ and Prob(train) $= \frac{1}{2}$
- with new choice set

$$\text{Prob(train)} = \frac{1}{3}$$
$$\text{Prob(blue bus)} = \frac{1}{3}$$
$$\text{Prob(red bus)} = \frac{1}{3}$$

- however, we would expect this:

$$\text{Prob(train)} = \frac{1}{2}$$
$$\text{Prob(blue bus)} = \frac{1}{4}$$
$$\text{Prob(red bus)} = \frac{1}{4}$$

Implications for Cross-Price Elasticities

- assume car sales:
  - $j = 1$: Ferrari
  - $j = 2$: Rolls Royce
  - $j = 3$: Dacia
- utility from product 1:

$$\text{Prob}(1) = \frac{\exp(\mu(\delta_1 - p_1))}{\sum_{j=1}^{3} \exp(\mu(\delta_j - p_j))}$$

- analogous for products 1 and 2
- cross-price elasticity between 1 and 2:

$$\frac{d\text{Prob}(1)}{dp_2} = \mu \text{Prob}(1)\text{Prob}(2)$$

- analogous for cross-price elasticity between 1 and 3 and between 2 and 3

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- not realistic, take for example
  $\text{Prob}(1) = \text{Prob}(2) = \text{Prob}(3) = 1/3$
- price increase of Rolls Royce has same effect on demand for Ferrari and Dacia!
  $(\mu\text{Prob}(1)\text{Prob}(2) = \mu\text{Prob}(1)\text{Prob}(3) = \mu/9)$
- we would expect the effect of a price increase of a Rolls Royce to be larger for Ferraris than for Dacias, since Rolls Royce and Ferrari both compete for the up-scale market segment
- this is an undesirable feature of logit demand that matters for many applications in industrial organization

Way Out

- Berry, Levinson, Pakes (1995) (BLP) and the subsequent literature show a way out
- just an outlook, this topic is outside of the scope of this lecture
- consumer i's utility from product j is

$$U_{ij} = \sum_{k=1}^{K} x_{jk}\beta_{ik} + \xi_j - \alpha_i p_j + \epsilon_{ij}$$

- new parameters
  - x_{jk} characteristic of product j (horse power, three vs five doors, etc.)
  - β_{ik} consumer i's weight on characteristic k
  - ξ_j unobserved quality of product j
  - α_i price sensitivity

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- difficulties:
  - estimate distributions of β_{ik} and α_i
  - estimate unobservable ξ_j
- approaches (in a nutshell):
  - exogenous cost shifters
  - non-price characteristics of some good
  - non-price characteristics of other goods
  - demographics variations across regions
    - high income regions with have a lower average price sensitivity α_i
    - rural regions will put a higher weight β_{ik} on e.g. four-wheel drive

Supply Side

- theory: firms choose prices to maximize profits

$$\max_{p_1} D_1(p_1, p_2)(p_1 - c_1)$$

and

$$\max_{p_2} D_2(p_1, p_2)(p_2 - c_2)$$

- Nash equilibrium prices given by first-order conditions:

$$\frac{\partial D_1(p_1^*, p_2^*)}{\partial p_1}(p_1^* - c_1) + D_1(p_1^*, p_2^*) = 0$$
$$\frac{\partial D_2(p_1^*, p_2^*)}{\partial p_2}(p_2^* - c_2) + D_2(p_1^*, p_2^*) = 0$$

Supply Side

- empirical estimation: solve first-order conditions for c_1 and for c_2 using estimated demand functions and observed prices p_1 and p_2
- for c_1:
$$p_1 + \frac{D_1(p_1, p_2)}{\partial D_1(p_1, p_2)/\partial p_1} = c_1$$
- analogous for c_2

Auctions: Second Price Auction

- two bidders, valuations $v_1, v_2 \sim F$ independently distributed
- submitted bids b_1 and b_2
- if bidder 1 wins, he pays second highest bid (b_2)
- utility from winning for bidder 1: $v_1 - b_2$
- it is optimal to bid one's valuation $b_1 = v_1$ and $b_2 = v_2$: take for example bidder 1
  - if $b_2 > v_1$ (bidder 2 wins the auction):
    - bidding $b_1 < b_2$ and $b_1 \neq v_1$ won't change the winner of the auction $\Rightarrow$ deviation not profitable
    - bidding $b_1 > b_2$ leads to bidder 1 winning the auction and getting negative utility $v_1 - b_2$ $\Rightarrow$ deviation not profitable
  - if $b_2 < v_1$ (bidder 1 wins the auction):
    - bidding $b_1 < b_2$ will lead to bidder 1 losing the auction $\Rightarrow$ deviation not profitable
    - bidding $b_1 > b_2$ and $b_1 \neq v_1$ will not change the price $\Rightarrow$ deviation not profitable

Auctions: Second Price Auction

- English auction is strategically equivalent
- reserve price p: no sale if $b_1 < p$ and $b_2 < p$
- if there is a sale, sale price is $\min\{b_1, b_2, p\}$
- optimal sale price depends on distribution F

Auction Econometrics

- second price auction: bid distribution is the same as valuation distribution
- English auction: additional difficulties:
  - we only observe the winning bid $\min\{v_1, v_2\}$
  - jump bids
- $\rightarrow$ decensoring (outside of the scope of this lecture)

First-Price Auctions

- two bidders, valuations $v_1, v_2 \sim F$ independently distributed
- submitted bids b_1 and b_2
- if bidder 1 wins, he pays his own bid b_1
- utility from winning for bidder 1: $v_1 - b_1$
- take F uniform distribution on $[0, 1]$
- conjecture: $b_1 = v_1/2$ and $b_2 = v_2/2$ are Nash equilibrium bids
- verification:
  - expected utility of bidder 1: $(v_1 - b_1)\text{Prob}(b_1 > b_2) = (v_1 - b_1)\text{Prob}(2b_1 > v_2) = (v_1 - b_1)F(2b_1) = (v_1 - b_1)2b_1$
  - utility maximization: $\max_{b_1}(v_1 - b_1)2b_1$
  - first-order condition $\partial((v_1 - b_1)2b_1)/\partial b_1 = 0$
  - solving for first-order condition yields $b_1 = v_1/2$
  - same for bidder 2

First-Price Auction: Econometrics

- again, two bidders, valuations $v_1, v_2 \sim F$ independently distributed
- submitted bids b_1 and b_2
- in symmetric equilibrium, bids are given by bidding function: $b_i = \beta(v_i)$ for $i = 1, 2$
- denote distribution of bids b_1 by G, that is, $b_1 \sim G(b_1) = F(\beta^{-1}(b_1))$
- expected utility of bidder 1: $(v_1 - b_1)\text{Prob}(b_1 \geq b_2) = (v_1 - b_1)G(b_1)$

First-Price Auction: Econometrics

- first-order condition can be rewritten as

$$v_1 = \underbrace{b_1 + \frac{G(b_1)}{g(b_1)}}_{=:\beta^{-1}(v_1)}$$

- same for bidder 2
- we observe bid distribution G in data
- $\Rightarrow$ for every bid b_1 we can infer the valuation from inverse bidding function, $v_1 = \beta^{-1}(b_1)$
- $\Rightarrow$ we can recover the distribution of v_1
- see Guerre, Perrigne, and Vuong (2000, Econometrica, "Optimal nonparametric estimation of first-price auctions") for more details (outside of the scope of this lecture)

Procurement Auctions

- procurement auctions similar to standard auctions, but in some sense, everything is inverted since bidders are sellers and not buyers
- bidders submit bids saying which price they demand for a certain service
- for example: construction companies submit bids stating how much they are asking to build a piece of a highway

Procurement Auctions

- two bidders, their costs are c_1 and c_2 drawn from F
- bidders submit bids b_1 and b_2
- bidder with *lowest* bid wins
- utility from winning auction for bidder 1: $b_1 - c_1$
- expected utility: $(b_1 - c_1)\text{Prob}(b_1 < b_2)$