Applied Environmental Economics.
Lecture 3: Discrete Choice Models

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Motivation

Let us suppose we are interested in:

- Estimating the economic value of water quality improvements
- Designing conservation programs
- Assessing the impacts of renewable energy policies
- Evaluating the impact of carbon taxes
- Predicting the effects of climate change on recreation demand

Why Discrete Choice Models are Crucial in Environmental Economics?

1. Understanding Human Behavior
2. Valuing Environmental Goods
3. Predicting Policy Outcomes
4. Measuring Trade-offs
5. Holistic View

Introduction

- We need a model that reflects how the attributes of choice alternatives and characteristics of the purchaser influence decision-making.
- Discrete choice models calculate the probability of each option being chosen, accounting for:
  - Households typically buying only one car at a time from many available models.
  - Durable appliance purchases like washing machines, where buyers choose from multiple types despite buying only one unit.

Theory

- The utility function is represented as $\mathcal{U}(x, z, q)$, with:
  - x as a J-dimensional vector of private goods,
  - q as a J-dimensional vector of quasi-fixed goods, correlating x_j and q_j as private and public goods respectively.
- Utility for choosing good x_j is:

$$V_j(y - p_j, q) = \mathcal{U}(x_1 = 0, ..., x_j = 1, ..., x_J = 0, y - p_j, q) \quad (1)$$

- A consumer maximizes utility by selecting x_j if $V_j(\cdot) \geq V_k(\cdot)$ for all $k \neq j$.

- A person's utility for choosing option j is $V_j(y - p_j, q_j) = \bar{u}$. To find the MWTP for a change in q_j, consider the total differential at constant utility $\bar{u}$:

this formular is called total differential

$$\frac{\partial V_j(\cdot)}{\partial y} dy + \frac{\partial V_j(\cdot)}{\partial q_j} dq = 0. \quad (2)$$

- This yields the MWTP for q_j:

$$\frac{dy}{dq} = -\frac{\partial V_j(\cdot)/\partial q_j}{\partial V_j(\cdot)/\partial y}. \quad (3)$$

--> MU derived

--> The MU of income

- *Attempt to derive Equation (3) yourself.*

$$dy = -\frac{\partial V_j(\cdot)/\partial q_j}{\partial V_j(\cdot)/\partial y} dq$$

Towards an Empirical Model

- We acknowledge that while individuals are aware of all factors influencing their choices, observers can only measure a subset.
- The conditional indirect utility function is expressed as:

$$V_j(y - p_j, q_j, s, \epsilon_j) = v_j(y - p_j, q_j, s) + \epsilon_j \tag{4}$$

Here, $v_j(\cdot)$ includes observable variables and household-specific characteristics s, while ϵ_j represents unobservable random components.

Empirical and Theoretical Overview

- Vehicle demand analysis is crucial for understanding the impact of environmental policies. Key data points include:
  - $I = 3,216$ new vehicle purchases in the US,
  - $J = 55$ manufacturer/vehicle class aggregates,
  - Vehicle characteristics: operating cost, wheelbase, MSRP.
  - Other characteristics: household size.

Conditional Logit Model

It calculates the probability that an individual i will choose alternative j from a set of J possible alternatives

- Choice probability for alternative j by individual i arises from a multivariate extreme value error distribution:

$$\mathbb{P}_{ij} = \frac{\exp(v_{ij}(\cdot))}{\sum_{k=1}^{J} \exp(v_{ik}(\cdot))}. \tag{5}$$

- This formulation assumes independence and identical distribution of extreme value errors across choices.

Exercise

Start with Exercise 16.3 and the Excel sheet you will find in StudIP. Now solve parts (a) and (b).

CLM - cont'd

- Observation of I agents making choices, where $d_{ij} = 1$ if agent i chose option j, otherwise $d_{ij} = 0$.
- The log-likelihood given Type I extreme value errors is:

$$
\begin{aligned}
LL(\beta) &= \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} \ln \mathbb{P}_{ij} \\
&= \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} \left\{ v_{ij}(\cdot) - \ln \left[\sum_{k=1}^{J} \exp(v_{ik}(\cdot)) \right] \right\}, \qquad (6)
\end{aligned}
$$

  where the independence of choices simplifies the expression to a sum of log probabilities.
- Goal: Obtain Maximum Likelihood Estimation (MLE) for the specified model.

Specification

- Two important features of RUM models condition the choice:
  1. The scale of utility is irrelevant, and
  2. Only utility difference matters.
- To understand the consequences of these features of RUM models, consider our vehicle purchase application.

$$V_{ij} = \beta_0(y_i - \text{price}_j) + \beta_1 \text{opper}_{ij} + \beta_2 wb_j + \epsilon_{ij}, \quad j = 1, ..., 55, \tag{7}$$

where y_i is hh income.

Specification - Cont'd

- Utility difference between alternatives j and k simplifies to:

$$\begin{aligned} V_{ij} - V_{ik} = &- \beta_0(\text{price}_j - \text{price}_k) + \beta_1(\text{opper}_{ij} - \text{opper}_{ik}) \\ &+ \beta_2(wb_j - wb_k) + \epsilon_{ij} - \epsilon_{ik}, \quad k \neq j. \end{aligned} \tag{8}$$

- Income term $\beta_0 y_i$ cancels out in the difference, so it is omitted in linear-in-income utility models:

$$V_{ij} = -\beta_0 \text{price}_j + \beta_1 \text{opper}_{ij} + \beta_2 wb_j + \epsilon_{ij}, \quad j = 1, ..., 55. \tag{9}$$

Empirical Example

MWTP = 0.021 / 0.051 = 0.418

- Model results:

$$V_{ij} = -0.051\text{price}_j + 0.038\text{opper}_{ij} + 0.021wb_j + \epsilon_{ij} \quad (10)$$

- Individual parameter interpretations:
  - The marginal utility of income ($\beta_0 = 0.051$) and wheelbase ($\beta_2 = 0.021$) are not directly interpretable.
  - However, their ratio ($\beta_2/\beta_0 = 0.418$) represents the marginal willingness to pay for a one-inch increase in vehicle length.
- Economic value:
  - On average, vehicle buyers are willing to pay approximately $418 for an additional inch of vehicle length.

Specification - Cont'd

- In RUM models, decision-maker characteristics can be included as interaction variables in two main ways:
  1. Interaction between household characteristics and choice alternative indicators affects utility. For example:

$$
\begin{aligned}
V_{ij} &= -\beta_0 price_j + \beta_1 oper_{ij} + \beta_2 wb_j + \gamma_1 hhsize_i, \quad j \in large \\
V_{ij} &= -\beta_0 price_j + \beta_1 oper_{ij} + \beta_2 wb_j, \quad j \notin large, \qquad (11)
\end{aligned}
$$

  where "large" refers to vehicles accommodating six or more passengers.
- γ_1 is estimable because it remains part of the utility differential.

Specification - Cont'd

2. Including interactions with alternative characteristics:

$$V_{ij} = -\beta_0 price_j + \beta_1 oper_{ij} + \beta_2 wb_j + \gamma_1 wb_j \times hhsize_i + \epsilon_{ij}, \quad \forall j. \tag{12}$$

- The marginal utility of the wheelbase (wb) changes with household size, defined as $\partial V / \partial wb = \beta_2 + \gamma_1 \times hhsize_i$.
- This model allows the estimation of γ_1, reflecting how vehicle size utility varies with household size.

Empirical Example

remember that we are taking the partial derivation of Vij with respect to wbj

- Estimation results for specification (16):

MWTP = (0.0009 + 0.0075 . hhsize) / 0.051

$$V_{ij} = -0.051 price_j + 0.0033 oper_{ij} + 0.0009 wb_j + 0.0075 \cdot wb_j \cdot hhsize_i + \epsilon_{ij} \quad (13)$$

- This specification highlights how household size affects preferences for larger cars.
- Marginal willingness to pay for larger wheelbase:
  - Two-person household: \$310 per extra inch of wheelbase.
  - Six-person household: \$900 per extra inch of wheelbase.

hhsize1 --> 0.0009 + (0.0075 . 1) / 0.051 = 0.164, x1000 = \$164

hhsize2 --> 0.0009 + (0.0075 . 2) / 0.051 = 0.312, x 1000 = \$312

Alternative Specific Constants (ASCs)

- ASCs, similar to time/spatial fixed effects in panel data, account for unmeasured attributes of choice alternatives.
- Key points about using ASCs:
  1. We can estimate only $J-1$ ASCs in a model with J alternatives to avoid redundancy and ensure identifiability.
  2. Estimating a complete set of $J-1$ ASCs alongside attributes that vary only by alternative is not feasible.

Identification

- *Identification* allows us to estimate the influence of attributes on utility consistently.
- Attributes of alternative j include:
  - Measured attributes: p_j, q_j, w_{ij} (data available to the analyst).
  - Unmeasured characteristic: ξ_j (unobservable).
- The utility function now expressed as:

$$V_{ij} = -\beta_0 p_j + \beta' q_j + \beta'_w w_{ij} + \xi_j + \sum_{m=1}^{Q} \gamma_m \times s_i \times q_{jm} + \epsilon_{ij} \quad (14)$$

- Here, β coefficients represent main effects and γ coefficients account for interaction effects.

Identification - cont'd

- It is useful to group factors that only vary over alternatives, and so we rewrite the indirect utility function as

$$V_{ij} = \delta_j + \beta_w^{'} w_{ij} + \sum_{m=1}^{Q} \gamma_m \times s_i \times q_{jm} + \epsilon_{ij}, \quad j = 1, ..., J, \quad i = 1, ..., I. \tag{15}$$

where

$$\delta_j = -\beta_0 p_j + \beta' q_j + \xi_j, \quad j = 1, ..., J.$$

- It will be critical to judge the extent to which ξ_j varies across alternatives and whether or not ξ_j is correlated with p_j and/or elements of q_j and w_{ij}.
- All RUM models employ one of two assumptions in this regard.

Assumptions

1. Assume that ξ_j is constant for all j so that $\xi_j = c$, in which case the specification reduces to

$$V_{ij} = c - \beta_0 p_j + \beta' q_j + \beta_w^{'} w_{ij} + \sum_{m=1}^{Q} \gamma_m \times s_i \times q_{jm} + \epsilon_{ij} \quad (16)$$

2. The second assumption is to explicitly allow $\xi_j \neq \xi_k$, which is closely related to using a full set of alternative specific constants.

Empirical Example

- Using the full set of ASCs from model (19), we estimate the linear regression:

$$\delta_j = \delta - \beta_0 price_j' + \beta_2 wb_j + \xi_j, \quad j = 1, \ldots, 55. \tag{17}$$

- OLS results:

$$\delta_j = -5.63 - 0.0028 price_j + 0.0042 wb_j + \xi_j, \quad j = 1, \ldots, 55, \tag{18}$$

  These results help estimate $\xi_1, \ldots, \xi_J$, contributing to preference component estimates in Eq. (18).

- Key points on Identification for $\xi_j \neq 0$:
  1. $price_j$ and ξ_j are uncorrelated.
  2. Feasibility of a second stage regression.

Features of the Logit Model

- The conditional logit model assumes that the unobserved utility components are independent across choices.
- *Example with vehicles*: Consider larger households favoring larger vehicles without household size data. This unobserved preference impacts the error term, suggesting a positive correlation among the errors for large vehicle alternatives.
- However, the conditional logit model assumes independence among these errors, which prevents such correlations.

Independence of Irrelevant Alternatives (IIA)

- In the conditional logit model, the ratio of choice probabilities for alternatives j and k simplifies to:

$$\frac{\mathbb{P}_{ij}}{\mathbb{P}_{ik}} = \frac{\exp(v_{ij}(\cdot))}{\exp(v_{ik}(\cdot))}.$$

- This ratio shows that the odds of choosing j over k depend solely on the attributes of j and k, and remain unaffected by the presence or attributes of other alternatives.

Welfare Computation

- We can calculate the "expected" Consumer's variation with the following formula

$$\mathbb{E}\left(CV_i\right) = \frac{1}{\beta_0}\left\{ \ln\left[\sum_{j=1}^{J} \exp\left(-\beta_0 p_j + \beta q_j^1\right)\right] - \ln\left[\sum_{j=1}^{J} \exp\left(-\beta_0 p_j + \beta q_j^0\right)\right] \right\} \tag{19}$$

which, given estimates of the utility function parameters, is simple to calculate for any values of q^1, q^0, and the other variables in the model.

Empirical Example

- Estimation formula:

$$V_{ij} = -0.0028 price_j - 0.437 oper_{ij} + 0.0042 wb_j + 0.0072 wb_j \times hhsize_i + \xi_j + \epsilon_{ij}, \quad j = 1, \ldots, 55. \quad (20)$$

  ξ_j values are recovered from residuals in (21).
- Welfare impact of a 5% improvement in fuel efficiency for minivans:
  - Adjusted operating costs are 5% lower for alternatives $j = 4, 13, 22, 38, 46$.
  - Willingness to pay is calculated for 3,216 households using Eq. (23).
  - Average willingness to pay is \$470 per vehicle for the enhancement.

The Role of Income

Our focus has been entirely on the linear-in-income specification. This has been motivated by two factors:

1. *Conceptual* - Income influences the quantity of purchase, which gives us the familiar concepts of income elasticity and normal/inferior goods.
2. The problem when income enters utility non-linearly is related to the *computation of welfare effects*.

Exercise - cont'd

Continue with part (d) of Exercise 16.3. Moreover, it shows how the IIA property applies in this exercise.

Part (c) is left for you as homework, and you will be shown the solution next week. **Hint:** Look at the solution of Exercise 16.2.

Idea

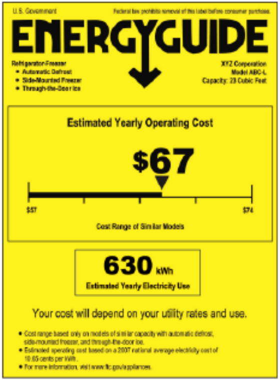
- **houde2018consumers**.
- Study focus: Consumer reaction to different complexities of information regarding energy efficiency.
- Example: In the US refrigerator market, consumers encounter:
  - Mandatory disclosure providing detailed energy cost information.
  - Simplified binary-star certification rating on energy use.
- **Findings**: While the simplified certification may direct some consumer attention towards energy efficiency, it can also overshadow more detailed and precise energy information for others, with unclear effects on overall energy consumption.

Data and Environment

- Transactions made at a retailer during 2008-2011.
  - Date, Model of Refrigerator, Detailed Attributes, MSRP, Retailer's price, Wholesale Price, Taxes Paid, and the Zip Code of the store where the transaction was made.
- Consumer demographics:
  - Household size, income, education, homeownership, housing type, political orientation, and age of the head of the household.
- Four variables for the Identification of the empirical model: *the ES certification*, *prices*, *electricity costs*, and *rebates.*

Figure - Energy labels

(a) ES label



(b) EnergyGuide label

FIGURE 1. Energy Labels for the U.S. Appliance Market

Summary Statistics

Table 1. Summary Statistics

	2008	2010
Choice Set		
# of Refrigerator Models, US Market	2,524	1,496
# of Decertified Refrigerator Models, US Market	1,278	21
# of Refrigerator Models, Retailer's Sample	1,483	1,174
# of Decertified Refrigerator Models, Retailer's Sample	674	14
Average Size of Choice Set (Store-Trimester)	99	92
SD Size of Choice Set (Store-Trimester)	44	37
Price and Duration		
Avg Retail Price	$1,325	$1,411
SD Retail Price Offered	$639	$693
Avg Weekly Price Change	11%	15%
Avg Duration Between Price Change (weeks)	1.4	3.1
Avg Retail Price ENERGY STAR	$1,426	$1,368
Avg Retail Price Non-ENERGY STAR	$1,240	$1,472
Avg Retail Price Decertified Model	$1,416	$2,468
Rebate		
# of Utility Rebate Programs for ENERGY STAR Refrigerators	87	133
# of State Rebate Programs for ENERGY STAR Refrigerators	0	44
Avg Rebate Offered	$48	$104
SD Rebate Offered	$54	$144
Electricity Costs: US Refrigerators		
Avg Elec. Price (County) ($/kWh)	0.113	0.113
Min Elec. Price ($/kWh)	0.03	0.03
Max Elec. Price ($/kWh)	0.420	0.368
Avg Elec. Consumption (kWh/y)	520	506
Avg Elec. Consumption ENERGY STAR (kWh/y)	500	501
Avg Elec. Consumption Decertified ENERGY STAR (kWh/y)	520	547
Avg Elec. Consumption Non-ENERGY STAR (kWh/y)	568	525

Notes: The sample consists of all transactions for which a refrigerator was bought at the retailer. The number of full-size refrigerator models for the whole United States was obtained from the US EPA. According to FTC data, 2,693 full-size refrigerator models were offered on the US market in 2008.

- **Note:** In the retailer's sample, there are 1,483 models for that year, with 674 decertified models.

Econometric Model

- Model for alternative-specific utility in the conditional logit:

$$U_{ijrt} = \tau D_{jt} - \eta P_{jrt} + \psi R_{rt} \times D_{jt} - \theta C_{jrt} + \delta_j + \epsilon_{ijrt}$$

- Variables defined:
  - C_{jrt}: Annual electricity cost for product j based on local expectations at time t.
  - P_{jrt}: Weekly retail price including sales taxes.
  - R_{rt}: Average rebate amount in zip code r during week t.
  - D_{jt}: Certification dummy (1 if certified, 0 otherwise).

Conditional Logit by Income group

Table 2. Conditional Logit by Income Group

	Income <$50,000			Income ≥$50,000 & <$100,000			Income ≥$100,000		
	I	II	III	I	II	III	I	II	III
Retail Price	-0.416***	-0.417***	-0.416	-0.365***	-0.365***	-0.365***	-0.32***	-0.32***	-0.319***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ENERGY STAR	0.125*		0.123*	0.163***		0.161***	0.181 ***		0.177***
	(0.05)		(0.05)	(0.05)		(0.05)	(0.04)		(0.04)
ENERGY STAR, 2008		0.070			0.138**			0.117 *	
		(0.05)			(0.05)			(0.05)	
ENERGY STAR, 2010		0.312*			0.103			0.222 *	
		(0.14)			(0.11)			(0.10)	
Rebate	0.086***	0.085***	0.084***	0.041**	0.041**	0.042 **	0.016	0.015	0.016
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Elec. Cost	-1.235***	-1.236***	-1.295***	-2.044***	-2.044***	-2.011***	-2.586***	-2.587***	-2.585***
	(0.23)	(0.23)	(0.22)	(0.25)	(0.25)	(0.25)	(0.26)	(0.26)	(0.26)
Product FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Demo × Attributes	No	No	Yes	No	No	Yes	No	No	Yes
# Obs	46,097	46,097	46,097	45,487	45,487	45,487	45,249	45,249	45,249
Interpretation									
Own-Price Elasticity	-5.41	-5.42	-5.41	-4.75	-4.75	-4.75	-4.16	-4.16	-4.15
Implicit Discount Rate	0.34	0.34	0.32	0.17	0.17	0.17	0.10	0.10	0.10
WTP ES Label	29.94	-	29.68	44.59	-	43.98	56.56	-	55.55
WTP ES Label, 2008	-	16.72	-	-	37.80	-	-	36.71	-
WTP ES Label, 2010	-	74.93	-	-	28.23	-	-	69.26	-
Prob. Taking Rebate	0.21	0.20	0.20	0.11	0.11	0.12	0.05	0.05	0.05

Notes: Standard errors clustered at the zip code level in parentheses: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Prices, rebates, and electricity costs measured in hundreds of dollars. Average price of $1,300 used to compute own-price elasticity. Refrigerator lifetime of 18 years used to compute implicit discount rate.

- **Note:** For all models, robust standard errors clustered at the zip code level are reported.
- What does the coefficient on electricity cost θ imply?

Econometric Model - Cont'd

- The value of energy information (VOI) for $e = ES$ is given by

$$VOI_i = \frac{1}{\eta}\left\{\ln\sum_{j}^{J}\exp\left(U_{ij}^{I}\right) - \ln\sum_{j}^{J}\exp\left(U_{ij}^{ES}\right) - \sum_{j}^{J}P_i^{ES}\left(U_{ij}^{I} - U_{ij}^{ES}\right)\right\}$$

Which corresponds to the opportunity cost of relying on the certification.

The Value of Energy Information

TABLE 4. The Value of Energy Information

	Income <\$50,000		Income ≥\$50,000 & <\$100,000		Income ≥\$100,000	
	Scenario 1	Scenario 2 $\tau_{ES} = 0$	Scenario 1	Scenario 2 $\tau_{ES} = 0$	Scenario 1	Scenario 2 $\tau_{ES} = 0$
CV (\$)	-4.7	-1.7	-5.1	-0.6	-11.8	-2.9
$VOI_{e=ES}$ (\$)	28.2	15.9	57.1	13.0	70.2	23.1
$VOI_{e=U}$ (\$)	15.9	15.9	13.2	13.2	23.3	23.3
Mispercetions, $e = ES$ (\$)	-123.5	0.5	-388.1	-5.6	-396.7	-12.8
Mispercetions, $e = U$ (\$)	-592.0	-592.0	-605.7	-605.7	-925.5	-925.5

Notes: To compute the CV measure, the baseline policy scenario, $\mathcal{P}$, is the market without certification, and the policy change scenario, $\tilde{\mathcal{P}}$, is the market with certification. A negative estimate for the CV implies that the certification reduces consumer welfare. For all income groups, the various estimates of CV are small and negative.

- **Note:** This table shows that consumers are slightly worse off in a market with certification.

Conclusion

- There is significant variation in consumer responses to energy information.
- Consumers valuing the Energy Star (ES) certification are willing to pay more than the actual energy savings justify.
- Many consumers, particularly in lower-income brackets, do not factor energy information into their appliance purchases.
- The econometric model indicates that the ES certification slightly disadvantages consumers at current prices.

Idea

- **fowlie2010emissions**
- Study overview: Analysis of an emissions trading program aimed at reducing pollution from large stationary sources.
- Key findings:
  1. Deregulated electricity plants were less likely to invest in capital-intensive environmental compliance compared to regulated or publicly owned facilities.
  2. Variations in electricity market regulations have resulted in more emissions in states with significant air quality issues.

NO_x Budget Program

- The *NO_x Budget Program* (NBP) is an emission trading program that caps NO_x emissions from large stationary sources across 19 eastern US states, applying uniform regulations despite varying state contributions to ozone nonattainment.
- Compliance methods include:
  - Purchasing permits for emissions that exceed allocations.
  - Installing NO_x control technologies.
  - Reducing operations at higher-emission plants during ozone season.

Estimated NO_x Control Cost

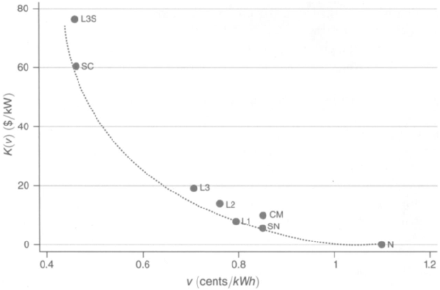


FIGURE 1. ESTIMATED NO_x CONTROL COSTS FOR A 512 MW T-FIRED BOILER

Notes: In generating this figure, I assume that the unit will achieve perfect compliance. This assumption finds empirical support (US EPA 2005). I further assume that compliance will not be achieved through reductions in output. Support for this assumption is provided in the Web Appendix. Section III includes a detailed discussion of how these cost estimates are generated.

Strategy code	Technology	lbs NO_x/mmBtu
N	No retrofit	0.42
SN	Selective Non-Catalytic Reduction (SNCR)	0.34
CM	Combustion modification	0.33
L1	Low NO_x burners with overfire air option 1	0.31
L2	Low NO_x burners with overfire air option 2	0.28
L3	Low NO_x burners with overfire air options 1&2	0.26
SC	Selective Catalytic Reduction (SCR)	0.13
L3S	L3 + SCR	0.11

Electricity Industry Restructuring and Environmental Compliance

- Historically, Investor-Owned Utilities (IOUs) regulated by state Public Utilities Commissions (PUCs) generated over 90
- Predominant regulatory approach was "rate of return" regulation.
- Restructuring in the 1990s aimed to replace traditional rate settings with competitive markets to enhance efficiency and lower prices.
- By 2001, 19 states with high electricity rates had enacted restructuring legislation due to significant rate discrepancies across states.

Data Overview

- The study includes 702 coal-fired units (regulated, unregulated, public) under the *NO_x Budget Program*.
- Compliance cost estimates are calculated using EPRI-developed software, which considers all major NO_x control options for coal-fired boilers.
- Cost estimation leverages detailed data on over 60 unit and plant-level characteristics, including boiler dimensions, emission rates, and operating costs.

Compliance Choices by Regulatory Regime

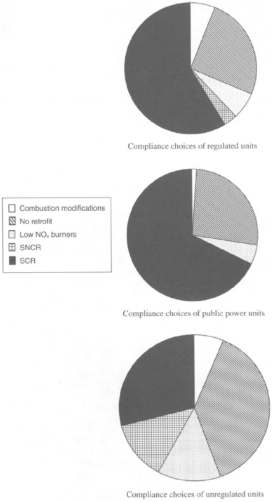


FIGURE 2. COMPLIANCE CHOICES BY REGULATORY REGIME
(*as a percentage of MW installed capacity*)

Summary Statistics

Table 1—Summary Statistics by Unit Type

Variable	Deregulated	Regulated	Public
Number of units	227	292	113
Number of facilities	86	100	34
Number of companies/public agencies	35	33	16
Capacity (MW)	248	314	208
	(212)	(279)	(227)
Unit age (years)	37	36	36
	(11)	(11)	(11)
Pre-retrofit heat rate (kWh/btu)	12,120	11,866	12,184
	(4,747)	(5,956)	(1,898)
Pre-retrofit NO_x emissions (lbs/mmBtu)	0.48	0.54	0.55
	(0.21)	(0.22)	(0.23)
Pre-retrofit summer capacity factor (percent)	63	67	68
	(17)	(14)	(13)

Notes: Standard deviations in parentheses. Summary statistics generated using the data from the 632 units used to estimate the model.

An Empirical Model of Compliance Choice

- Plant managers choose a compliance strategy to minimize the latent value C_{nj}, which represents the total cost:

$$C_{nj} = \alpha_j + \beta_n^v \nu_{nj} + \beta_n^K K_{nj} + \beta_n^{KA} K_{nj} \text{Age}_{nj} + \epsilon_{nj}$$

- The deterministic component of C_{nj} combines:
  - Expected annual compliance costs ν_{nj},
  - Capital costs K_{nj} from initial retrofits and installations,
  - An age-adjustment factor for technology (Age_{nj}),
  - $\nu_{nj} = (V_{nj} + \tau m_{nj}) Q_n$, linking operational and market conditions to costs.

Summary Statistics 2

TABLE 2—COMPLIANCE COST SUMMARY STATISTICS FOR COMMONLY SELECTED CONTROL TECHNOLOGIES

	Capital cost ($/kW)			Operating costs (cents/kWh)		
	Deregulated	Regulated	Public	Deregulated	Regulated	Public
Combustion modification	12.63 (4.19)	12.46 (5.02)	11.85 (4.20)	0.91 (0.37)	1.05 (0.39)	1.08 (0.38)
Low NO_x burners	19.10 (5.89)	17.20 (3.16)	18.79 (4.20)	0.83 (0.30)	0.86 (0.23)	0.85 (0.21)
SNCR	17.36 (14.45)	15.69 (14.59)	25.24 (30.85)	0.95 (0.42)	1.00 (0.36)	1.06 (0.23)
SCR	71.21 (22.17)	68.38 (19.91)	81.01 (30.90)	0.53 (0.35)	0.50 (0.16)	0.59 (0.22)
No retrofit	0	0	0	1.25 (0.58)	1.34 (0.57)	1.50 (0.67)

Note: Standard deviations are in parentheses.

- **Note:** The considerable overlap in the distributions of these costs across the three groups.

Results

Table 4—Estimation Results

	Conditional logit			Random parameter logit		
	Pooled (1)	Deregulated (2)	Regulated (3)	Pooled (4)	Deregulated (5)	Regulated (6)
Technology type constants						
α_{POST}	−2.31***	−1.50***	−2.67***	−2.46***	−0.41	−3.15***
	(0.21)	(0.37)	(0.39)	(0.30)	(0.61)	(0.60)
α_{CM}	−2.06***	−1.54***	−1.91***	−2.06***	−1.48***	−2.08***
	(0.16)	(0.29)	(0.26)	(0.18)	(0.39)	(0.29)
α_{LNB}	−2.03***	−1.55***	−2.21***	−1.97***	−0.96	−2.42
	(0.19)	(0.37)	(0.30)	(0.22)	(0.46)	(0.31)
Annual compliance costs ($100,000)						
Mean	−0.31***	−0.19***	−0.28***	−0.96***	−1.21***	−0.72***
β^V	(0.05)	(0.07)	(0.12)	(0.14)	(0.25)	(0.14)
Capital cost ($100,000)						
Mean	0.01	−0.06**	0.01	−0.23***	−0.78***	−0.11
β^K	(0.02)	(0.03)	(0.06)	(0.05)	(0.21)	(0.07)
K × Age	−0.02**	−0.04	−0.02	−0.14***	−0.25***	−0.09**
	(0.01)	(0.02)	(0.03)	(0.02)	(0.07)	(0.04)
K × D^{DEREG}	−0.06***	—	—	−0.11 **	—	—
	(0.01)			(0.05)		
σ^V	—	—	—	0.68***	1.68***	0.42***
				(0.11)	(0.35)	(0.11)
σ^K	—	—	—	0.23***	0.52***	0.10***
				(0.05)	(0.13)	(0.03)
δ^{DEREG}	0.32**	—	—	0.19	—	—
	(0.15)			(0.14)		
δ^{PUB}	−0.33***	—	—	−0.51***	—	—
	(0.08)			(0.07)		
Number of units	632	227	292	632	227	292
log-likelihood	−808.1	−339.1	−359.7	−685.6	−276.1	−320.7

Notes: Robust standard error are in parentheses.
*** Indicates significance at 1 percent.
** Indicates significance at 5 percent.

- The inclusion of additional interaction terms does not significantly improve the model fit.
- All technology-fixed effects are negative and significant at the one percent level.

Conclusion

- Deregulated generators in restructured markets are less inclined to adopt capital-intensive pollution controls.
- Under various scenarios, total costs to meet emissions caps remain similar to those in the benchmark case.
- Asymmetric regulation has exacerbated health and environmental damages by influencing the geographical distribution of pollution abatement and emissions. Adopting symmetric regulation might mitigate these damages by allocating more emissions in areas with lower associated harm.

Summary

- Discrete choice models analyze individual environmental preferences.
- The conditional logit model assumes that individuals make choices based on each alternative's attributes and characteristics.
- Data on choices and alternative attributes is needed to estimate model parameters.
- IIA states that the odds of choosing A or B over C should remain constant, regardless of other alternatives in the choice set.

Summary 2

- ASCs are additional parameters in the logit model that capture unobserved factors affecting option selection.
- ASCs can be included in the model as additional attributes that vary across different options but are constant for each individual.
- The economic interpretation of ASCs is ambiguous as they can be influenced by sample and choice set.
- Alternative-specific constants can be used to predict the choices of new or hypothetical options by capturing unique factors that affect each option.

Summary Points 3

- To calculate compensating variation, simulate the model under different market conditions.
- To calculate consumer surplus, compare the utility of the chosen option to the maximum utility of any other option.
- Compensating variation helps policymakers assess market changes and minimize negative consumer impact.
- Assumptions about consumers can impact the accuracy of the expected CV.

References

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- **fowlie2010emissions**
- **houde2018consumers**