



The Abdus Salam
International Centre
for Theoretical Physics



Fondazione
Eni
Enrico Mattei

The Beijer International Institute
of Ecological Economics -
The Royal Swedish
Academy of Sciences

1st Teaching Workshop on Environmental Economics

for the Middle East and North Africa

December 5-16, 2005 - ICTP, Trieste, Italy

Valuing Environmental and Natural Resources: An Introduction to the Econometrics of Non-Market Valuation

Arcadio Cerda

University of Talca

Valuing Environmental and Natural Resources: An Introduction to the Econometrics of Non- Market Valuation

Arcadio Cerda, Ph.D., MBA, MSc., Ing.

Universidad de Talca

Talca, Chile

acerda@utalca.cl

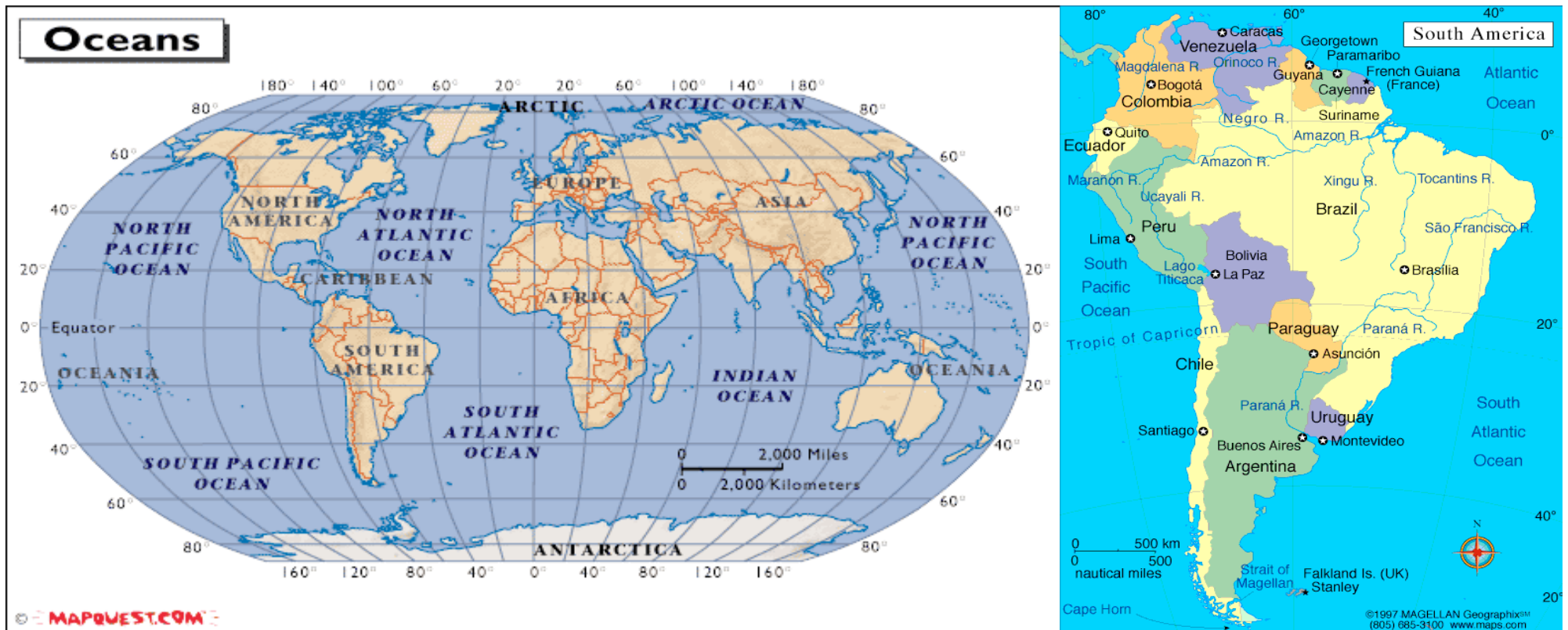


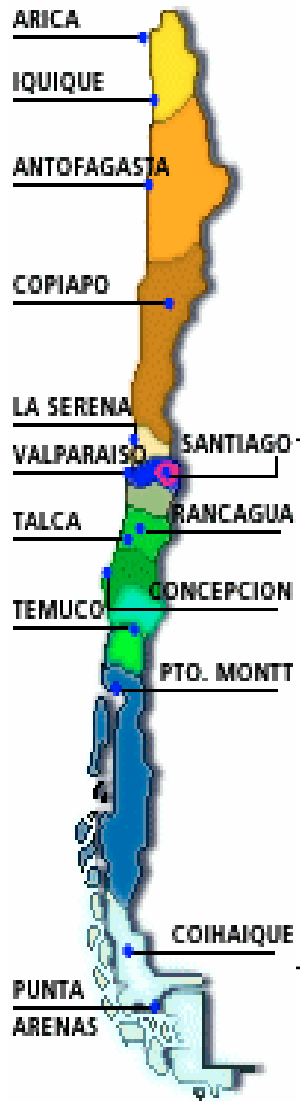
<http://riat.utalca.cl/> riat@utalca.cl

Interamerican Journal of Environment and Tourism – New Journal

<http://face.utalca.cl>

Valuing Environmental and Natural Resources: An introduction to the econometrics of non-Market Valuation





Contents

- Introduction to Environmental Evaluation (EV)
- Introduction to Econometrics

Some concepts ... many concepts...perhaps too much!!!

- What is econometrics?
- Model Building in Econometrics
- Desirable properties of estimators
- Estimation Platforms
 - Likelihood function
- Estimation Methods
- Econometric Models (Linear, Discrete: Logit, Probit)

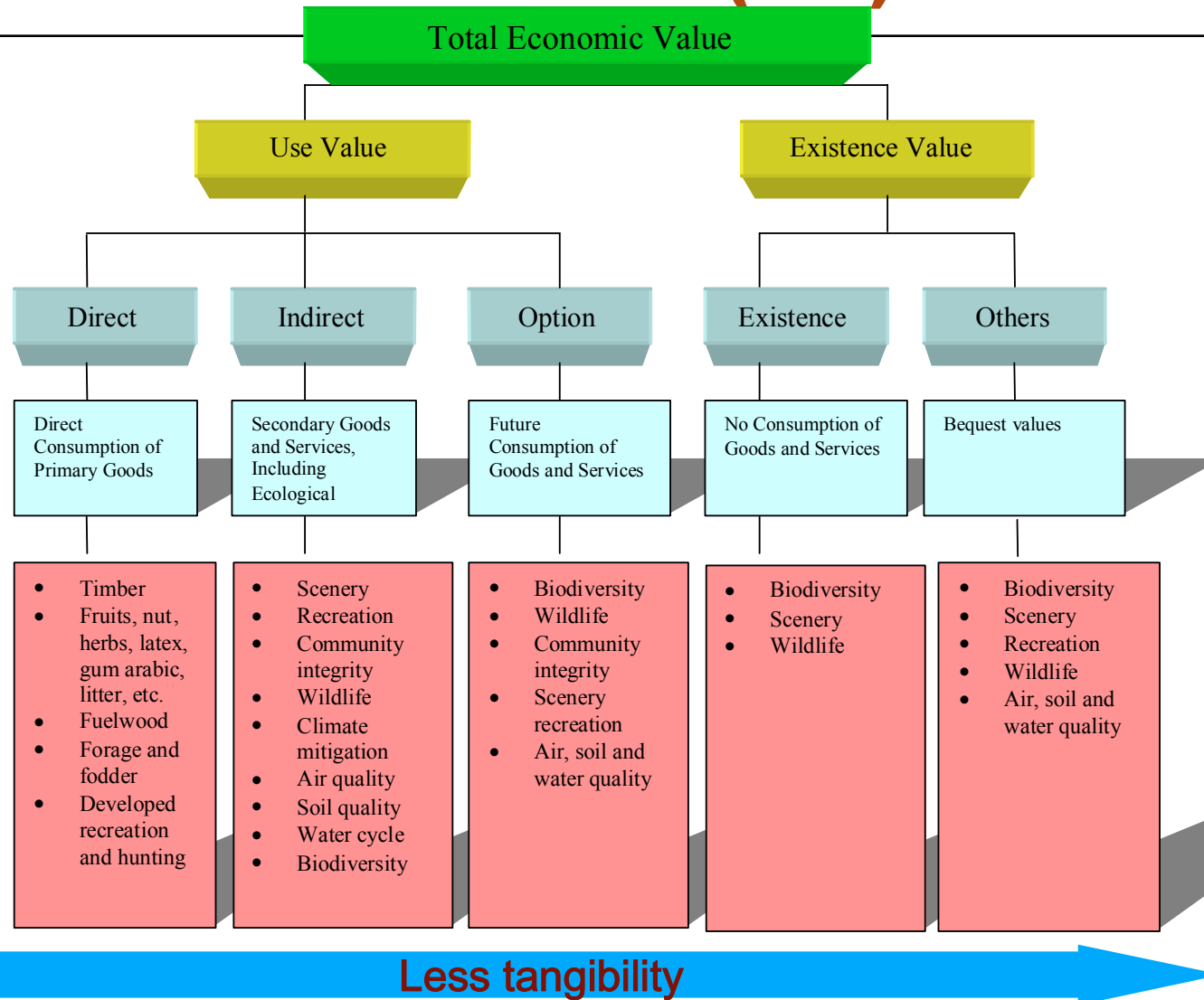
Contents

- Applications
 - Contingent evaluation Method
 - *Doubled Bounded Dichotomic-choice Model*
 - *Parametric, semi-parametric, non-parametric estimations*
 - Travel Cost Method
 - *Estimating Welfare Measures Using Travel Cost Method with Truncated and Censored Data*

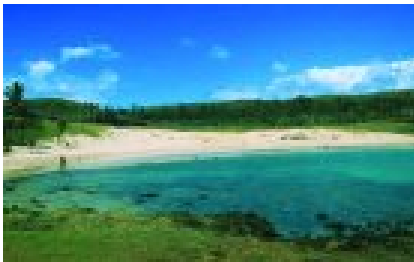
Introduction to Environmental Valuation (EV)

- **Economic value** is one way to measure the value of a resource
- Economic values are useful to consider when making economic choices – tradeoffs in allocating resources.
- Measures of economic value are based on individual preferences
- Theory of economic valuation is based on individual preferences and choices.
- People express their preferences via the choices and tradeoffs that they make, given some constraints (income, time, etc)
- Economic value is measured by the most someone is willing to give up in other goods and services in order to obtain a good, service, or state of the world.

Introduction to Environmental Valuation (EV)



How can we give a value to these (Chilean?) resources?



Introduction to Econometrics

What is Econometrics?

What is Econometrics?

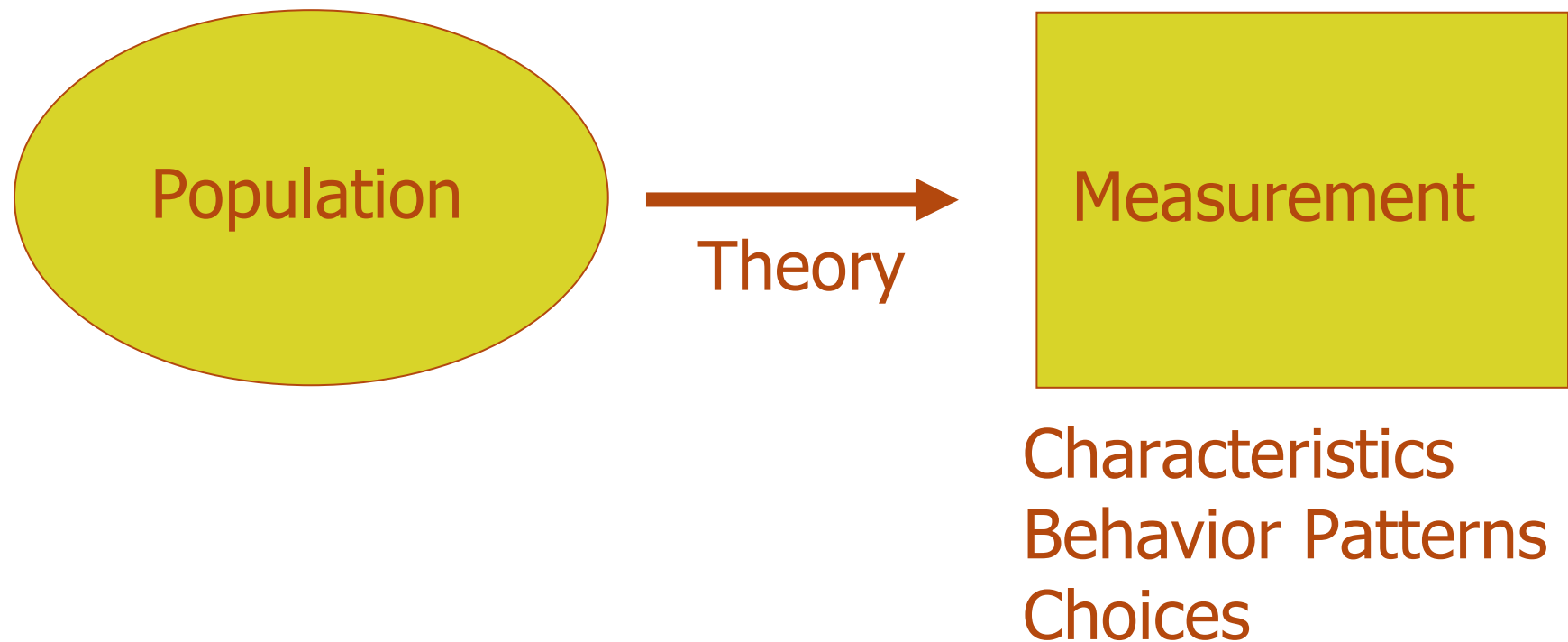
Theoretical foundations:
Microeconomics
and macroeconomics

Mathematical Elements

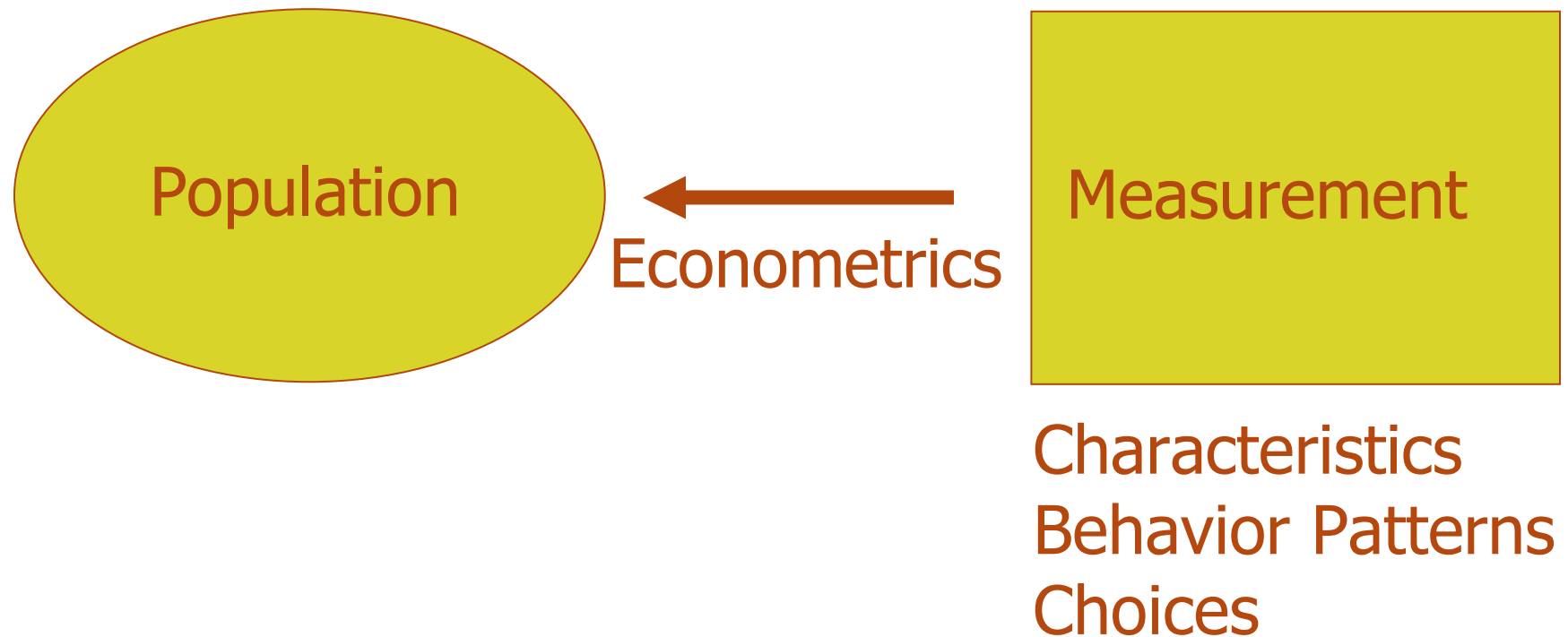
Statistical foundations

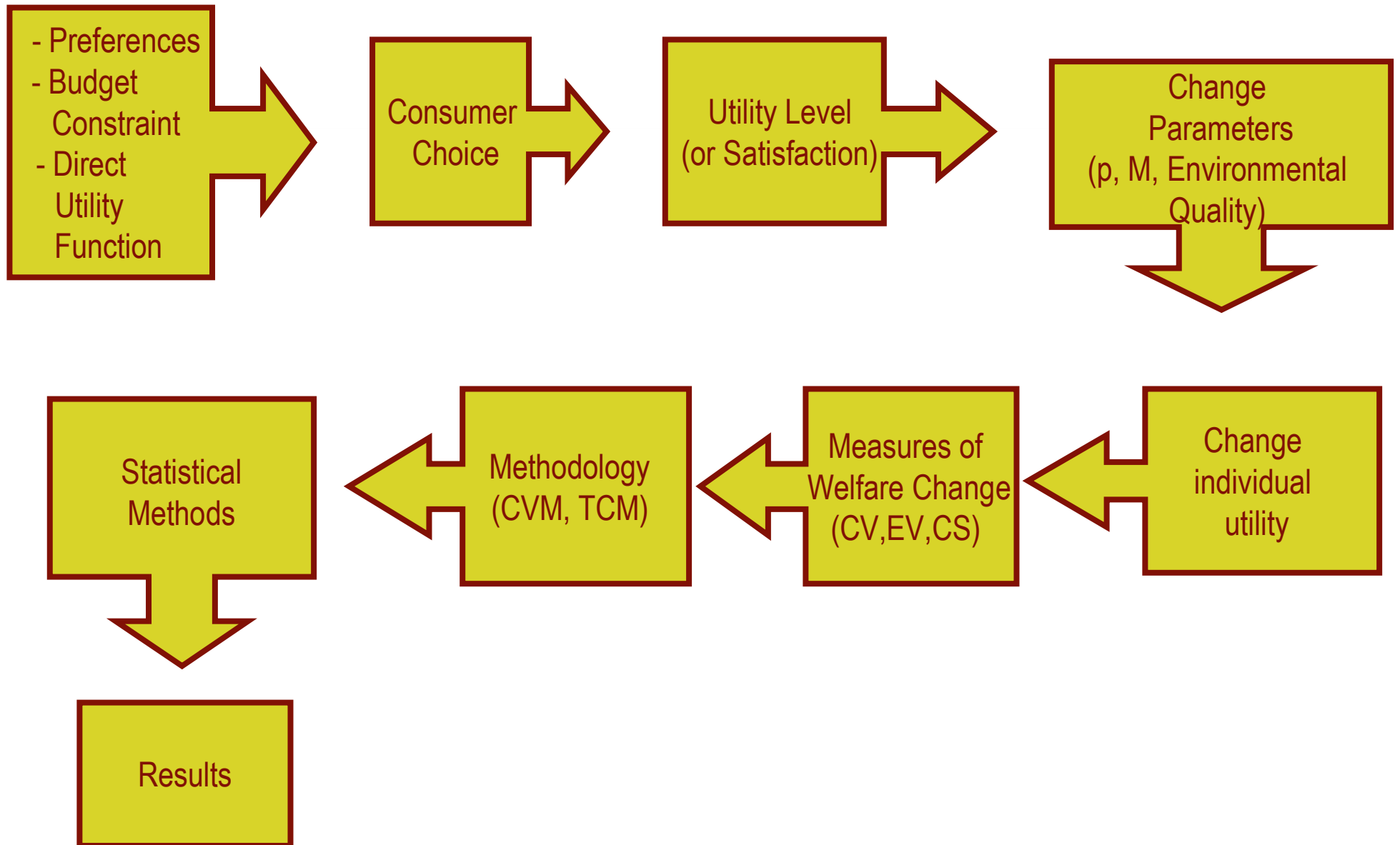
'Model' building – the econometric model

Measurement as Observation



Inference





Why Use This Framework?

- Understanding the relationship:
 - Estimation of quantities of interest such as elasticities or willingness to pay

- Prediction of the outcome of interest

- Controlling future outcomes using knowledge of relationships

Desirable properties of estimators

Linearity

Unbiasedness

Consistency

Efficiency

Estimators

- A rule (or procedure) for constructing an estimate of a population parameter.
- Example:

$$\bar{X} = \frac{\sum_{i=1}^N X_i}{N} \text{ is an estimator for } \mu_X$$

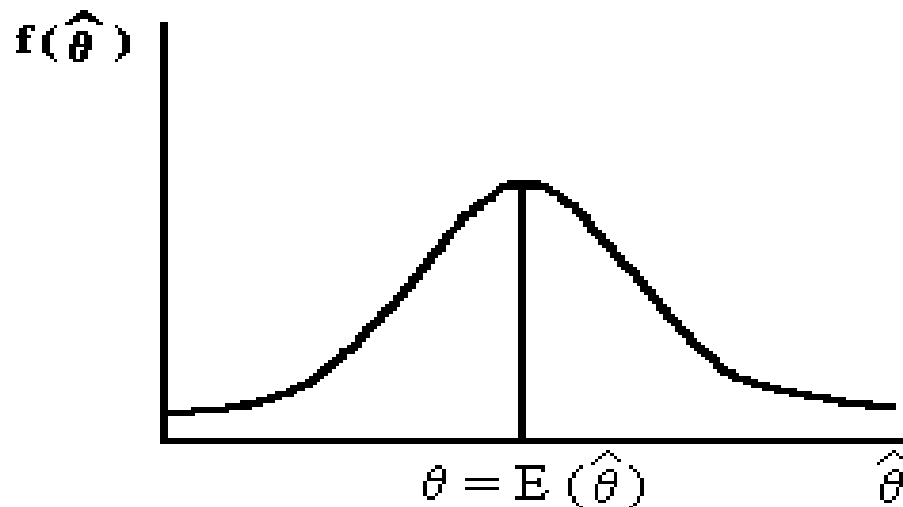
Linearity

- A linear estimator may be expressed as a linear function of observable random variables.
- Lower computational cost (not as important today given high-speed and low-cost computing technology)

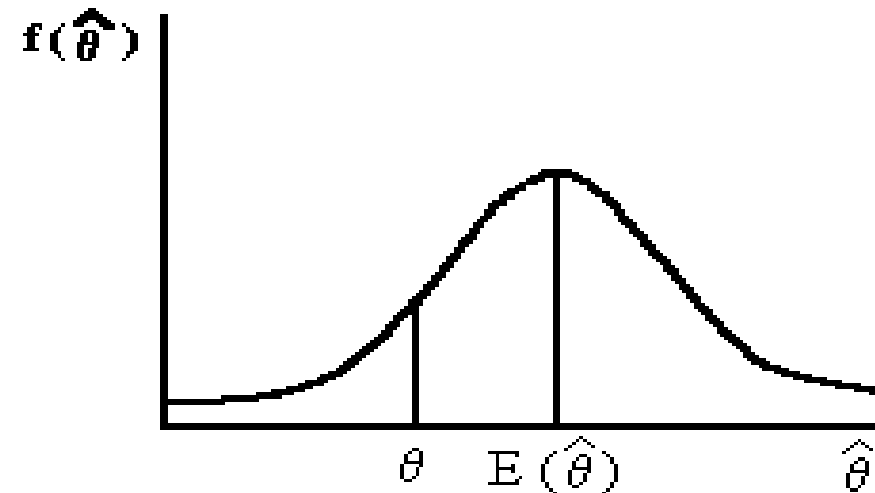
Unbiasedness

- Expected value of the estimator equals the population parameter:

$$E(\hat{\theta}) = \theta$$



Unbiased estimator



Biased estimator

Unbiasedness

Three econometricians went out hunting, and came across a large deer.

The first econometrician fired, but missed, by a meter to the left.

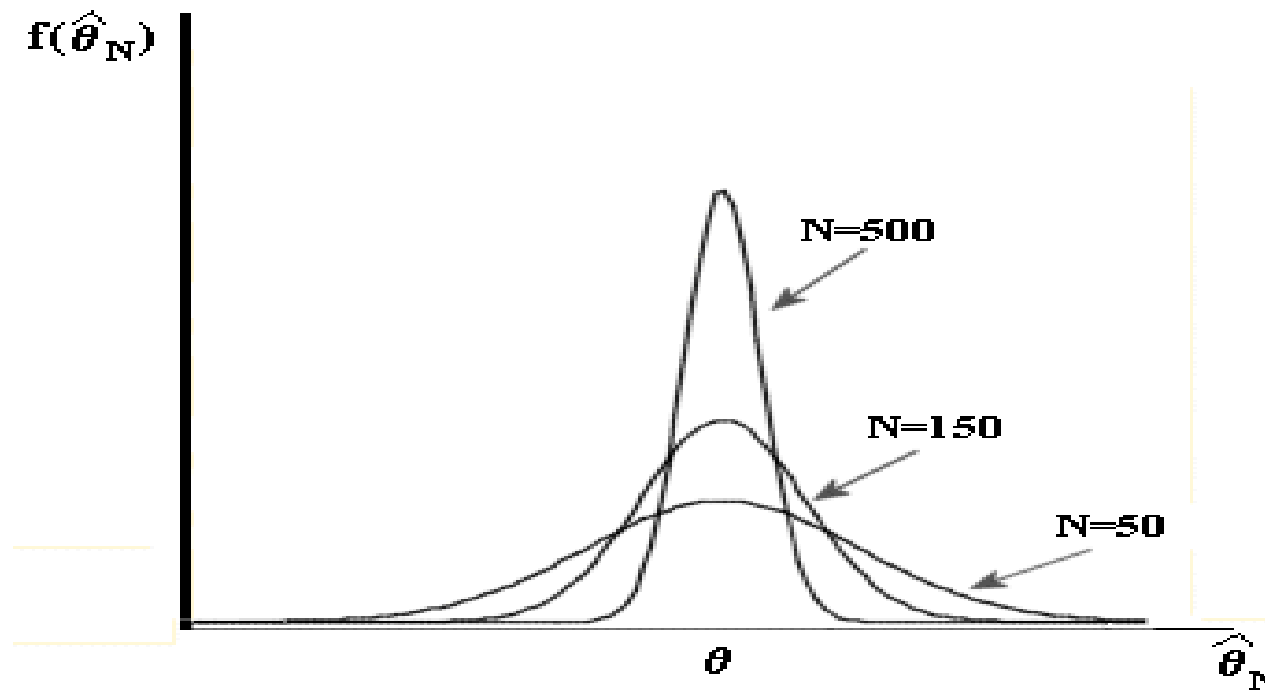
The second econometrician fired, but also missed, by a meter to the right.

The third econometrician didn't fire, but shouted in triumph, "We got it! We got it!"

Source: <http://netec.mcc.ac.uk/JokEc.html>

Consistency

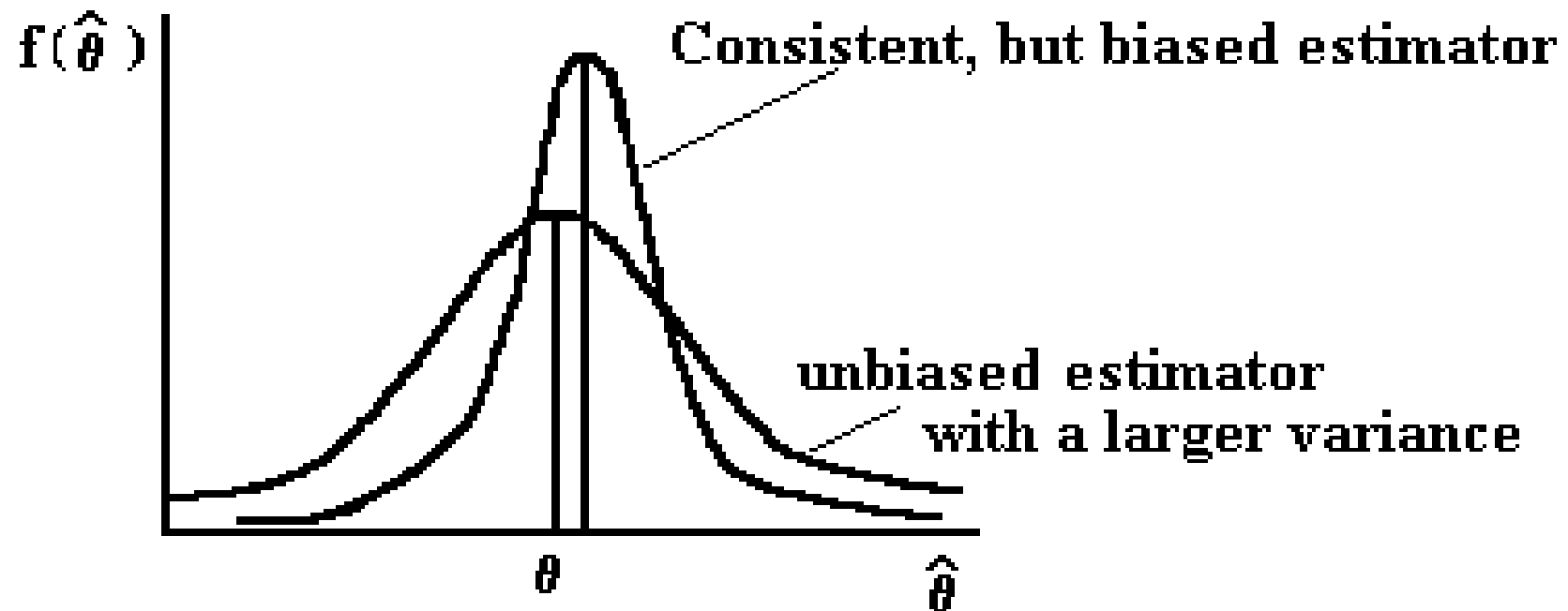
- Estimator converges to the value of the population parameter as the size of the sample rises



Unbiasedness vs. consistency

- Unbiased if the average value *in an infinite number of samples* equals the population parameter
- Consistent if the estimator converges to the population parameter as the *size of the sample tends toward infinity*

Unbiasedness vs. consistency



Efficiency

- An unbiased estimator is efficient if the variance of this estimator is less than or equal to the variance of any other unbiased estimator:

$\text{var}(\hat{\theta}_N) \leq \text{var}(\tilde{\theta}_N)$, where $\tilde{\theta}$ is any other unbiased estimator, and

$$\text{var}(\hat{\theta}_N) = E[\hat{\theta}_N - E(\hat{\theta}_N)]^2$$

Model Building in Econometrics

Introduction:

- Role of the assumptions

- Sharpness of inference

- Applications

Parameterizing the model

- Nonparametric analysis

- Semiparametric analysis

- Parametric analysis

Nonparametric regression

- Kernel Regression is one class of modeling methods that belongs to the smoothing methods family
- Kernel estimation is local averaging with weighting, such that cases nearer to the center of the bin are weighted more.
- Kernel weighting is usually of the normal distribution type, but other weighting distributions are possible.

Nonparametric Regression

Kernel Regression

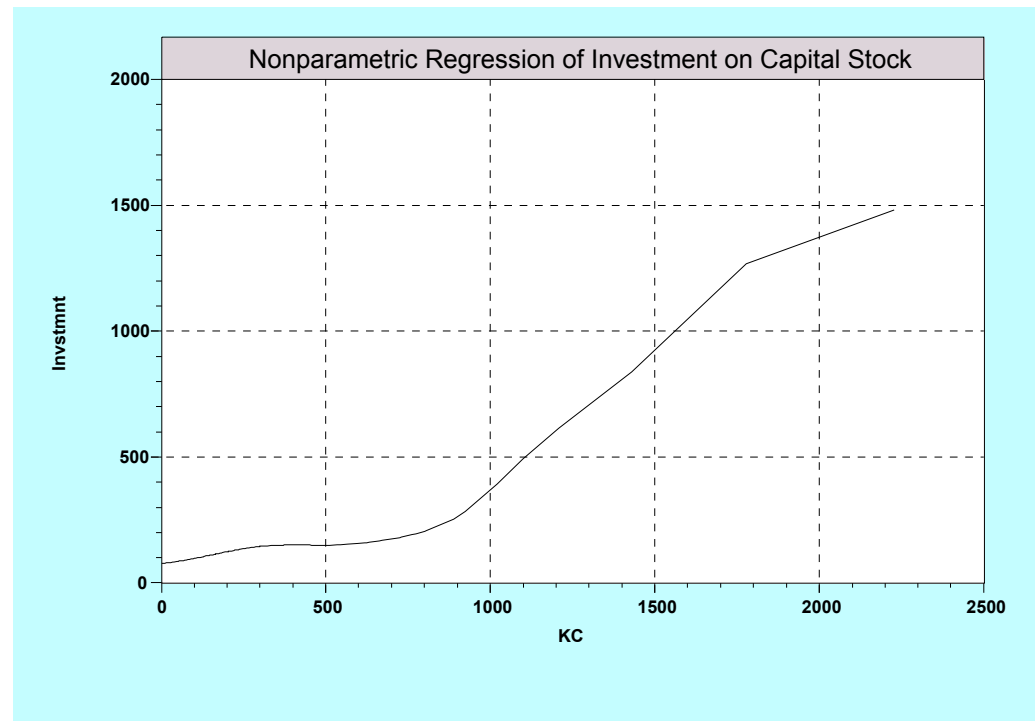
$$\hat{F}(z) = \frac{\sum_{i=1}^N w_i(z) y_i}{\sum_{i=1}^N w_i(z)}$$

$$w_i(z) = \frac{1}{\lambda} K \left[\frac{x_i - z}{\lambda} \right]$$

$$\lambda = .9Q / N^2$$

$$K(t) = \Lambda(t)[1 - \Lambda(t)]$$

$$\Lambda(t) = \frac{\exp(t)}{1 + \exp(t)}$$



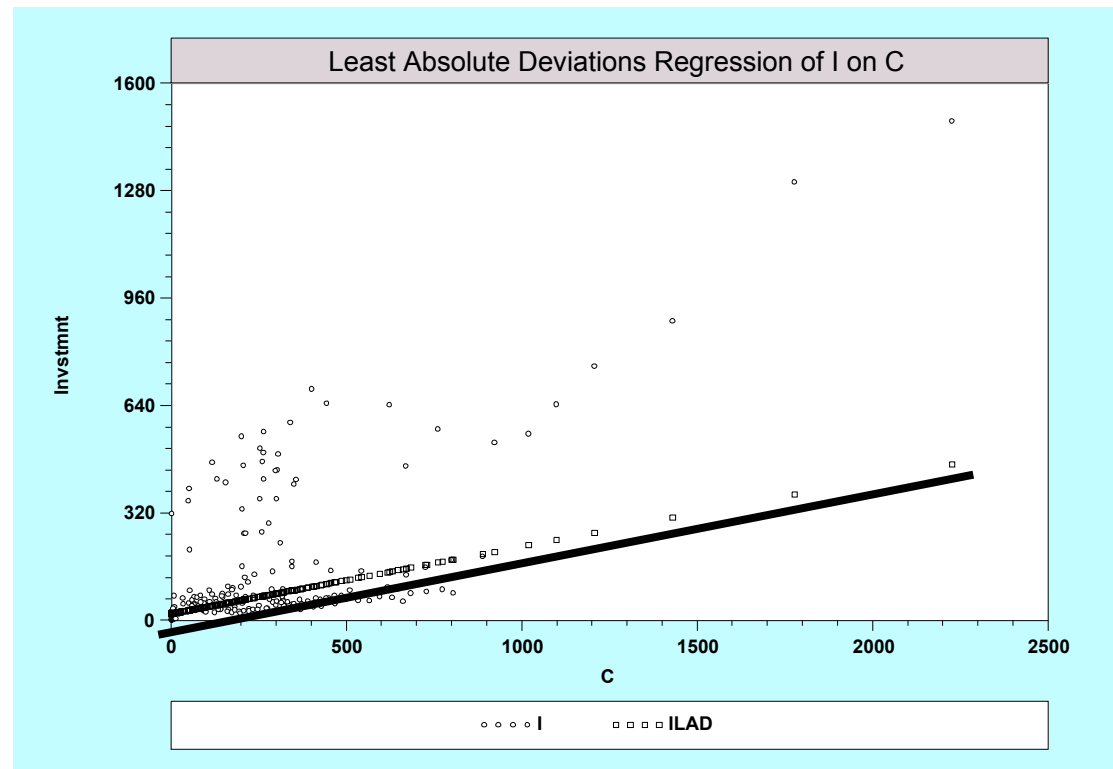
Semiparametric Regression

- Investment_{i,t} = a + b*Capital_{i,t} + u_{i,t}
- Median[u_{i,t} | Capital_{i,t}] = 0

Least Absolute Deviations

$$\hat{F}(x) = \hat{a} + \hat{b}x$$

$$\hat{a}, \hat{b} = \text{ArgMin}_{a,b} \sum_{i=1}^N |y_i - a - bx_i|$$



Parametric Regression

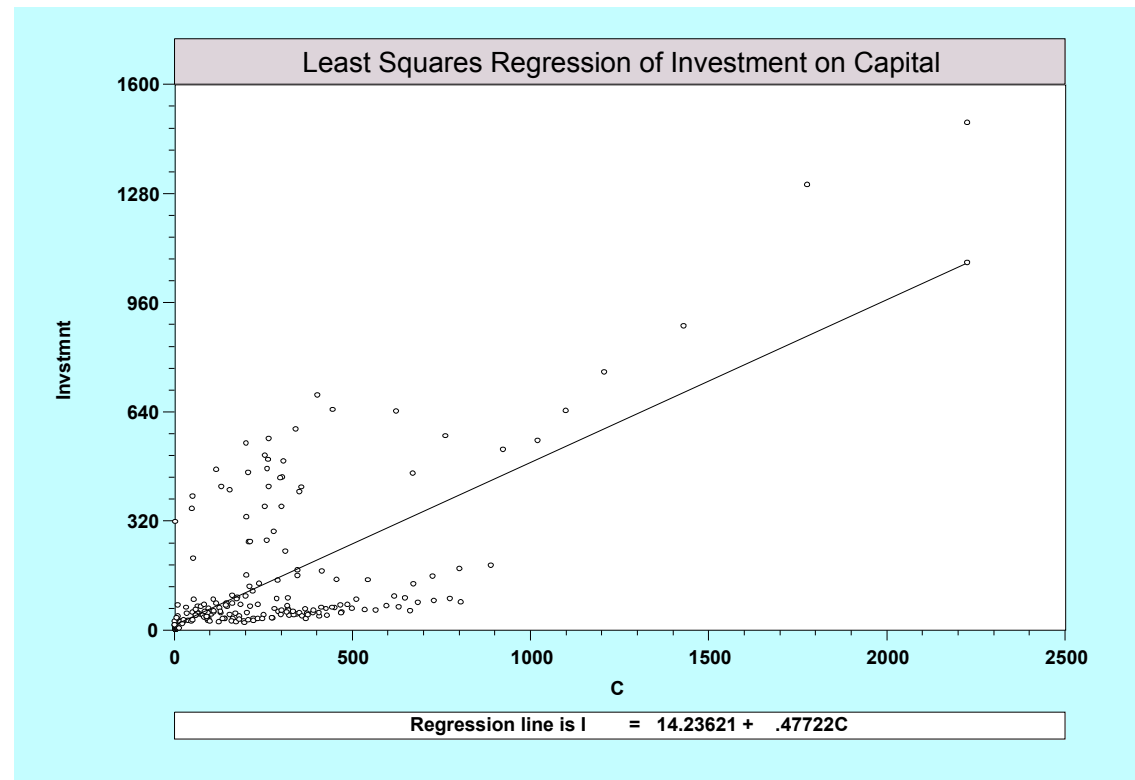
- Investment_{i,t} = a + b*Capital_{i,t} + u_{i,t}
- u_{i,t} | Capital_{j,s} ~ N[0,σ²] for all i,j,s,t

Least Squares Regression

$$\hat{F}(x) = \hat{a} + \hat{b}x$$

$$\hat{a}, \hat{b} = \text{ArgMin}_{a,b} \sum_{i=1}^N (y_i - a - bx_i)^2$$

$$= \left[\sum_{i=1}^N \begin{pmatrix} 1 \\ x_i \end{pmatrix} \begin{pmatrix} 1 \\ x_i \end{pmatrix}' \right]^{-1} \left[\sum_{i=1}^N \begin{pmatrix} 1 \\ x_i \end{pmatrix} y_i \right]$$



Difference between parametric and nonparametric model:

- a parametric model is known up to a (small) finite set of parameters
- a nonparametric model is characterized by an infinite set of parameters (a smooth function)
- Smoothing is fitting a nonlinear line through the points on a scatterplot
- Nonlinear regression is adding polynomial terms to the regression equation, or it is nonparametric regression. Fox (2000a) covers various types of smoothing and nonparametric regressions

Estimation Platforms

Model based

Kernels and smoothing methods (nonparametric) Moments and Quantile regression (semiparametric) Maximum likelihood and M-Estimators (parametric)

Methodology based

Classical – parametric and semiparametric Bayesian analysis – strongly parametric

Maximum likelihood

- Maximum likelihood estimation begins with the mathematical expression known as a likelihood function of the sample data.

$$L(\alpha) = f(x_1; \alpha) \cdots f(x_n; \alpha)$$

- the likelihood of a set of data is the probability of obtaining that particular set of data given the chosen probability model (here normal distribution).

$$f(x_1, \dots, x_n | \mu, \sigma) = \prod \frac{1}{\sigma \sqrt{2\pi}} e^{-(x_i - \mu)^2 / 2\sigma^2}$$

- This expression contains the unknown parameters.
- Those values of the parameter that maximize the sample likelihood are known as the maximum likelihood estimates.



Likelihood functions for various distributions used in Economic Valuation

$$f(x_1, \dots, x_n | \lambda) = \frac{e^{-\lambda} \lambda^{x_1}}{x_1!} \dots \frac{e^{-\lambda} \lambda^{x_n}}{x_n!} = \frac{e^{-n\lambda} \lambda^{\sum x_i}}{x_1! \dots x_n!} \quad \text{Poisson}$$

$$f(x_1, \dots, x_n | \mu, \sigma) = \prod \frac{1}{\sigma_i \sqrt{2\pi}} e^{-(x_i - \mu)^2 / 2\sigma_i^2} \quad \text{Weighted Normal}$$

$$f(x_1, P(X_1 = x_1), \dots, X_n = x_n | p) = p^{x_1} (1-p)^{1-x_1} \dots p^{x_n} (1-p)^{1-x_n} \\ p^{\sum x_i} (1-p)^{\sum (1-x_i)} = p^{\sum x_i} (1-p)^{n - \sum x_i},$$

Bernoulli Distribution

- The Bernoulli distribution is a discrete distribution having two possible outcomes labeled by $n=0$ and $n=1$ in which $n=1$ ("success") occurs with probability p and $n=0$ ("failure") occurs with probability $(1-p)$,
- The probability function and the corresponding distribution function are:

$$P(n) = \begin{cases} 1 - p & \text{for } n = 0 \\ p & \text{for } n = 1, \end{cases}$$

$$D(n) = \begin{cases} 1 - p & \text{for } n = 0 \\ 1 & \text{for } n = 1. \end{cases}$$

- The Bernoulli distribution is the simplest discrete distribution, and it the building block for other more complicated discrete distributions.
- The distributions of a number of variate types defined based on sequences of independent Bernoulli trials that are curtailed in some way are summarized in the following table (Evans *et al.* 2000, p. 32).

Distribution	Definition
<u>binomial distribution</u>	number of successes in n trials
<u>geometric distribution</u>	number of failures before the first success
<u>negative binomial distribution</u>	number of failures before the x th success

$$L(\alpha) = f(x_1; \alpha) \cdots f(x_n; \alpha)$$

Maximum likelihood

- Likelihood is the hypothetical probability that an event that has already occurred would yield a specific outcome.
- The concept differs from that of a probability in that a probability refers to the occurrence of future events, while a likelihood refers to past events with known outcomes.
- Maximum likelihood, also called the maximum likelihood method, is the procedure of finding the value of one or more parameters for a given statistic which makes the *known likelihood* distribution a maximum.

Maximum likelihood (advantages)

- MLE's and Likelihood Functions generally have very desirable large sample properties:
 - they become unbiased minimum variance estimators as the sample size increases
 - they have approximate normal distributions and approximate sample variances that can be calculated and used to generate confidence bounds
- likelihood functions can be used to test hypotheses about models and parameters



Maximum likelihood (disadvantage)

- The likelihood equations need to be specifically worked out for a given distribution and estimation problem.
- The numerical estimation is usually non-trivial. Except for a few cases where the maximum likelihood formulas are in fact simple, it is generally best to rely on high quality statistical software to obtain maximum likelihood estimates.
- Maximum likelihood estimates can be heavily biased for small samples. The optimality properties may not apply for small samples.



Econometric Models

Linear; static and dynamic

Discrete choice

Censoring and truncation

Structural models and demand systems

How can we estimate these models?

□ Estimation Methods

- *Least squares etc. – OLS, GLS, etc.*
- *Maximum likelihood*
- Instrumental variables and GMM
- Bayesian estimation – Markov Chain Monte Carlo methods

Linear model

- Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data.
- "Linear" refers to the assumption of a linear relationship between y and x , which could be modeled - in a simple form - as $y = \alpha + \beta x$
- **linear regression** is a method of estimating the conditional expected value of one variable y given the values of some other variable or variables x .
- If the independent variable is a vector, one speaks of multiple regression.

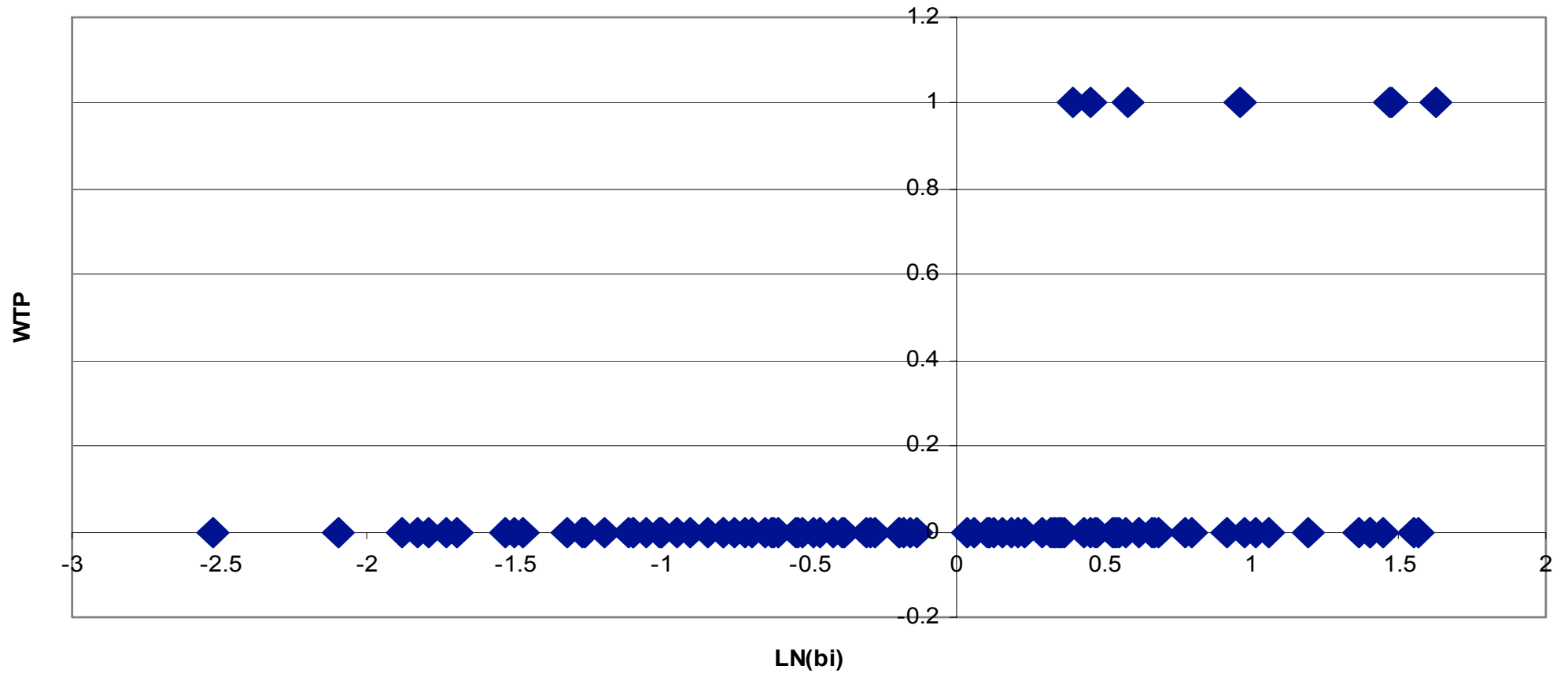
Discrete choice

- Binary choice models are models for which the dependent variable takes values 0 and 1,

- e.g.:
 $y_i = 1$, if individual i is willingness to pay b_i
0, otherwise

Discrete Choice

Diagrama de Dispersión



Discrete Choice

- OLS - Ordinary Least Squares

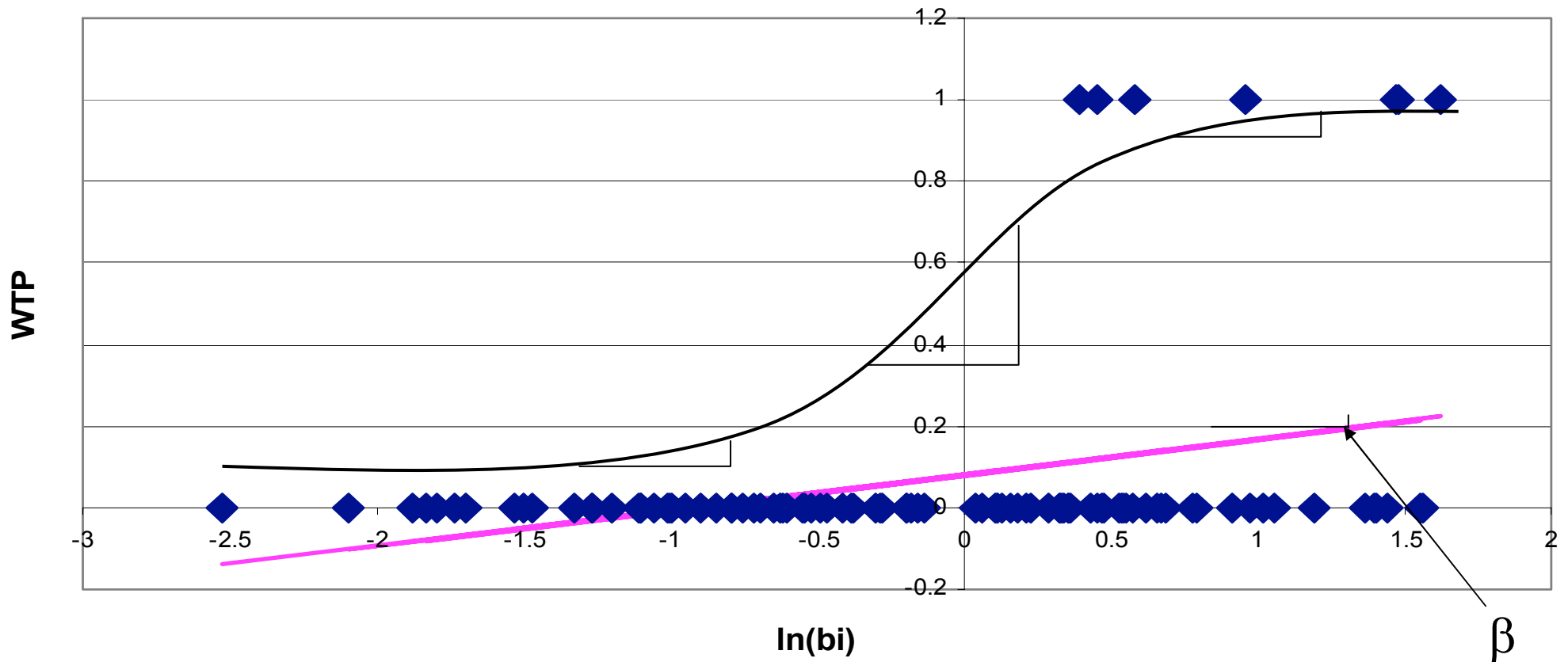
$$\hat{Y}_i = 0.08 + 0.087 X_i, \quad i = 1, 2, \dots, 100$$

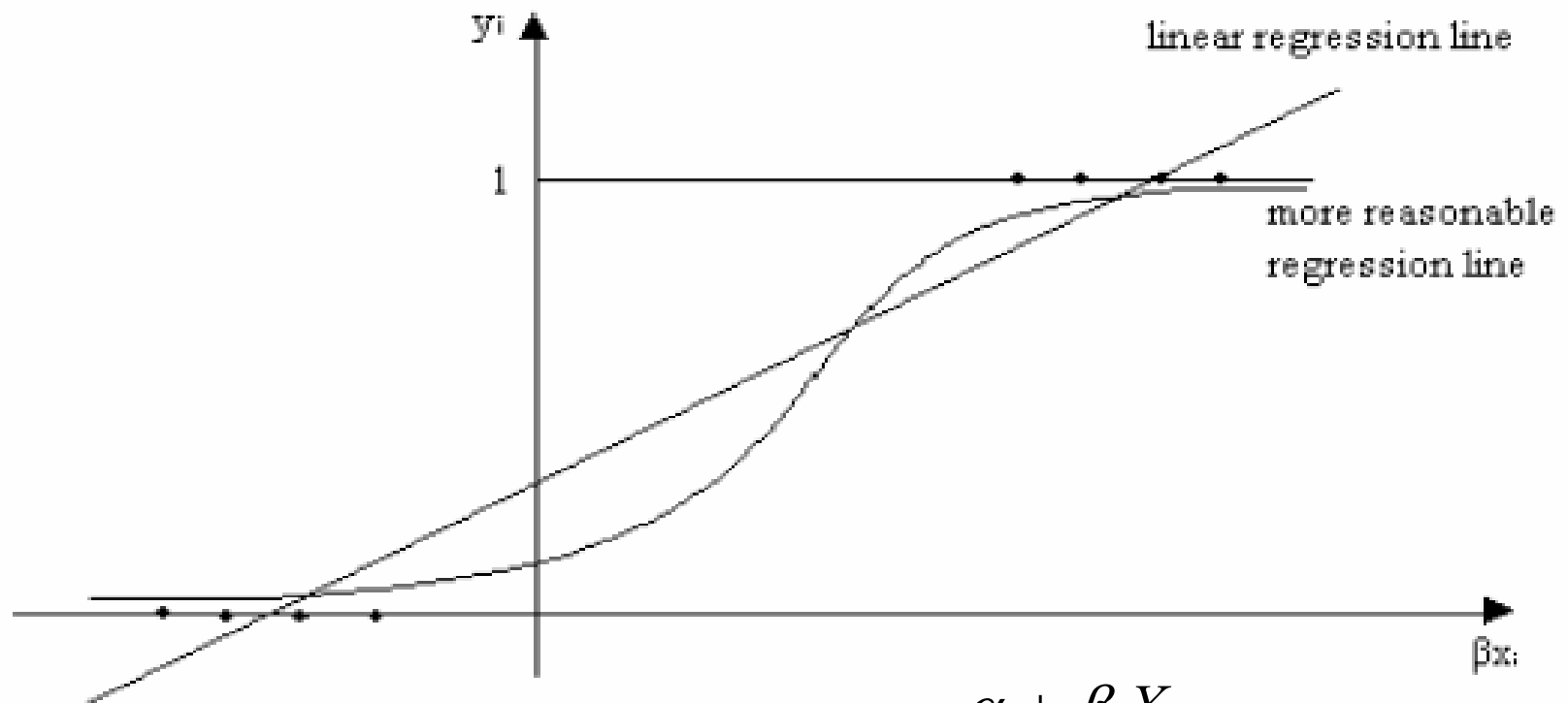
(3.2) (3.4)

- Positive relationships y w.r.t x

Discrete choice

Gráfico de Dispersión





$$F(\alpha + \beta X_i) = \frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}}$$

Logit Model

- A z variable has logistic distribution when the probability distribution function is

$$f(z) = \frac{e^z}{1 + e^z}$$

Logit Model

- $U_{iy} = \alpha_y + \beta_y X_i + \varepsilon_{iy}$
- $U_{io} = \alpha_o + \beta_o X_i + \varepsilon_{io}$

- U_{iy} utility individual i when he\she says yes
- U_{io} utility individual i he\she says no

Logit Model

$$\begin{aligned}
 \Pr[Y_i=1 \mid X_i] &= \Pr[U_{iy} > U_{io} \mid X_i] \\
 &= \Pr[\alpha_y - \alpha_o + (\beta_y - \beta_o)X_i > \varepsilon_{io} - \varepsilon_{iy} \mid X_i] \\
 &= \Pr[\varepsilon_i \leq \alpha + \beta X_i \mid X_i]
 \end{aligned}$$

- $\varepsilon_i = \varepsilon_{io} - \varepsilon_{iy}$ $\alpha = \alpha_y - \alpha_o$ $\beta = (\beta_y - \beta_o)$.
- Now let express the model in term of an accumulative probability function $\alpha + \beta X_i$ for the random variable ε_i .

Logit Model

- Assuming ε_i has a logistic distribution

$$F(\alpha + \beta X_i) = \frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}}$$

- No lineal relationship. We can NOT use OLS

Logit Model

$$\frac{\partial F(\alpha + \beta X_i)}{\partial X_i} = F(\alpha + \beta X_i)[1 - F(\alpha + \beta X_i)]\beta$$

- Change in X_i depends not only on β but also the value of the logistic function.

Logit Model

- Likelihood function:

$$L(\alpha, \beta; X_i) = \prod_{i=1}^n \left[\frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}} \right]^{Y_i} \left[1 - \frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}} \right]^{1 - Y_i}$$

- Natural log function

$$\ell = \sum_{i=1}^n \left\{ Y_i \operatorname{Ln} \left[\frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}} \right] + (1 - Y_i) \operatorname{Ln} \left[1 - \frac{e^{\alpha + \beta X_i}}{1 + e^{\alpha + \beta X_i}} \right] \right\}$$

Logit Model

□ FOC

$$\frac{\partial \ell}{\partial \hat{\alpha}} = \sum_{i=1}^n \left(Y_i - \frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) = 0$$

$$\frac{\partial \ell}{\partial \hat{\beta}} = \sum_{i=1}^n \left(Y_i - \frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) X_i = 0$$

Logit Model

□ SOC

$$\frac{\partial^2 \ell}{\partial \hat{\alpha}^2} = - \sum_{i=1}^n \left(\frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) \left(1 - \frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right)$$

$$\frac{\partial \ell}{\partial \hat{\alpha} \partial \hat{\beta}} = - \sum_{i=1}^n \left(\frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) \left(1 - \frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) X_i$$

$$\frac{\partial^2 \ell}{\partial \hat{\beta}^2} = - \sum_{i=1}^n \left(\frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) \left(1 - \frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}} \right) X_i^2$$

Logit Model

□ If $P_i = \frac{e^{\hat{\alpha} + \hat{\beta} X_i}}{1 + e^{\hat{\alpha} + \hat{\beta} X_i}}$

$$H(\hat{\alpha}, \hat{\beta}) = - \begin{bmatrix} \sum_{i=1}^n P_i(1-P_i) & \sum_{i=1}^n P_i(1-P_i)X_i \\ \sum_{i=1}^n P_i(1-P_i)X_i & \sum_{i=1}^n P_i(1-P_i)X_i^2 \end{bmatrix}$$

Logit Model

- Estimators maximum likelihood are consistent

$$\begin{pmatrix} \hat{\alpha} \\ \hat{\beta} \end{pmatrix} \stackrel{A}{\sim} N \left(\begin{pmatrix} \alpha \\ \beta \end{pmatrix}, (-H(\hat{\alpha}, \hat{\beta}))^{-1} \right)$$

Probit Model

- t variable has a normal distribution

$$F(z) = \Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{t^2}{2}\right)} dt$$

Probit Model

$$\Pr(Y_i = 1 | X_i) = \Phi(\alpha + \beta X_i) = \int_{-\infty}^{\alpha + \beta X_i} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

$$\frac{\partial \Phi(\alpha + \beta X_i)}{\partial X_i} = \phi(\alpha + \beta X_i) \beta$$

$$L(\alpha, \beta; X_i) = \prod_{i=1}^n [\Phi(\alpha + \beta X_i)]^{Y_i} [1 - \Phi(\alpha + \beta X_i)]^{1-Y_i}$$

$$\ell = \sum_{i=1}^n \{Y_i \text{Ln}[\Phi(\alpha + \beta X_i)] + (1 - Y_i) \text{Ln}[1 - \Phi(\alpha + \beta X_i)]\}$$

Model Probit

□ FOC

$$\frac{\partial \ell}{\partial \hat{\alpha}} = \sum_{i=1}^n \left(\frac{Y_i - \Phi(\hat{\alpha} + \hat{\beta} X_i)}{\Phi(\hat{\alpha} + \hat{\beta} X_i) [1 - \Phi(\hat{\alpha} + \hat{\beta} X_i)]} \phi(\hat{\alpha} + \hat{\beta} X_i) \right) = 0$$

$$\frac{\partial \ell}{\partial \hat{\beta}} = \sum_{i=1}^n \left(\frac{Y_i - \Phi(\hat{\alpha} + \hat{\beta} X_i)}{\Phi(\hat{\alpha} + \hat{\beta} X_i) [1 - \Phi(\hat{\alpha} + \hat{\beta} X_i)]} \phi(\hat{\alpha} + \hat{\beta} X_i) \right) X_i = 0$$

Censoring and truncation

- Censoring: a range of values of the variable of interest is censored
 - (e.g.: incomes below the poverty line are reported as if they were at the poverty line).
 - Non-users are reported a 0

- Truncation: sample data are drawn from a subset of a larger population of interest
 - (e.g.: very small and very large incomes are not considered).
 - No users are not considered

Applications

Introduction

Contingent valuation method

Case 1

Case 2

Travel cost method

Case 1

Introduction:

Revealed and stated preferences

- When there is no market for an asset, obviously there is no market price that reveals the lower bound of individual's maximum WTP and the upper bound of the minimum WTA.
- How to derive the measures of change in welfare

REVEALED PREFERENCES

The analyst recovers from the **actual behaviour** the consumer's preferences, and uses this information to work out money measures of the consumer's welfare changes.

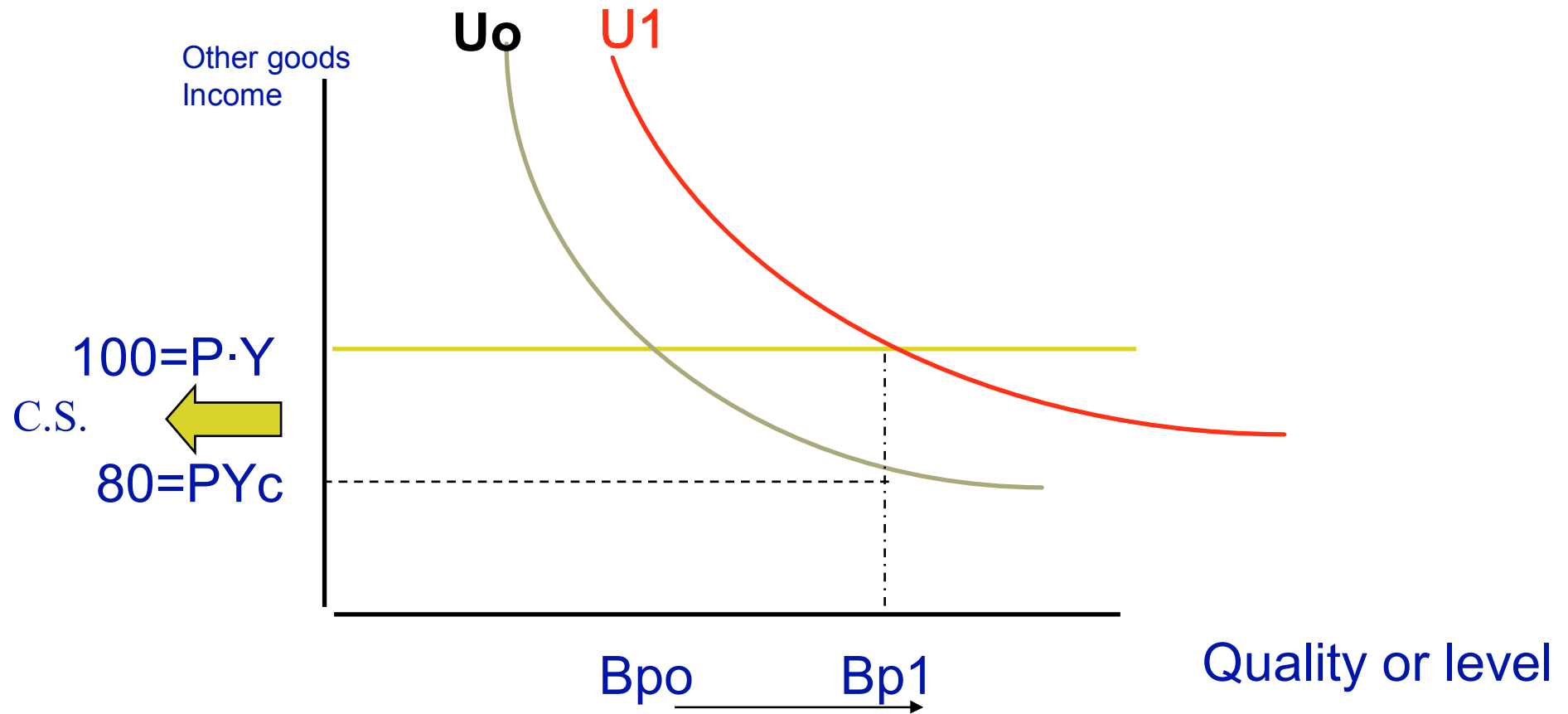
Travel cost

STATED PREFERENCES

The analyst uses information that is based on what the consumer states when directly asked to express his value judgement.

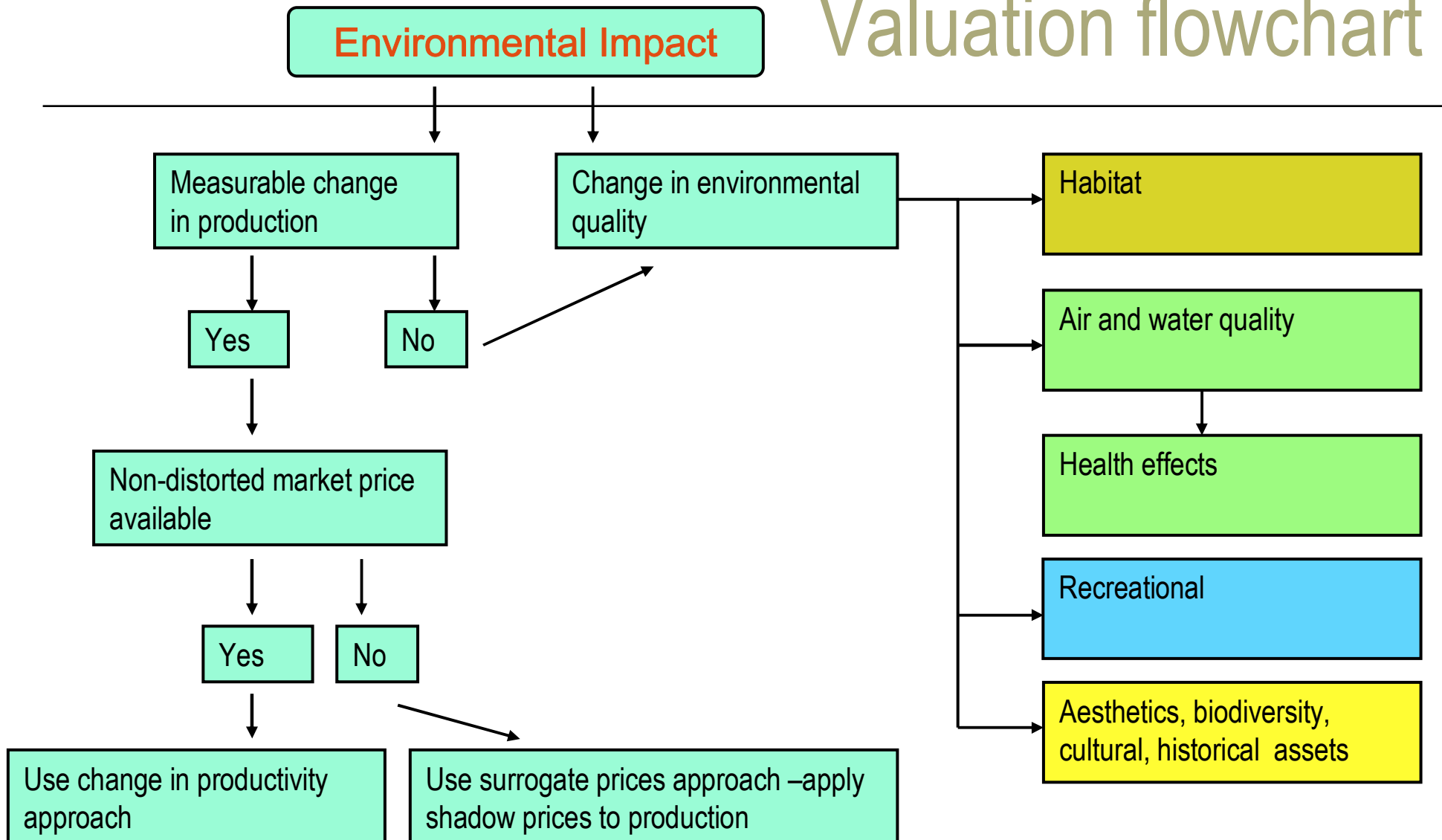
Contingent valuation

Compensating surplus

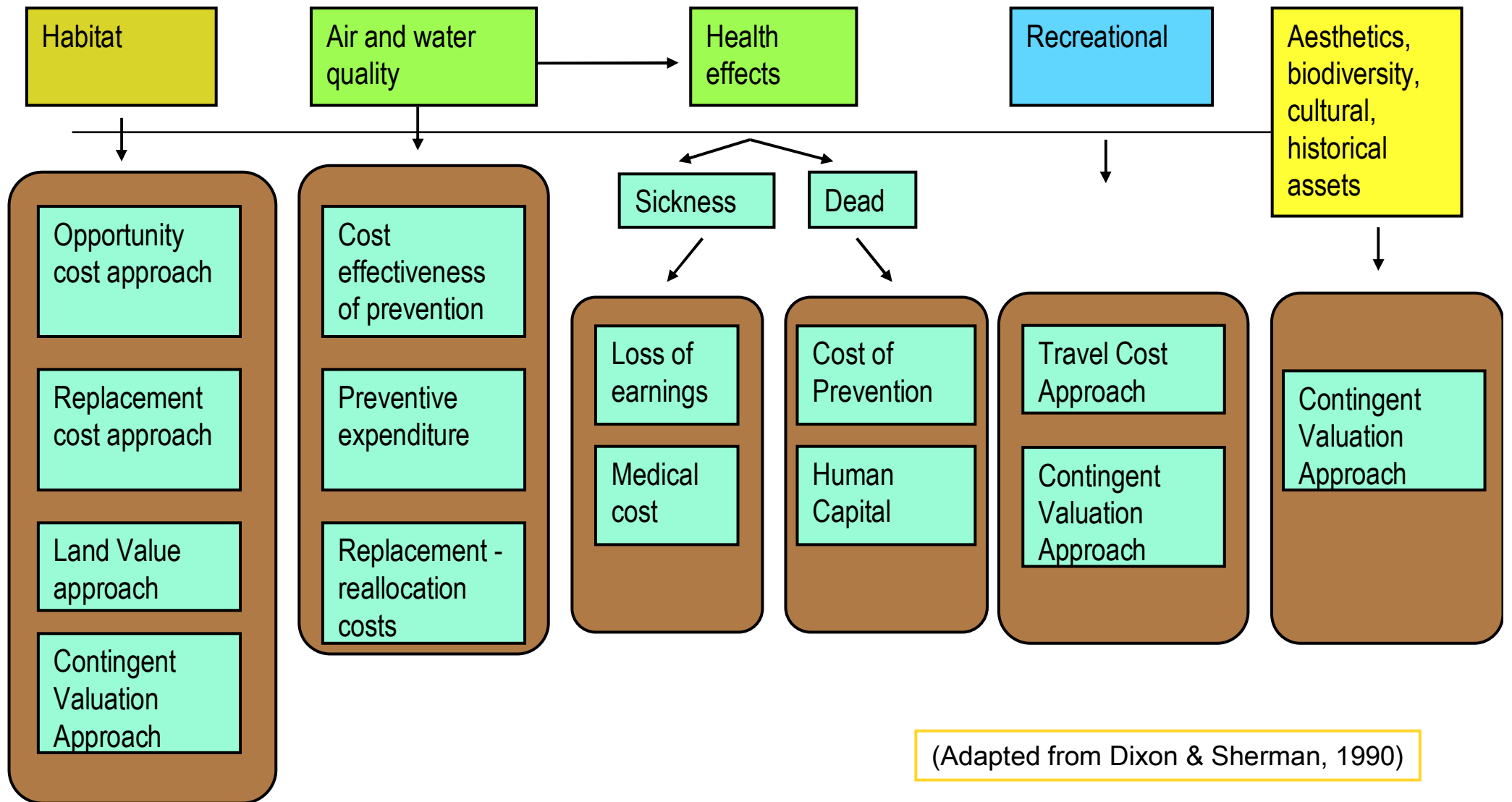


Valuation flowchart

Valuation flowchart



(Adapted from Dixon & Sherman, 1990)



(Adapted from Dixon & Sherman, 1990)

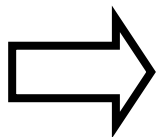
Contingent Valuation Applications

**WTP for water quality improvement
proportional and non-proportional
(stratified) samples**

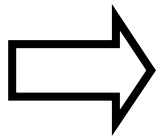
Resume of Case Studies

- WTP for Protected areas
 - Embedding effect (Cerda et al. 1987)

- WTP for Water rights and water quality improvement
 - monthly and annual payments (Cerda et al. 1989)



- WTP for water quality improvement
 - proportional and non-proportional stratified sample (Vásquez, Cerda, et al., 2001)



- WTP for air quality improvement
 - Parametric, semi-parametric, non-parametric estimations (Campos, Vásquez, and Cerda, 2001)

WTP for water quality improvement **proportional and non-proportional** **(stratified) samples**

Basic theoretical aspects

Functional forms and welfare measures

Maximum likelihood function

Case description

Theoretical Aspects

$$U(X, m; q) \rightarrow V(P, m; q)$$

$$v_j = v_j(P, m; q_j) + \varepsilon_j$$

$j = 0$ initial situation
 $j = 1$ with improvement
 q = environmental quality
 P = Prices
 m = Income
 ε = Random Error

$$P(\text{yes}) = \text{Prob}(v_1(P, m - b_i; q_1) + \varepsilon_1 > v_0(P, m; q_0) + \varepsilon_0)$$

$$\eta = \varepsilon_0 - \varepsilon_1$$

$$\Delta v = v_1(P, m - b_i; q_1) - v_0(P, m; q_0) > \eta$$

$$P(\text{yes}) = \text{Prob}(\Delta v > \eta) = F_\eta(\Delta v)$$

F_η = accumulate distribution function

The probability of a positive answer is given by

$$P(\text{yes}) = \text{Prob}(B > b_i) = 1 - F_{\eta}(b_i / \theta)$$

F_{η} = accumulate distribution function for the WTP given the parameters (θ).

Maximum likelihood Function

$$L = \prod_{t=1}^n F(x' \beta)^{y_t} [1 - F(x' \beta)]^{1-y_t}$$

$$\ln L = \sum_{t=1}^n y_t \cdot \ln F(x' \beta) + \sum_{t=1}^n (1 - y_t) \cdot \ln[1 - F(x' \beta)]$$

Los estimadores de máxima verosimilitud (β_{MV}) están definidos como los valores de β que maximizan la función

Las formas de las Funciones de Probabilidad comúnmente usada en las aplicaciones son los modelos Probit y Logit.

Los que poseen una función de distribución normal estandarizada y una función de distribución logística.

Functional forms and welfare measures

- The welfare measures associated to this method are obtained by the estimation of the WTP, **media and median**, for the different functional forms of indirect utility functions.

Functional forms and welfare measures

Functional forms for indirect utility function

<i>FUNCTIONAL FORM</i> v	<i>FUNCTIONAL FORM</i> Δv
I. $v_i = \alpha_i + \beta y + \varepsilon_i$	$\Delta v = \alpha - \beta b_t$
II. $v_i = \alpha_i + \beta \ln y + \varepsilon_i$	$\Delta v = \alpha + \beta \ln[1 - (b_t / y)]$
III. <i>sin formulaci3n</i>	$\Delta v = \alpha - \beta \ln b_t$

Source: Hanemann (1984), Bishop (1979).

Con $\beta > 0$ y $\alpha = (\alpha_1 - \alpha_0)$.

Mean and median traditional functional forms

<i>MODEL</i>	<i>MEAN</i>	<i>MEDIAN</i>
I $B = [\alpha + \eta] / \beta$	α / β	α / β
II $B = y(1 - e^{-\alpha/\beta} e^{\eta/\beta})$	$y(1 - e^{-\alpha/\beta} E\{e^{\eta/\beta}\})$	$y(1 - e^{-\alpha/\beta})$
III $B = e^{\alpha/\beta} e^{\eta/\beta}$	$e^{\alpha/\beta} E\{e^{\eta/\beta}\}$	$e^{\alpha/\beta}$

Source: Ardila (1993).

$E\{e^{\eta/\beta}\} = \exp[1/(2\beta^2)]$, para la FDA normal (Probit).

Case Description

- Water quality improvement for recreational uses in the Río Claro - Talca



Data

-
- | □ Two samples (498) | Proportional | Aproportional |
|-----------------------|--------------|---------------|
| ■ High income level | 5% | 33% |
| ■ Medium income level | 57% | 33% |
| ■ Low income level | 38% | 33% |
-
- **To Compare:** Confidence intervals Park, Loomis and Greel (1991) to see overlapping among both situations.

 - Vectors of payments (bid) (Cooper, 1993)

 - Double-bounded dichotomous choice

Vectors of payments

- The CV dichotomy format faces the individuals with a decision to accept or reject buying a good or service at a given level of price.
- We obtain m different prices b_1, b_2, \dots, b_m
- We apply this value in a hypothetical question to n_1, n_2, \dots, n_m sub-samples.
- Each individual accept or reject b_i

Vectors of Payment (Bid)

Tabla 3: Vectores de pagos

$b_i(p)$	100	500	850	1.200	1.500	1.800	2.200	2.600	3.200
$n_i(p)$	34	63	60	58	58	60	63	71	31
$b_i(a)$	100	600	1.000	1.400	1.800	2.200	2.700	3.200	3.900
$n_i(a)$	36	63	60	57	57	60	63	72	30

Fuente: Elaboración propia en base a datos obtenidos de preencuestas con modelo DWEABS2.

(p): Estratificación proporcional.

(a): Estratificación aproporcional.

$b_i()$: cantidad de dinero en pesos (\$).

b_i en Chilean pesos. 1EURO=600 Chilean pesos

n_i = sub-sample

Copper (1993) Optimal bid selection for dichotomous choice Contingent Valuation survey
(Minimization Quadratic error WTP)

Doubled-Bounded likelihood function

$$\Pr(y = 1) = \Pr(b \leq B) = 1 - F(b) = 1 - \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{T_i} e^{-t^2/2} dt$$

con $t \sim N(0,1)$ y $T_i = (x'\beta)$;

$$\ln L = \sum_{i=1}^n \left\{ d_i^{yy} \ln[1 - F(b_{i+1})] + d_i^{nn} \ln[F(b_{i-1})] + d_i^{yn} \ln[F(b_{i+1}) - F(b_i)] + d_i^{ny} \ln[F(b_i) - F(b_{i-1})] \right\}$$

d_{ij} : Variables take values (0, 1), [j: yes (y), no (n)].

b_i : First offered bid

b_{i+1} : Upper level bid

b_{i-1} : Lower level bid

RESULTADOS (1)

Tabla 4: Coeficientes para muestra estratificada proporcionalmente

		α	β	δ
FORMA FUNCIONAL LINEAL $\Delta v = \alpha - \beta b + \delta Y$	coef.	0,61030	-0,88220	0,32630
	s.e.	0,10437	0,04580	0,03789
	t	(5,848)	(-19,261)	(8,610)
FORMA FUNCIONAL LOGARÍTMICA $\Delta v = \alpha - \beta \ln b + \delta \ln Y$	coef.	-3,12350	-0,92900	0,56960
	s.e.	0,34212	0,04663	0,06465
	t	(-9,130)	(-19,923)	(8,812)

Fuente: Elaboración propia en base a datos obtenidos de encuestas.

Tabla 5: Coeficientes para muestra estratificada a proporcionalmente

		α	β	δ
FORMA FUNCIONAL LINEAL $\Delta v = \alpha - \beta b + \delta Y$	coef.	0,54400	-0,67890	0,17110
	s.e.	0,11524	0,04141	0,02198
	t	(4,721)	(-16,395)	(7,783)
FORMA FUNCIONAL LOGARÍTMICA $\Delta v = \alpha - \beta \ln b + \delta \ln Y$	coef.	-2,41090	-0,90670	0,42660
	s.e.	0,29379	0,04869	0,05062
	t	(-8,206)	(-18,622)	(8,427)

Fuente: Elaboración propia en base a datos obtenidos de encuestas.

RESULTADOS (2)

Tabla 6: Medidas de bienestar muestra estratificada proporcionalmente

		Media ₀	Mediana ₀	Media ₁	Mediana ₁
FORMA FUNCIONAL LINEAL	m.b.	1.030,7	1.030,7	1.028,5	1.028,5
$\Delta v = \alpha - \beta b + \delta Y$	s.e.	(72,8)	(72,8)	(72,91)	(72,91)
FORMA FUNCIONAL LOGARÍTMICA	m.b.	1.555,5	871,5	1.347,5	746,1
$\Delta v = \alpha - \beta \ln b + \delta \ln Y$	s.e.	(122,53)	(46,68)	(124,25)	(47,76)

Fuente: Elaboración propia en base a regresiones ejecutadas.

m.b.: valor de la medida de bienestar en pesos (\$). 540\$=1US\$

Tabla 7: Medidas de bienestar muestra estratificada apropiadamente

		Media ₀	Mediana ₀	Media ₁	Mediana ₁
FORMA FUNCIONAL LINEAL	m.b.	1.264,9	1.264,9	1.258,9	1.258,9
$\Delta v = \alpha - \beta b + \delta Y$	s.e.	(99,41)	(99,41)	(97,77)	(97,77)
FORMA FUNCIONAL LOGARÍTMICA	m.b.	1.969,6	1.072,2	1.701,3	917,6
$\Delta v = \alpha - \beta \ln b + \delta \ln Y$	s.e.	(153,87)	(59,79)	(160,54)	(60,49)

Fuente: Elaboración propia en base a regresiones ejecutadas.

m.b.: valor de la medida de bienestar en pesos (\$). 540\$=1US\$

RESULTADOS (3)

Tabla 8: Intervalos de confianza al 95%

	FORMA FUNCIONAL LINEAL			FORMA FUNCIONAL LOGARÍTMICA		
	$\Delta v = \alpha - \beta b + \delta Y$			$\Delta v = \alpha - \beta \ln b + \delta \ln Y$		
	l.i.	v.c.	l.s.	l.i.	v.c.	l.s.
Media _p	879,48	1.030,7	1.165,20	1.131,40	1.555,5	1.610,00
Media _a	1.064,70	1.264,9	1.444,90	1.425,60	1.969,6	2.042,40
Mediana _p	879,48	1.030,7	1.165,20	656,46	871,5	849,83
Mediana _a	1.064,70	1.264,9	1.444,90	796,14	1.072,2	1.043,90

Fuente: Elaboración propia en base a datos obtenidos del proceso de simulación.

v.c.: Valor calculado de la medida de bienestar.

l.i.: Límite inferior, l.s.: Límite superior.

Tabla 9: Pruebas t-estadísticas

	$M_p - M_a$	$\sqrt{Var(M_p) + Var(M_a)}$	t_c
T ₁	-234,2	123,216	-1,9
T ₂	-414,1	196,696	-2,105
T ₃	-234,2	123,216	-1,9
T ₄	-200,68	75,854	-2,645

T₁: Diferencia de medias para la forma funcional lineal.

T₂: Diferencia de medias para la forma funcional logarítmica.

T₃: Diferencia de medianas para la forma funcional lineal.

T₄: Diferencia de medianas para la forma funcional logarítmica.

CASE 1 → CONCLUSIONS

□ Economic Value

- From the lineal model, it is obtain a WTP =US\$2 monthly per one year
- People are WTP more if you ask for a monthly payment per a year than for just one annual payment
- The benefits are much lower that the investment cost in abatement technology
- Valuation included only recreational value. It did not consider the benefits for agricultural user down the river
- Presently, the water treatment cost is charged directly to potable water users

□ Sample and functional forms

- For the lineal functional forms all the measures resulted significant and were within the confidence intervals for both samples.
- It did not happen, in the log functional form, for the median

WTP for air quality improvement

Parametric, semi-parametric, non-parametric estimations

Case Description

Hanemann (1984) Parametric Estimation

Kriström (1990) Non-parametric

Haab & McConnell (1997) Non-Parametric

Creel & Loomis (1997) semi-parametric

Case Description

- Air quality improvement - Talcahuano
- Fishmeal industry air (bad odors) pollution
- Some Iron & Steel industry



Data

bi	Total responses	Yes responses	No responses
200	266 (27%)	213 (80%)	53 (20%)
2800	237 (23%)	125 (53%)	112 (47%)
5300	257 (25%)	69 (27%)	188 (73%)
7900	251 (25%)	64 (25%)	187 (75%)

References

- Hanemann (1984) Parametric Estimation
- Kriström (1990) Non-parametric
- Haab & McConnell (1997) Non-Parametric
- Creel & Loomis (1997) semi-parametric

Hanemann (1984) Parametric Estimation

Difference in indirect utility function

$$v_j = v_j(P, m; q_j) + \varepsilon_j \quad j = 0 \text{ initial situation}$$

$j = 1$ with improvement

q = environmental quality

P = Prices

Y = Income

ε = Random Error

-
- Individual may pay b_i for quality improvement (vector of payment value), but it is not the true WTP (B).

$$P(\text{yes}) = \text{Prob}(v_1(P, m - b_i; q_1) + \varepsilon_1 > v_0(P, m; q_0) + \varepsilon_0)$$

$$\eta = \varepsilon_0 - \varepsilon_1$$

$$\Delta v = v_1(P, m - b_i; q_1) - v_0(P, m; q_0) > \eta$$

$$P(\text{yes}) = \text{Prob}(\Delta v > \eta) = F_\eta(\Delta v)$$

$$F_\eta = \text{accumulate distribution function}$$

-
- To obtain the welfare measure, the indifference level, between pay or not, is when $b_i = B$.
 - For an specific lineal indirect utility function

$$v = \alpha - \beta m + \varepsilon$$

The difference in the utility function is :

$$\Delta v = \alpha - \beta b_i$$

The mean and median are :

$$E(C) = C^* = \alpha / \beta$$

Kriström (1990)

Non-parametric

- The model is based in the *Survivor WTP Function*
- The investigation is motivated from environmental economics where data from contingent valuation surveys are often used to non-parametrically estimate the willingness to pay distribution
- Work directly with:
 - the responses (b_i)
 - the positive responses (k_i) from total surveys (n_i)
- Construct a sequence of accepted proportion, π

Maximum likelihood
estimate of free
distribution of
accepting probability
(Ayer et al., 1955)

$$\pi_i = \frac{k_i}{n_i}$$

Mean (Duffield and Patterson, 1991)

$$E(B) = \sum \Delta b_i \pi_i$$

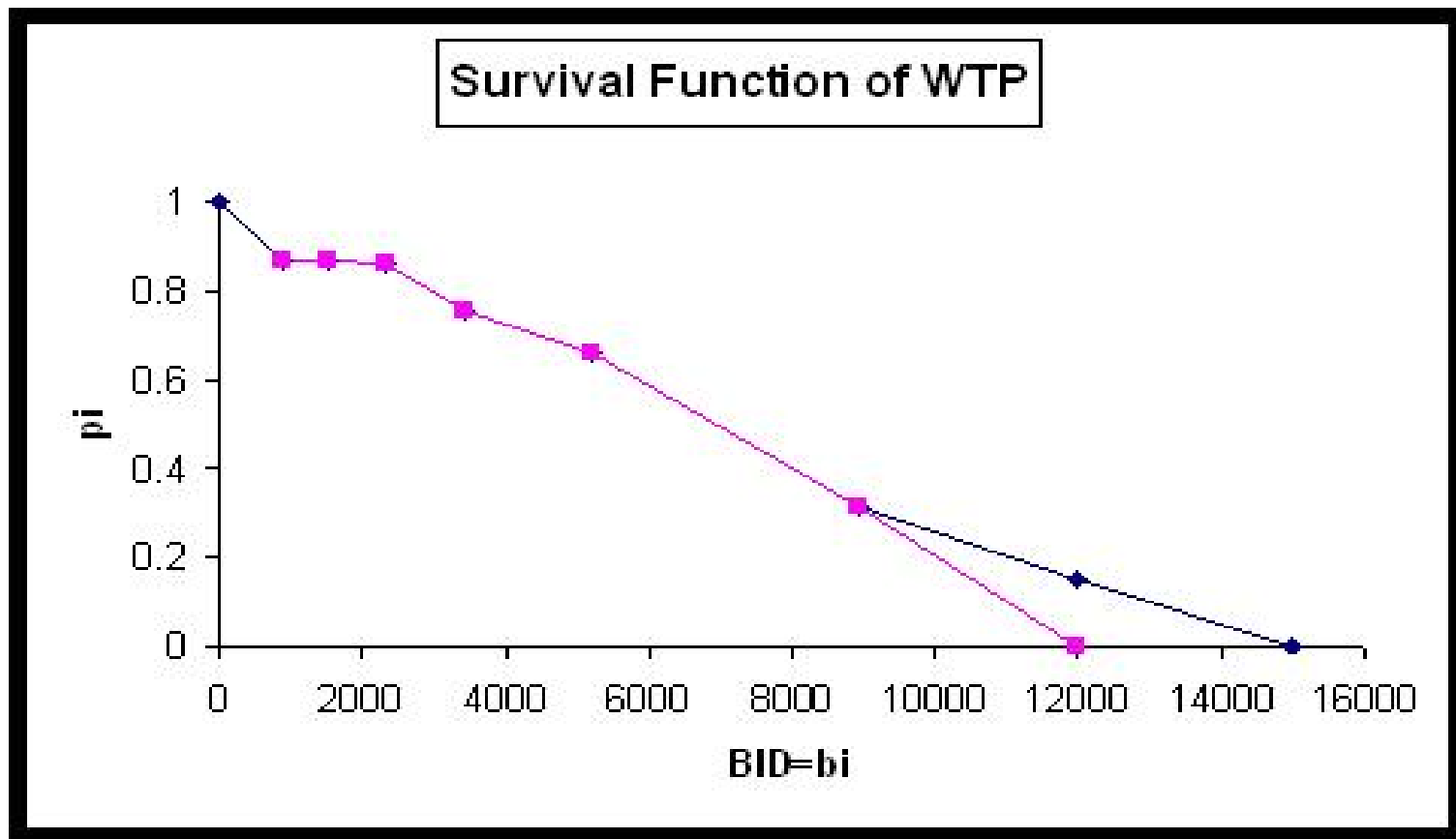
$$\Delta b_i = (b_{i+1} - b_{i-1}) \quad i = 2, \dots, k-1$$

$$\Delta b_i = b_i + \frac{(b_2 - b_1)}{2}$$

$$\Delta b_k = \frac{(b_k - b_{k-1})}{2} + (T - b_k)$$

k = last amount offer

Horizontal Axis : $b_i = T \rightarrow \pi_i = 0$



Haab & McConnell (1997) Non-Parametric

- The analysis here is with the negative responses (h_i)

$$F_i = \frac{h_i}{h_i + k_i}$$

$$p_i = F_i - F_{i-1} \quad F_0 = 0$$

- Here p_i is the probability that the true WTP(B) is within the interval (b_{i-1}, b_i) . F_i the accumulative distribution function (monotonically increasing)

Mean :

(lower bound individual WTP)

$$E(\lim \rightarrow \infty WTP) = \sum_{i=1}^{i+1} b_{i-1} p_i$$

Creel and Loomis (1997) (semi-parametric)

- The probability to accept a given amount is:

$$P(x, b) = F_{\varepsilon}(\Delta v)$$

x = exogenous variables (income, socioeconomic)

b = amount offered

$F_{\varepsilon}()$ and (Δv) are unknown

$F_{\varepsilon}(\Delta v)$ = continue and increasing

The idea is to estimate $P(x, b)$ using a logit distribution function (increasing)

$$\Delta(\varepsilon) = [1 + \exp(-\varepsilon)]^{-1}$$

.....

Mean:

$$E(B) = \int p(x, b) db$$

Comparing the results?

- Confidence intervals. Is there overlapping?
- For Parametric and semi-parametric estimates, the welfare measures are random variables, but to know the variance, it used the steps proposed by Krinsky and Robb (1986)
- For non-parametric estimates no problem. The variance are obtained directly (see papers)

Results

Model	Mean (\$/month) 1EURO=600\$	Median (\$/month) 1EURO=600\$
Hanemann (1984) Parametric Estimation	3518 (3091-3914)	3518 (3091-3914)
Kriström (1990) Non- parametric	3786 (3535-4037)	3065 (2800-5300)
Haab & McConnell (1997)Non- parametric	2866 (2232-3499)	3065 (2800-5300)
Creel & Loomis (1997) Semi-parametric	3392 (3115-3661)	2837 (2263-3316)

Conclusions

□ Mean:

- The measures are not statistically different for the models, with the exception of the mean estimated by the Haab & McConnell Approach, where the confidence interval does not overlap with the mean estimated by Kristöm.
- This can be explained because the mean from Haab & McConnell approach represent a lower bound of the welfare measure.

□ Median:

- There are no statistically differences for the median among models

How can we compare cost & benefits?

- Industry Expenditures in abatement technologies (5 years)
 - 20.000.000 USD = \$9.600 millions (480\$/USD - 1990)

- Relevant population: 148.573 → 37.143 families

- Using a conservative measure (\$2.800-3.800)
 - Benefits Interval \$104.000.400 – 141.143.400
 - Average Monthly benefits \$1.053.744.691
 - Five year payment: 6240 millions to 8648 millions
(no discounting)

→ Close to industry expenditures in abatement technologies

Estimating Welfare Measures Using Travel Cost Method with Truncated and Censored Data

1. Introduction

2. Objectives

3. The Travel Cost Method (TCM)

Theoretical Aspects / Truncated and Censored Models / Maximum likelihood (ML) and Ordinary Least Squares (OLS) estimators / Count Distribution functions

4. Methodology

5. Results

6. Conclusions

1. Introduction

- TCM is used to value recreational uses of the environment:
 - Value the recreational benefits associated to improvement in water quality
 - Value the recreational loss associated with a beach closure
- Since TCM is based on observed behavior, it is used to estimate use values only.
- It is useful split travel cost models in single-site and multiple-site models

-
- Single-site models work like conventional downward sloping demand functions
 - The demand function slopes downward, if trips decline with distance to the recreational-site
 - Single-site are useful when the goal is to estimate the total use or access value of a site (Parson, 2003)
 - There are some variations of the single-site model that can be used for valuing changes in site characteristics such as improvement in water quality



2. Objectives

- estimate welfare measures using truncated and censored data
 - compare the results of different functional forms
 - compare the results of different estimation methods



3. The Travel Cost Method

- *Theoretical Aspects*
- *Truncated and Censored Models*
- *Maximum likelihood (ML) and Ordinary Least Squares (OLS) estimators*
- *Count distribution functions*

Theoretical Aspects

$$MAX U(y, z)$$

$$s.a : m = d + wt_w = z + (c_1 + c_2)y$$

$$T = t_w + (t_1 + t_2)y$$

donde:

y : number of visist

z : composite hicksian gods

d: non-wage income

w: wages rate

m: total income

tw: labour time

t1: travel time

t2: time in situ

T : total time

c1: travel monetary cost

c2: site monetray cost

$$t_w = T - (t_1 + t_2)y$$

$$m = d + w[T - (t_1 + t_2)y] = z + (c_1 + c_2)y$$

$$d + wT = w(t_1 + t_2)y + z + (c_1 + c_2)y$$

$$d + wT = z + [(c_1 + wt_1) + (c_2 + wt_2)]y$$



Labour Income



travel cost



permanency cost

$$m^* = z + p_y y$$

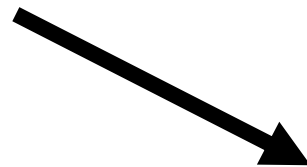
$$m^* = d + wT$$

$$p_y = (c_1 + wt_1) + (c_2 + wt_2)$$

$$\begin{aligned} & \text{MAX } U(y, z) \\ \text{s.a.: } & m^* = z + p_y y \end{aligned}$$

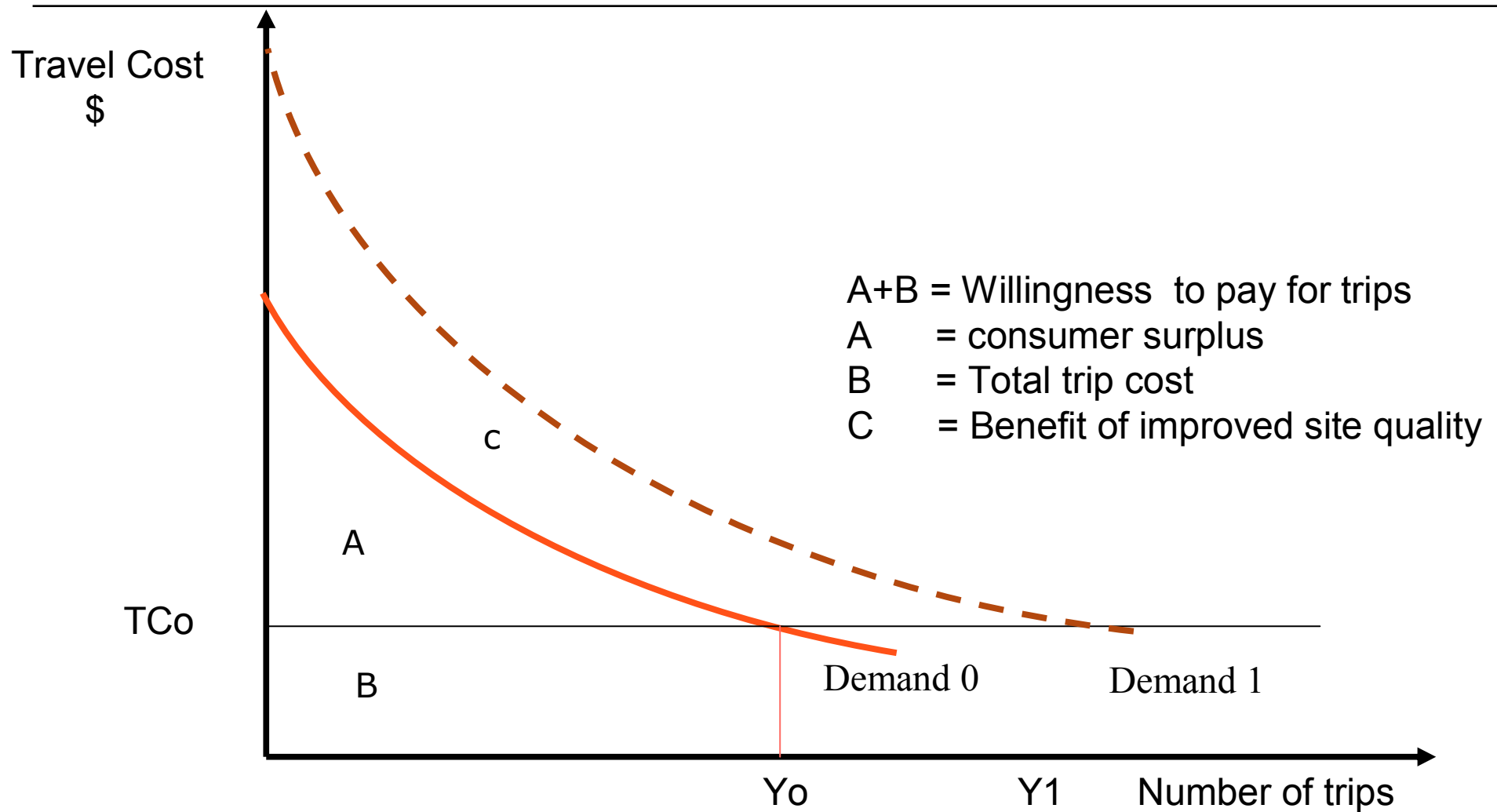
$$y = y(p_y, m^*)$$

$$z = z(p_z, m^*)$$



$$y_{ij} = f(P_{y_{ij}}, Z_{ij}, e_{ij})$$

Graphically



Some Implicit Assumptions

- Number of trips are complement of site- environmental quality
- Individual responds to the travel cost in the same way as they would do to a change in access cost
- Visit only one site
- Time in the recreational site is exogenous and fixed
- No substitution
- Rate of wage represents the opportunity cost of time

Truncated and Censored Models

$$y = x\beta + \mu, \text{ if } y > 0$$

$$y = 0, \text{ otherwise}$$

Tobin (1958)

For a recreational-site demand :

$$y_i = y_i(p_y, p_s, m) + \varepsilon_i, \text{ if } y_i > 0$$

$$y_i = 0, \text{ if } y_i < 0$$

Modelo Tobit

Therefore for a recreational-site demand:

Censored in zero - for on site-sampling truncated in 1

Maximum likelihood (ML) and Ordinary Least Squares (OLS) estimators

Pro example: Linear Function

$$Y = \beta_0 + \beta_1 X + \epsilon$$

adf

df

Maximum Likelihood Function
Censored sampling

$$L(\beta_0, \beta_1) = \prod_{i=1}^n \left[1 - \Phi\left(\frac{\beta_0 + \beta_1 X_i - Y_i}{\sigma}\right) \right] \prod_{j=1}^m \left[\Phi\left(\frac{\beta_0 + \beta_1 X_j - Y_j}{\sigma}\right) \right]$$

OLS → MLE : Reduce bias

Count Distribution Functions (1)

Poisson Distribution Fn.

$$f_i(y_i = n_i) = \frac{e^{-\lambda_i} \lambda_i^{n_i}}{n_i!}; \quad n_i = 0, 1, 2, \dots$$

Poisson
Likelihood Fn.

$$L(\beta | y_i, n_i) = \prod_{i=1}^N \frac{\exp(-\lambda_i) \lambda_i^{n_i}}{n_i!}; \quad n_i = 0, 1, 2, \dots$$

$$y \approx P(\lambda)$$

Tobit → Poisson: Integer & non-negative

Count Distribution Functions (2)

Negative Binomial

$$f_i = \exp(-\alpha) \alpha^i$$

$$\exp(-\xi) \approx \text{Gamma}(1, \alpha)$$

$$y \approx \text{NB}(\lambda, \lambda + \alpha\lambda^2)$$

$$\alpha \rightarrow 0 \rightarrow \text{Poisson}$$

Poisson \rightarrow NB: Consider the possibility of overdispersion



4. Methodology

- Description
- The model
- Consumer surplus estimates

Description

- Dichato Beach, Chile
- N=161 (truncated sample)
- Censored (85% zeros)
- Censored (flexible Haab & McConnell, 1996) 20%



The model

$$y_i = \beta_0 + \beta_1 P_{y_i} + \beta_2 P_{ij} + \beta_3 D_{1i} + \beta_4 D_{2i} + \beta m_i + \xi_i$$

y_i = number of trips

P_{y_i} = travel Costs

P_{ij} = price of substitutes

D_{1i} = accessibility

D_{2i} = water quality

m_i = income

ξ_i = error term

$$P_i = \text{Dist} [\text{Cost} / \text{Km} + (\%w [\text{Annual Income} / 2000] / \text{Speed})]$$

Models

OLSL: $Y \sim N(X\beta, \sigma^2)$

OLSS: $Y \sim N(\exp(X\beta), \sigma^2)$

MLEL: $Y \sim N(X\beta, \sigma^2)$
Y is observed if $Y > 0$

MLES: $Y \sim N(\exp(X\beta), \sigma^2)$
Y is observed if $Y > 0$

POIS: $Y \sim \text{Poisson}(\lambda = \exp(X\beta))$

TPOIS: $Y \sim \text{Poisson}(\lambda = \exp(X\beta))$
Y is observed if $Y > 0$

BNEG: $Y \sim \text{BinNega}(\lambda = \exp(X\beta), \alpha)$

TBNEG: $Y \sim \text{BinNega}(\lambda = \exp(X\beta), \alpha)$
Y is observed if $Y > 0$

Consumer Surplus Estimates

OLSL

MLEL

Otherwise

$$- y_0^2 / 2\beta_1$$

$$- 1 / \beta_1$$



5. Results

**Tabla 2. Truncated models
(opportunity cost of time =30%)**

<i>Param.</i>	<i>OLSL</i>	<i>OLSS</i>	<i>MLEL</i>	<i>MLES</i>	<i>POIS</i>	<i>TPOIS</i>	<i>BNEG</i>	<i>TBNEG</i>
<i>Constante</i>	3,1053** (3,118)	1,2289** (7,464)	-13,7210 (-1,390)	1,1837** (6,474)	1,1370** (7,793)	1,0809** (6,778)	1,0742** (4,126)	0,54941 (1,250)
<i>TCP-30</i>	-0,00056864** (-3,363)	-0,000087179** (-3,119)	-0,0031267* (-2,345)	-0,000099454** (-3,099)	-0,00015241** (-5,969)	-0,00017222** (-6,131)	-0,00012506** (-5,206)	-0,00015011** (-3,696)
<i>TCS-30</i>	0,00013063* (2,053)	0,000017790 (1,691)	0,00070383 (1,679)	0,000019674 (1,699)	0,000033229** (3,612)	0,000036997** (3,683)	0,000033650* (2,026)	0,000049151 (1,844)
<i>ACCESO</i>	1,1539 (1,409)	0,15948 (1,178)	4,1299 (1,233)	0,17221 (1,198)	0,22929* (2,428)	0,23865* (2,468)	0,20358 (1,128)	0,25715 (0,694)
<i>AGUA</i>	0,70745 (1,118)	0,13645 (1,304)	3,1381 (1,096)	0,15005 (1,331)	0,16230* (2,050)	0,17480* (2,126)	0,14636 (1,111)	0,19679 (0,807)
<i>INGRESO</i>	0,000001673 (1,903)	0,000000355* (2,442)	0,000008592 (1,869)	0,000000395* (2,513)	0,000000428** (3,863)	0,000000477** (4,118)	0,000000413* (2,140)	0,000000579 (1,519)
σ	-	-	7,7313** (4,619)	0,64609** (15,439)	-	-	-	-
α	-	-	-	-	-	-	0,37565** (4,197)	1,17410** (2,728)
<i>R² ajustado</i>	0,08641	0,07504	-	-	-	-	-	-
<i>log-L</i>	-	-	-387,9332	-148,1669	-452,1419	-446,8533	-393,4177	-370,9551

Valores de *t* entre paréntesis. ** indica que es estadísticamente significativo a un nivel del 99%. * indica que es estadísticamente significativo a un nivel del 95%. *n* = 161 observaciones

$$L(\beta|y_i, n_i) = \prod_{i=1}^N \frac{\exp(-\lambda_i) \lambda_i^{n_i}}{n_i!}; \quad n_i = 0, 1, 2, \dots$$

Regular Poisson

$$L(\beta|y_i, n_i) = \prod_{i=1}^N \frac{\exp(-\lambda_i) \lambda_i^{(n_i-1)}}{(n_i - 1)!}; \quad n_i = 1, 2, \dots$$

Truncated Poisson

**Table 11. Censored models (20%)
(opportunity cost of time 30%)**

<i>Parámetro</i>	<i>OLSL</i>	<i>OLSS</i>	<i>MLEL</i>	<i>MLES</i>	<i>POIS</i>	<i>BNEG</i>
<i>Constante</i>	1,5510 (1,927)	0,6034** (3,625)	-0,1348 (-0,134)	0,6034** (3,680)	0,4900** (3,362)	0,4190 (1,681)
<i>TCP-30</i>	-0,00041980** (-2,744)	-0,000049976 (-1,580)	-0,00038365* (-2,103)	-0,000049976 (-1,604)	-0,00012477** (-5,213)	-0,000091874** (-2,933)
<i>TCS-30</i>	0,00015230** (2,936)	0,000033078** (3,084)	0,00021298** (3,312)	0,000033078** (3,131)	0,000054470** (5,875)	0,000055173** (3,428)
<i>ACCESO</i>	2,0745** (2,648)	0,47410** (2,927)	2,7149** (2,943)	0,47410** (2,971)	0,48443** (5,153)	0,49674 (1,890)
<i>AGUA</i>	1,7711** (3,063)	0,52329** (4,377)	2,6516** (3,839)	0,52329** (4,443)	0,48387** (6,116)	0,49992** (2,658)
<i>INGRESO</i>	0,000000950 (1,302)	0,000000147 (0,977)	0,000000716 (0,806)	0,000000147 (0,992)	0,000000292** (2,785)	0,000000228 (1,079)
σ	-	-	4,3465** (17,329)	0,75601** (20,199)	-	-
α	-	-	-	-	-	0,79914** (5,928)
<i>R² ajustado</i>	0,12475	0,15376	-	-	-	-
<i>log-L</i>	-	-	-500,3408	-232,4033	-588,3837	-469,7138

Valores de *t* entre paréntesis.

** indica que es estadísticamente significativo a un nivel del 99%.

* indica que es estadísticamente significativo a un nivel del 95%. *n* = 204 observaciones

Average Consumer Surplus per family & trip (\$) (truncated sample)

	<i>OLSL</i>	<i>OLSS</i>	<i>MLEL</i>	<i>MLES</i>	<i>POIS</i>	<i>TPOIS</i>	<i>BNEG</i>	<i>TBNEG</i>
<i>TCP-30</i>	3.886,47 (US\$ 9.72)	11.470,65 (US\$ 28.7)	706,82 (US\$ 1.8)	10.054,90 (US\$ 25)	6.561,25 (US\$ 16.4)	5.806,53 (US\$ 14.5)	7.996,16 (US\$ 20)	6.661,78 (US\$ 16.7)
<i>TCP-40</i>	4.623,91	13.777,52	836,42	12.087,51	7.830,85	6.941,07	9.570,29	7.982,12
<i>TCP-50</i>	5.380,14	16.155,35	968,96	14.186,01	9.138,26	8.110,30	11.180,93	9.330,97

Exchange rate 1US\$ = 400\$

(Today is about 500\$)

**Average Consumer Surplus per Family & per year (\$)
(truncated sample)**

	<i>OLSL</i>	<i>OLSS</i>	<i>MLEL</i>	<i>MLES</i>	<i>POIS</i>	<i>TPOIS</i>	<i>BNEG</i>	<i>TBNEG</i>
<i>TCP-30</i>	17.178,20	50.700,27 (US\$ 127)	3.124,14 (US\$ 7.8)	44.442,66	29.000,73	25.664,86	35.343,03	29.445,07
<i>TCP-40</i>	20.437,68	60.896,64	3.696,98	53.426,79	34.612,36	30.679,53	42.300,68	35.280,97
<i>TCP-50</i>	23.780,22	71.406,65	4.282,80	62.702,16	40.391,11	35.847,53	49.419,71	41.242,89

**Tabla 6. Total annual Consumer Surplus
(Truncated sample)**

	<i>OLSL</i>	<i>OLSS</i>	<i>MLEL</i>	<i>MLES</i>	<i>POIS</i>	<i>TPOIS</i>	<i>BNEG</i>	<i>TBNEG</i>
<i>TCP-30</i>	4.988.217	8.155.633 (US\$ 20389)	907.186 (US\$ 9.72)	7.149.033	4.665.048	4.128.440	5.685.271	4.736.526
<i>TCP-40</i>	5.934.721	9.795.817	1.073.537,	8.594.222	5.567.736	4.935.100,9	6.804.478	5.675.287
<i>TCP-50</i>	6.905.324	11.486.453	1.243.642	10.086.250	6.497.304	5.766.423	7.949.641	6.634.319

Tabla 14. Average Consumer Surplus per Family (censored sample)

Average Consumer Surplus per Family per trip (\$)

	<i>OLSL</i>	<i>MLEL</i>	<i>POIS</i>	<i>BNEG</i>
<i>TCP-30</i>	4.156,74	4.548,42	8.014,75	10.884,47
<i>TCP-40</i>	5.098,31	5.638,67	9.845,43	13.341,69
<i>TCP-50</i>	6.074,64	6.773,81	11.747,15	15.871,76

Tabla 14b. Average Consumer Surplus per Family (censored sample)

Average Consumer Surplus per Family & per year (\$)

	<i>OLSL</i>	<i>MLEL</i>	<i>POIS</i>	<i>BNEG</i>
<i>TCP-30</i>	14.507,02	15.873,99	27.971,48	37.986,80
<i>TCP-40</i>	17.793,10	19.678,96	34.360,55	46.562,50
<i>TCP-50</i>	21.200,49	23.640,60	40.997,55	55.392,44

**Tabla 15. Total Annual Consumer Surplus
(Censored sample)**

	<i>OLSL</i>	<i>MLEL</i>	<i>POIS</i>	<i>BNEG</i>
<i>TCP-30</i>	6.756.788	7.393.457	5.698.485	7.738.859
<i>TCP-40</i>	8.287.317	9.165.670	7.000.098	9.485.944
<i>TCP-50</i>	9.874.329	11.010.830	8.352.226	11.284.818

Tabla 16. Comparison of Benefits

Average Consumer Surplus per family & per trip (\$)

	<i>OLSL Trun.</i>	<i>OLSL cens20</i>	<i>MLEL Trun.</i>	<i>MLEL cens20</i>	<i>TPOIS Trun.</i>	<i>POIS cens20</i>	<i>TBNEG Trun.</i>	<i>BNEG cens20</i>
<i>TCP-30</i>	3.886	4.156	706	4.548	5.806	8.014	6.661	10.884
<i>TCP-40</i>	4.623	5.098	836	5.638	6.941	9.845	7.982	13.341
<i>TCP-50</i>	5.380	6.074	968	6.773	8.110	11.747	9.330	15.871

Average Consumer Surplus per family & per year (\$)

	<i>OLSL Trun.</i>	<i>OLSL cens20</i>	<i>MLEL Trun.</i>	<i>MLEL cens20</i>	<i>TPOIS Trun.</i>	<i>POIS Cens20</i>	<i>TBNEG Trun.</i>	<i>BNEG cens20</i>
<i>TCP-30</i>	17.178	14.507	3.124	15.873	25.664	27.971	29.445	37.986
<i>TCP-40</i>	20.437	17.793	3.696	19.678	30.679	34.360	35.280	46.562
<i>TCP-50</i>	23.780	21.200	4.282	23.640	35.847	40.997	41.242	55.392

6. Conclusions

-
- There are differences among models:
 - Sampling
 - Statistical distributions
 - Value of the opportunity cost of time

Truncated Models

- Advantage:
 - Truncated methods are easy & cheaper to apply

- Disadvantage:
 - Estimation bias
 - inadequate participation and lack of randomness

 - Exclusion of information of non-participants

 - Use of distribution functions that allow negative trips.

Censored Models

- Advantages:
 - Reduce bias of truncated models
 - More Robust
- Disadvantage:
 - Survey cost

Thank you
¡Gracias por su atención!

