

Advanced Structural Modeling

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0.1 Prerequisites

You should know everything in PhD Econometrics I and Econometrics II before taking this class.

0.2 What is Structural Modeling?

In this chapter, I explain what structural modeling is and how it can be useful to economists. A nice treatment of this topic is ?, which I borrow some materials from.

In the simplest sense, structural modeling (or, interchangeably, structural econometrics) is a combination of economic and statistical models. Structural models are used in every empirical field of economics: from dynamic stochastic general equilibrium (DSGE) models in macroeconomics to models of firm decision-making in industrial organization to individual choice models in labor.

More formally, a structural model is an attempt to estimate **policy-invariant fundamental parameters**, also known as structural parameters. The parameter estimates can then be used to predict outcomes in a counterfactual setting. Typically, structural parameters are those parameters which enter an agent's utility function or production function (and cost function). Structural models may also incorporate constraints faced by the agent(s), strategic behavior among competing agents, or other aspects of economic theory such as moral hazard in a principal-agent scenario. Once the econometrician knows the preferences, production technology, and constraints of the agent(s), she can predict how the agent(s) will behave in a new scenario for which there is no existing data.

Structural models are especially useful in settings where an experiment cannot be undertaken. In this case, one must specify how the unobservables are related to the observables, because this relationship cannot be ignored without the randomization that occurs in an experiment.

0.2.1 Advantages and Disadvantages of Structural Models

Many economists shy away from structural models because using them forces the researcher to make strong assumptions about how the world works. In essence a structural model is a researcher's view of the world. To the extent that the model includes unreasonable or unrealistic assumptions, one must discount any results derived from the model.

Another reason some economists dislike structural models is because they can be difficult to estimate. Structural models typically are nonlinear (even if they are linear-in-parameters) and estimation typically requires using maximum likelihood or method of moments estimation as opposed to linear regression techniques.

The main advantage of using a structural model is that it can be a powerful tool for predicting the effects of potential policies. If one knows the data generating process (DGP), then one does not need to do any statistical estimation. Structural modeling is an attempt to estimate the parameters of the DGP. Once the DGP is known, one can use it to simulate what might happen under counterfactual scenarios.

0.2.2 A simple structural model

One toy example that often appears in introductory econometrics textbooks is the effect of education on earnings. Typically, the textbook presents an equation like this:

$$\log(wage_i) = \beta_0 + \beta_1 educ_i + \varepsilon_i$$

where $wage_i$ is the individual's wage as an adult, and $educ_i$ is the individual's years of completed education (e.g. 12 for a high school graduate, 16 for a college graduate, etc.).

0.2.3 Other examples

- Tuition subsidy (?)
- IO demand estimation (BLP, etc.)
- IO production function estimation (Collard-Wexler papers)
- IO entry games (...)
- Trade markups (?)
- Development (...)
- Migration (?)
- Regional demand and commuting flows (?)

You can label chapter and section titles using `{#label}` after them, e.g., we can reference Chapter 0.2. If you do not manually label them, there will be automatic labels anyway, e.g., Chapter 0.4.

Figures and tables with captions will be placed in `figure` and `table` environments, respectively.

```
par(mar = c(4, 4, .1, .1))
plot(pressure, type = 'b', pch = 19)
```

Reference a figure by its code chunk label with the `fig:` prefix, e.g., see Figure 1. Similarly, you can reference tables generated from `knitr::kable()`, e.g., see Table 1.

```
knitr::kable(
  head(iris, 20), caption = 'Here is a nice table!',
  booktabs = TRUE
)
```

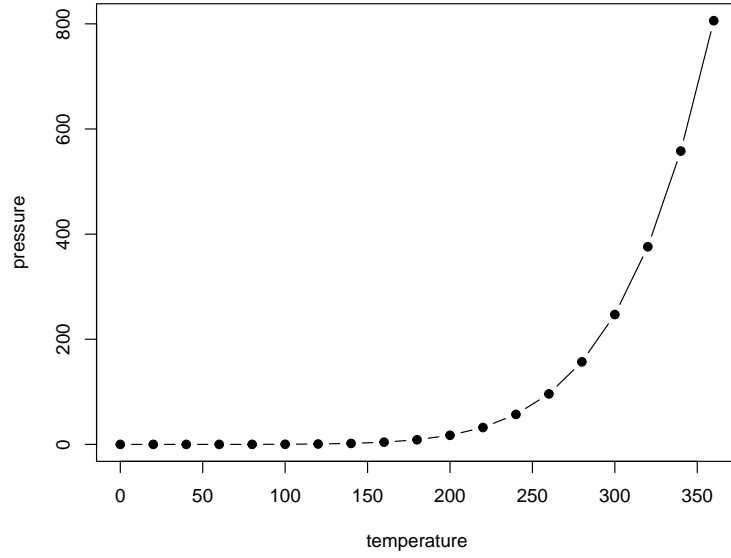


Figure 1: Here is a nice figure!

0.3 Static Discrete Choice Models

0.3.1 In this chapter

1. Describe static discrete choice models
2. Derive logit probabilities
3. Show how to estimate logits and multinomial logits
4. Cover the IIA property
5. Discuss expected utility and consumer surplus

0.3.2 Notation

Let d_i indicate the choice individual i makes where $d_i \in \{1, \dots, J\}$. Individuals choose d to maximize their utility, U . U generally is written as:

$$U_{ij} = u_{ij} + \varepsilon_{ij}$$

where:

1. u_{ij} relates observed factors to the utility individual i receives from choosing option j

Table 1: Here is a nice table!

| Sepal.Length | Sepal.Width | Petal.Length | Petal.Width | Species |
|--------------|-------------|--------------|-------------|---------|
| 5.1 | 3.5 | 1.4 | 0.2 | setosa |
| 4.9 | 3.0 | 1.4 | 0.2 | setosa |
| 4.7 | 3.2 | 1.3 | 0.2 | setosa |
| 4.6 | 3.1 | 1.5 | 0.2 | setosa |
| 5.0 | 3.6 | 1.4 | 0.2 | setosa |
| 5.4 | 3.9 | 1.7 | 0.4 | setosa |
| 4.6 | 3.4 | 1.4 | 0.3 | setosa |
| 5.0 | 3.4 | 1.5 | 0.2 | setosa |
| 4.4 | 2.9 | 1.4 | 0.2 | setosa |
| 4.9 | 3.1 | 1.5 | 0.1 | setosa |
| 5.4 | 3.7 | 1.5 | 0.2 | setosa |
| 4.8 | 3.4 | 1.6 | 0.2 | setosa |
| 4.8 | 3.0 | 1.4 | 0.1 | setosa |
| 4.3 | 3.0 | 1.1 | 0.1 | setosa |
| 5.8 | 4.0 | 1.2 | 0.2 | setosa |
| 5.7 | 4.4 | 1.5 | 0.4 | setosa |
| 5.4 | 3.9 | 1.3 | 0.4 | setosa |
| 5.1 | 3.5 | 1.4 | 0.3 | setosa |
| 5.7 | 3.8 | 1.7 | 0.3 | setosa |
| 5.1 | 3.8 | 1.5 | 0.3 | setosa |

2. ε_{ij} are unobserved to the econometrician but observed to the individual
3. $d_{ij} = 1$ if $u_{ij} + \varepsilon_{ij} > u_{ij'} + \varepsilon_{ij'}$ for all $j' \neq j$

0.3.3 Probabilities

With the ε 's unobserved, the probability of individual i making choice j is given by:

$$\begin{aligned}
 P_{ij} &= \Pr(u_{ij} + \varepsilon_{ij} > u_{ij'} + \varepsilon_{ij'} \forall j' \neq j) \\
 &= \Pr(\varepsilon_{ij'} - \varepsilon_{ij} < u_{ij} - u_{ij'} \forall j' \neq j) \\
 &= \int_{\varepsilon} I(\varepsilon_{ij'} - \varepsilon_{ij} < u_{ij} - u_{ij'} \forall j' \neq j) f(\varepsilon) d\varepsilon
 \end{aligned}$$

Note that, regardless of what distributional assumptions are made on the ε 's, the probability of choosing a particular option does not change when we:

1. Add a constant to the utility of all options (utility is relative to one of the options, only differences in utility matter)

2. Multiply by a positive number (need to scale something, generally the variance of the ε 's)

0.3.4 Variables

Suppose we have:

$$u_{i1} = \alpha Male_i + \beta_1 X_i + \gamma Z_1$$

$$u_{i2} = \alpha Male_i + \beta_2 X_i + \gamma Z_2$$

Since only differences in utility matter:

$$u_{i1} - u_{i2} = (\beta_1 - \beta_2)X_i + \gamma(Z_1 - Z_2)$$

Thus, we cannot tell whether men are happier than women, but can tell whether men have a preference for a particular option over another. We can only obtain differenced coefficient estimates on X 's, and can obtain an estimate of a coefficient that is constant across choices only if the variable it is hitting varies by choice.

0.4 Methods

We describe our methods in this chapter.

0.5 Applications

Some *significant* applications are demonstrated in this chapter.

0.5.1 Example one

0.5.2 Example two

0.6 Final Words

We have finished a nice book.