Introduction to Experimental Design for Discrete-Choice Models

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with apologies to Warren Kuhfeld

Why Should We Concern Ourselves with Experimental Design?

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- We can always observe how people make choices in the real world. (i.e., we can study their *revealed preference*)
- Where IIA is a reasonable approximation of reality, simple discrete-choice produces good forecasts.
  - BART example from Dan McFadden's Nobel lecture:
    - Official forecast of projected ridership: 15%
    - McFadden's projected share: 6.2%
    - Actual ridership: 6.3%

Source: http://www.nobel.se/economics/laureates/2000/mcfadden-lecture.pdf

Often, However, We Want to Study Alternatives That Don't Yet Exist

- ***Revealed preference***: observing choices that people have made in the real world
- ***Stated preference***: asking people to choose among hypothetical choices
- Both types of data can be combined and estimated jointly (see Ben-Akiva and Lehrman). However, this is beyond the scope of this lecture.
- Revealed preference data can be used to calibrate stated preference models.
- Other combinations are possible, such as estimating stated preference models from initial revealed-preference states.

Both Approaches Have Strengths And Weaknesses

Issue	Stated Preference	Revealed Preference
Range of information	• You can get more information than is available in a real marketplace.	• Study is limited by the range of products available in the marketplace. • Awareness of attributes varies among subjects.
Variety of observations	• Experimental design can control for interactions among attributes.	• Real-world attributes are often highly correlated, making it difficult to distinguish interactions.
Degree of control	• Permits tight control over alternatives and information available to the subject.	• The decision process, including the sales environment and timing, differs from ideal market conditions.
Relevance	• Allows distinction between perceptions and taste, and identifies factors that influence perceptions. • Choice is unburdened by supply constraints.	• The decision process, including timing and social interactions, differs in real vs. constructed markets. • What people say they intend is not necessarily what they do.

Stated preference research always requires an experimental design.

Steps in Generating an Experimental Design

1. Break the product or service into a set of attributes and levels.
2. Choose an appropriate vehicle for generating your design.
   - Tables
   - Software
   - Expert
3. Construct your design.
4. Evaluate the results.
   - Check business validity of attributes and levels.
   - Pre-test the questionnaire.
5. Return to step 1 if necessary.

Guidelines for Developing an Attribute List

- Define the marketplace. Identify all relevant substitutes.
- Ensure attributes are independent.
- For levels, use precise, concrete statements, with metrics if possible.
- Levels within each attribute should be mutually exclusive and collectively exhaustive.
- Levels should contain ranges sufficiently extreme to cover the shelf life of the research.
- Try to balance the number of levels across attributes.
- For quantitative levels, use realistic points.

Source: Orme, “Formulating Attributes and Levels…”, Boomer.

A Simple Shoe Example

Attributes:	Fashion	Quality	Price
Levels:	Traditional	Standard	$25
	Modern	High	$149

Number of levels: 2 2 2

Nomenclature: 2^3

Number of levels

Number of attributes

Shoe Example with Dummy Coding

Attributes:	Fashion	Quality	Price
Levels:	0 (Traditional)	0 (Standard)	0 ($25)
	1 (Modern)	1 (High)	1 ($149)

Runs	F	Q	P
1	0	0	0
2	0	0	1
3	0	1	0
4	0	1	1
5	1	0	0
6	1	0	1
7	1	1	0
8	1	1	1

Factors

One approach: Use all possible combinations.

$2^3 = 8$

This design consists of 3 ***factors*** and 8 ***runs***.

Some Characteristics of This Design

- It is ***orthogonal***
  - Rows are perfectly uncorrelated
  - Each pair of levels occurs equally often
- It is ***balanced***
  - Each level appears an equal number of times

	F	Q	P
1	0	0	0
2	0	0	1
3	0	1	0
4	0	1	1
5	1	0	0
6	1	0	1
7	1	1	0
8	1	1	1
Sum	4	4	4

More Characteristics of This Design

- This is a ***full factorial*** design.
  - It contains all possible levels of the factors.
  - It allows you to estimate *main effects* and two-way or higher *interactions*, which we will explain later.
- It also happens to be an ***orthogonal array***.
  - All possible interactions are estimable.

	F	Q	P
1	0	0	0
2	0	0	1
3	0	1	0
4	0	1	1
5	1	0	0
6	1	0	1
7	1	1	0
8	1	1	1

Moving from Design to Choice Set

Design

	1	2	3	4	5	6	7	8
F	0	1	1	1	0	0	0	1
Q	0	0	0	1	0	1	1	1
P	0	0	1	0	1	0	1	1

Choice set

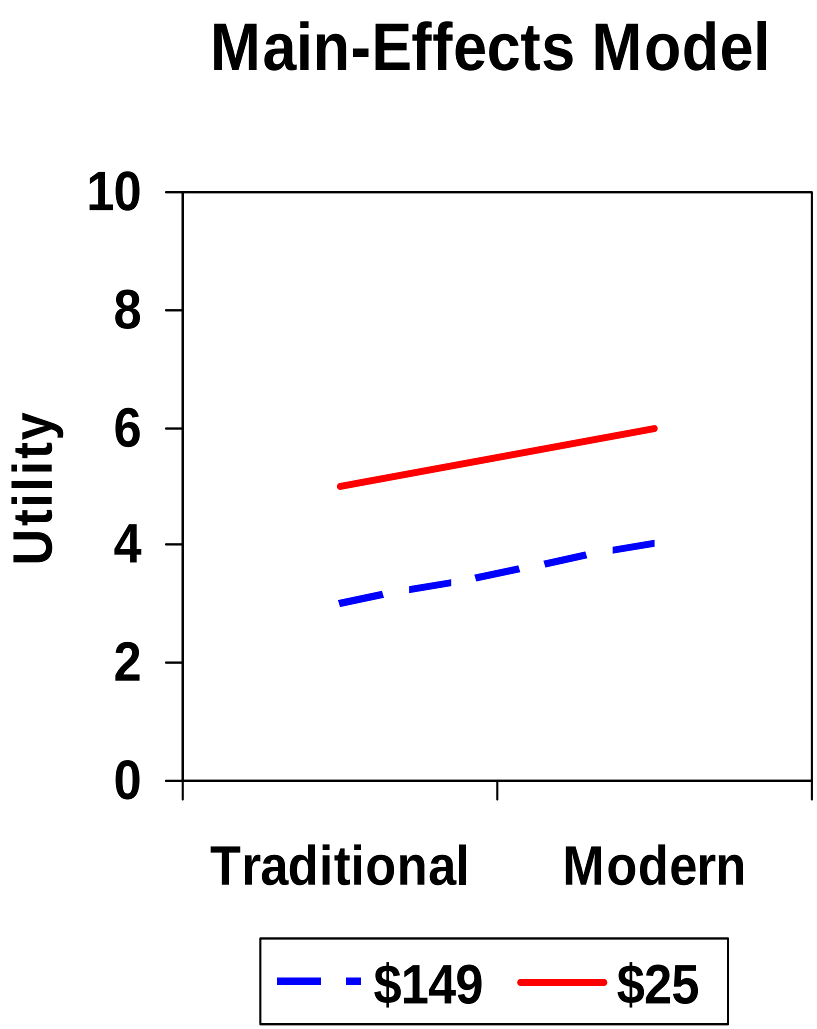
Choose one:	1	2	3	4	5	6	7	8	9
Fashion	Traditional	Modern	Modern	Modern	Traditional	Traditional	Traditional	Modern	None
Quality	Standard	Standard	Standard	High	Standard	High	High	High	of these
Price	\$25	\$25	\$149	\$25	\$149	\$25	\$149	\$149	

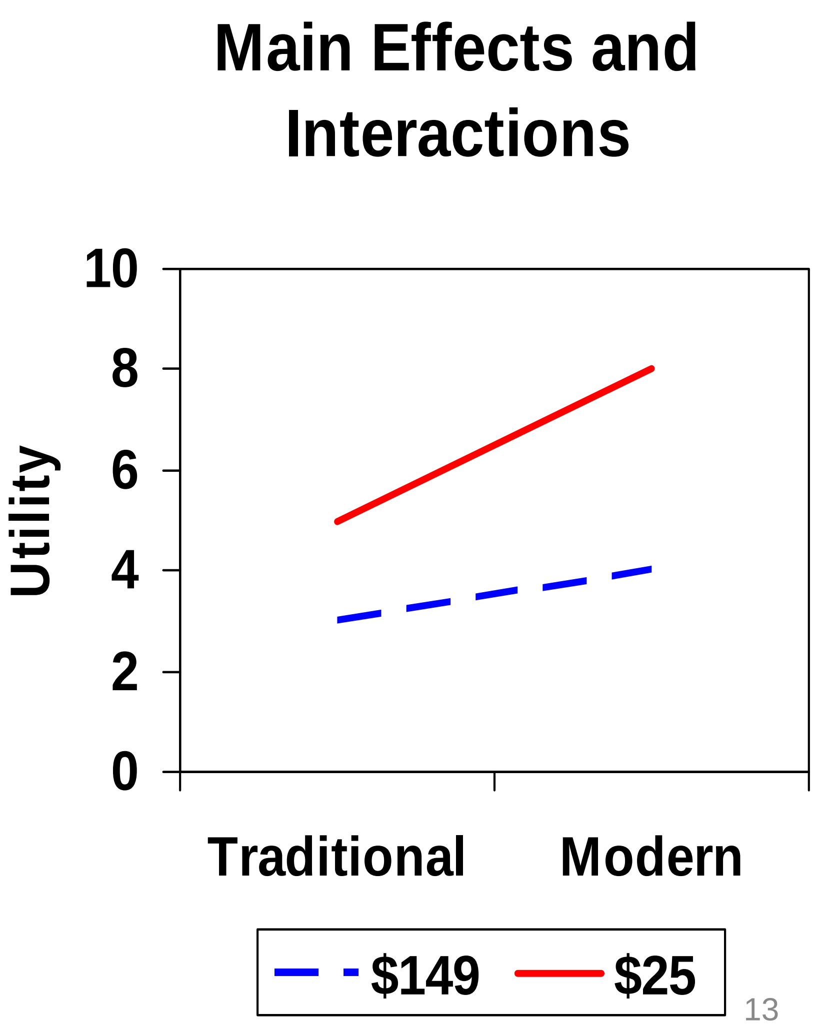
- We randomize the rows from the matrix on the previous slide and transpose the rows and columns.
- Next we map the 0's and 1's to the levels for each attribute , then add a "None" alternative.
- This design has one choice set with 9 alternatives (8 + None).
- We could break this into two choice sets with 5 alternatives (4 + None).
- Most non-trivial designs require multiple choice sets.

Main Effects and Interactions

- ***Main effects***
  - Simple effect, such as price or brand effect.
  - Effect is independent of the levels of other attributes.
  - For example, quality impact is the same at a price of $25 or $149.
- ***Interactions***
  - Involve two or more factors.
  - Effect of one factor depends on the level of another.
  - For example, the impact of quality differs when the price is $25 vs. $149.

Example of Interactions





Larger Designs Require Compromise…

- Let's say we have five attributes, two with 4 levels and three with 5 levels: in our notation, a $4^2 5^3$ problem.
- A full-factorial design for this problem would require 4 x 4 x 5 x 5 x 5 = 2000 profiles. That's too many for a survey to handle, even if we partitioned them into blocks and submitted them to groups of respondents.
- For this reason, we resort to a ***fractional factorial*** design that has fewer runs. These designs are quite common.

… But This Comes at a Price: Aliasing

- Some higher-order effects are confounded, or ***aliased***.
- In this example, factors A and B are aliased with D.
  - The modulo sum A + B = D
  - In other words, columns A and B are perfectly correlated with column D.
  - If in the real world an interaction existed between A and B, we would not be able to estimate it.
  - We call this a second-order interaction because 2 variables are involved.
- One way to resolve this is to assume that some interaction effects either don't exist or are irrelevant. We simply don't model them.

A	B	C	D
1	1	0	0
0	0	0	0
0	1	0	1
1	0	1	1
0	1	1	1
0	0	1	0
1	1	0	0
1	0	1	1

Design Efficiency

- ***Efficiency*** measures goodness of design.
- It is inversely related to the variance of the parameter estimates.
- We start with measures of efficiency for linear, rather than logit, models, because the results are roughly proportional and the mathematics are simpler.
- One common measure is ***D-efficiency***, a value scaled from 0 to 100.

Balance and Orthogonality Revisited

- To be ***balanced***, the off-diagonal elements of the first row and first column of $(X'X)^{-1}$ must = 0.
- To be ***orthogonal***, the sub-matrix excluding the first row and column must be diagonal.
- As you can see, this design is neither balanced nor orthogonal.

Balance

$$(X'X)^{-1} = \begin{bmatrix} 0.188 & 0 & 0.063 & 0 \\ 0 & 0.188 & 0 & 0.063 \\ 0.063 & 0 & 0.188 & 0 \\ 0 & 0.063 & 0 & 0.188 \end{bmatrix}$$

Orthogonality

From Factor List To Design Table …

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Factor list

Alternatives	*Attributes*		
Brand	Size	Price	Top type
Brand 1	16 oz.	$0.89	Pop-up
Brand 2	20 oz.	$0.99	Twist 1
Brand 3	24 oz.		Twist 2

- In this example we have 3 alternatives, so the number of runs must be a multiple of 3.
- We pick a good $2^1 3^2$ design in 18 runs. (We'll show you how to do this later.) This happens to be a full-factorial design.

	x1	x2	x3
Brand 1	0	1	0
	0	1	1
	-1	-1	1
	-1	1	-1
	0	1	-1
	1	-1	-1
Brand 2	-1	1	0
	0	-1	1
	-1	1	1
	1	-1	1
	1	-1	0
	-1	-1	-1
Brand 3	1	1	-1
	-1	-1	0
	0	-1	0
	1	1	1
	1	1	0
	0	-1	-1

… To Linear Design …

- We un-stack the design from the prior page.
- We then substitute level values for codes.

Coded Linear Design

Brand 1			Brand 2			Brand 3		
x1	x2	x3	x4	x5	x6	x7	x8	x9
0	1	0	-1	1	0	1	1	-1
0	1	1	0	-1	1	-1	-1	0
-1	-1	1	-1	1	1	0	-1	0
-1	1	-1	1	-1	1	1	1	1
0	1	-1	1	-1	0	1	1	0
1	-1	-1	-1	-1	-1	0	-1	-1

Linear Design

Brand 1			Brand 2			Brand 3		
x1	x2	x3	x4	x5	x6	x7	x8	x9
20 oz.	$0.99	Twist 1	16 oz.	$0.99	Twist 1	24 oz.	$0.99	Pop-up
20 oz.	$0.99	Twist 2	20 oz.	$0.89	Twist 2	16 oz.	$0.89	Twist 1
16 oz.	$0.89	Twist 2	16 oz.	$0.99	Twist 2	20 oz.	$0.89	Twist 1
16 oz.	$0.99	Pop-up	24 oz.	$0.89	Twist 2	24 oz.	$0.99	Twist 2
20 oz.	$0.99	Pop-up	24 oz.	$0.89	Twist 1	24 oz.	$0.99	Twist 1
24 oz.	$0.89	Pop-up	16 oz.	$0.89	Pop-up	20 oz.	$0.89	Pop-up

… To Choice Design

We rearrange the data into 6 ***choice sets***. Add a "None" alternative if appropriate (this is not done here). The result is a ***choice design***.

Linear Design									Choice Design			
Brand 1			Brand 2			Brand 3						
x1	x2	x3	x4	x5	x6	x7	x8	x9	Brand	x1	x2	x3
20 oz.	$0.99	Twist 1	16 oz.	$0.99	Twist 1	24 oz.	$0.99	Pop-up	1	20 oz.	$0.99	Twist 1
									2	16 oz.	$0.99	Twist 1
									3	24 oz.	$0.99	Pop-up
20 oz.	$0.99	Twist 2	20 oz.	$0.89	Twist 2	16 oz.	$0.89	Twist 1	1	20 oz.	$0.99	Twist 2
									2	20 oz.	$0.89	Twist 2
									3	16 oz.	$0.89	Twist 1
16 oz.	$0.89	Twist 2	16 oz.	$0.99	Twist 2	20 oz.	$0.89	Twist 1	1	16 oz.	$0.89	Twist 2
									2	16 oz.	$0.99	Twist 2
									3	20 oz.	$0.89	Twist 1
16 oz.	$0.99	Pop-up	24 oz.	$0.89	Twist 2	24 oz.	$0.99	Twist 2	1	16 oz.	$0.99	Pop-up
									2	24 oz.	$0.89	Twist 2
									3	24 oz.	$0.99	Twist 2
20 oz.	$0.99	Pop-up	24 oz.	$0.89	Twist 1	24 oz.	$0.99	Twist 1	1	20 oz.	$0.99	Pop-up
									2	24 oz.	$0.89	Twist 1
									3	24 oz.	$0.99	Twist 1
24 oz.	$0.89	Pop-up	16 oz.	$0.89	Pop-up	20 oz.	$0.89	Pop-up	1	24 oz.	$0.89	Pop-up
									2	16 oz.	$0.89	Pop-up
									3	20 oz.	$0.89	Pop-up

Blocking

- Let’s say we need a high-resolution design with a large number of choice sets, say 48.
- That’s too much for one respondent to handle, so we break the choice sets into blocks. Each respondent sees only one randomly-assigned block. In this example, our 48-set design can be organized as:
  - 2 blocks of 24 sets each
  - 4 blocks of 12 sets each
  - 8 blocks of 6 sets each
- Make sure you have an ***anchor*** alternative (such as “None”) that is common to each block.
  - The IIA property allows us to do this.
  - Sometimes it helps to have more than one anchor.
- You can tie completely different designs together using blocks, as long as you have a common anchor in each one.

Additional Considerations for Choice Designs

- ***Overlap*** – Minimize the number of times each level appears in a choice set (*i.e.*, store visit)
  - Solution: swap design rows until overlap is minimized.
- ***Utility Balance*** – Ensure that no choice set contains either a dominant alternative that every rational person would want or a terrible alternative that no one would want.
  - Huber and Zwerina paper
  - Solution: swap design rows until utility balance is achieved.
- ***M-Efficiency*** – A measure that makes allowance for management's focus on a particular variable, such as price.
  - Hauser and Toubia paper

Non-Standard Designs

- **Availability designs**
  - Control whether or not products appear on shelves.
  - See papers by Anderson and Lazari.
- **Menus and configurators**
  - Respondents see a series of ***menus***. From one menu to the next, the options stay the same, but the prices change according to an experimental design.
  - A ***configurator*** is a special case for menus. To the respondent, a configurator looks like the Dell web site, where you can configure a PC to suit your needs.
  - For both of these designs, the alternatives in each choice set consist of all possible combinations of menu choices.
    - For example, a menu with 7 binary choices would be coded as a choice set with $2^8 = 128$ alternatives.
    - Designs with many menu choices must be divided into blocks.
- **Prices based on contribution margins**
  - ***Contribution margin*** is the unit profit margin on a widget before any burdening with fixed costs, interest, etc.
  - Obtain unit manufacturing costs for each feature in the design.
  - Use an experimental design to vary the markup for the overall product.
  - Present only the total price (=$\sum$costs + markup) to the respondent.
  - Advantage: Builds in a degree of utility balance
  - Beware of aliasing! Use a high-resolution design if possible.

Concerns for Practitioners

Real-world problem	Solution
• Not all attribute levels may be of equal interest.	• Unbalance the design in favor of important levels. See M-efficiency.
• Some levels always occur in the real world with very low frequency.	• Substitute “None”, “N/A” or blank as a level and consider over-balancing it.
• Some configurations are unrealistic or absurd.	• Swap design rows, use software to exclude absurd products, or consider keeping them (!).
• Client presents you with too many attributes, alternatives and/or levels.	• Pare the list to fit an available design. Retain what is strategically important. Examine alias patterns to avoid problems.

Parting Advice to Practitioners

"The best is the enemy of the good."

- Voltaire

"You need only enough precision to get the right answer."

- Dr. Evan Dudik
  McKinsey & Co.

Obtaining a Design

- Do it yourself
  - See Street & Burgess, "Quick and Easy Choice Sets ..." for a how-to guide.
  - Get designs from http://www.research.att.com/~njas/oadir/
- Use commercial software
  - Packages that construct general experimental designs
  - Packages that specialize in generating choice sets
  - List appears on next slide
- Hire an expert
  - Don Anderson at StatDesign
    - (303) 674-5671
    - danderson@aol.com
  - Warren Kuhfeld at SAS, if you are a SAS user.

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