Differential Attention to Attributes in Utility-Theoretic Choice Models

Trudy Ann Cameron
University of Oregon

J.R. DeShazo
School of Public Affairs, UCLA
Motivation

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- “People don’t take these choice tasks seriously enough, so the choice data are unreliable”
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- If attention to different aspects of a choice task can be manipulated, can this be done with malign intent?
Acknowledgements

Evolution of paper

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Attention in Choice Models

- Typical assumptions: up to a random component, investigator knows all information that individual uses to make choice—individuals fully attend to, and costlessly process, all the information presented to them within a choice set.
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- This paper – attention to attributes (attention to alternatives in a separate paper).
Basics - Similarity in Attribute Space

"Similar" in Attribute Space

"Different" in Attribute Space
Basics - Similarity in Utility Space

“Similar” in attribute space and also in utility level provided

“Different” in attribute space, but similar in utility levels...for someone with these preferences
Which attribute of these cars seems most important to consider?

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<thead>
<tr>
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- **Opportunity**: the individual may be time-constrained in making a choice (opportunity cost of time)
Attention - versus marginal utility

We do not normally observe *attention* to a choice problem.

- Time on task? - may be longer if distracted, or longer if inferior cognitive skills
- Subjective attention? - difficult to elicit ("Were you paying attention to that choice?" "Huh? Of course I was!")
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"Don’t know...Don’t Care?" Zero apparent marginal effect for an attribute can mean
- Respondent *didn’t notice* the differences in this attribute across alternatives
- The respondent *did notice* these differences but they have *no effect* on his/her utility
Attention - range

Suppose individual *does* value a particular attribute

**Case 1**: not resource-constrained; full attention to levels of all attributes

- “true” marginal utilities (MUs) can be estimated
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**Case 3:** heavily resource-constrained; no attention to levels of some attribute
- apparent MU of attribute is zero (hasty choice, didn’t think to consider X)
Suppose individual does value a particular attribute

**Case 1:** not resource-constrained; full attention to levels of all attributes
- “true” marginal utilities (MUs) can be estimated

**Case 2:** somewhat resource-constrained; incomplete attention to levels of some attributes
- apparent MU is attenuated in some or all cases

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Attention - consequences

What happens when cognitive resource constraints are binding?

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  - Less attenuation in the estimated marginal utility of net income (WTP denominator stays large)
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- Row amounts have declining variances (fewer surprises)
- Time-constrained choices
- Directed cognition (i.e. attention), bounded rationality
Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model

By Xavier Gabaix, David Laibson, Guillermo Moloche, and Stephen Weinberg
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- No need to worry about differences across individuals in these attribute marginal utilities
Related Research


- Their insights can be translated to match the two main drivers of attention we identify from our model (in a special case where boxes are revealed one whole column at a time)
- An *elegant* start on the attention problem, but all of the “attributes” in the experiment are money
- No need to worry about the distinction between attribute-space and utility-space (they are the same)
- No need to worry about differing marginal utilities for different attributes
- No need to worry about differences across individuals in these attribute marginal utilities
- All of these concerns are relevant for real choice problems
David Hensher et al. Design-of-designs study (several papers))

- Ask respondents explicitly about which attributes they ignored in making their choices (overall, not on a choice-by-choice basis)
Related Research

David Hensher et al. Design-of-designs study (several papers))

- Ask respondents explicitly about which attributes they *ignored* in making their choices (overall, not on a choice-by-choice basis)
- Finding: Number of attributes considered is *lower* when sets of attributes are drawn from distributions with *narrower ranges* (i.e. when alternatives are less different)
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- Individuals’ information processing strategies “should be built into the estimation of choice data from stated choice studies”
- *Exactly* what we endeavor to do here
Binary Choice Model

Indirect utility function: linear, additively separable in
- net income \((Y_i \text{ minus } T_i^j, \text{ the cost of option } j)\),
- each of several attributes, \(X_{ki}, k=1,\ldots,K\).

Alternative 1: \[ V_i^1 = \beta_1 (Y_i - T_i^1) + \sum_{k=2}^{K} \beta_k X_{ki}^1 + \epsilon_i \]
Alternative 0: \[ V_i^0 = \beta_1 (Y_i - T_i^0) + \sum_{k=2}^{K} \beta_k X_{ki}^0 + \epsilon_i \]
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Utility-difference:
\[ V_i^1 - V_i^0 = \beta_1 (T_i^0 - T_i^1) + \sum_{k=2}^{K} \beta_k (X_{ki}^1 - X_{ki}^0) + (\epsilon_i^1 - \epsilon_i^0) \]
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Indirect utility function: linear, additively separable in
- net income ($Y_i$ minus $T^j_i$, the cost of option j),
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Alternative 0: $V^0_i = \beta_1 (Y_i - T^0_i) + \sum_{k=2}^{K} \beta_k X^0_{ki} + \varepsilon^0_i$

Utility-difference:

$$V^1_i - V^0_i = \beta_1 (T^0_i - T^1_i) + \sum_{k=2}^{K} \beta_k (X^1_{ki} - X^0_{ki}) + (\varepsilon^1_i - \varepsilon^0_i)$$

$$= -\beta_1 t_i + \sum_{k=2}^{K} \beta_k x_{ki} + \varepsilon_i$$

where $(T^0_i - T^1_i) = (X^1_{1i} - X^0_{1i}) = x_{1i} = -t_i$ is treated differently, due to the special role of $\beta_1$ in calculating WTP.
Willingness to pay (WTP)

WTP is that program cost which makes the individual just indifferent between

- paying for the program and enjoying its benefits, and
- not paying for the program and doing without its benefits

\[ WTP_i = t_i^* = \frac{\sum_{k=2}^{K} \beta_k x_{ki} + \varepsilon_i}{\beta_1} \]
Willingness to pay (WTP)

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- paying for the program and enjoying its benefits, and
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\[ WTP_i = t^*_i = \sum_{k=2}^{K} \beta_k x_{ki} + \varepsilon_i \]

*Expected* WTP, given *true* parameter values, is the expectation across \( \varepsilon_i \), which is a mean-zero error term.

\[ E[ WTP_i ] = \left[ \frac{\sum_{k=2}^{K} \beta_k x_{ki}}{\beta_1} \right] + E\left[ \frac{\varepsilon_i}{\beta_1} \right] \]
Benefits and Costs of Attention

Benefits from attention to marginal attribute?

- *Avoided expected utility loss* from wrong choice when attribute is overlooked
- Reflects consequentiality of choice problem
Benefits and Costs of Attention

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Cost of attention to marginal attribute?

- Depends on cognitive abilities
- Depends on time budget (op cost of time)
- Can differ by attribute: order in attribute list, “fine print,” “contact dealer for price”
Benefits and Costs of Attention

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Cost of attention to marginal attribute?
- Depends on cognitive abilities
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This paper?
- Our data have insufficient variation in costs of attention to different attributes...so treat as constant
- Focus on *benefits* side of story
Expected Utility Loss from Wrong Choice

Optimal choice (full information)

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>No lost utility</td>
<td>Pr(0 chosen ∩ 0 optimal)</td>
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Observed choice (incomplete information)
Expected Utility Loss from Wrong Choice

Optimal choice (full information)

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Observed choice (incomplete information)

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No lost utility

Pr(0 chosen $\cap$ 0 optimal)

Utility loss $= V^1 - V^0$

Pr(0 chosen $\cap$ 1 optimal)

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No lost utility

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Pr(1 chosen $\cap$ 1 optimal)
Expected Utility Loss from Wrong Choice

Optimal choice (full information)

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<td>No lost utility</td>
<td>Utility loss $= V^V_8 - V^\text{beer}$</td>
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</table>

Pr(beer chosen $\cap$ beer optimal)

Pr(V8 chosen $\cap$ V8 optimal)

Utility loss $= V^\text{beer} - V^V_8$

No lost utility

Pr(V8 chosen $\cap$ beer optimal)

Pr(V8 chosen $\cap$ V8 optimal)

Observed choice (incomplete information)
Expected Utility Loss from Wrong Choice

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“$I could’ve had a V8!”

Observed choice (incomplete information)

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# Expected Utility Loss from Wrong Choice

## Optimal choice (full information)

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**“I could’ve had a beer!”**
Expected Utility Loss from Wrong Choice

To calculate expected utility loss from a wrong choice, need:
- The probability of each way this could happen
- The amount of utility lost in each case

### Optimal choice (full information)

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Expected Utility Loss from Wrong Choice

Random Utility Model (RUM) error term? (\(\varepsilon\))

- Stuff that is known to the respondent, but unobserved by the investigator
- Assume \(\varepsilon\) remains fully known to the respondent, regardless of whether he/she pays attention to some specific attribute, \(k\), in the choice scenario
- Important: then same error distribution is involved, with or without attention to \(k^{th}\) specific attribute
Given that there are two ways to lose utility by a wrong choice when information is ignored:

\[
E[U \text{ Loss}] = Pr[1 \text{ chosen} | 0 \text{ optimal}] (V_i^0 - V_i^1) \\
+ Pr[0 \text{ chosen} | 1 \text{ optimal}] (V_i^1 - V_i^0)
\]

where \( V_i^1 - V_i^0 = x_i' \beta + \epsilon_i \)

\[
= x_{-ki} \beta_{-k} + x_{ki} \beta_k + \epsilon_i
\]

other-attrs \hspace{1cm} own-attribs \hspace{1cm} error difference

where \( x_{ki} = X_{ki}^1 - X_{ki}^0 \) is the \( k^{th} \) attribute-difference
Expected Utility Loss from Wrong Choice - binary case

Choice probabilities based upon *complete information*:

- \( \Pr(1 \text{ optimal}) = \Pr \left( x_i' \beta + \varepsilon_i > 0 \right) = \Pr \left( \varepsilon_i < x_i' \beta \right) \)
- \( \Pr(0 \text{ optimal}) = \Pr \left( \varepsilon_i > x_i' \beta \right) \)
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Choice probabilities based on *all but the \( k \)th attribute*:
- \( Pr(1 \text{ chosen}) = Pr \left[ x_{-k}i' \beta_{-k} + \varepsilon_i > 0 \right] = Pr \left[ \varepsilon_i < x_{-k}i' \beta_{-k} \right] \)
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Choice probabilities based on all but the \( k^{th} \) attribute:

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- \( Pr(0 \text{ chosen}) = Pr \left[ \varepsilon_i > x_{-k}' \beta_{-k} \right] \)

Probability of wrong choice when \( k^{th} \) attribute is ignored:

- \( Pr(1 \text{ optimal} \cap 0 \text{ chosen}) = Pr \left[ (\varepsilon_i < x_i' \beta) \cap (\varepsilon_i > x_{-k}' \beta_{-k}) \right] \)
- \( Pr(0 \text{ optimal} \cap 1 \text{ chosen}) = Pr \left[ (\varepsilon_i > x_i' \beta) \cap (\varepsilon_i < x_{-k}' \beta_{-k}) \right] \)
Empty versus non-empty sets?

Case 1: if utility from $k^{th}$ attribute, $x_{ki} \beta_k$, is positive, intervals overlap, probability > 0

Case 2: if utility from $k^{th}$ attribute, $x_{ki} \beta_k$, is negative, no overlap, probability is zero
Probability of one type of choice mistake

Given that $x_{k}^{'}\beta - x_{k}^{'}\beta = x_{i}^{'}\beta$, and same $\varepsilon_{i}$ ...

$$\Pr(1 \text{ optimal} \cap 0 \text{ chosen}) = \Pr \left[ \varepsilon_{i} < x_{i}^{'}\beta \cap \varepsilon_{i} > x_{-k}^{'}\beta - k \right] \quad \ldots \text{substitute, rearrange}$$
$$= \Pr \left[ \left( x_{-k}^{'}\beta - k \right) < \varepsilon_{i} < \left( x_{-k}^{'}\beta - k + x_{k}^{'}\beta \right) \right]$$
$$= F \left( x_{-k}^{'}\beta - k + x_{k}^{'}\beta \right) - F \left( x_{-k}^{'}\beta - k \right)$$

...can be nonzero only when $x_{k}^{'}\beta$ is positive

...i.e. attention to $k^{th}$ attribute would have made alt. 1 look better

...will be differences in cumulative densities over a range given by $x_{k}^{'}\beta$, the contribution to utility by $k^{th}$ attribute
Probability of the other type of choice mistake

Given that $x'_{-k_i} \beta_{-k} + x_{ki} \beta_{k} = x_i \beta$, and same $\varepsilon_i$...

$$\Pr(0 \text{ optimal } \cap 1 \text{ chosen})$$

$$= \Pr \left[ \varepsilon_i > x_i \beta \cap \varepsilon_i < x'_{-k_i} \beta_{-k} \right] \quad \text{...substitute, rearrange}$$

$$= \Pr \left[ \left( x'_{-k_i} \beta_{-k} + x_{ki} \beta_{k} \right) < \varepsilon_i < \left( x'_{-k_i} \beta_{-k} \right) \right]$$

$$= F \left( x'_{-k_i} \beta_{-k} \right) - F \left( x'_{-k_i} \beta_{-k} + x_{ki} \beta_{k} \right)$$

...can be nonzero only when $x_{ki} \beta_{k}$ is negative

...i.e. attention to $k^{th}$ attribute would have made alt. 0 look better

...will be differences in cumulative densities over a range given by $x_{ki} \beta_{k}$, the contribution to utility by $k^{th}$ attribute
**Review: Two Ways to Make a Mistake**

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Expected utility loss due to a wrong choice

Expectation is each probability times the associated lost utility:

\[
E[U\ \text{loss}] = \left[ F\left(x'_{-ki}\beta_{-k} + x_{ki}\beta_k\right) - F\left(x'_{-ki}\beta_{-k}\right) \right] (V^1 - V^0) \\
+ \left[ F\left(x'_{-ki}\beta_{-k}\right) - F\left(x'_{-ki}\beta_{-k} + x_{ki}\beta_k\right) \right] (V^0 - V^1) \\
= 2 \left[ F\left(x'_{-ki}\beta_{-k} + x_{ki}\beta_k\right) - F\left(x'_{-ki}\beta_{-k}\right) \right] (V^1 - V^0)
\]
Expected utility loss due to a wrong choice

Expectation is each probability times the associated lost utility:

\[ E[U\ loss] = \left[ F \left( x'_i \beta - k + x_i \beta_k \right) - F \left( x'_i \beta - k \right) \right] (V^1 - V^0) + \left[ F \left( x'_i \beta - k \right) - F \left( x'_i \beta - k + x_i \beta_k \right) \right] (V^0 - V^1) \]

\[ = 2 \left[ F \left( x'_i \beta - k + x_i \beta_k \right) - F \left( x'_i \beta - k \right) \right] (V^1 - V^0) \]

Either \[ F \left( x'_i \beta - k + x_i \beta_k \right) - F \left( x'_i \beta - k \right) \] and \( (V^1 - V^0) \) are both positive, or they are both negative.
Expected utility loss due to a wrong choice

Expectation is each probability times the associated lost utility:

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E[U \text{ loss}] = \left[ F \left( x'_{-ki} \beta - k + x_{ki} \beta_k \right) - F \left( x'_{-ki} \beta - k \right) \right] (V^1 - V^0) \\
+ \left[ F \left( x'_{-ki} \beta - k \right) - F \left( x'_{-ki} \beta - k + x_{ki} \beta_k \right) \right] (V^0 - V^1) \\
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\[
E[U \text{ loss}] = 2 \left| F \left( x'_{-ki} \beta - k + x_{ki} \beta_k \right) - F \left( x'_{-ki} \beta - k \right) \right| \left| x_i \beta + \varepsilon_i \right|
\]
Expected utility loss due to a wrong choice

Benefits from attention to $k^{th}$ attribute increase in the expected utility loss from making a wrong choice by failing to consider this attribute.

This expected utility loss is given by:

$$E[U \text{ loss}] = 2 \left| F \left( x'_{-ki} \beta_k + x_{ki} \beta_k \right) - F \left( x'_{-ki} \beta - k \right) \right| \left| x'_{i} \beta + \varepsilon_i \right|$$

Will be larger as the true but unobserved utility difference, $V^1 - V^0 = x'_i \beta + \varepsilon_i$, is larger in absolute value.

For a given unobserved utility difference, $E[U \text{ loss}]$ will be larger as more of the probability density for $\varepsilon$ is captured within an interval of width $x_{ki} \beta_k$, anchored at $x'_{-ki} \beta - k$. 
Effect of $|x_{-ki}' \beta_{-k}|$ on $E[U \text{ loss}]$

An interval of a given width captures more probability if it is near the center of the distribution
Effect of $|x_{ki} \beta_k|$ on $E[U \text{ loss}]$

For any given anchoring point, a wider interval captures more probability.
Effect of $|x_{ki} \beta_k|$ on $E[U \text{ loss}]$

For any given anchoring point, a wider interval captures more probability.
Own-attribute utility differences

Interval of $\varepsilon$ density: $x_{ki}\beta_k = \text{“own-attribute utility difference”}$

Interval width, $|x_{ki}\beta_k|$ will be larger
  - if $x_{ki}$ (amount of attribute) is large in absolute magnitude
  - if $\beta_k$ (its marginal utility) is large in absolute terms

Implications

We expect that the propensity to attend to the $k$th attribute will be greater, the greater the (positive or negative) contribution of any given amount of this attribute to overall utility levels, ($\beta_k$)

If an attribute does not differ at all across alternatives, it should get little attention in the choice process (e.g. $x_{ki} = 0$)
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- If an attribute does not differ at all across alternatives, it should get little attention in the choice process (e.g. $x_{ki} = 0$)
\( x'_{-k_i} \beta_{-k} = \text{“other-attribute utility difference”} \)

For a given value of \( |x_{ki} \beta_k| \), the absolute difference

\[
\left| F \left( x'_{-k_i} \beta_{-k} + x_{ki} \beta_k \right) - F \left( x'_{-k_i} \beta_{-k} \right) \right|
\]

will be larger as the amount of cumulative density in this given-width interval of the distribution of \( \varepsilon_i \) is larger.
Other-attribute utility differences

\[ x'_{-ki}\beta_{-k} = "\text{other-attribute utility difference}" \]

For a given value of \(|x_{ki}\beta_k|\), the absolute difference

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will be larger as the amount of cumulative density in this given-width interval of the distribution of \(\varepsilon_i\) is larger.

This captured density is larger:

- when \(x'_{-ki}\beta_{-k}\) lies nearer to zero (as opposed to farther out in either tail of the distribution)
\( x'_{-ki} \beta_{-k} = \text{“other-attribute utility difference”} \)

For a given value of \( |x_{ki} \beta_k| \), the absolute difference
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This captured density is larger:

- when \( x'_{-ki} \beta_{-k} \) lies nearer to zero (as opposed to farther out in either tail of the distribution)
- when the indirect utility-difference across alternatives, ignoring the \( k^{th} \) attribute, is nearer to zero
Other-attribute utility differences

\[ x'_{-ki} \beta_{-k} = \text{“other-attribute utility difference”} \]

For a given value of \(|x_{ki} \beta_k|\), the absolute difference

\[ \left| F \left( x'_{-ki} \beta_{-k} + x_{ki} \beta_k \right) - F \left( x'_{-ki} \beta_{-k} \right) \right| \]

will be larger as the amount of cumulative density in this given-width interval of the distribution of \( \varepsilon_i \) is larger.

This captured density is larger:

- when \( x'_{-ki} \beta_{-k} \) lies nearer to zero (as opposed to farther out in either tail of the distribution)
- when the indirect utility-difference across alternatives, ignoring the \( k^{th} \) attribute, is nearer to zero
- In words, when the alternatives confer similar utility, in terms of all other attributes
Dissimilarity based on other attributes?

With just two alternatives

- The simple absolute difference in systematic utilities according to other attributes, $|x_{-ki}^\prime \beta_{-k}|$, will adequately capture the relevant properties of the choice set.
With just two alternatives

- The simple absolute difference in systematic utilities according to other attributes, $|x'_{ki} - k\beta_k|$ will adequately capture the relevant properties of the choice set.

With three or more alternatives

- Need to resort to analog measures:

$$\text{dissim}(x'_{ki} - k\beta_k)$$

...the extent to which there is a clear-cut "best" option among the available alternatives, based on all attributes other than this one.
Candidate measures for $\text{dissim}(x_{-ki}^\prime \beta_{-k})$

Candidate 1: $\text{lead}(x_{-ki}^\prime \beta_{-k})$

- The utility difference between the two leading alternatives, based on all attributes other than the one in question
- Compute each of the indirect utility differences, relative to the third alternative $x_{-ki}^1\beta_{-k}$, $x_{-ki}^2\beta_{-k}$, and 0
- Identify the maximum and the median values and calculate their absolute difference
- Disadvantage for estimation: not smoothly differentiable
Candidate measures for $\text{dissim}(x'_{-k_i}\beta_{-k})$

Candidate 2: \( \text{stdev}(x'_{-k_i}\beta_{-k}) \)

- Standard deviation of $x_{1,k_i}\beta_{-k}, \ x_{2,k_i}\beta_{-k},$ and 0
- The greater the standard deviation in these measures, the more “different” are the alternatives in terms of utility from all other attributes
- Advantage for estimation: differentiable
Candidate 3: \( \text{skew}(x'_{-ki} \beta_{-k}) \)

- Skewness of \( x'_{-ki} \beta_{-k} \), \( x'_{-ki} \beta_{-k} \), and 0
- The more positively skewed, the farther apart are the two highest values, relative to the lowest value
- More of a “clear winner” among the three alternatives in terms of “all but the \( k^{th} \) attribute.”
- However, can have high skewness but low variance

Candidate 4: entropy measure (e.g. Swait and Adamowicz)
Own-attribute dissimilarity?

With just two alternatives

- The absolute value of the additive component of utility associated with the $k^{th}$ attribute $|x_{ki}\beta_k|$ will adequately capture the relevant term in the theoretical model.
Own-attribute dissimilarity?

With just two alternatives

- The absolute value of the additive component of utility associated with the \(k^{th}\) attribute \(|x_{ki} \beta_k|\) will adequately capture the relevant term in the theoretical model.

With three or more alternatives

- Need to resort to analog measures:

\[
dissim(x_{ki} \beta_k)
\]

... the extent to which the utility due to the \(k^{th}\) attribute varies “greatly” across the available alternatives.
Analogous candidate measures for $\text{dissim}(x_{ki}\beta_k)$

For three alternatives, there will be three terms for the contribution to net utility from the attribute in question:

\[ x_{ki1}\beta_k, \quad x_{ki2}\beta_k, \quad \text{and} \quad 0 \]

Candidate 1: $\text{lead}(x_{ki}\beta_k)$
- the absolute size of the “lead” for the largest value

Candidate 2: $\text{stdev}(x_{ki}\beta_k)$
- the standard deviation of the three values

Candidate 3: $\text{skew}(x_{ki}\beta_k)$
- the skewness of the three values
We use an existing survey of WTP for health risk reductions by Cameron and DeShazo (2006).

Survey fielded using the standing consumer panel maintained by Knowledge Networks, Inc.
  - Internet and Web TV

Use 1519 US subjects

79 percent response rate overall (selection effects minimal)

Pretesting
  - One-on-one focus sessions
  - External panel of distinguished reviewers
  - Canadian sample pre-test (more than 1000)
The Survey

Five Modules:

1. Evaluation of health conditions and perceived threats
2. Illness profile tutorial
   - An illness profile is a sequence of future health states (latency, sick-years, post-illness years and lost life-years)
3. Risk tutorial (Krupnick, Hoffman, et al. 1,000 square risk grid)
4. Conjoint choice sets
   - 3 alternatives per choice set (extensive randomized design) (Program A, Program B, Neither Program)
     - Each program: purchase annual non-invasive test that will reduce probability of illness profile (characterized by illness label, onset, duration, symptoms, treatment and outcome)
   - 5 choice sets per respondent (independent choices)
5. Debriefing questions (studied in Cameron, DeShazo and Johnson, 2007)
   - Allow researcher to know if an individual adjusts the choice scenario and by how much
The Survey: One Randomized Choice Scenario

Choose the program that reduces the illness that you most want to avoid. But think carefully about whether the costs are too high for you. If both programs are too expensive, then choose Neither Program.

If you choose “neither program”, remember that you could die early from a number of causes, including the ones described below.

<table>
<thead>
<tr>
<th></th>
<th>Program A for Diabetes</th>
<th>Program B for Heart Attack</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Symptoms/Treatment</strong></td>
<td>Get sick when 77 years-old</td>
<td>Get sick when 67 years-old</td>
</tr>
<tr>
<td></td>
<td>6 weeks of hospitalization</td>
<td>No hospitalization</td>
</tr>
<tr>
<td></td>
<td>No surgery</td>
<td>No surgery</td>
</tr>
<tr>
<td></td>
<td>Moderate pain for 7 years</td>
<td>Severe pain for a few hours</td>
</tr>
<tr>
<td><strong>Recovery/Life expectancy</strong></td>
<td>Do not recover</td>
<td>Do not recover</td>
</tr>
<tr>
<td></td>
<td>Die at 84 instead of 88</td>
<td>Die suddenly at 67 instead of 88</td>
</tr>
<tr>
<td><strong>Risk Reduction</strong></td>
<td>10% From 10 in 1,000 to 9 in 1,000</td>
<td>10% From 40 in 1,000 to 36 in 1,000</td>
</tr>
<tr>
<td><strong>Costs to you</strong></td>
<td>$12 per month [ = $144 per year]</td>
<td>$17 per month [ = $204 per year]</td>
</tr>
<tr>
<td><strong>Your choice</strong></td>
<td>☐ Reduce my chance of diabetes</td>
<td>☐ Reduce my chance of heart attack</td>
</tr>
<tr>
<td></td>
<td>☐ Neither Program</td>
<td>☐ Neither Program</td>
</tr>
</tbody>
</table>

Choose the program that reduces the illness that you most want to avoid. But think carefully about whether the costs are too high for you. If both programs are too expensive, then choose Neither Program.
Random Utility Model with 3 alternatives

- Simpler version of model in Cameron and DeShazo (2006) (no quadratic or interaction terms, no age heterogeneity)
- Simple linear models are where most choice researchers start
- Choices assumed to maximize present discounted expected utility defined over
  - net income
  - a **complete time profile** of avoided adverse health states, relative to status quo, consisting of illness-years, post-illness years, and lost life-years
- Probabilities? $\Rightarrow$ expected values ($\Delta \Pi_i^{JS} = \text{change Pr(sick)}$)
- Time profiles? $\Rightarrow$ discounting (5% rate assumed)
- Preliminary work shows utility not linear in present-discounted value (pdv) of health-state years, so use
  - $\log(pdvi + 1)$ for illness-years
  - $\log(pdvr + 1)$ for post-illness (recovered) years
  - $\log(pdvl + 1)$ for lost life-years
## Descriptive Statistics

Table 1a: Raw illness/program attributes (14074 programs)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>Annual cost of program (paid when neither sick nor dead)</td>
<td>355.00</td>
<td>341.14</td>
<td>24</td>
<td>1680</td>
</tr>
<tr>
<td>ΔΠ_i^AS</td>
<td>Risk change (i.e. negative, a risk reduction)</td>
<td>-0.0034</td>
<td>0.0017</td>
<td>-0.006</td>
<td>-0.001</td>
</tr>
<tr>
<td>Latency</td>
<td>Years until illness/injury begins</td>
<td>19.65</td>
<td>12.03</td>
<td>1</td>
<td>60</td>
</tr>
<tr>
<td>Sick years</td>
<td>Duration of illness/injury (years)</td>
<td>6.53</td>
<td>7.21</td>
<td>0</td>
<td>52</td>
</tr>
<tr>
<td>Recovered years</td>
<td>Number of years in post-illness health state</td>
<td>1.62</td>
<td>4.62</td>
<td>0</td>
<td>55</td>
</tr>
<tr>
<td>Lost life-years</td>
<td>Number of life-years lost</td>
<td>10.87</td>
<td>10.32</td>
<td>0</td>
<td>55</td>
</tr>
</tbody>
</table>
### Table 1b: Constructed attributes (14074 programs)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>(income term)</td>
<td>Net income under each alternative</td>
<td>-0.052747</td>
<td>0.048772</td>
<td>-0.2513</td>
<td>0.1083</td>
</tr>
<tr>
<td>$\Delta\Pi_{i}^{AS} \log(pdvi+1)$</td>
<td>Term in present discounted sick-years</td>
<td>-0.003111</td>
<td>0.003006</td>
<td>-0.01710</td>
<td>0</td>
</tr>
<tr>
<td>$\Delta\Pi_{i}^{AS} \log(pdvr+1)$</td>
<td>Term in present discounted recovered-years</td>
<td>-0.003374</td>
<td>0.003189</td>
<td>-0.01711</td>
<td>0</td>
</tr>
<tr>
<td>$\Delta\Pi_{i}^{AS} \log(pdvl+1)$</td>
<td>Term in present discounted lost life-years</td>
<td>-0.000746</td>
<td>0.001841</td>
<td>-0.01648</td>
<td>0</td>
</tr>
<tr>
<td>Sasubrsk (mean = msasubrsk)</td>
<td>Same-illness subjective risk rating (-2 = low, 2=high)</td>
<td>-0.2593</td>
<td>1.2531</td>
<td>-2</td>
<td>2</td>
</tr>
<tr>
<td>Cosubrsk (mean = mcosubrsk)</td>
<td>Average subjective risk rating (other major health risks)</td>
<td>-0.2537</td>
<td>0.8670</td>
<td>-2</td>
<td>2</td>
</tr>
<tr>
<td>(benefits never)</td>
<td>=1 if expects never to benefit from this program</td>
<td>0.0759</td>
<td>0.2648</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>(min overest latency)</td>
<td>Minimum overestimate of the latency of the health risk</td>
<td>-7.483</td>
<td>11.98</td>
<td>-58</td>
<td>29</td>
</tr>
</tbody>
</table>
Table 1c: Respondent characteristics (1519 respondents)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>Annual income ($)</td>
<td>51,048</td>
<td>33,781</td>
<td>5000</td>
<td>150,000</td>
</tr>
<tr>
<td>Female</td>
<td>=1 if female</td>
<td>0.5135</td>
<td>0.5000</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>age (mean = mage)</td>
<td>Age in years at time of response</td>
<td>50.11</td>
<td>15.18</td>
<td>25</td>
<td>93</td>
</tr>
</tbody>
</table>
Full information maximum likelihood (FIML) estimation is always preferred, but each systematically varying “observed” marginal utility parameter is a function of

- The “true” underlying marginal utility
- Two different (non-trivial) functions of these same parameters (the dissimilarity measures)

Log-likelihood function can be programmed, but optimization is difficult.
Resort to an iterative two-step method:

- Estimate initial values of “true” marginal utilities, use to calculate dissimilarity measures.
Resort to an iterative two-step method:

- Estimate initial values of “true” marginal utilities, use to calculate dissimilarity measures
- Treat dissimilarity measures as exogenous slope-shift variables, estimate new “true” marginal utilities and coefficients on dissimilarity shifters
Resort to an iterative two-step method:

- Estimate initial values of “true” marginal utilities, use to calculate dissimilarity measures
- Treat dissimilarity measures as exogenous slope-shift variables, estimate new “true” marginal utilities and coefficients on dissimilarity shifters
- Recalculate dissimilarity measures based on updated “true” marginal utilities
Resort to an iterative two-step method:

- Estimate initial values of "true" marginal utilities, use to calculate dissimilarity measures
- Treat dissimilarity measures as exogenous slope-shift variables, estimate new "true" marginal utilities and coefficients on dissimilarity shifters
- Recalculate dissimilarity measures based on updated "true" marginal utilities
- Continue until permutation in parameter vector disappears

Final step standard errors are conditioned on prevailing parameter estimates from last round
For correct standard errors, insert converged parameters into log-likelihood and calculate numeric Hessian to derive vcov matrix
Estimation

Resort to an iterative two-step method:

- Estimate initial values of “true” marginal utilities, use to calculate dissimilarity measures
- Treat dissimilarity measures as exogenous slope-shift variables, estimate new “true” marginal utilities and coefficients on dissimilarity shifters
- Recalculate dissimilarity measures based on updated “true” marginal utilities
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Resort to an iterative two-step method:

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- Final step standard errors are conditioned on prevailing parameter estimates from last round
- For correct standard errors, insert converged parameters into log-likelihood and calculate numeric Hessian to derive vcov matrix
## Estimates

Homogeneous Preferences – Simple linear additive utility

<table>
<thead>
<tr>
<th>SD1</th>
<th>Income term ($\beta_0$)</th>
<th>Sick-years term ($\alpha_1$)</th>
<th>Recovered-years term ($\alpha_2$)</th>
<th>Lost life-years term ($\alpha_3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline variable</td>
<td>3.148 (7.77)***</td>
<td>-27.06 (4.50)***</td>
<td>-24.03 (2.51)**</td>
<td>-29.82 (5.68)***</td>
</tr>
<tr>
<td>Observations</td>
<td>21111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log L</td>
<td>-10992.674</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Heterogeneous Preferences – Several important shifters on marginal utilities

<table>
<thead>
<tr>
<th></th>
<th>SD2</th>
<th>Income term (β₀)</th>
<th>Sick-years term (α₁)</th>
<th>Recovered-years term (α₂)</th>
<th>Lost life-years term (α₃)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline variable</td>
<td></td>
<td>2.941</td>
<td>-14.39</td>
<td>-40.55</td>
<td>-21.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5.16)***</td>
<td>(1.93)*</td>
<td>(3.98)***</td>
<td>(3.23)***</td>
</tr>
<tr>
<td>...*female</td>
<td></td>
<td>3.916</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5.58)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>...*(age-mage)</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-1.305</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(1.95)*</td>
<td></td>
</tr>
<tr>
<td>...*(sasubrsk-masubrsk)</td>
<td></td>
<td>-</td>
<td>-22.09</td>
<td>-</td>
<td>-40.67</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.80)***</td>
<td></td>
<td>(7.48)***</td>
</tr>
<tr>
<td>...*(cosubrsk-mcosubrsk)</td>
<td></td>
<td>-</td>
<td>27.44</td>
<td>-</td>
<td>30.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.20)***</td>
<td></td>
<td>(3.84)***</td>
</tr>
<tr>
<td>...*(benefits never)</td>
<td></td>
<td>-</td>
<td>137.4</td>
<td>-</td>
<td>217.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.14)***</td>
<td></td>
<td>(6.63)***</td>
</tr>
<tr>
<td>...*(min overest latency)</td>
<td></td>
<td>-</td>
<td>8.13</td>
<td>-</td>
<td>8.219</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(12.53)***</td>
<td></td>
<td>(13.65)***</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td>21111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log L</td>
<td></td>
<td>-10326.046</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## Estimates

### Expected Signs (based on theory)

<table>
<thead>
<tr>
<th></th>
<th>stdev models</th>
<th>Income term ($\beta_1$)</th>
<th>Sick-years term ($\beta_2$)</th>
<th>Recovered-years term ($\beta_3$)</th>
<th>Lost life-years term ($\beta_4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline variable</td>
<td></td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>...*(sd(U othr attr)-mean sd)</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>...*(sd(U this attr)-mean sd)</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
### Results

Dissimilarity measures based on **Homogeneous Preferences** specification

<table>
<thead>
<tr>
<th>SD3; 30 iterations</th>
<th>Income term ($\beta_0$)</th>
<th>Sick-years term ($\alpha_1$)</th>
<th>Recovered-years term ($\alpha_2$)</th>
<th>Lost life-years term ($\alpha_3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline variable</td>
<td>2.759</td>
<td>-23.61</td>
<td>-72.19</td>
<td>-45.62</td>
</tr>
<tr>
<td></td>
<td>(3.96)***</td>
<td>(2.46)**</td>
<td>(3.69)***</td>
<td>(5.18)***</td>
</tr>
<tr>
<td>...*(sd(U othr attr)-mean sd)</td>
<td>7.715</td>
<td>-48.13</td>
<td>-57.4</td>
<td>96.09</td>
</tr>
<tr>
<td></td>
<td>(2.86)***</td>
<td>(1.04)</td>
<td>(0.51)</td>
<td>(1.83)*</td>
</tr>
<tr>
<td>...*(sd(U this attr)-mean sd)</td>
<td>4.882</td>
<td>-4.894</td>
<td>122.3</td>
<td>102.2</td>
</tr>
<tr>
<td></td>
<td>(1.08)</td>
<td>(0.04)</td>
<td>(1.92)*</td>
<td>(1.99)**</td>
</tr>
<tr>
<td>Observations</td>
<td>21111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log L</td>
<td>-10976.589</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Dissimilarity measures based on Heterogeneous Preferences specification

<table>
<thead>
<tr>
<th></th>
<th>Income term ($\beta_0$)</th>
<th>Sick-years term ($\alpha_1$)</th>
<th>Recovered-years term ($\alpha_2$)</th>
<th>Lost life-years term ($\alpha_3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline variable</td>
<td>3.455 (5.89)**</td>
<td>-20.57 (2.65)**</td>
<td>-43.81 (2.28)**</td>
<td>-21.59 (3.14)**</td>
</tr>
<tr>
<td>*(sd(U other attr)-mean sd)</td>
<td>3.152 (3.11)**</td>
<td>-21.01 (1.05)</td>
<td>.3823 (0.01)</td>
<td>17.12 (0.80)</td>
</tr>
<tr>
<td>*(sd(U this attr)-mean sd)</td>
<td>-3.507 (1.92)*</td>
<td>21.08 (0.92)</td>
<td>13.45 (0.13)</td>
<td>-10.95 (0.61)</td>
</tr>
<tr>
<td>*female</td>
<td>5.473 (5.30)**</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>*(age-mage)</td>
<td>-</td>
<td>-</td>
<td>-1.348 (1.62)</td>
<td>-</td>
</tr>
<tr>
<td>*(sasubrsk-msasubrsk)</td>
<td>-</td>
<td>-26.32 (4.32)**</td>
<td>-</td>
<td>-41.03 (7.07)**</td>
</tr>
<tr>
<td>*(cosubrsk-mcosubrsk)</td>
<td>-</td>
<td>31.64 (3.61)**</td>
<td>-</td>
<td>30.45 (3.78)**</td>
</tr>
<tr>
<td>*(benefits never)</td>
<td>-</td>
<td>130 (3.82)**</td>
<td>-</td>
<td>215.8 (6.42)**</td>
</tr>
<tr>
<td>*(min overest latency)</td>
<td>-</td>
<td>9.24 (11.88)**</td>
<td>-</td>
<td>8.415 (12.54)**</td>
</tr>
<tr>
<td>Observations</td>
<td>21111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log L</td>
<td>-10316.015</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Estimates

What might we be missing?

- With homogeneous preferences, the other-attribute utility from any given configuration of attributes will be identical across individuals...insufficient variation?
- What if researcher is estimating a naive linear specification assuming homogeneous preferences, but any given configuration of “other attributes” is viewed differently by different consumers?
- Suppose the heterogeneity in actual preferences creates differences across people in the other-attribute and own-attribute dissimilarity measures.
- How do the researcher’s marginal utility estimates from the naive model vary with the level of this ”unobservable to the researcher” heterogeneity in the dissimilarity measures?
### Estimates ....Ah hah!

Dissimilarity measures based on **Heterogeneous Preferences specification**

<table>
<thead>
<tr>
<th></th>
<th>SD5</th>
<th>Income term ($\beta_0$)</th>
<th>Sick-years term ($\alpha_1$)</th>
<th>Recovered-years term ($\alpha_2$)</th>
<th>Lost life-years term ($\alpha_3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline variable</strong></td>
<td></td>
<td>1.514 (2.93)*****</td>
<td>-7.124 (1.02)</td>
<td>-33.92 (2.16)**</td>
<td>-20.23 (3.30)*****</td>
</tr>
<tr>
<td><em>(sd(U other attr)-mean sd)</em></td>
<td></td>
<td>-1.505 (1.78)*</td>
<td>91.18 (5.36)*****</td>
<td>31.98 (1.49)</td>
<td>94.09 (4.95)*****</td>
</tr>
<tr>
<td><em>(sd(U this attr)-mean sd)</em></td>
<td></td>
<td>2.361 (1.89)*</td>
<td>-106.1 (6.48)*****</td>
<td>56.41 (0.68)</td>
<td>-43.3 (3.78)*****</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>21111</td>
</tr>
<tr>
<td><strong>Log L</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-10915.004</td>
</tr>
</tbody>
</table>
### Estimates ....Again

Dissimilarity measures based on **Heterogeneous Preferences** specification

<table>
<thead>
<tr>
<th>Lead5; 30 iterations</th>
<th>Income term ( (\beta_0) )</th>
<th>Sick-years term ( (\alpha_1) )</th>
<th>Recovered-years term ( (\alpha_2) )</th>
<th>Lost life-years term ( (\alpha_3) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline variable</td>
<td>2.685</td>
<td>-11.23</td>
<td>-45.3</td>
<td>-7.846</td>
</tr>
<tr>
<td></td>
<td>(5.82)**</td>
<td>(1.69)*</td>
<td>(2.99)**</td>
<td>(1.33)</td>
</tr>
<tr>
<td>...*(ld(U othr attr)-mean ld)</td>
<td>-.4693</td>
<td>63.95</td>
<td>39.68</td>
<td>78.25</td>
</tr>
<tr>
<td></td>
<td>(0.74)</td>
<td>(4.24)**</td>
<td>(2.12)**</td>
<td>(4.62)**</td>
</tr>
<tr>
<td>...*(ld(U this attr)-mean ld)</td>
<td>1.545</td>
<td>-136.8</td>
<td>32.27</td>
<td>-116.5</td>
</tr>
<tr>
<td></td>
<td>(1.38)</td>
<td>(10.94)**</td>
<td>(0.58)</td>
<td>(12.04)**</td>
</tr>
<tr>
<td>Observations</td>
<td>21111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log L</td>
<td>-10771.54</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
• Similar results for “size-of-lead” measure of dissimilarity, but NOT for skewness or entropy measures

• Corrected standard errors case with “stdev” measure of dissimilarity (Matlab, one-step efficient)

• In progress: Matlab version of model with scaling, rather than translation, of marginal utilities (allows signs to be constrained to be always positive or always negative)

• Spun off: analogous story for attention to alternatives
WTP implications

$$WTP = \left[ \frac{1}{\beta_{1i}} \right]$$

$$= \beta_{2i} \left\{ \Delta \Pi^j_i \log (pdvi^j_i + 1) \right\}$$

$$+ \beta_{3i} \left\{ \Delta \Pi^j_i \log (pdvr^j_i + 1) \right\}$$

$$+ \beta_{4i} \left\{ \Delta \Pi^j_i \log (pdvl^j_i + 1) \right\}$$
WTP implications

\[
WTP = \left[ \frac{1}{\beta_{1i}} \right] \left[ \beta_{2i} \left\{ \Delta \Pi^i_j \log \left( pdvi^i_j + 1 \right) \right\} \\
+ \beta_{3i} \left\{ \Delta \Pi^i_j \log \left( pdvr^i_j + 1 \right) \right\} \\
+ \beta_{4i} \left\{ \Delta \Pi^i_j \log \left( pdvl^i_j + 1 \right) \right\} \right]
\]

Nonlinear in shifted logs of PDV of time in each health state.

WTP will depend upon the **health profile** to be avoided and on the change in its probability of occurring, \( \Delta \Pi^i_j \).

- MU(\( Y \)) forms the *denominator* \( (\beta_{1i}) \)
- Other MUs are in the *numerator* \( (\beta_{2i}, \beta_{3i}, \beta_{4i}) \)
WTP implications

\[
WTP = \left[ \frac{1}{\beta_{1i}} \right] \left[ \begin{array}{c}
\beta_{2i} \left\{ \Delta \Pi_i^j \log (pdvi_i^j + 1) \right\} \\
+ \beta_{3i} \left\{ \Delta \Pi_i^j \log (pdvr_i^j + 1) \right\} \\
+ \beta_{4i} \left\{ \Delta \Pi_i^j \log (pdvl_i^j + 1) \right\}
\end{array} \right]
\]

Nonlinear in shifted logs of PDV of time in each health state.

WTP will depend upon the health profile to be avoided and on the change in its probability of occurring, \( \Delta \Pi_i^j \).

- MU(Y) forms the denominator \( (\beta_{1i}) \)
- Other MUs are in the numerator \( (\beta_{2i}, \beta_{3i}, \beta_{4i}) \)

Need to consider how the two types of dissimilarity variables influence the apparent size of each systematically varying \( \beta \) parameter.
Effects on Marginal Utilities

Apparent marginal utility of $k^{th}$ attribute is

$$\beta_k^* = \beta_k^{true} + \beta_k^{other} (sd(U \ other \ attr) - mean \ sd))$$

$$+ \beta_k^{own} (sd(U\ own\ attr) - mean \ sd))$$
Effects on Marginal Utilities

Apparent marginal utility of $k^{th}$ attribute is

$$\beta_k^* = \beta_k^{true} + \beta_k^{other} (sd(U \ other \ attr) - mean \ sd)$$

$$+ \beta_k^{own} (sd(U \ own \ attr) - mean \ sd)$$

Next slide: magnitudes other-attribute and own-attribute dissimilarity effects on apparent MUs

- $\beta_k^{true}$ (when attention is “leveled” at sample means)
- $\beta_k^* = \beta_k^{true} + \beta_k^{other} (sd(U \ other \ attr) - mean \ sd)$
  - at selected percentiles of the distr. of the shift variable
- $\beta_k^* = \beta_k^{true} + \beta_k^{own} (sd(U \ own \ attr) - mean \ sd)$
  - at selected percentiles of the distr. of the shift variable
### Effects on Marginal Utilities

#### Denominator of WTP

- Dissimilarity variables normalized so that sample mean = 0

#### In numerator of WTP

<table>
<thead>
<tr>
<th>Dissimilarity variables normalized so that sample mean = 0</th>
<th>Income term ($\beta_1$)</th>
<th>Sick-years term ($\beta_2$)</th>
<th>Recovered-years term ($\beta_3$)</th>
<th>Lost life-years term ($\beta_4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MU at &quot;mean&quot; dissimilarity = 1.514</td>
<td>1.514</td>
<td>-7.124</td>
<td>-33.92</td>
<td>-20.23</td>
</tr>
<tr>
<td>Effects of other-attribute utility dissimilarity (percentiles):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5th</td>
<td>2.24</td>
<td>-38.04</td>
<td>-49.38</td>
<td>-47.83</td>
</tr>
<tr>
<td>25th</td>
<td>2.01</td>
<td>-28.85</td>
<td>-44.52</td>
<td>-38.91</td>
</tr>
<tr>
<td>50th</td>
<td>1.68</td>
<td>-16.37</td>
<td>-37.64</td>
<td>-27.48</td>
</tr>
<tr>
<td>75th</td>
<td>1.19</td>
<td>6.03</td>
<td>-27.63</td>
<td>-8.16</td>
</tr>
<tr>
<td>95th</td>
<td>0.21</td>
<td>50.81</td>
<td>-4.99</td>
<td>30.20</td>
</tr>
<tr>
<td>Effects of own-attribute utility dissimilarity (percentiles):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5th</td>
<td>1.01</td>
<td>20.08</td>
<td>-35.90</td>
<td>-7.53</td>
</tr>
<tr>
<td>25th</td>
<td>1.12</td>
<td>12.77</td>
<td>-35.90</td>
<td>-10.76</td>
</tr>
<tr>
<td>50th</td>
<td>1.33</td>
<td>1.08</td>
<td>-35.90</td>
<td>-15.94</td>
</tr>
<tr>
<td>75th</td>
<td>1.70</td>
<td>-18.80</td>
<td>-33.47</td>
<td>-25.07</td>
</tr>
<tr>
<td>95th</td>
<td>2.67</td>
<td>-62.93</td>
<td>-25.82</td>
<td>-48.23</td>
</tr>
</tbody>
</table>
Conclusions and Caveats

Don't ignore cross-sectional heterogeneity in preferences.
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At least in *naïve* models of choice, preference heterogeneity (interacting with the mix of attributes across alternatives in a choice set) can influence attention to different attributes. For any given attribute, the *apparent* size of MUs can vary directly with

- the extent to which utility-based-on-other-attributes fails to produce a clear winner among alternatives
- the extent to which utility is very different, across alternatives, based on this attribute

Thus, WTP can vary with these factors as well.
Conclusions and Caveats

Suggestion from my group at the Choice Symposium at Wharton:


Q: Could we design “paired resume” experiments to maximize and/or minimize the apparent effects of race on estimates of an employer’s preferences across prospective employees?

A: If candidates are similar on all other dimensions, or even if they are just close substitutes on all other dimensions, the apparent influence of inferred race on call-back decisions could be exaggerated.
Implication: It may be possible (inadvertently or intentionally) to produce different estimates of MUs and thus WTP by steering respondents’ relative attention to different attributes via the mixes of attributes presented in their choice sets.
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Under incomplete attention, if the cost attribute captures respondents’ attention more than other attributes, then we expect inattention to produce a downward bias in WTP estimates.
Implication: It may be possible (inadvertently or intentionally) to produce different estimates of MUs and thus WTP by steering respondents’ relative attention to different attributes via the mixes of attributes presented in their choice sets.

Under incomplete attention, if the cost attribute captures respondents’ attention more than other attributes, then we expect inattention to produce a downward bias in WTP estimates.

Escape hatch? We may be able to avoid attention-based biases to a considerable extent by recognizing systematic heterogeneity in preferences and taking care to accommodate it in our empirical models.
End of presentation

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