Subjective Choice Difficulty as a Context Effect in Stated Preference Surveys

Eric Duquette[1], Trudy Ann Cameron[1], and J.R. DeShazo[2]

[1]Dept. of Economics, University of Oregon
[2]Dept. of Public Policy, School of Public Affairs, Univ. of California - Los Angeles

July 1, 2009

UNIVERSITY OF OREGON

RAYMOND F. MIKESELL LABORATORY
ENVIRONMENTAL AND RESOURCE ECONOMICS

Subjective Choice Difficulty as a Context Effect in Stated Preference Surveys

Eric Duquette[1], Trudy Ann Cameron[1], and J.R. DeShazo[2]

[1]Dept. of Economics, University of Oregon
[2]Dept. of Public Policy, School of Public Affairs, Univ. of California - Los Angeles

July 1, 2009

UNIVERSITY OF OREGON

RAYMOND F. MIKESELL LABORATORY
ENVIRONMENTAL AND RESOURCE ECONOMICS

Motivation

Is preference elicitation innocent?

If not, are the effects predictable? Controllable?

Choice Context

For example,

- # of alternatives
- # of attributes
- Objective measures of "choice complexity" (Swait and Adamowicz (2001), Hensher et al., and others)

Behaviorally, respondents might have larger levels of choice inconsistency (i.e., an increase error variance)

Are respondents knowledgable of their own errors? If so, what do they do? (e.g., That's too hard. I give up.)

Are these behavioral manifestations simple cognitive constraints during the decision-making process?

Design

How should researchers account for these context effects?

Ex-ante survey design or ex-post empirical modeling?

For choice set complexity, existing research has focused on identifying measures and controlling for these ex-post.

Should ex-post analysis also consider individual-level heterogeneity as contextual factors that affect choice outcomes?

Our Efforts

In our stated preference survey, we elicited subjective ratings of **"choice difficulty"** after each choice task.

- How difficult was your choice on the previous screen?
  (Answer options: $1 =$ Easy to $7 =$ Very Difficult)

We investigate the many potential contextual factors of choice difficulty and their effects on choice consistency and estimated WTP.

We follow-up up work by Swait and Adamowicz (2001) that examines the role of preferences in affecting choice consistency. Specifically, we examine an alternative utility-space measure of alternatives in a choice set - **the standard deviation of utilities**.

Preview of Findings

We find that

- previously identified measures of choice set complexity do not fully explain subjective difficulty.
- the characteristics of the decision-maker are also important to perceived difficulty.
- our WTP measure for marginal health risk reductions varies with the subjective difficulty ratings.
- most existing determinants fail to account for utility-space effects.

Consumer Choice Theory

What are the determinants choice inconsistency?

- RATIONAL CHOICE THEORY:
  Errorless decisions

- BOUNDED RATIONALITY:
  Decision errors are tied to *task difficulty* and *limitations on information processing*. All kinds of errors are possible.

- RATIONALLY ADAPTIVE BEHAVIOR:
  Individuals adopt *choice heuristics* and, by doing so, mitigate and limit choice inconsistencies.

Consumer Choice Theory

What are the determinants choice inconsistency?

- RATIONAL CHOICE THEORY:
  Errorless decisions

- BOUNDED RATIONALITY:
  Decision errors are tied to *task difficulty* and *limitations on information processing*. All kinds of errors are possible.

- RATIONALLY ADAPTIVE BEHAVIOR:
  Individuals adopt *choice heuristics* and, by doing so, mitigate and limit choice inconsistencies.

Bounded rationality and rationally adaptive behavior suggest that inconsistencies may be related to:

(1) objective measures of choice set complexity

(2) decision-maker characteristics and cognitive abilities.

Behavioral Model

Choice set complexity

\# of alternatives
\# of attributes
etc.

Choice consistency

Behavioral Model

Choice set complexity

# of alternatives
# of attributes
etc.

Individual

age
cognitive abilities
preferences
etc.

Choice consistency

Existing Research

Objective determinants of “Choice set complexity”

- # of alternatives, # of attributes per alternative, # of attributes constant across alternatives; Measures of “information structure” - across-alternative mean and dispersion of the within-alternative of attribute standard deviation
  (DeShazo and Fermo, 2002)
- range of attribute values
  (Hensher, 2004 & 2006)

Existing Research

Objective determinants of "Choice set complexity"

- # of alternatives, # of attributes per alternative, # of attributes constant across alternatives; Measures of "information structure" - across-alternative mean and dispersion of the within-alternative of attribute standard deviation
(DeShazo and Fermo, 2002)
- range of attribute values
(Hensher, 2004 & 2006)

Existing empirical strategies allow these determinants to affect:

- the variance of individuals' responses via the error term in a heteroscedastic conditional logit model
(DeShazo and Fermo, 2002; Swait and Adamowicz, 2001a)
- the estimates of the preference parameters via a mixed logit model
(Hensher, 2004)
- the "preference class" probabilities in a latent class model
(Swait and Adamowicz, 2001b)

Choice set complexity - Entropy

Entropy - Swait and Adamowicz (2001a)

- Defined over "a probability space of uncertain events"

$$\text{Entropy}_{nc} = -\sum_{J} \hat{P}_{ncj} \log \hat{P}_{ncj}$$

- In RUT, this space can be the set of choice probabilities for the alternatives in a choice set (obtained from a DCM).

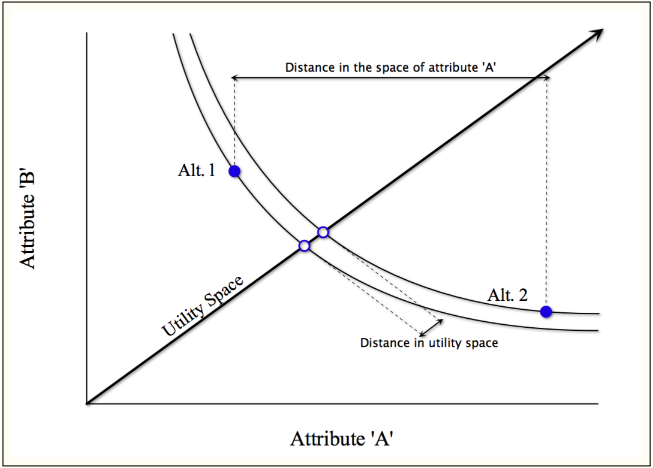
$$\hat{P}_{ncj} = \frac{\exp(\hat{\beta}' X_{ncj})}{\sum_{J} \exp(\hat{\beta}' X_{ncj'})}$$

- Entropy incorporates:
  1. levels of the attributes
  2. number of alternatives
  3. (estimated) preferences
- Entropy appears to be the only "utility-space" measure to have been explored empirically

An alternative utility space measure

The standard deviation in utility differences (SDU)

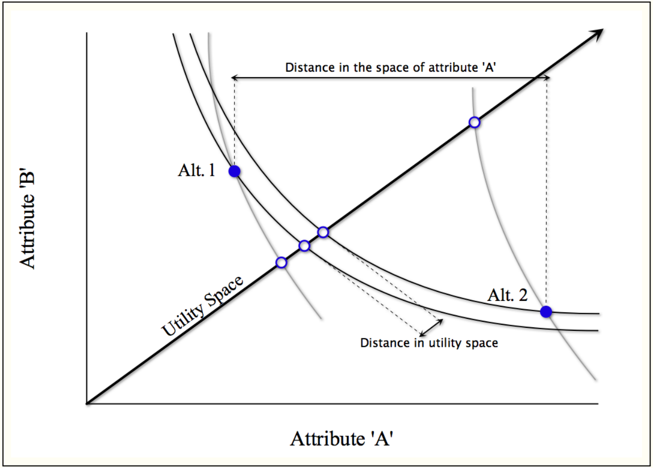
- The SDU is a measure of the "distance" between alternatives in a one-dimensional utility space, as opposed to a multi-dimensional attribute space. (Utility-space diagram after Mas-Colell, 1995)



An alternative utility space measure

The standard deviation in utility differences (SDU)

- The SDU is a measure of the "distance" between alternatives in a one-dimensional utility space, as opposed to a multi-dimensional attribute space (after Mas-Colell, 1995)



An alternative utility space measure

The standard deviation in fitted utility (SDU)

- Provides an intuitive summary of the subjective “closeness” of alternatives in terms of the objective function which drives consumer choices
- Incorporates:
  - levels of the attributes
  - number of alternatives
  - preferences

An alternative utility space measure

The standard deviation in fitted utility (SDU)

- Provides an intuitive summary of the subjective “closeness” of alternatives in terms of the objective function which drives consumer choices
- Incorporates:
  - levels of the attributes
  - number of alternatives
  - preferences

SDU for each choice is calculated from the fitted utility “indexes” from a DCM.

$$\widehat{SDU}_{nc} = \sqrt{\left[\sum_{J} \left(\hat{\beta}' X_{ncj} - \overline{\hat{\beta}' X_{nc}}\right)^2\right] / (J-1)}$$

Behavioral Model

Choice set complexity

# of alternatives
# of attributes
SDU, etc.

Individual

age
cognitive abilities
preferences
etc.

Choice consistency

Empirical strategy of behavioral model

Choice set complexity

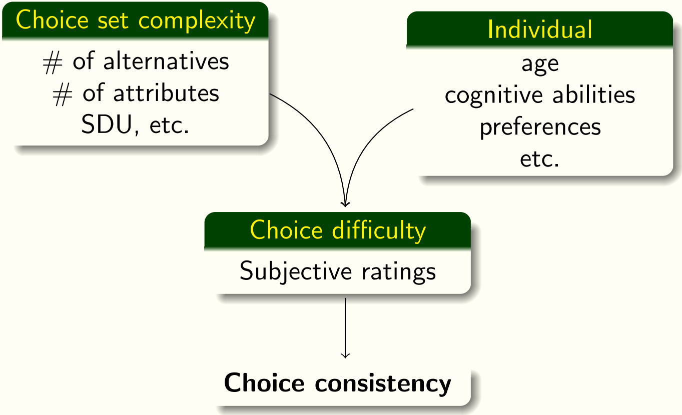
# of alternatives
# of attributes
SDU, etc.

Individual

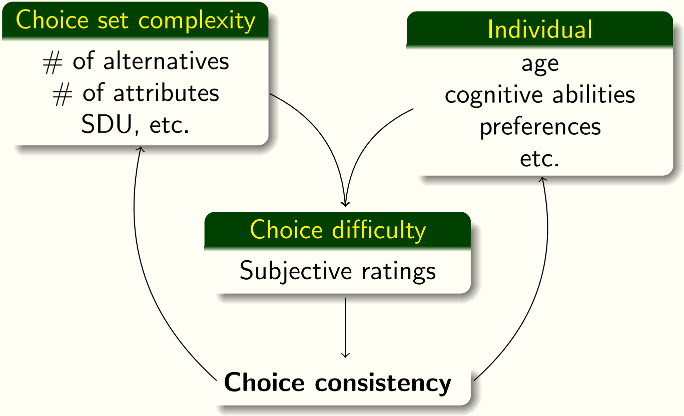
age
cognitive abilities
preferences
etc.

Choice consistency

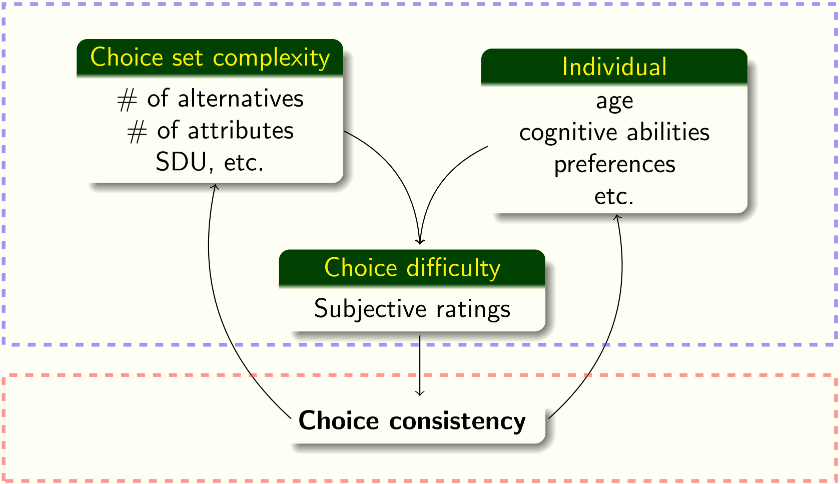
Empirical strategy of behavioral model



Empirical strategy of behavioral model



Two Submodels



Two Submodels

Choice submodel:
Conditional logit probabilities with scale parameterization,

$$P_{ncj} = \frac{\exp(\beta' X_{ncj}/\sigma_{nc})}{\sum_{j'=1}^{J} \exp(\beta' X_{ncj'}/\sigma_{nc})}$$

where $\sigma_{nc} = exp(\mu_{uc})$ and $\mu_{nc} = \gamma * \widehat{difficulty}_{nc}$

Two Submodels

Choice submodel:
Conditional logit probabilities with scale parameterization,

$$P_{ncj} = \frac{\exp(\beta' X_{ncj}/\sigma_{nc})}{\sum_{j'=1}^{J} \exp(\beta' X_{ncj'}/\sigma_{nc})}$$

where $\sigma_{nc} = exp(\mu_{uc})$ and $\mu_{nc} = \gamma * \widehat{difficulty}_{nc}$

$\rightarrow$ Obtain utility indexes (i.e., $\widehat{\beta}' X_{ncj}/\sigma_{nc}$) to construct the entropy or SDU measures for the *choice difficulty submodel*

Two Submodels

Choice submodel:
Conditional logit probabilities with scale parameterization,

$$P_{ncj} = \frac{\exp(\beta' X_{ncj}/\sigma_{nc})}{\sum_{j'=1}^{J} \exp(\beta' X_{ncj'}/\sigma_{nc})}$$

where $\sigma_{nc} = exp(\mu_{uc})$ and $\mu_{nc} = \gamma * \widehat{difficulty}_{nc}$

→ Obtain utility indexes (i.e., $\widehat{\beta}' X_{ncj}/\sigma_{nc}$) to construct the entropy or SDU measures for the *choice difficulty submodel*

Difficulty submodel:

$difficulty_{nc} = g(contextual\ factors\ of\ choice\ set)$

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

Two Submodels

Choice submodel:
Conditional logit probabilities with scale parameterization,

$$P_{ncj} = \frac{\exp(\beta' X_{ncj}/\sigma_{nc})}{\sum_{j'=1}^{J} \exp(\beta' X_{ncj'}/\sigma_{nc})}$$

where $\sigma_{nc} = exp(\mu_{uc})$ and $\mu_{nc} = \gamma * \widehat{difficulty}_{nc}$

→ Obtain utility indexes (i.e., $\widehat{\beta}' X_{ncj}/\sigma_{nc}$) to construct the entropy or SDU measures for the *choice difficulty submodel*

Difficulty submodel:

$$difficulty_{nc} = g(contextual\ factors\ of\ choice\ set)$$

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

→ Obtain fitted choice difficulty measures (i.e., $\widehat{difficulty}_{nc}$) needed for the *discrete choice submodel*

Two Submodels

Choice submodel:
Conditional logit probabilities with scale parameterization,

$$P_{ncj} = \frac{\exp(\beta' X_{ncj}/\sigma_{nc})}{\sum_{j'=1}^{J} \exp(\beta' X_{ncj'}/\sigma_{nc})}$$

where $\sigma_{nc} = exp(\mu_{uc})$ and $\mu_{nc} = \gamma * \widehat{difficulty}_{nc}$

$\rightarrow$ Obtain utility indexes (i.e., $\widehat{\beta}' X_{ncj}/\sigma_{nc}$) to construct the entropy or SDU measures for the *choice difficulty submodel*

Difficulty submodel:

$difficulty_{nc} = g(contextual\ factors\ of\ choice\ set)$

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

$\rightarrow$ Obtain fitted choice difficulty measures (i.e., $\widehat{difficulty}_{nc}$) needed for the *discrete choice submodel*

**These models should be estimated jointly*

Estimation

Challenge:
Utility-space measures depend endogenously on each individual's preference parameters

Limitations:
The HCL model does not easily converge for all specifications.

Currently relying mostly on an iterated sequential estimation strategy:

Our stated preference survey

In our survey, we elicit individuals' stated preferences across *privately* provided programs that achieve marginal reductions in different types of health risks ("illness profiles")

U.S. representative survey of 1789 adults 25 years and older (Knowledge Networks, Inc., standing consumer panel)

Several survey modules

1. Health and lifestyle assessment
2. Explanation of illness profile
3. 5 randomized conjoint choice tasks with 3 alternatives each
   - Debriefing questions - "How difficult?"
4. Sociodemographic characteristics

The stated preference survey - Example choice task

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.

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

Choice model for health risk-reductions

Ad hoc model (in paper, not presented here)

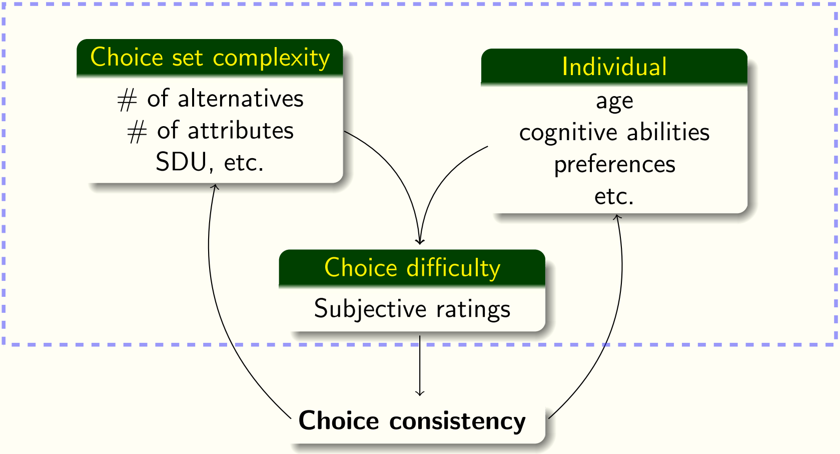
- *Ad hoc attributes:*
  Monthly cost, risk difference, latency, sick years, lost life-years

Structural model (based on Cameron and DeShazo, 2006)

$$PDV\left(E_{S,H}\left[\Delta V_i^A\right]\right) =$$

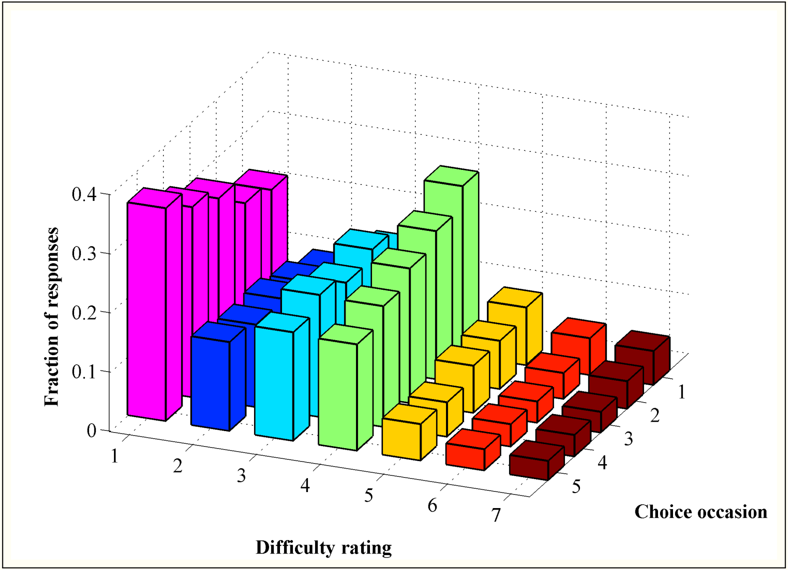
$\beta_0 \left\{\left(Y_i - c_i^A\right) cterm_i^A + Y_i yterm_i^A\right\}$	linear term in net income
$+ \beta_1 \left\{\left(Y_i - c_i^A\right)^2 cterm_i^A + Y_i^2 yterm_i^A\right\}$	quadratic term in net income
$+ \alpha_1 \left\{\Delta\Pi_i^{AS} \log(pdvi_i^A + 1)\right\}$	sick-years term
$+ \alpha_2 \left\{\Delta\Pi_i^{AS} \log(pdvr_i^A + 1)\right\}$	recov./remiss.-years term
$+ \alpha_3 \left\{\Delta\Pi_i^{AS} \log(pdvl_i^A + 1)\right\}$	lost life-years term
$+ \varepsilon_i^A$	heteroscedastic error term

Difficulty Submodel



Choice Difficulty Submodel

Observed subjective choice difficulty ratings



Choice Difficulty Submodel

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

SDU and/or Entropy

Choice Difficulty Submodel

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

Std. dev. of attribute levels
Mean std. dev. of within-alternative attribute std. dev.
Disp of std. dev. of within-alternative attribute std. dev.
(as in DeShazo and Fermo, 2002)

Choice Difficulty Submodel

e.g., $\mathit{difficulty}_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

Choice set indicators (i.e. choice1, ..., choice5)

Choice Difficulty Submodel

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

Age, Age^2, Gender
Income
Marital status
Ethnicity
Household structure

Choice Difficulty Submodel

e.g., $\textit{difficulty}_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

Illness experience (number of major illnesses)
Avg. subj. risk of future health threats
Subjective controllability of health risks

Choice Difficulty Submodel

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

Level of education
Average duration of on other choice tasks

Choice Difficulty Submodel

e.g., $difficulty_{nc} = g_1 * \widehat{SDU}_{nc} + ... + \varepsilon_{nc}$

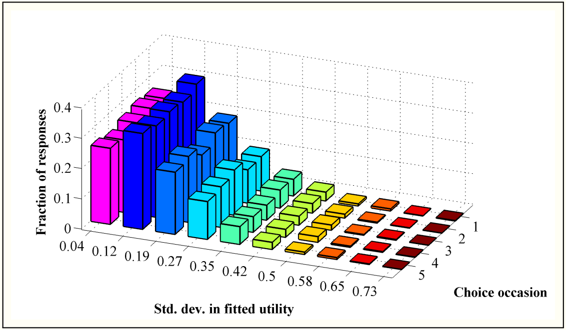
The determinants we use:

1. Objective choice set complexity (in utility space)
2. Objective choice set complexity (in attribute space)
3. Choice set effects
4. Individual sociodemgraphic characteristics
5. Survey-specific respondent characteristics
6. Cognitive resource constraints
7. Respondent attention behavior

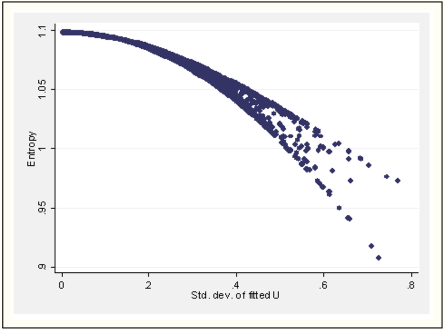
All 'status quo' for conjoint choices
No change in difficulty rating

Fitted values of *SDU* and *Entropy* from choice submodel

Dist. of
Std. dev. of fitted U



Entropy vs.
Std. dev. of fitted U



SDU vs. Entropy

Difficulty Submodel:
(1)-(3) Ord. Probit

COEFFICIENT	Model 1	Model 2	Model 3
Measures of choice set complexity:			
(a) In utility space:			
Std. dev. of fitted U	-0.398***	-	0.211
	(-2.96)		(0.40)
Entropy	-	3.379***	5.001
		(3.16)	(1.18)
Constant	-	-	-
Observations	8807	8807	8807
LogL	-15141.55	-15140.93	-15140.85

Difficulty Submodel:
(4)-(5) Ord. Probit
(6) Linear FE

COEFFICIENT	Model 4	Model 5	Model 6
Measures of choice set complexity:			
(a) In utility space:			
Std. dev. of fitted U	-0.459***	-0.500***	-0.553***
	(-2.83)	(-2.80)	(-2.73)
(b) In attribute space:			
Within-alternative attrib. correlation			
Mean std. dev.	0.080	0.737	1.449**
	(0.16)	(1.34)	(2.38)
Disp. of std. dev.	0.483	0.487	1.016**
	(1.32)	(1.32)	(2.47)
Across-alternative attrib. correlation			
Std. dev. of annualized costs	0.059**	0.100***	0.078**
	(2.24)	(3.67)	(2.42)
" risk difference	-0.056	-0.072**	0.039
	(-1.61)	(-2.05)	(0.98)
" latency	0.037	-0.112**	-0.142**
	(1.25)	(-2.08)	(-2.36)
" years sick	0.079***	0.020	0.021
	(4.16)	(0.84)	(0.77)
" unexpctd. lost life years	0.013	-0.057*	-0.069*
	(0.52)	(-1.68)	(-1.83)
Choice occasion indicators	No	Yes	Yes
Observable proxies for cognitive capacity	"	"	"
Obs. measures of sociodemographics	"	"	n/a
Survey-specific health characteristics	"	"	n/a
Attention behavior controls	"	"	n/a
Constant	-	-	5.451***
			(9.92)
Observations	8807	8807	8807
LogL	-15129.47	-14646.02	-11964.89

Single equation results for the difficulty submodel

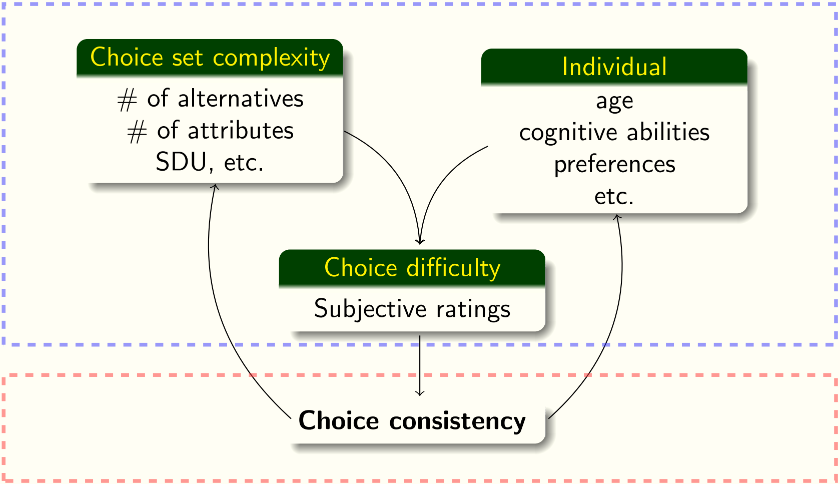
Findings:

- Std. dev. of fitted U and Entropy have no significant difference in their incremental contribution.
- Utility-space *and* attribute-space complexity are important to explaining difficulty.
- Tradeoffs between some attributes appear more difficult than others due to attribute information structure.
- Unobserved determinants matter.

Other determinants:

- Proxies for cognitive capacity:
  (1) Gradient in the effect of education; (2) Time-on-task proxy
- Testing confirms a strong decreasing trend in difficulty.
- Age(+), Ethnicity, Number of children (-), Dual income (-), Single parent (-)
- Number of prior illnesses (-); Subj risk/controllability illness (+)

Joint model


Choice set complexity
# of alternatives
# of attributes
SDU, etc.
Individual
age
cognitive abilities
preferences
etc.
Choice difficulty
Subjective ratings
Choice consistency

Choice Model		
COEFFICIENT	One Eqn.	Two Eqn.
Structural attributes:		
Linear net income term	8.831***	6.714***
	(4.87)	(4.67)
Quadratic net income term	-2.951***	-2.314***
	(-3.36)	(-3.20)
$\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-42.96***	-33.82***
	(-3.65)	(-3.36)
$\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-39.17**	-27.63**
	(-2.29)	(-2.07)
$\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-53.61***	-42.14***
	(-4.63)	(-4.25)
Heteroscedastic components:		
(neg. sign -> increase in scale)		
Difficulty (raw)	-.210**	-
	-2.544	
Difficulty (predicted)	-	-0.099
		(-1.41)
LogL	-8055.37	-8055.37

Difficulty Model	
COEFFICIENT	Two Eqn.
Measures of choice set complexity:	
(a) In utility space:	
Std. dev. of fitted U	-0.247
	(-1.32)
(b) In attribute space:	
Within-alternative attrib. correlation	
Mean std. dev.	1.568**
	(2.22)
Disp. of std. dev.	0.984**
	(2.06)
Across-alternative attrib. correlation	
Std. dev. of annualized costs	0.052
	(1.37)
" risk difference	0.043
	(0.89)
" latency	-0.120*
	(-1.75)
" years sick	0.014
	(0.44)
" unexpctd. lost life years	-0.090**
	(-2.06)
LogL	-10305.74

Notes: Cond. logit estimation for choice model (z stats in parentheses); Linear FE estimation for difficulty model (t stats in parentheses); *** p<0.01, ** p<0.05, * p<0.1; Additional covariates not shown include *Choice occasion indicators* and *Observable proxies for cognitive capacity*. Results include a total of 7392 observations.

Choice Model

COEFFICIENT	One Eqn.	Two Eqn.
Structural attributes:		
Linear net income term	8.831***	6.714***
	(4.87)	(4.67)
Quadratic net income term	-2.951***	-2.314***
	(-3.36)	(-3.20)
$\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-42.96***	-33.82***
	(-3.65)	(-3.36)
$\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-39.17**	-27.63**
	(-2.29)	(-2.07)
$\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-53.61***	-42.14***
	(-4.63)	(-4.25)
Heteroscedastic components:		
(neg. sign -> increase in scale)		
Difficulty (raw)	-.210**	-
	-2.544	
Difficulty (predicted)	-	-0.099
		(-1.41)
LogL	-8055.37	-8055.37

Difficulty Model

COEFFICIENT	Two Eqn.
Measures of choice set complexity:	
(a) In utility space:	
Std. dev. of fitted U	-0.247
	(-1.32)
(b) In attribute space:	
Within-alternative attrib. correlation	
Mean std. dev.	1.568**
	(2.22)
Disp. of std. dev.	0.984**
	(2.06)
Across-alternative attrib. correlation	
Std. dev. of annualized costs	0.052
	(1.37)
" risk difference	0.043
	(0.89)
" latency	-0.120*
	(-1.75)
" years sick	0.014
	(0.44)
" unexpctd. lost life years	-0.090**
	(-2.06)
LogL	-10305.74

Notes: Cond. logit estimation for choice model (z stats in parentheses); Linear FE estimation for difficulty model (t stats in parentheses); *** p<0.01, ** p<0.05, * p<0.1; Additional covariates not shown include *Choice occasion indicators* and *Observable proxies for cognitive capacity*. Results include a total of 7392 observations.

Choice Model		
COEFFICIENT	One Eqn.	Two Eqn.
Structural attributes:		
Linear net income term	8.831***	6.714***
	(4.87)	(4.67)
Quadratic net income term	-2.951***	-2.314***
	(-3.36)	(-3.20)
$\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-42.96***	-33.82***
	(-3.65)	(-3.36)
$\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-39.17**	-27.63**
	(-2.29)	(-2.07)
$\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-53.61***	-42.14***
	(-4.63)	(-4.25)
Heteroscedastic components:		
(neg. sign -> increase in scale)		
Difficulty (raw)	-.210**	-
	-2.544	
Difficulty (predicted)	-	-0.099
		(-1.41)
LogL	-8055.37	-8055.37

Difficulty Model	
COEFFICIENT	Two Eqn.
Measures of choice set complexity:	
(a) In utility space:	
Std. dev. of fitted U	-0.247
	(-1.32)
(b) In attribute space:	
Within-alternative attrib. correlation	
Mean std. dev.	1.568**
	(2.22)
Disp. of std. dev.	0.984**
	(2.06)
Across-alternative attrib. correlation	
Std. dev. of annualized costs	0.052
	(1.37)
" risk difference	0.043
	(0.89)
" latency	-0.120*
	(-1.75)
" years sick	0.014
	(0.44)
" unexpctd. lost life years	-0.090**
	(-2.06)
LogL	-10305.74

Notes: Cond. logit estimation for choice model (z stats in parentheses); Linear FE estimation for difficulty model (t stats in parentheses); *** p<0.01, ** p<0.05, * p<0.1; Additional covariates not shown include *Choice occasion indicators* and *Observable proxies for cognitive capacity*. Results include a total of 7392 observations.

Findings for the joint model

Determinants of perceived difficulty

- Objective choice set complexity measures do not completely explain subjective difficulty.
- Individual characteristics, cognitive resource constraints, and other factors are also important.

Our findings suggest that subjective choice difficulty ratings can serve as a sound univariate summary of these numerous determinants of choice difficulty.

Future research and questions to address

Estimation

- In the works - generalized specification of the scale parameter in the heteroscedastic model based on the determinants of difficulty
- Potential adoption of Bayesian estimation techniques

Questions

- Would it be beneficial for researchers to employ choice tasks that are initially easy and then increase in difficulty so as to obtain higher resolution information on preferences?
- Difficulty is largest in the initial choice tasks. Should other controllable covariates of difficulty be counter-adjusted to level out difficulty for these "burn-in" choice sets? What effects would these have on the choice task "learning" of respondents?

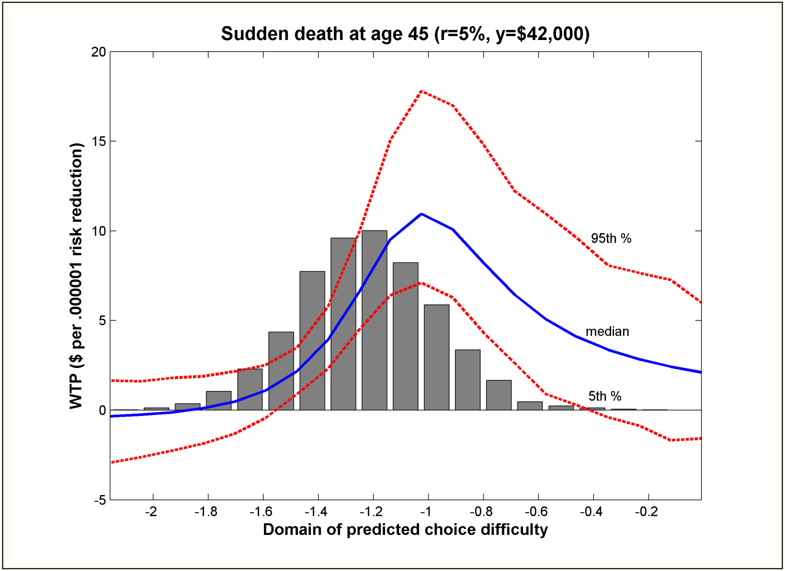
Open for questions and comments.

Eric Duquette
University of Oregon
eduquett@uoregon.edu

Counterfactual simulations of WTP

COEFFICIENT	Model 2	Model 3	Model 4		
Structural attributes:				**x Diff**	**x Diff^2**
Linear net income term	5.355***	5.184***	3.86***	-12.0***	20.3***
	(9.19)	(8.29)	(5.14)	(4.12)	(2.75)
Quadratic net income term	-2.193***	-2.026***	-1.50***	4.45E-10	3.83E-10
	(-4.68)	(-4.29)	(2.72)	(2.14)**	(-0.68)
$\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-24.79***	-48.61***	-71.87***	-243***	211.8*
	(-4.23)	(-5.42)	(6.49)	(5.35)	(1.95)
$\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-22.16**	-16.76*	5.00***	1.101	-21.34
	(-2.37)	(-1.79)	(2.89)	(-0.15)	(-1.24)
$\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-30.71***	-598.9***	-15.88	-25.31	-214.1**
	(-6.02)	(-3.35)	(-1.35)	(-0.57)	(1.97)
$\left[P(sel)-\overline{P}\right]\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	-	3.448**	-626.4***	-973.8	-1636
		(2.38)	(2.85)	(-1.25)	(-0.72)
$age_{i0}\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-	21.08***	20.36**	20.71	66.2
		(2.90)	(2.28)	(-0.65)	(-0.73)
$age_{i0}{}^2\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-	-0.192***	-0.198***	-0.134	-0.3333
		(-2.76)	(2.31)	(-0.44)	(-0.38)
$\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-	203.536**	192*	237.9	841.1
		(2.46)	(1.89)	(-0.62)	(-0.77)
$age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-	-7.889**	-7.428*	-3.92	-29.14
		(-2.34)	(1.79)	(-0.25)	(-0.66)
$age_{i0}{}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-	0.074**	0.076*	-0.00132	0.1302
		(2.27)	(1.90)	(-0.01)	(-0.31)
$\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	-	106.782	127.3	646.4*	1471
		(1.46)	-(1.39)	(1.84)	(-1.44)
$age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	-	-4.653	-5.028	-20.82	-48.22
		(-1.63)	(-1.41)	(-1.54)	(-1.24)
$age_{i0}{}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	-	0.058**	0.0639*	0.2016	0.332
		(2.15)	(1.91)	(-1.6)	(-0.91)
Observations	22485	22485	22242		
LogL	-11687.13	-11651.51	-11354.7		

Counterfactual simulations of WTP



Effects of difficulty on WTP estimates

- There appears to be a measurable systematic effect of choice difficulty on WTP estimates.
- However, the appropriate empirical methodology for introducing the heterogeneity is unclear.
- Other methods to include context heterogeneity be more appropriate such as RPL or latent class models?

Choice submodel - Ad hoc vs. structural attributes

Revisiting the estimation of preferences:

COEFFICIENT	Model 1	Model 2
Ad hoc attributes:		
Annualized costs	-0.007***	-
	(-9.29)	
Risk difference	-50.920***	-
	(-4.40)	
Latency	0.002	-
	(1.30)	
Years sick	0.009***	-
	(3.92)	
Unexpected lost life years	0.012***	-
	(7.27)	
Structural attributes:		
Linear net income term	-	5.355***
		(9.19)
Quadratic net income term	-	-2.193***
		(-4.68)
$\Delta\Pi_i^{AS} \log(pdvi_i^A + 1)$	-	-24.793***
		(-4.23)
$\Delta\Pi_i^{AS} \log(pdvr_i^A + 1)$	-	-22.166**
		(-2.37)
$\Delta\Pi_i^{AS} \log(pdvl_i^A + 1)$	-	-30.717***
		(-6.02)
Observations	22485	22485
LogL	-11662.73	-11687.13