Bounded Rationality I: Consideration Sets

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What is Bounded Rationality?

- Start with a 'standard' economic model
  - e.g. utility maximization

$$C(A) = \max_{x \in A} u(x)$$

- If the model is wrong how can we adjust it?
- Two 'minimal' adjustments we could make
  1. Modify objective
  2. Modify constraints
- Most of behavioral economics concerned with approach 1
  - Loss aversion
  - Ambiguity aversion
  - etc
- Bounded rationality concerned with approach 2
  - Optimal behavior within some additional costs/constraints

What is Bounded Rationality?

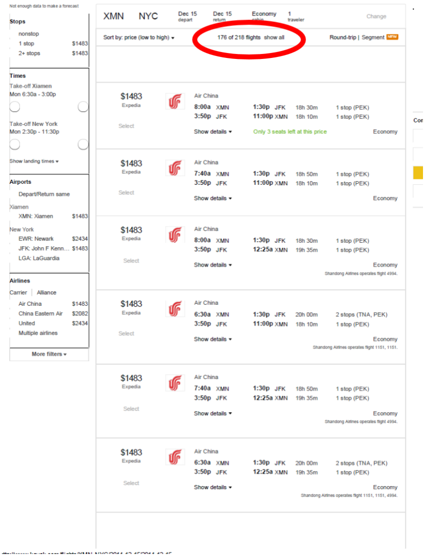
- Costs to acquiring or processing information
  - E.g. Simon [1955], Stigler [1961], Sims [2003]
- Limits on reasoning
  - E.g. Camerer [2004], Crawford [2005]
- Thinking Aversion
  - E.g. Ergin and Sarver [2010], Ortoleva [2013]
- Bounded memory
  - E.g. Wilson [2014]
- Automata
  - E.g. Piccione and Rubinstein [1993]
- Semi-Rational Models
  - E.g. Gabaix et al. [2008], Esponda [2008], Rabin and Vayanos [2010], Gabaix [2013],
- Heuristics
  - Tversky and Kahneman [1974], Gigerenzer [2000]

Advantages and Disadvantages of Bounded Rationality

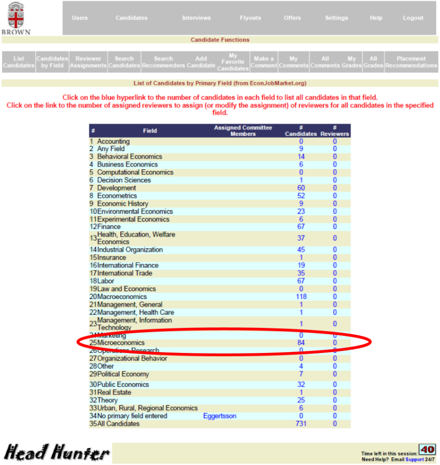
- Advantage:
  - Intuitive plausibility
    - Evolution equipped us to optimize within constraints
  - Can 'microfound' behavioral models
  - Leads to new predictions: how behavioral phenomena can change with the environment
- Disadvantages:
  - May be wrong!
  - What is correct constraint?
  - Regress issue

- Start with one particular constraint on decision making: Limits on attention
- Attention is a scare resource
- The constraint is binding in economic choice

Choice Problem 1



Choice Problem 2



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List of Candidates by Primary Field (from EconJobMarket.org)

Click on the blue hyperlink to the number of candidates in each field to list all candidates in that field.
Click on the link to the number of assigned reviewers to assign (or modify the assignment) of reviewers for all candidates in the specified field.

#	Field	Assigned Committee Members	# Candidates	# Reviewers
1	Accounting		0	0
2	Any Field		9	0
3	Behavioral Economics		14	0
4	Business Economics		6	0
5	Computational Economics		0	0
6	Decision Sciences		1	0
7	Development		60	0
8	Econometrics		52	0
9	Economic History		9	0
10	Environmental Economics		23	0
11	Experimental Economics		6	0
12	Finance		67	0
13	Health, Education, Welfare Economics		37	0
14	Industrial Organization		45	0
15	Insurance		1	0
16	International Finance		19	0
17	International Trade		35	0
18	Labor		67	0
19	Law and Economics		0	0
20	Macroeconomics		118	0
21	Management, General		1	0
22	Management, Health Care		1	0
23	Management, Information Technology		1	0
24	Marketing		0	0
25	Microeconomics		84	0
26	Operations Research		0	0
27	Organizational Behavior		0	0
28	Other		4	0
29	Political Economy		7	0
30	Public Economics		32	0
31	Real Estate		1	0
32	Theory		25	0
33	Urban, Rural, Regional Economics		6	0
34	No primary field entered	Eggertsson	0	0
35	All Candidates		731	0

Head Hunter

Time left in this session: 40
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- Choice Problem 1 and 2 are difficult
  - Lots of available alternatives
  - Understanding each available alternative takes time and effort
- Do people really think hard about each available alternative?
- The marketing literature thinks not
- Since the 1960s have made use of the concept of consideration (or evoked) set
  - A subset of the available options from which the consumer makes their choice
  - Alternatives outside the consideration set are ignored
- Some key references
  - Hauser and Wernerfelt [1990]
  - Roberts and Lattin [1991]

Consideration Sets

- What was the evidence that convinced marketers that consideration sets played an important role in choice?
  - Intuitive plausibility
  - Verbal reports (e.g. Brown and Wildt 1992)
  - Lurking around supermarkets and seeing what people look at (e.g. Hoyer 1984)
- What are the implications for choice?
  - i.e. how could we test a model of consideration set formation?
  - What are its implications?

A (Naive) Model of Choice with Consideration Sets

- Let
  - $u : X \rightarrow \mathbb{R}$ be a utility function
  - $E : \mathcal{X} \rightarrow \mathcal{X}$ describe the evoked set
    - $E(A) \subseteq A$ is the set of considered alternatives from choice problem A
- Choice is given by

$$C(A) = \arg\max_{x \in E(A)} u(x)$$

- What are the testable implications of this model?
- Nothing!
- Any data set can be rationalized by assuming utility is constant and setting $E(A) = C(A)$ for all A

A Testable Model of Choice with Consideration Sets

- In order to be able to test the consideration set model we need to do (at least) one of two things
  - Put more *structure* on the way consideration sets are formed
  - Enrich the *data* we use to test the model
- Will start by studying an approach that does a little bit of both.

Satisficing as Optimal Stopping

- Satisficing model (Simon 1955) was an early model of consideration set formation
- Very simple model:
  - Decision maker faced with a set of alternatives A
  - Searches through this set one by one
  - If they find alternative that is better than some threshold, stop search and choose that alternative
  - If all objects are searched, choose best alternative
- Proved extremely influential in economics, psychology and ecology

Satisficing as Optimal Stopping

- Usually presented as a compelling description of a 'choice procedure'
- Can also be derived as optimal behavior as a simple sequential search model with search costs
- Primitives
  - A set A containing M items from a set X
  - A utility function u: $X \rightarrow \mathbb{R}$
  - A probability distribution f: decision maker's beliefs about the value of each option
  - A per object search cost k

The Stopping Problem

- At any point DM has two options

1. Stop searching, and choose the best alternative so far seen (search with recall)
2. Search another item and pay the cost k

- Familiar problem from labor economics

- Can solve for the optimal strategy by backwards induction
- Choice when there is 1 more object to search and current best alternative has utility $\bar{u}$

1. Stop searching: $\bar{u} - (M-1)k$
2. Search the final item:

$$\int_{-\infty}^{\bar{u}} \bar{u} f(u) du + \int_{\bar{u}}^{\infty} u f(u) du - Mk$$

- Stop searching if

$$\bar{u} - (M-1)k \leq \int_{-\infty}^{\bar{u}} \bar{u} f(u) du + \int_{\bar{u}}^{\infty} u f(u) du - Mk$$

- Implying

$$k \leq \int_{\bar{u}}^{\infty} (u - \bar{u}) f(u) du$$

- Value of RHS decreasing in $\bar{u}$
- Implies cutoff strategy: search continues if $\bar{u} > u^*$ solving

$$k = \int_{u^*}^{\infty} (u - u^*) f(u) du$$

Optimal Stopping

- Now consider behavior when there are 2 items remaining
- $\bar{u} < u^*$ Search will continue
  - Search optimal if one object remaining
  - Can always operate continuation strategy of stopping after searching only one more option
- $\bar{u} > u^*$ search will stop
  - Not optimal to search one more item only
  - Search will stop next period, as $\bar{u} > u^*$

Optimal Stopping

- Optimal stopping strategy is satisficing!
- Find u^* that solves

$$k = \int_{u^*}^{\infty} (u - u^*) \, f(u) du$$

- Continue searching until find an object with $u > u^*$, then stop
- Model of underlying constrains allow us to make predictions about how reservation level changes with environment
  - u^* decreasing in k
  - increasing in variance of f (for well behaved distributions)
  - Unaffected by the size of the choice set
- Comes from optimization, not reduced form satisficing model

Optimal Stopping - Extensions and Notes

- Satisficing as Framing
  - Imagine you are provided with some ranking of alternatives
  - You believe that this ranking is correlated (arbitrarily weakly) with your preferences
  - This is the only thing you know ex ante about each alternative. (e.g. Google searches)
  - What should your search order be?
  - Should search in the same order as the ranking
  - If list is long and correlation is low
    - Ex ante difference in quality between the first and last alternative is very low
    - But you will never pick the last alternative!
- Satsificing is a knife edge case
  - If one changes the problem
    - Learning
    - Varying information costs
  - Then reservation level will change over time
  - Testable prediction about the 'satisficing' model

Optimal Stopping - Extensions and Notes

- Solubility
  - The fact that we can solve this search problem depends on its simple structure
  - Things can get hairy very quickly
    - Explore/exploit
    - Multiple attributes
  - There are some mathematical tools that can help
    - Gittens indicies
  - But often have to rely on arprroximate solutions
    - e.g. Gabaix et al [2006]

Testing Satisficing: The Problem

- Satisficing models difficult to test using choice data alone
- If search order is fixed, behavior is indistinguishable from preference maximization
  - Define the binary relation $\trianglerighteq$ as $x \trianglerighteq y$ if
    - x, y above satisficing level and x is searched before y
    - x is above the satisficing level and y below it
    - x, y both satisficing level and $u(x) \geq u(y)$
  - Easy to show that $\trianglerighteq$ is a complete preorder, and consumer chooses as if to maximize $\trianglerighteq$
- If search order changes between choice sets, then any behavior can be rationalized
  - Assume that all alternatives are above satisficing level
  - Chosen alternative is then assumed to be the first alternative searched.

Choice Process Data

- Need to either
  - Add more assumptions
  - Enrich the data
- Examples
  - Search order observed from internet data [De los Santos, Hortacsu, and Wildenbeast 2012]
  - Stochastic choice data [Aguiar, Boccardi and Dean 2016]

Choice Process Data

- We will start by considering one possible data enrichment: 'choice process' data
- Records how choice changes with contemplation time
  - $C(A)$: Standard choice data - choice from set A
  - $C_A(t)$: Choice process data - choice made from set A after contemplation time t
- Easy to collect such data in the lab
  - Possible outside the lab using the internet?
- Has been used to
  - Test satisficing model [Caplin, Dean, Martin 2012]
  - Understand play in beauty contest game [Agranov, Caplin and Tergiman 2015]
  - Understand fast and slow processes in generosity [Kessler, Kivimaki and Niederle 2016]

Notation

- How can we use choice process data to test the satisficing model?
- First, introduce some notation:
  - X : Finite grand choice set
  - $\mathcal{X}$: Non-empty subsets of X
  - $Z \in \{Z_t\}_t^{\infty}$: Sequences of elements of $\mathcal{X}$
  - $\mathcal{Z}$ set of sequences Z
  - $\mathcal{Z}_A \subset \mathcal{Z}$: set of sequences s.t. $Z_t \subset A \in \mathcal{X}$

Definition

A Choice Process Data Set (X, C) comprises of:

- finite set X
- choice function $C : \mathcal{X} \rightarrow \mathcal{Z}$

such that $C(A) \in \mathcal{Z}_A \ \forall \ A \in \mathcal{X}$

- $C_A(t)$: choice made from set A after contemplation time t

Characterizing the Satisficing Model

- Two main assumptions of the satisficing model of consideration set formation

1. Search is **alternative-based**
   - DM searches through items in choice set sequentially
   - Completely understands each item before moving on to the next
2. Stopping is due to a **fixed reservation rule**
   - Subjects have a fixed reservation utility level
   - Stop searching if and only if find an item with utility above that level

- First think about testing (1), then add (2)

- DM has a fixed utility function
- Searches sequentially through the available options,
- Always chooses the best alternative of those searched
- May not search the entire choice set

- DM is equipped with a utility function

$$u : X \rightarrow \mathbb{R}$$

- and a search correspondence

$$S : \mathcal{X} \rightarrow \mathcal{Z}$$

  with $S_A(t) \subseteq S_A(t+s)$
- Such that the DM always chooses best option of those searched

$$C_A(t) = \arg\max_{x \in S_A(t)} u(x)$$

- Key to testing the model is understanding what revealed preference means in this setting
- This is true for many models of incomplete consideration
  - Identify what behavior implies strict and weak revealed preference
  - Insist that these behaviors satisfy GARP
  - Use this to construct utility orders and consideration sets
- Possible general theorem?

Revealed Preference and ABS

- What type of behavior reveals preference in the ABS model?
- Finally choosing x over y does *not* imply (strict) revealed preference
  - DM may not know that y was available
- Replacing y with x *does* imply (strict) revealed preference
  - DM must know that y is available, as previously chose it
  - Now chooses x, so must prefer x over y
- Choosing x and y at the same time reveals indifference
- Use $\succ^{ABS}$ to indicate ABS strict revealed preference
- Use $\sim^{ABS}$ to indicate revealed indifference

- Choice process data will have an ABS representation if and only if $\succ^{ABS}$ and $\sim^{ABS}$ can be represented by a utility function u

$$\begin{aligned} x &\succ^{ABS} y \Rightarrow u(x) > u(y) \\ x &\sim^{ABS} y \Rightarrow u(x) = u(y) \end{aligned}$$

- Necessary and sufficient conditions for utility representation GARP
  - Let $\succeq^{ABS} = \succ^{ABS} \cup \sim^{ABS}$
  - $xT(\succeq^{ABS})y$ implies not $y \succ^{ABS} x$

Theorem

Choice process data admits an ABS representation if and only if $\succ^{ABS}$ *and* $\sim^{ABS}$ *satisfy GARP*

Proof.

(Sketch of Sufficiency)

1. *Generate* U *that represents* $\succeq^{ABS}$
2. *Set* $S_A(t) = \cup_{s=1}^{t} C_A(s)$

$\square$

- Choice process data admits an **satisficing representation** if we can find
    - An ABS representation (u, S)
    - A reservation level ρ
- Such that search stops if and only if an above reservation object is found
    - If the highest utility object in $S_A(t)$ is above ρ, search stops
    - If it is below ρ, then search continues
- Implies complete search of sets comprising only of below-reservation objects

Revealed Preference and Satisficing

- Final choice can now contain revealed preference information
  - If final choice is **below-reservation** utility
- How do we know if an object is below reservation?
- If they are **non-terminal**: Search continues after that object has been chosen

Directly and Indirectly Non-Terminal Sets

- Directly Non-Terminal: $x \in X^N$ if
    - $x \in C_A(t)$
    - $C_A(t) \neq C_A(t+s)$
- Indirectly Non Terminal: $x \in X^I$ if
    - for some $y \in X^N$
    - $x, y \in A$ and $y \in \lim_{t \to \infty} C_A(t)$
- Let $X^{IN} = X^I \cup X^N$

Add New Revealed Preference Information

- If
  - one of x,$y \in A$ is in X^{IN}
  - x is finally chosen from some set A when y is not,
- then, $x \succ^S y$
  - If x is is in X^{IN}, then A must have been fully searched, and so x must be preferred to y
  - If y is in X^{IN}, then either x is below reservation level, in which case the set is fully searched, or x is above reservation utility
- Let $\succ = \succ^S \cup \succ^{ABS}$

Theorem 2

Theorem

Choice process data admits an satisficing representation if and only if $\succ$ and $\sim^{ABS}$ satisfy GARP

Experiments and Bounded Rationality

- The experimental lab is often a good place to test models of bounded rationality
- Pros
  - Easy to identify choice mistakes
  - Can collect precisely the type of data you need
  - Can control the parameters of the problem
- Cons
  - Lack of external validity?
- A good approach (and good dissertation!) is to combine
  - Theory
  - Lab experiments
  - Field experiments/non experimental data

Experimental Design

- Experimental design has two aims
  - Identify choice ‘mistakes’
  - Test satisficing model as an explanation for these mistakes
- Two design challenges
  - Find a set of choice objects for which ‘choice quality’ is obvious but subjects do not always choose best option
  - Find a way of eliciting ‘choice process data’
- We first test for 'mistakes' in a standard choice task...
- ... then add choice process data in same environment
- Make life easier for ourselves by making preferences directly observable

- Subjects choose between ‘sums’

four plus eight minus four

- Value of option is the value of the sum
- 'Full information’ ranking obvious, but uncovering value takes effort
- 6 treatments
  - 2 x complexity (3 and 7 operations)
  - 3 x choice set size (10, 20 and 40 options)
- No time limit

Size 20, Complexity 7

- ○ zero
- ○ seven minus four minus two minus four minus two plus eleven minus four
- ○ six plus five minus eight plus two minus nine plus one plus four
- ○ seven minus two minus four plus three plus four minus three minus three
- ○ seven plus five minus two minus two minus three plus zero minus two
- ○ six plus seven plus six minus two minus six minus eight plus four
- ○ six plus two plus five minus four minus two minus seven plus three
- ○ six minus four minus one minus one plus five plus three minus six
- ◉ two plus six plus seven minus two minus four minus two plus zero
- ○ two minus three minus five plus nine minus one plus five minus three
- ○ three plus zero plus two plus zero plus one minus three minus one
- ○ four plus three plus zero minus two plus three plus four minus ten
- ○ seven plus two plus seven minus seven plus three minus two minus two
- ○ three plus three minus two plus zero plus zero minus four plus five
- ○ two minus two plus zero plus nine minus two minus one minus one
- ○ three plus four minus three plus three minus four plus three minus four
- ○ three plus five plus seven plus five minus two minus seven minus ten
- ○ three plus six minus eight plus one plus two minus two plus zero
- ○ three plus five plus zero plus four plus three minus four minus two
- ○ eight minus one plus one minus four minus four minus five plus six
- ○ four minus five plus four minus one minus four plus zero plus four

Finished

Failure rates (%) (22 subjects, 657 choices)

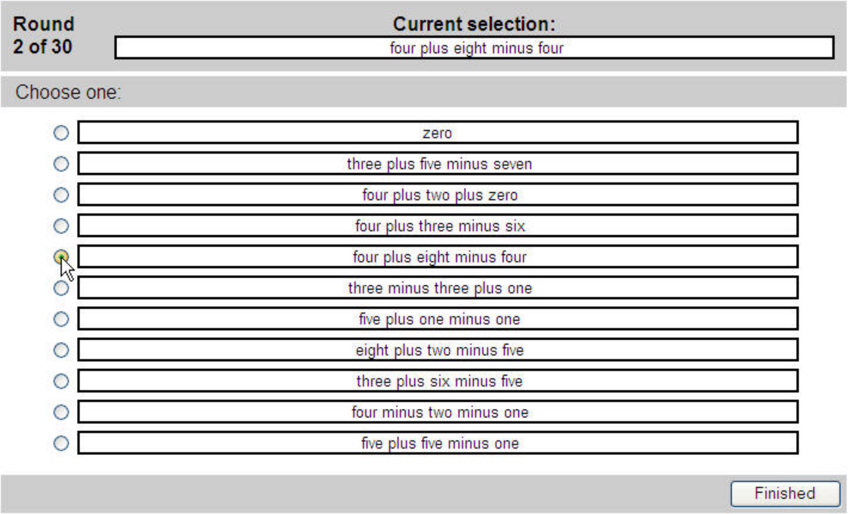
Failure rate		
	Complexity	
Set size	3	7
10	7%	24%
20	22%	56%
40	29%	65%

Average Loss ($)		
	Complexity	
Set size	3	7
10	0.41	1.69
20	1.10	4.00
40	2.30	7.12

Eliciting Choice Process Data

1. Allow subjects to select any alternative at any time
   - Can change selection as often as they like
2. Choice will be recorded at a random time between 0 and 120 seconds unknown to subject
   - Incentivizes subjects to always keep selected current best alternative
   - Treat the sequence of selections as choice process data
3. Round can end in two ways
   - After 120 seconds has elapsed
   - When subject presses the 'finish' button
   - We discard any rounds in which subjects do not press 'finish'

Stage 1: Selection



Stage 2: Choice Recorded

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Choice Recorded

In this round, your choice was recorded after **9** seconds. At that time, you had selected:

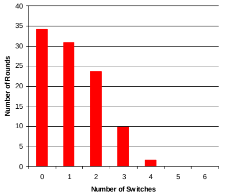
four plus four minus six

Next

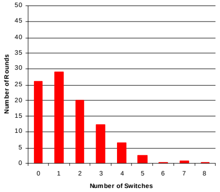
Do We Get Richer Data from Choice Process Methodology?

978 Rounds, 76 Subjects

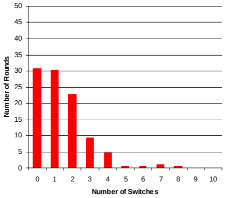
10 Options, Complexity 3



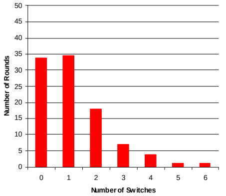
20 Options, Complexity 3



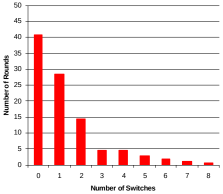
40 Options, Complexity 3



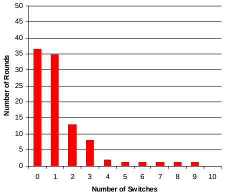
10 Options, Complexity 7



20 Options, Complexity 7



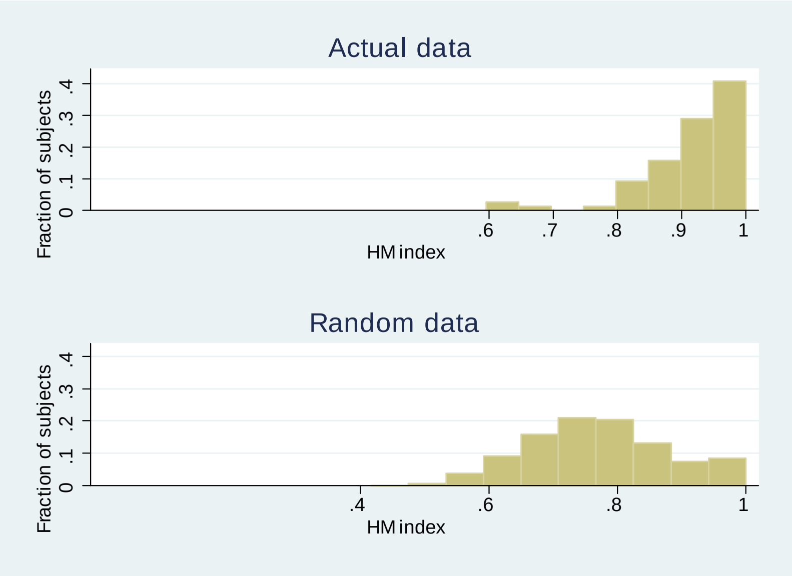
40 Options, Complexity 7



Testing ABS

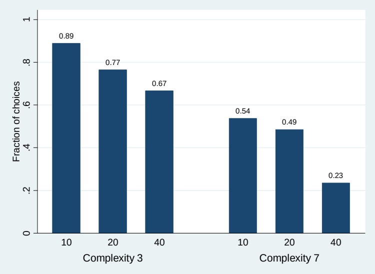
- Choice process data has ABS representation if $\succ^{ABS}$ is *consistent*
- Assume that more money is preferred to less
- Implies subjects must always switch to higher-valued objects **(Condition 1)**
- Calculate Houtman-Maks index for Condition 1
    - Largest subset of choice data that is consistent with condition

Houtman-Maks Measure for ABS

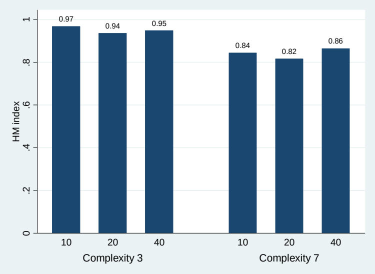


Traditional vs ABS Revealed Preference

Traditional

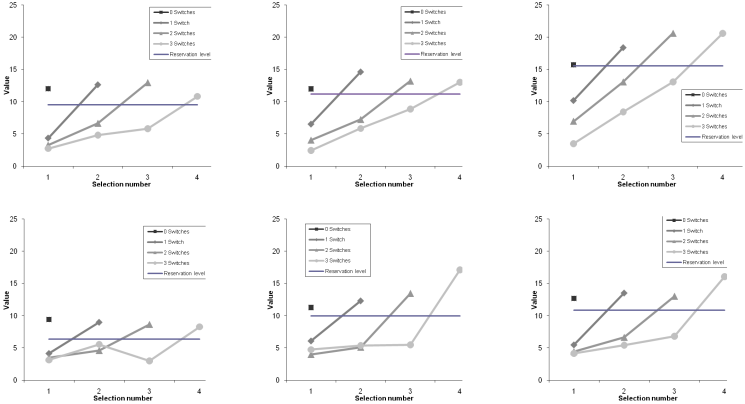


ABS



Satisficing Behavior

10 20 40



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Estimating Reservation Levels

- Choice process data allows observation of subjects
  - Stopping search
  - Continuing to search
- Allows us to estimate reservation levels
- Assume that reservation level is calculated with some noise at each switch
- Can estimate reservation levels for each treatment using maximum likelihood

Estimated Reservation Levels

	Complexity			
Set size	3		7	
10	9.54	(0.20)	6.36	(0.13)
20	11.18	(0.12)	9.95	(0.10)
40	15.54	(0.11)	10.84	(0.10)

Estimating Reservation Levels

- Increase with 'Cost of Search'
  - In line with model predictions
- Increase with size of choice set
  - In violation of model predictions
- See Brown, Flinn and Schotter [2011] for further insights

Masatlioglou et. al. [2012]

- Model choice with consideration sets using standard choice data
- Add an additional assumption to make consideration set model testable

$$E(S/x) = E(S) \text{ if } x \notin E(S)$$

- Removing an item that is not in the consideration set does not affect the consideration set
- Allows the researcher to identify objects that were in the consideration set, and preferences

$$x \neq y = C(S) \neq C(S/x)$$

  implies
  - x was in $E(S)$
  - y is strictly preferred to x
- Leads to testable predictions

De los Santos et al [2012]

- Use data from internet search engines on book purchases
- Makes visible what was *searched* not just what was *chosen*
  - People often do not search all available sellers
- Use this to derive testable predictions of the satisficing model
  - Chosen item should be the last item searched, unless search is complete
  - Search should be more likely to stop after a high value (low price) alternative
- Find evidence against the satisficing model
  - Favor a model in which size of consideration set is fixed in advance

Manzini and Mariotti [2014]

- Model choice with consideration sets using *stochastic* choice data
  - $p(a, A)$: probability of alternative a chosen from set A
- Assume that every alternative has a fixed, strictly positive probability that it will be included in the consideration set
  - There is a default alternative which is always considered
- As usual, chosen item is the highest utility alternative in the consideration set.
- Allows preferences to be identified

$$\frac{p(a, A/b)}{p(a, A)} > 1 \Leftrightarrow u(b) > u(a)$$

- Provides testable predictions: e.g.

$$\frac{p(a, A/b)}{p(a, A)} > 1 \Rightarrow \frac{p(b, A/a)}{p(b, A)} = 1$$

Abaluck and Adams [2017]

- There is also a significant literature on this in consumer choice/IO
- Recent example is Abaluck and Adams [2017]
  - Also surveys previous literature
- Consideration sets can lead to violations of **Slutsky Symmetry**
  - Absent income effects the following should be equal
    - The impact of a price change in good j on demand for good i
    - The impact of a price change of good i on demand for good j

- Simple example:
  - Two products, 0 and 1
  - x_j price of good j
  - 0 is default - always observed
  - 1 is alternative - whether it is looked at depends on the price of 0
  - $\mu(x_0)$ probability that good 1 will be looked at give x_0

Abaluck and Adams [2017]

- $s_i^*(x_0, x_1)$ probability of buying good i given prices **if both are observed**
  - Derived from maximizing a quasilinear utility function
  - Probabalistic due to some random utility component
- $s_i(x_0, x_1)$ probability that good i is chosen:

$$\begin{aligned} s_0(x_0, x_1) &= (1 - \mu(x_0)) + \mu(x_0) s_0^*(x_0, x_1) \\ s_1(x_0, x_1) &= \mu(x_0) s_1^*(x_0, x_1) \end{aligned}$$

- Claim: with quasi-linear utility and no outside option

$$\frac{\partial s_0^*(x_0, x_1)}{\partial x_1} = \frac{\partial s_1^*(x_0, x_1)}{\partial x_0}$$

- What if consideration is imperfect?

$$\begin{aligned}
\frac{\partial s_0(x_0,x_1)}{\partial x_1} &= \mu(x_0)\frac{\partial s_0^*(x_0,x_1)}{\partial x_1} \\
\frac{\partial s_1(x_0,x_1)}{\partial x_0} &= \frac{\partial \mu(x_0)}{\partial x_0} s_1^*(x_0,x_1) + \mu(x_0)\frac{\partial s_1^*(x_0,x_1)}{\partial x_0}
\end{aligned}$$

impying

$$\begin{aligned}
\frac{\partial s_1(x_0,x_1)}{\partial x_0} - \frac{\partial s_0(x_0,x_1)}{\partial x_1} &= \frac{\partial \mu(x_0)}{\partial x_0} s_1^* = \frac{\partial \ln \mu(x_0)}{\partial x_0} s_1 \\
\frac{\partial \ln \mu(x_0)}{\partial x_0} &= \frac{1}{s_1}\left[\frac{\partial s_1(x_0,x_1)}{\partial x_0} - \frac{\partial s_0(x_0,x_1)}{\partial x_1}\right]
\end{aligned}$$

- Attention changes with prices if and only if Slutsky symmetry is violated
- Level of attention can be identified by integrating this expression

Summary

- There is good evidence that people do not look at all the available alternatives when making a choice
  - Lab experiments
  - Internet search
  - Verbal reports
  - Direct observation of search
- Pure consideration set models cannot be tested on choice data alone
- Need either more data or more assumptions
- A variety of both approaches have been applied in the literature
  - Choice process
  - Internet search
  - Stochastic choice
- As yet, no real consensus on what is the correct model of consideration set formation
  - Though we do have some hints.