The Evolution of Choice Research:

Understanding Customer Decision Making

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Vice President, Marketing Sciences

March 2008

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Commonly Asked Questions

- Will I be able to get copies of the slides after the event?

Yes

- Is this web seminar being taped so I or others can view it after the fact?

Yes

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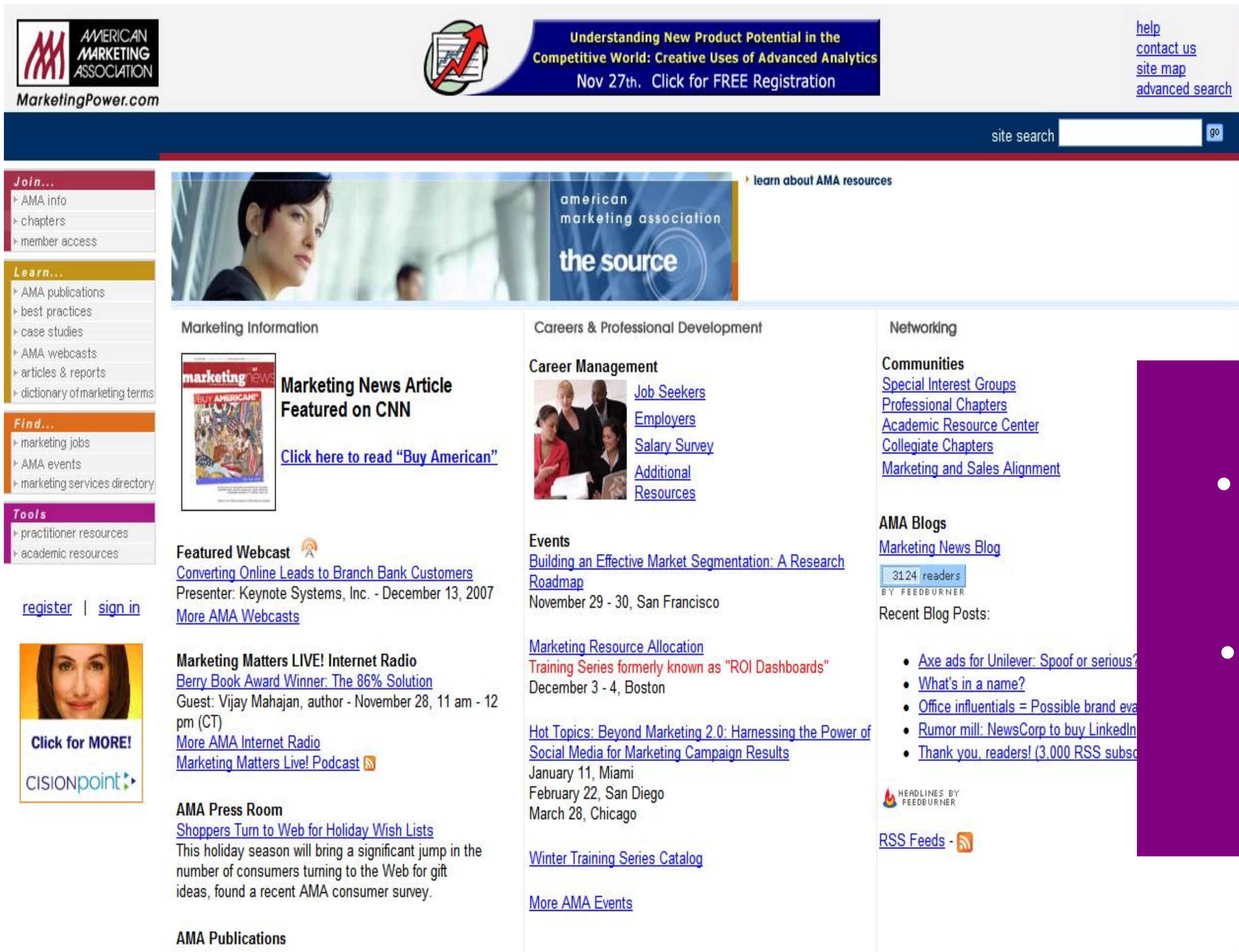

- Podcasts
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How People Choose:
Understanding Customer Decision Making

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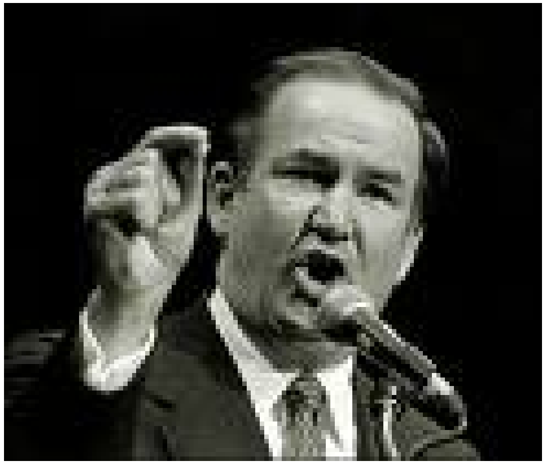
Agenda

- An offer you can’t resist
- Some history
  - *homo economicus*
  - Inconsistencies
  - Attributes
  - Bringing it all together
  - Experiments
- Dissent
- Integration
- Summary

The offer: your dream job, plus benefits



Exercise – make a choice

	Salary	Travel %	Vacation (weeks)	Bonus %
Position A	1.2	0	2	10
Position B	1.2	25	3	20
Position C	1.2	75	4	30
Position D	1.5	25	2	30
Position E	1.5	75	3	10
Position F	1.5	0	4	20
Position G	1.8	75	2	20
Position H	1.8	0	3	30
Position I	1.8	25	4	10

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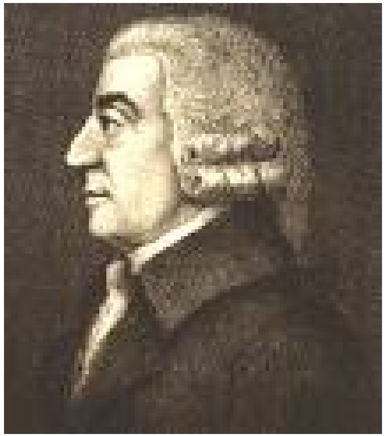
Polling question

- Which of these best describes how you made your choice?
  1. I attached a weight to each attribute and then multiplied each level times its weight, then summed the products and chose the alternative with the highest score
  2. I chose the options with the feature I liked best, and then resolved ties by choosing the options with the next most important feature and so on
  3. I eliminated options that lacked something I wanted, then eliminated options that lacked something else I wanted
  4. Some combination of 1-3 above

A convenient fiction – *homo economicus*

- Rational economic man wants to attain his goals, as completely as possible, in the most efficient (lowest cost) way, subject to whatever constraints face him
- He's "utility maximizer" who always chooses the alternative with the highest utility to him
  - If two banks are alike in all other ways except one offers him free checking, he chooses the bank with free checking
  - If two hotels are equivalent in all other ways but one offers him a perk he likes, he chooses the brand offering the perk
- Many of us behave like rational economic man, much of the time



Choices can be inconsistent

- Faced with identical choices, a person may chose differently at one time than at another
- Where does this indeterminacy come from?
  - Maybe our measures of utility are imperfect
  - Maybe the choice process is inherently probabilistic

Random utility

- Imperfect utility measures
  - Maybe people always choose the highest utility alternative at the time, but utilities change a little from one time to the next (Thurstone 1927)
  - Or maybe our measures of utility are incomplete (there are unmeasured attributes or taste variations or other measurement errors)
- The utility we measure may differ by some small random amount ε from the utility at the time of choice
- This ε is randomly distributed, so models following Thurstone are called "random utility models"

Probabilistic choice

- Luce (1959): maybe people are only *proportionally* more likely to choose the thing with highest utility for them
- The Choice Axiom: a simple ratio of utilities might be related to brand choice:

$$ShareA = \frac{f(U_A)}{f(U_A) + f(U_B) + \ldots f(U_n)}$$

- So, how might a brand lose share, even while increasing its satisfaction scores?

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Pigeons are simple creatures

- Work at the Harvard Pigeon lab discovered the Matching Law: for pigeons, Luce's equation works when f is frequency with which pecking at a feeder gets a pigeon food
- People are more complicated

Actionability through attributes

- We don’t just want to understand the utility of our brands, we want to know how to improve their utility – “actionability”
- An economist named Lancaster (1966) suggested viewing the utility of a brand as the weighted sum of the utilities of the attributes that describe it:

$$U = b_1 x_1 + b_2 x_2 + \ldots b_k x_k$$

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Tying it all together

- Dan McFadden won the 2000 Nobel prize in Economics in part for his work bring all the pieces together into the multinomial logit (MNL) model:

$$ShareA = \frac{\exp(U_A)}{\exp(U_A) + \exp(U_B) + \ldots \exp(U_n)}$$

and

$$U = b_1 x_1 + b_2 x_2 + \ldots b_k x_k$$

A messy world

- In any brand image study, we have the brand shares and we have brand attribute ratings, so we can run MNL
- But the real world is a messy place
  - The halo effect and other correlation effects add noise to the attribute measures, and this in turn adds error to MNL analysis
  - Limited variation across brands - we are unlikely to observe poor performance on table stakes attributes (those brands are already out of business)
  - Existing brands do not include future attributes

Add experimental control

- In 1983, Jordan Louviere and George Woodworth married MNL with an experimental design theory
- The result is choice-based conjoint analysis, AKA discrete choice experiments
- Now we can run MNL models of choice that control variance, that avoid the correlation effects and that allow future attributes
- Now choice research is *really* actionable

Rat troubles

- So far, we've assumed that choices are "compensatory"
  - Because the attribute utilities are additive, doing poorly on one of them can be outweighed, or compensated, by another
    - "I didn't like the color of the car, but the dealer offered better financing"
    - "It doesn't taste quite as good, but it's low in fat and high in fiber"
  - But some choices aren't like that
    - "I don't care how much they take off the price, my pizza had a RAT on it"
    - "The Samsung MP3 player has lots of great features, but it doesn't work with iTunes"
- Choices like these are called "non-compensatory"

Compensatory choice example

	Salary	Travel %	Vacation (weeks)	Bonus %
Position A	1.2	0	2	10
Position B	1.2	25	3	20
Position C	1.2	75	4	30
Position D	1.5	25	2	30
Position E	1.5	75	3	10
Position F	1.5	0	4	20
Position G	1.8	75	2	20
Position H	1.8	0	3	30
Position I	1.8	25	4	10

Compensatory choice example

	Salary .3333	Travel % -.01	Vacation (weeks) 1.00	Bonus % 0.1	Utility
Position A	1.2	0	2	10	3.40
Position B	1.2	25	3	20	5.15
Position C	1.2	75	4	30	6.65
Position D	1.5	25	2	30	5.50
Position E	1.5	75	3	10	4.75
Position F	1.5	0	4	20	6.50
Position G	1.8	75	2	20	4.6
Position H	1.8	0	3	30	6.60
Position I	1.8	25	4	10	5.60

Non-compensatory models

- Some non-compensatory models (Green and Wind 1973)
  - Lexicographic
  - Disjunctive
  - Conjunctive
- Amos Tversky (1972) proposed a non-compensatory model he called Elimination by Aspects (EBA)
- EBA models have been too computationally intensive to calculate
- Recently three academic efforts have produced computationally feasible EBA or EBA-like non-compensatory models
  - Batsell's EBA
  - Gilbride and Allenby's conjunctive/disjunctive model
  - Swait's soft cutoff model

Lexicographic choice model

- Sequential – considers attributes one at a time
- Look for top score on most important attribute
- If a tie, look for top score on next most important attribute
- Continue until you identify a single winner
- Example – Jones prefers salary first, then vacation, then bonus and finally amount of travel

Jones first cut on salary

	Salary	Travel %	Vacation (weeks)	Bonus %
Position A	**1.2**	**0**	**2**	**10**
Position B	**1.2**	**25**	**3**	**20**
Position C	**1.2**	**75**	**4**	**30**
Position D	**1.5**	**25**	**2**	**30**
Position E	**1.5**	**75**	**3**	**10**
Position F	**1.5**	**0**	**4**	**20**
Position G	1.8	75	2	20
Position H	1.8	0	3	30
Position I	1.8	25	4	10

Jones second cut on vacation

	Salary	Travel %	Vacation (weeks)	Bonus %
Position A	1.2	0	2	10
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Position F	1.5	0	4	20
Position G	**1.8**	**75**	**2**	**20**
Position H	**1.8**	**0**	**3**	**30**
Position I	**1.8**	**25**	**4**	**10**

Non-compensatory models for brand image studies

- Careful questionnaire construction allows a lexicographic model and also MNL
- Randy Batsell has devised a way to run EBA from deceptively simple inputs collected in a brand image survey (more on this at a later webcast)
- So now brand image studies can be used to assess how customers make brand choices, whether by compensatory or a non-compensatory choice process

Frozen pizza study

- Data collected February 2008
- 402 respondents
- Web-based survey
- 5 brands and 7 attributes of frozen pizzas
- Choice models from brand image data
- Discrete choice analysis from conjoint questions

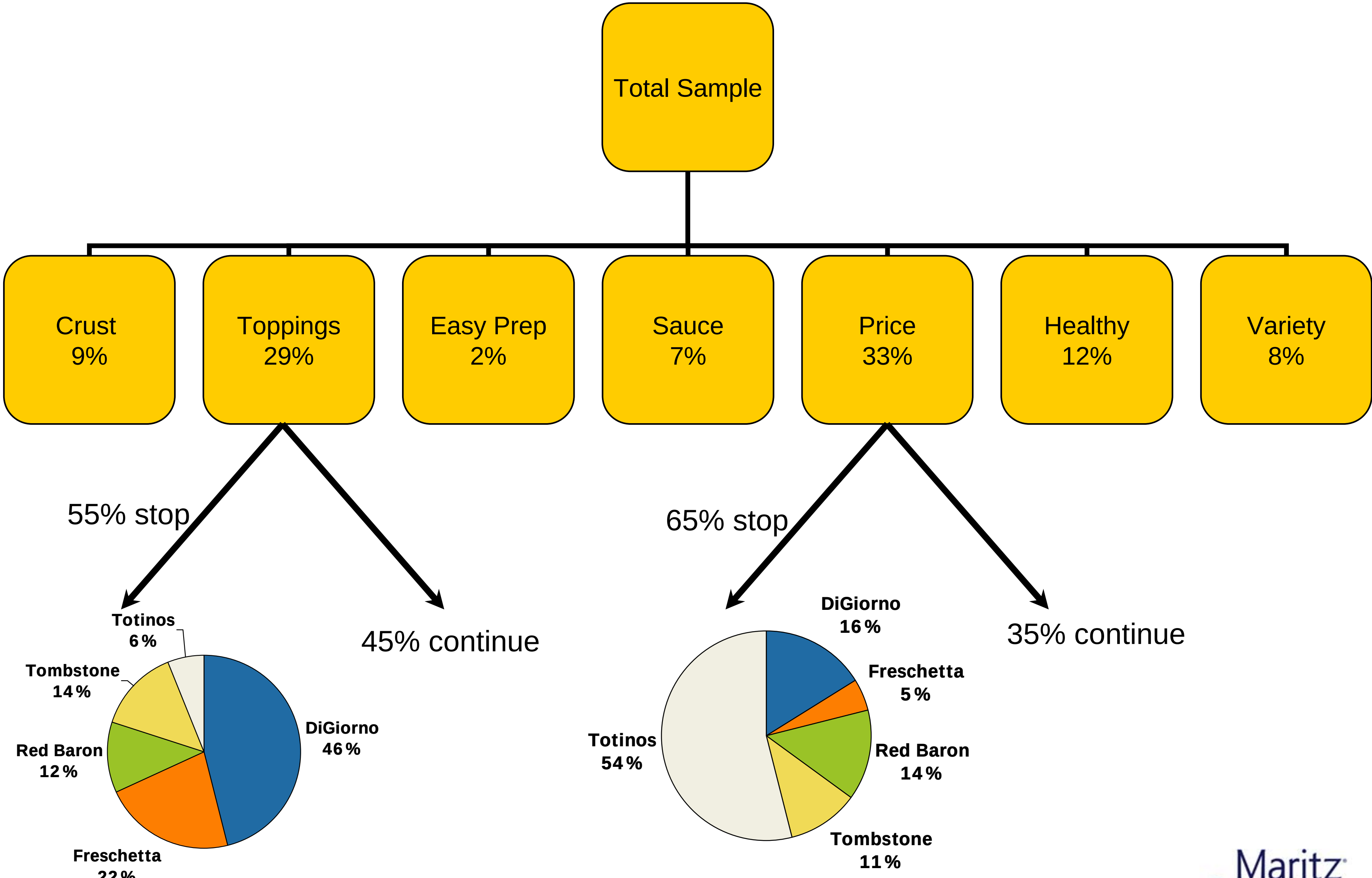
MNL vs lexicographic model for frozen pizza

- Attribute importances

Attribute	MNL	Lex	% Screening on
Toppings	.26	.28	25
Healthy	.11	.11	12
Easy	.01	.04	1
Crust	.24	.09	10
Sauce	.18	.09	9
Price	.11	.30	34
Variety	.10	.09	8

- Model fit – average probability of correct predictions
  - MNL: .48
  - Lexicographic: .52

Lecocographic model's hierarchical decision process



Non-compensatory conjoint models

- Two ways to build non-compensatory discrete choice experiments
  - Joffre Swait has developed a "soft cutoff" model that resembles EBA
    - Better-fitting than MNL
    - More accurate predictions
    - Yields additional actionable information about choice
  - Tim Gilbride and Greg Allenby have developed yet another non-compensatory model – a Bayesian conjunctive/disjunctive screening model
- We have a test of these two methods in the field that we will share at a future webcast

Standard compensatory model of frozen pizza choice

- Utilities

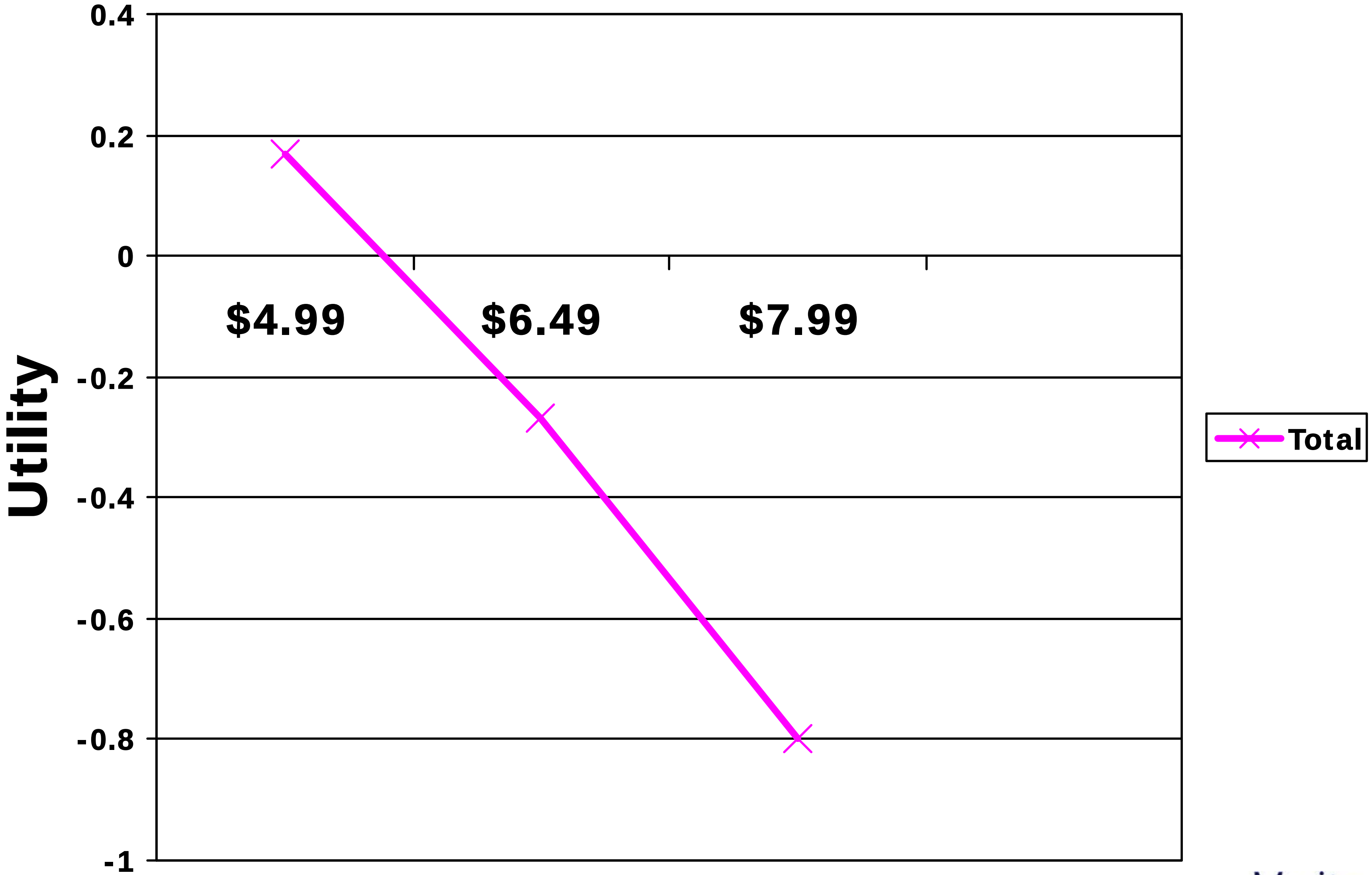
Attribute	Std
DiGiorno	.35
Freschetta	.12
Red Baron	-.08
Tombstone	-.04
Totinos	-.35
Cheese	.02
Pepperoni	.09
Veggie	-.41
Supreme	.30
. . .	
$4.99	.47
$6.49	.03
$7.99	-.50

Unique learnings from soft cutoff model

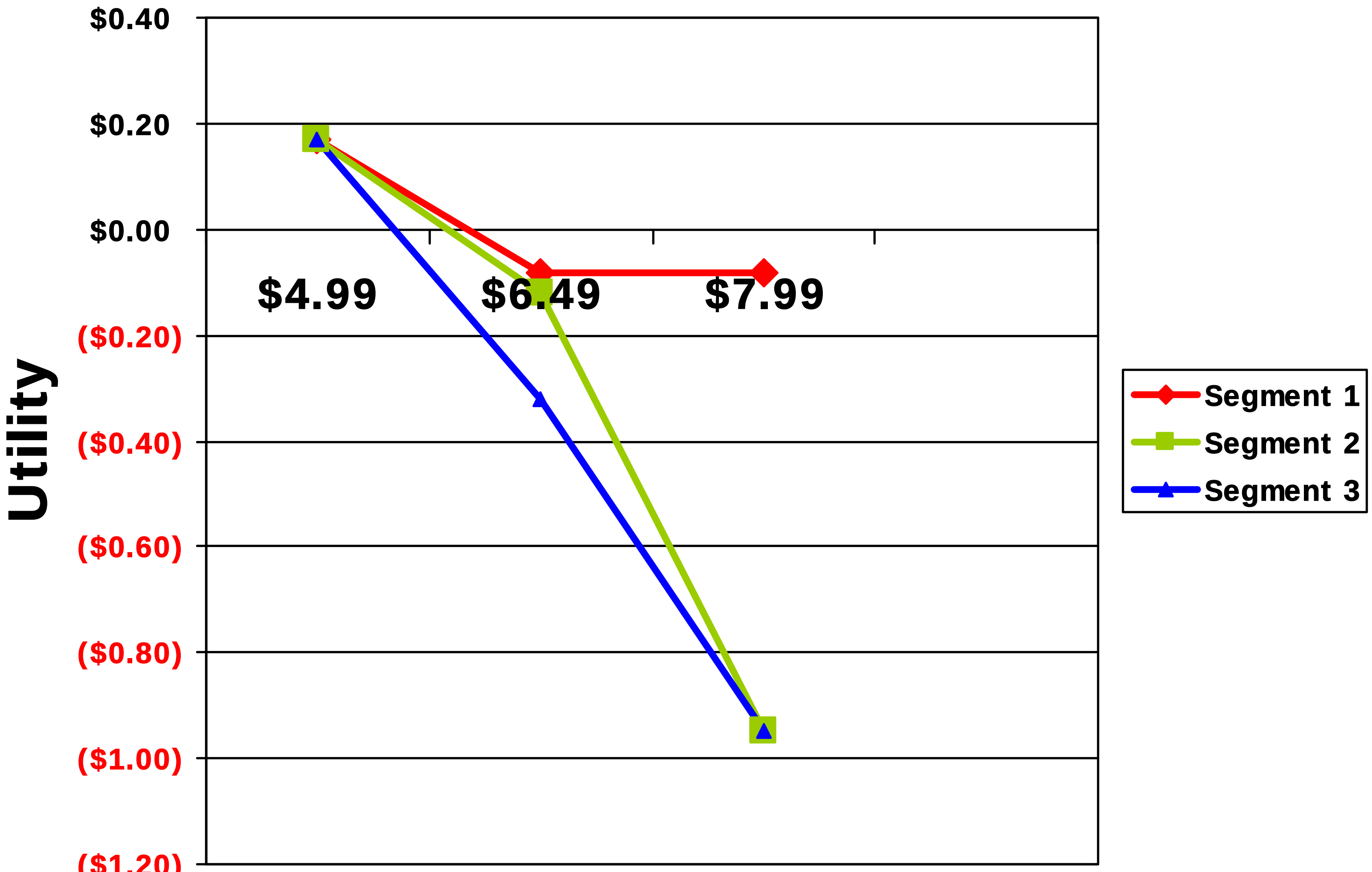
- Utilities and penalties

Attribute	Std	Base	% penalizing	Penalty
DiGiorno	.35	.34	3	-1.33
Freschetta	.12	.06	7	-.22
Red Baron	-.08	-.08	11	-1.33
Tombstone	-.04	-.08	7	-.73
Totinos	-.35	-.24	24	-1.21
Cheese	.02	-.09	14	-1.13
Pepperoni	.09	-.01	10	-1.27
Veggie	-.41	-.39	23	-1.86
Supreme	.30	.48	28	-2.14
. . .				
$4.99	.47	.17	9	-
$6.49	.03	-.12	53	-.20
$7.99	-.50	-.05	90	-.90

Total sample price sensitivity



Model reveals different price sensitivity segments



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Soft cutoff model explains better

- Better fit to choice data:
  - ρ^2 = .07 for standard choice-based conjoint model
  - ρ^2 = .18 for soft-cutoff model
- Need to test prediction of holdout data (holdout choices, holdout respondents)
- Need to compare the results of Swait's soft cutoff model with those of Gilbride-Allenby conjunctive/disjunctive model

Summary

- There’s a rich history of thought about how customers choose
- Recent innovations in modeling have improved our ability to model choices realistically
- If you understand how your customers choose, you can better understand how to influence their choices
- If you do this, $ results

Questions & Answers

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