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A Breakthrough Technique For Forecasting Markets Outside FMCG In This New Millennium

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1980s Emerged Proven Forecasting Techniques for Fast Moving Consumable Goods (FMCG) Markets

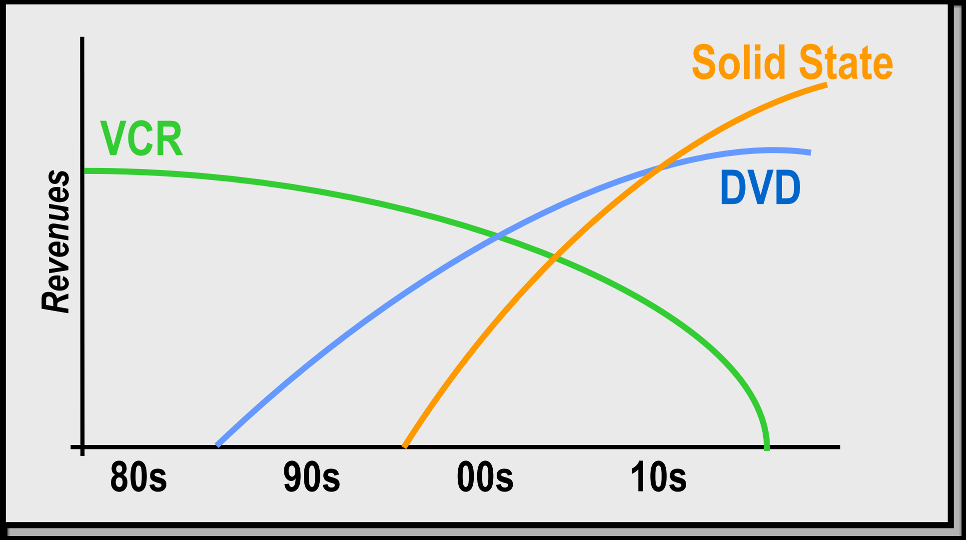
- Branded Products
  - BASES
  - MicroTest
  - Assessor
  - ESP
- Designed for FMCG categories
  - Low price points ⇒ low risk (impulse) buying
  - Short purchase cycles ⇒ trial and repeat models
  - Specific marketing levers ⇒ advertising, distribution & promotion

These Branded Services Are Inappropriate For Forecasting Markets Outside FMCG

- Decisions based upon 5-year (or more) forecasts
- More involved purchase decision requires understanding relationship between product features and price
- Competition may be among technology platforms and not just brands

Example:
Revenue Engines in Consumer Electronics

- More frequently leading to "leap frog" effect
- Complex interactive effects not solely predicted by price changes



Will these predictions become realized? What will be the driving forces?

Critical Ingredient is "Integration"

A portfolio of analyses are manufactured from an array of tools:

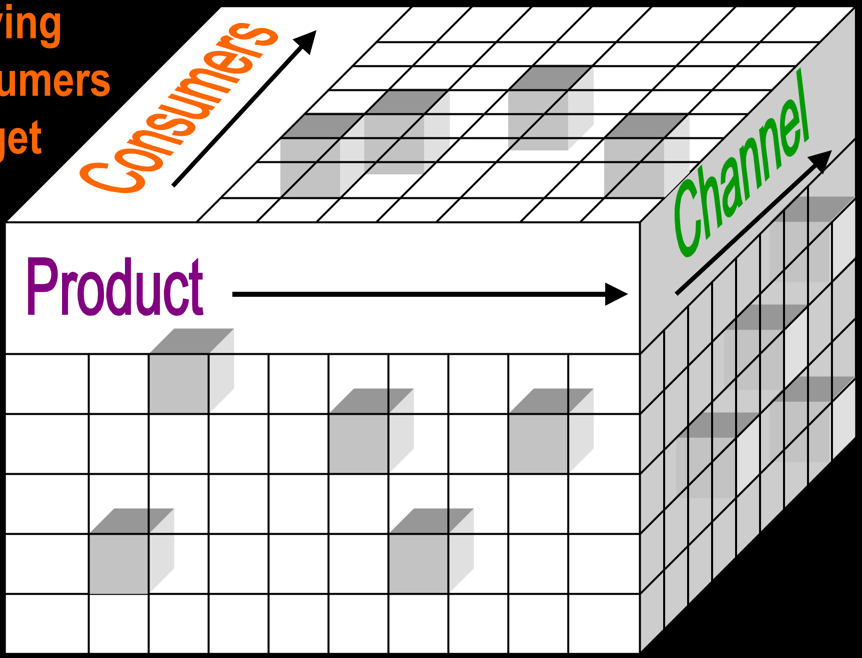
- Demand Forecasting
- Cannibalization Estimates
- Discrete Choice Analyses
- Financial Analyses

Independently, these tools offer limited value.
Working together, they offer a powerful capability.

Actionable Segmentation

A segmentation framework supports an integrated analysis.

Identifying new consumers to target

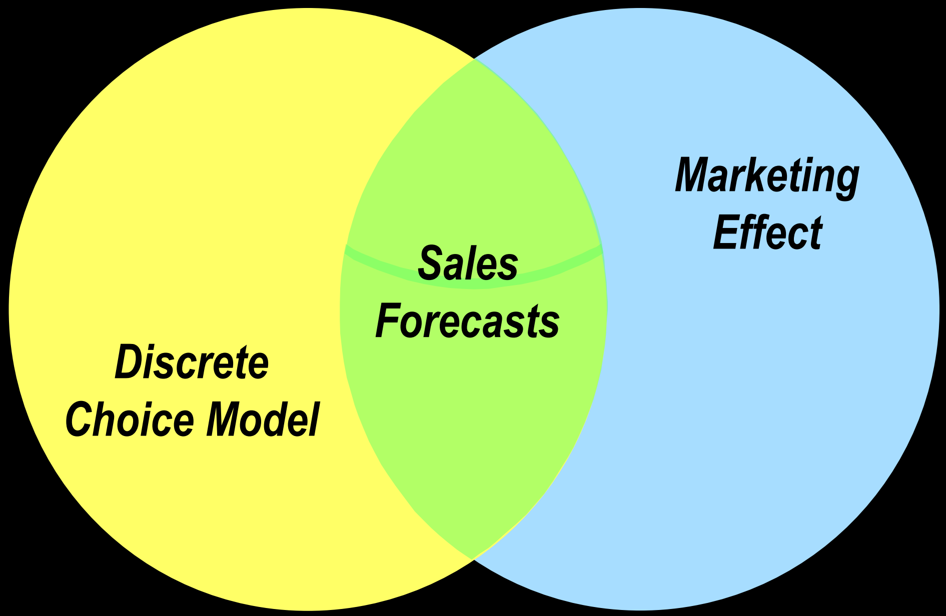


Channel Management to sell where and when consumers want it

Product Road Mapping to align needs against value propositions

Forecasting Accuracy Outside FMCG

The accuracy of forecasting models for markets, product segments and brands can be improved by *integrating* the **marketing effect** with **Discrete Choice Analysis**.



Example:
Discrete Choice Exercise

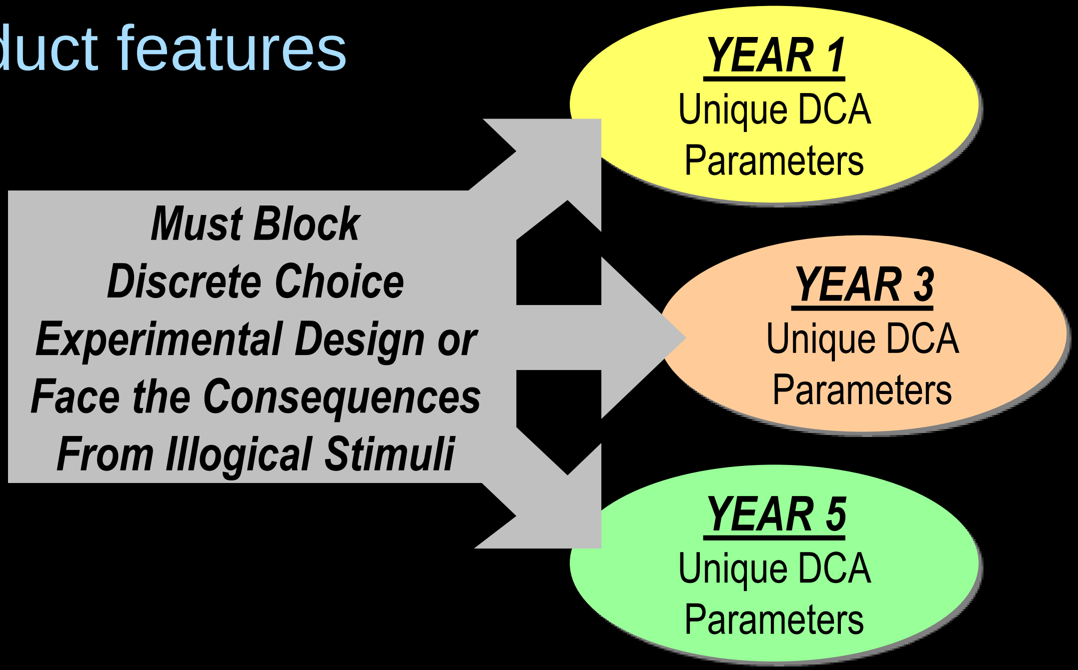
Which Smart Phone, if any, would you most likely buy?

	Nokia	*Ericsson*	*Motorola*	
Display	Large	Standard	Standard	None
Video	Yes	No	No	of
Internet	Yes	Yes	No	These
Price	1,000 DM	800 DM	500 DM	
	❑	❑	❑	❑

Discrete Choice intended to simulate "buying situation" – It differs from conjoint where focus is "trade-off"

Caution:
Markets Change Through the Years

- Considerable price erosion
- New technologies
- Evolving product features



Experience With Choice Models

- Consumers **UNDERstate** the *"No Choice"* option
- Consumers **OVERstate** *price sensitivity*
- Consumers **OVERstate** preference for *new features*

Choice models, by themselves, should not be used for predicting behavior

Overstatement Must Be Removed From The Data

Convert Discrete Choice (0,1) to “probability of choice” matrix.

Which Smart Phone, if any, would you most likely buy?

	Nokia	**Ericsson**	**Motorola**	
Display	Large	Standard	Standard	None
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Internet	Yes	Yes	No	These
Price	1,000 DM	800 DM	500 DM	
	☐	☑	☐	☐

Probability of Purchase

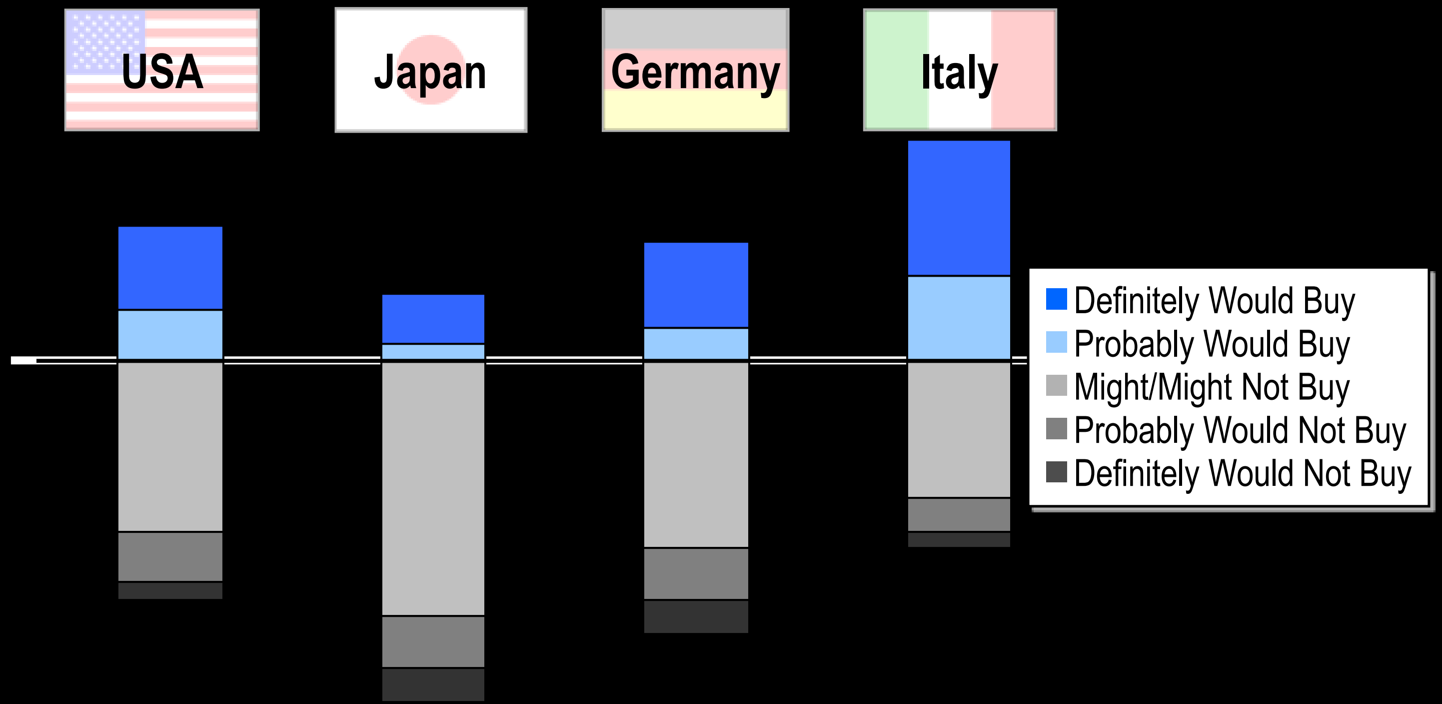
How likely would you be to buy your choice above?

- ☐ Definitely Would Buy
- ☒ Probably Would Buy
- ☐ Might/Might Not Buy
- ☐ Probably Would Not Buy
- ☐ Definitely Would Not Buy

Remove Overstatement

Many Factors Contribute to Choice Overstatement

An example of how overstatement differs by culture ...



	USA	Japan	Germany	Italy
Actual Penetration	8%	10%	9%	6%

Discrete Choice Calibration

The logit utility for a product bundle looks like:

$$U = B_O + B_P \text{ x Price} + B_2 \text{ x Feature}_1 + B_2 \text{ x Feature}_2 + \ldots + B_K \text{ Feature}_K$$

Discrete choice models should be calibrated for ...

- Overstatement to buy
- Oversensitivity to price
- Overemphasis on features

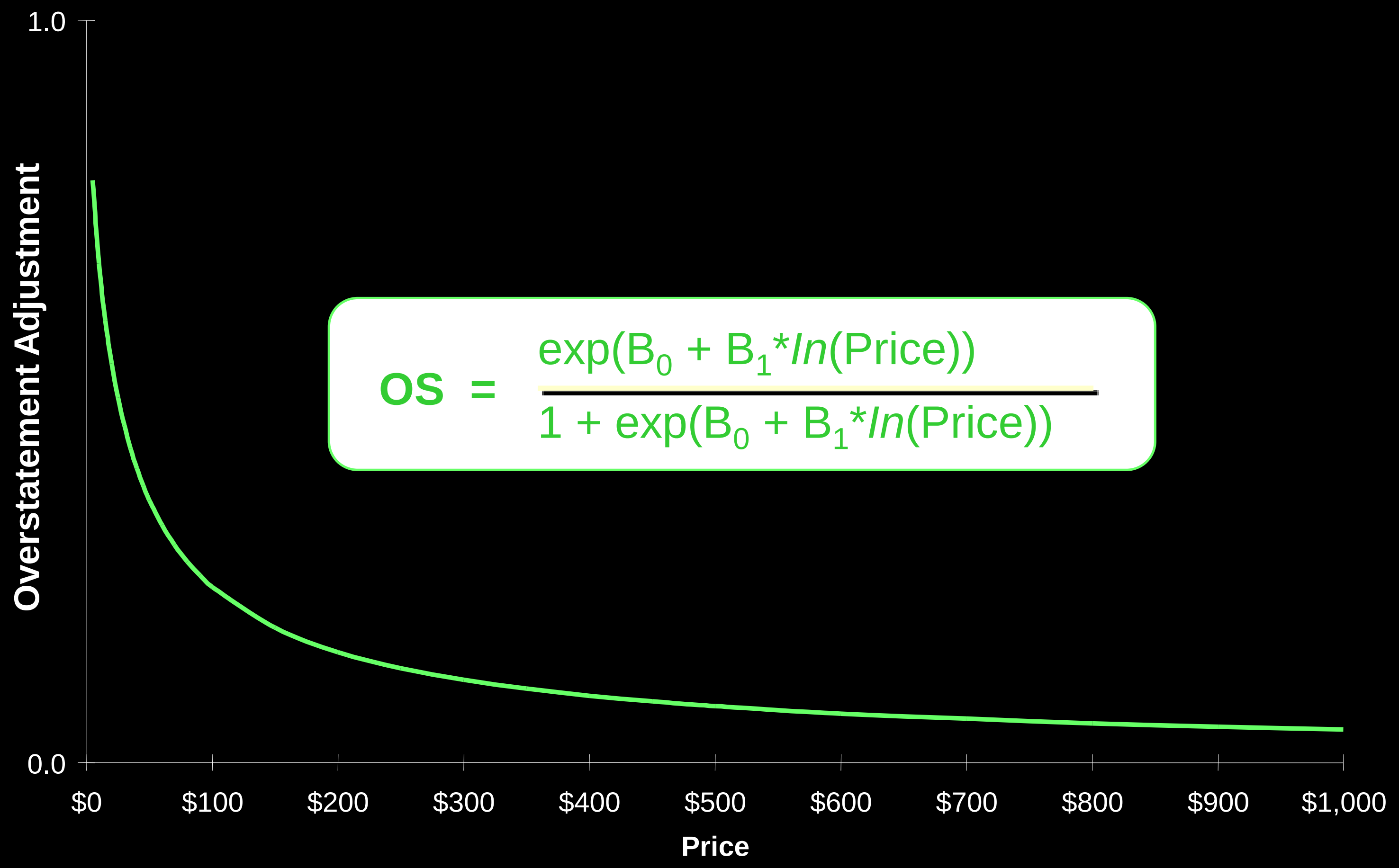
The calibrated discrete choice model looks like:

$$U = B_O - C_O + C_P \text{ x } B_P \text{ x Price} + C_F \text{ x } (B_1 \text{ x Feature}_1 + B_2 \text{ x Feature}_2 + \ldots + B_K \text{ Feature}_K)$$

Where:

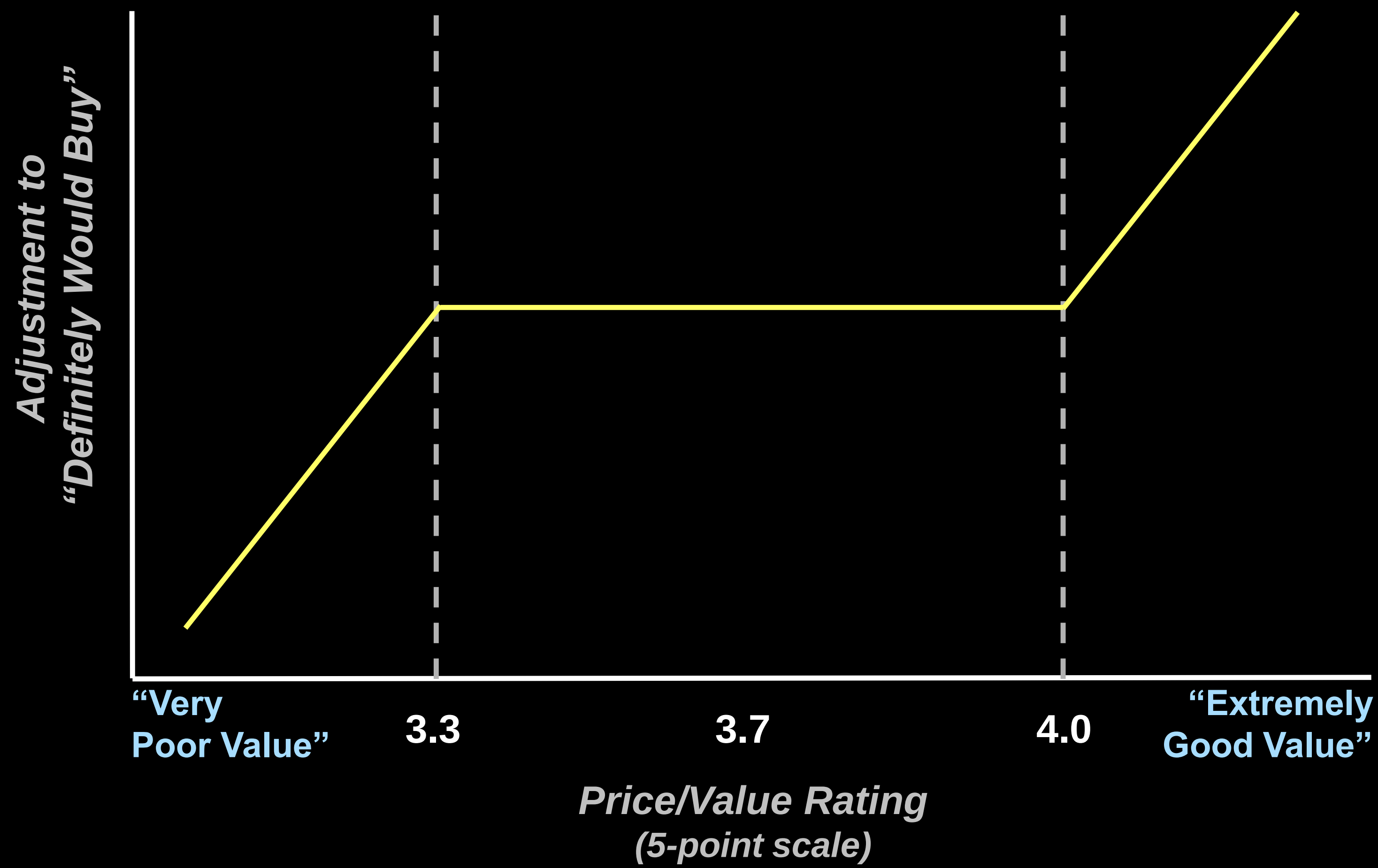
- C_O calibration removes overstatement to buy ($C_O>0$)
- C_P calibration removes oversensitivity to price ($C_P<1$)
- C_F calibration removes overemphasis on features ($C_F<1$ and usually $C_F<C_P$)

Example:
Overstatement as a Function of Price

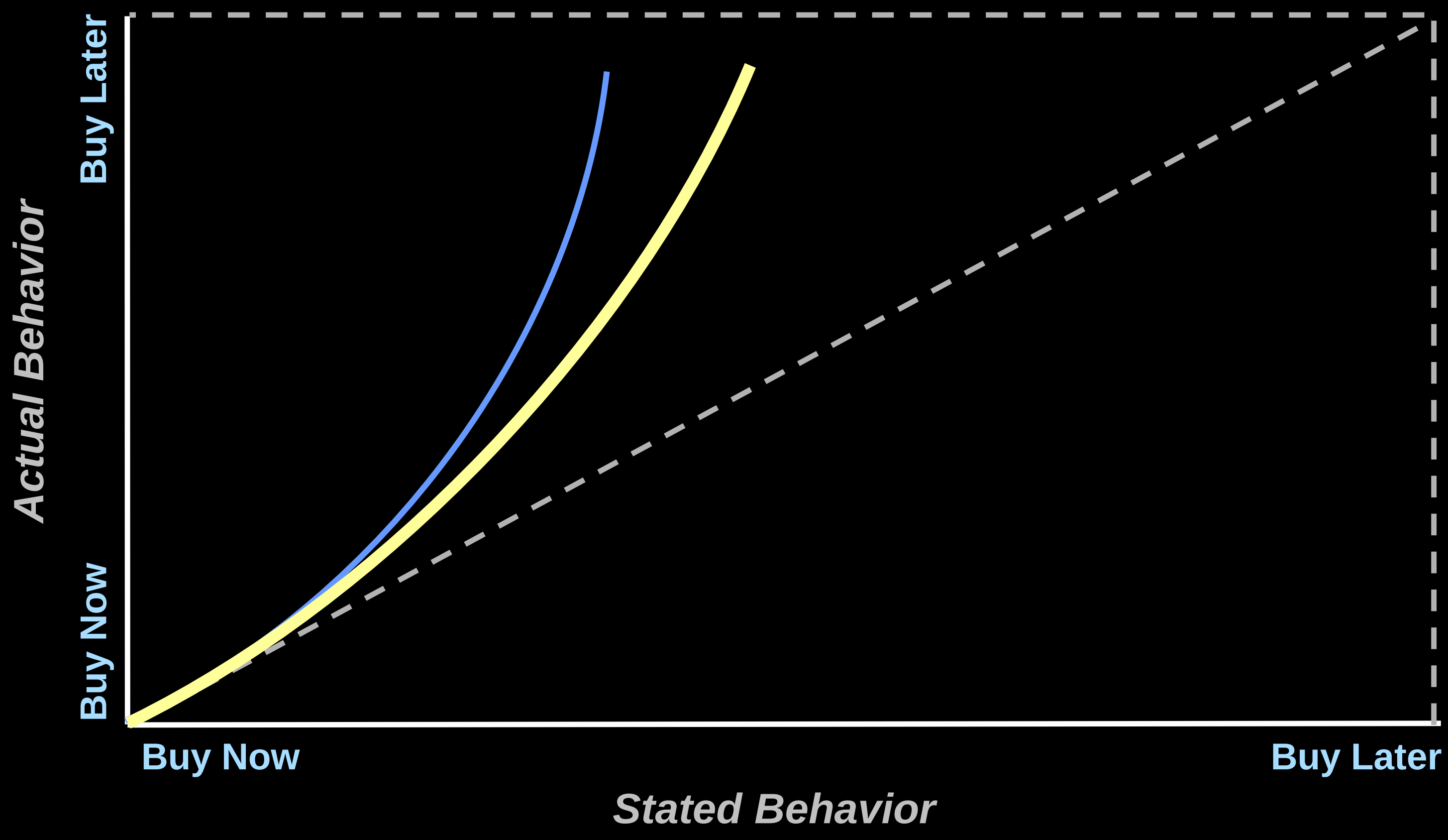


$$OS = \frac{\exp(B_0 + B_1 * \mathit{ln}(\text{Price}))}{1 + \exp(B_0 + B_1 * \mathit{ln}(\text{Price}))}$$

Greater Overstatement Adjustment With Lower Value Perceptions



Overstatement Inherent In Purchase Timing



Discrete Choice Is Only Part of the Answer

Discrete Choice Analysis can address only a subset of the variables required to model future markets:

- Technologies/Platforms
- Brand Participation
- Functionality/Features
- Pricing

Discrete Choice Analysis can predict PREFERENCE…
but more information is needed to predict SALES

Predicting Consumer Behavior

Consumer behavior can be predicted by integrating Discrete Choice Analysis with the effects of marketing ...

- Distribution
- Shelf Facings
- POS Activity
- Relative Pricing
- Promotion
- Advertising

It is the timing of these marketing effects which determines sales for markets, product segments and brands in Years 1 through 5

Effective Distribution

$$\text{EFFECTIVE DISTRIBUTION} = \underbrace{\text{A.DISTR}}_{\textit{Base}} + \underbrace{[(1-\text{A.DISTR}) \times \text{SI} \times \text{AD.AWARE}]}_{\textit{Motivated to Cross Shop}}$$

where,

A.DISTR = Actual Distribution in market

SI = Percent of relevant universe that will search for new product (Seek Information survey response adjusted for overstatement)

AD.AWARE = Percent of relevant universe made aware of category via advertising (function of co-op and mass advertising spending)

Estimating Functional Awareness Build

F.AWARE(t + 1) = F.AWARE(t) + [K - F.AWARE(t)] x COEF

where,

F. AWARE = Functional Awareness in Year 1 (function of distribution and spending)

K = Functional Awareness in Year 5 (function of segment growth and purchase probability)

COEF = $0.2 \leq \text{Range} \leq 0.5$

$$\text{COEF} = f\left[\frac{\text{Ad Spending}(t+1)}{\text{Ad Spending}(t)},\ \frac{\text{SKUs}(t+1)}{\text{SKUs}(t)},\ (1+\frac{\text{Penetration}(t+1)}{\text{Penetration}(t)}\ \text{X Uniqueness})\right]$$

Key Stages In Preparing The Forecasts

Consumer Research

- Retail store simulation
- Discrete Choice exercise
- Key drivers of demand
- Likely buyer profile

Research

Marketing Plans

- Distribution, shelf space
- Advertising support
- Retail pricing plans
- Brand participation
- Products Offered

Plans

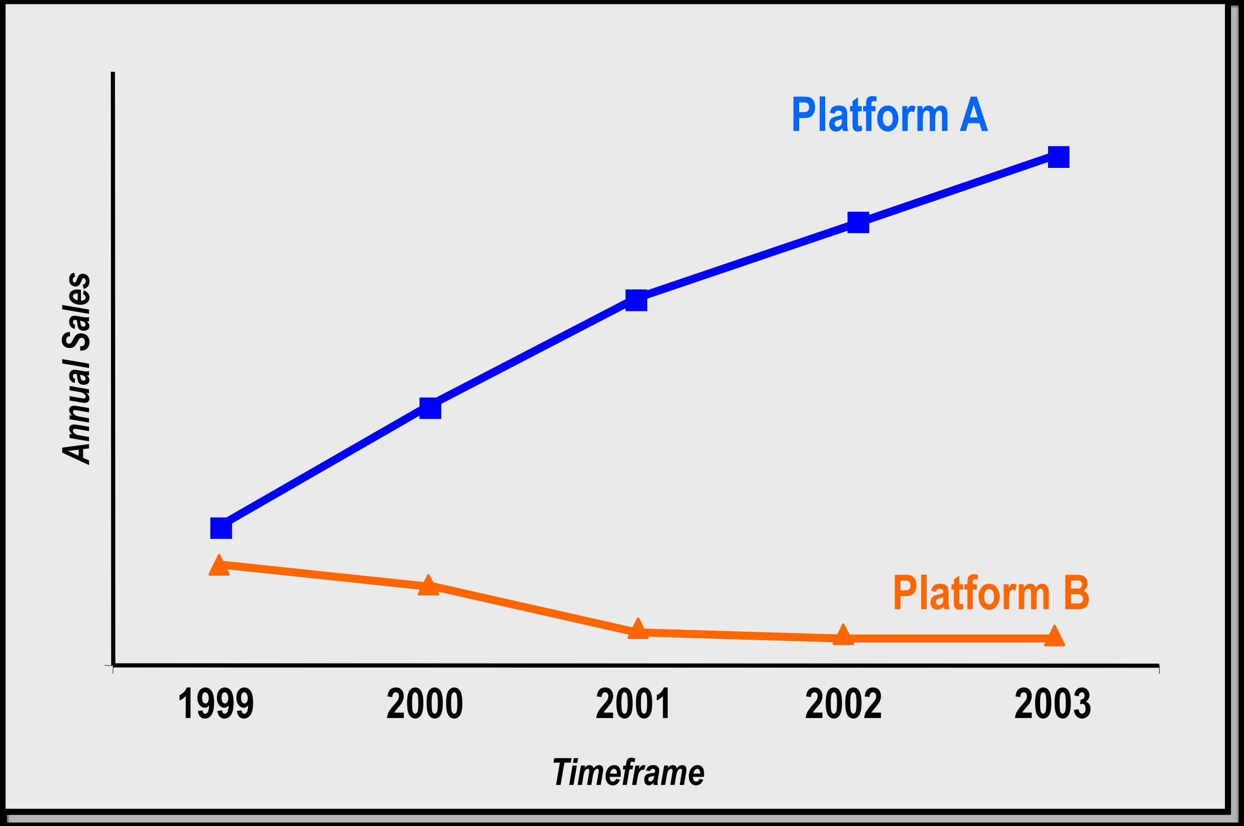
Simulations

- Using alternative plans
- Assumptions for competition
- Category forecasts
- Brand forecasts

Forecasts

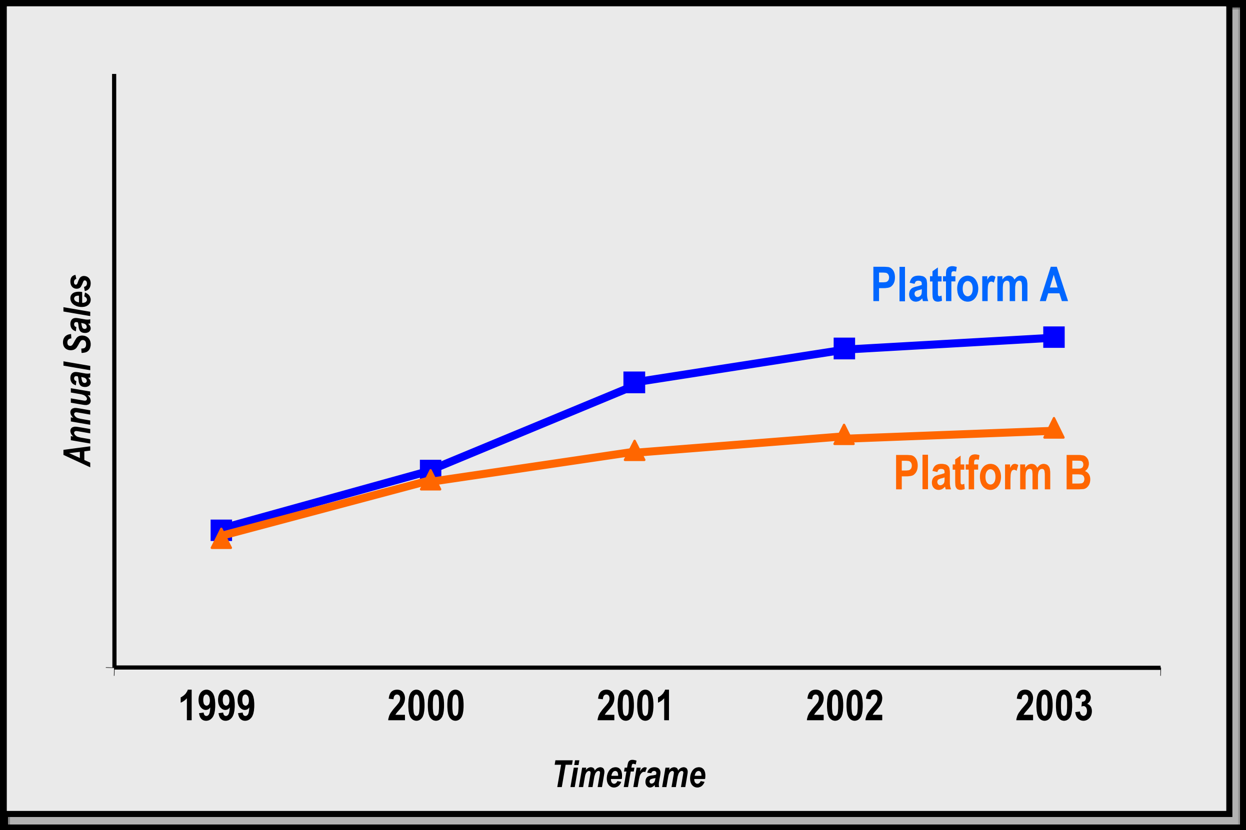
Actual Simulations of Demand

Price at Parity *and* Aggressive Marketing Plan



Actual Simulations of Demand

Priced at Premium *and* Reduced Marketing Spending



Learning From Modeling Marketing Effects

- Categories differ. Customize model to capture the buying process and marketing “levers” which drive sales.
- Tie model calibration to variables that can be tracked.
- Continuously re-calibrate model as new observations come available.
- Database your learning.

There are no “off the shelf” models … not today.