MKTG 645: Empirical Analysis of Dynamic Decision Contexts

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SYLLABUS

Next step
during Spring Break
Discuss
simple setting
2 estimate logit

Data
Basics
① predeep
② Kean & Erdem
③ logit model
understand Complexity
④ Kenneth Train book
Discrete choice

1 Introduction

This course will focus on empirical tools for analyzing dynamic decision contexts, wherein current actions of firms or consumers have effects on future payoffs, profits and/or competitive conduct. The course will build the relevant material generally, but our applications will be mostly focused on empirical marketing and industrial organization problems. The course will be oriented primarily toward empirical work, although we will cover theoretical background for each topic at varying degrees of depth, and the empirical work studied will almost always have a close tie to an economic model. We will have an applied focus overall, heavily emphasizing the practical aspects of implementation, especially programming.

⑤ Estimate
SAS, MATLab
Excel
math lab
⑥ This one later
talk about

The overall aim of the class is to help you obtain the skills to implement these methods in your research. By the end of the class, I expect you to be able to formulate a dynamic decision problem, program it in a language such as Matlab or C, and to estimate the model from data. My goals in the course are to help you (1) understand some key papers in the applied "empirical dynamics" literature (2) master key methodological developments in the field, (3) think critically about research questions and methods in the field, (4) begin to develop your own ideas for research, and (5) most importantly, get comfortable with computational dynamic programming. Our plan for the quarter will be as follows. We will start with an overview of static models of decision making. We will build on this material and introduce discrete choice markovian decision problems, and continuous markovian decision problems, and focus on building our computational toolkit for the numerical analysis of these problems. We then move on to specific applications. Finally, we will discuss recently proposed advanced methods for alleviating computational burden in dynamic models.

2 Plan for the quarter

CONSUMER THEORY

2.1 Week 1

Review of Consumer Utility Theory; The Logit Model as a Utility Maximization Problem; Discrete/Continous Demand Systems

Reading

- Hanemann W. M. (1984), "Discrete/Continuous Models of Consumer Demand", Econometrica 52:541-561.

2.2 Week 2

Modeling Consumer Demand under Multiple Discreteness. Preference for variety.

Reading

- Hendel, I. (1999) "Estimating multiple-discrete choice models: An application to computerization returns." Review of Economic Studies 66 (2), 423–446.
- J.P. Dube (2004), "Multiple Discreteness and Product Differentiation: Demand for Carbonated Soft Drinks," Marketing Science, 23 (1).
- Kim, Jaehwan, Greg M. Allenby, and Peter E. Rossi (2002) "Modeling Consumer Demand for Variety," Marketing Science, 21, 3, 229-250.

SINGLE-AGENT MODELS

2.3 Week 3

Discrete-Choice Markovian Decision Problems

Reading

- Rust, John. (1994). "Structural Estimation of Markov Decision Processes," Handbook of Econometrics, Volume 4, Chapter 51.

2.4 Week 4

Numerical Dynamic Programming: Implementation and coding. Representing a state space on a computer; Function Approximation, Interpolation, and Numerical Integration.

Reading

- Chapters from Kenneth Judd (1998), "Numerical Methods in Economics," MIT Press

2.5 Week 5

Application: Inventory accumulation and stockpiling models; dynamics of tied goods.

Reading

- Erdem, T., Imai, S. and Keane, M., (2003). "Brand and Quantity Choice Dynamics under Price Uncertainty", Quantitative Marketing and Economics, 1, 5-64.
- Hendel, I. and Aviv Nevo (2006) "Measuring the Implications of Sales and Consumer Inventory Behavior," Econometrica, November 74(6), 1637-73.
- Wes Hartmann and Harikesh Nair (2007). "Retail Competition and the Dynamics of Consumer Demand for Tied Goods."

2.6 Week 6

Continuous Markovian Decision Problems. Policy Iteration. Modified Policy Iteration. Parametric Policy Iteration. Application: Bayesian learning; Learning about a demand curve; Dynamic monopolistic advertising; Product exit; Discrete/continuous state spaces

Reading

- Rust, J. (1996). "Numerical Dynamic Programming in Economics", in Amman, H., Kendrick, D. and Rust, J. (eds.), Handbook of Computational Economics, Elsevier, North Holland.
- Rust, J. (2000), "Parametric Policy Iteration: An Efficient Algorithm for Solving Multidimensional DP Problems?", mimeo, University of Maryland
- Guenter Hitsch (2006). "An Empirical Model of Optimal Dynamic Product Launch and Exit Under Demand Uncertainty," Marketing Science, 25 (1), 25-50.

2.7 Week 7

Durable Goods. Demand for durable technology products. Dynamic models of aggregate demand.

Reading

- Melnikov, O. (2000). "Demand for Differentiated Durable Products: The Case of the U.S. Computer Printer Market", working paper, Cornell University.
- Song I. and Chintagunta, P. (2003). "A Micromodel of New Product Adoption with Heterogeneous and Forward-looking Consumers: Application to the Digital Camera Category", Quantitative Marketing and Economics 1(4), 371-407.
- Gowrisankaran, G. and Rysman, M. (2007). "Dynamics of Consumer Demand for New Durable Goods," working paper, Boston University.

Multi-agent Models

2.8 Week 8

Markov-Perfect Equilibrium. The Erickson-Pakes Model of Oligopoly. Application: Dynamic Advertising Equilibrium.

Reading of an application

- Dubé, J.P, Hitsch, G. and Manchanda, P. (2005). "An Empirical Model of Advertising Dynamics", Quantitative Marketing & Economics, 3, 107-144.

2.9 Week 9

2-Step methods for alleviating computational burden. The Hotz and Miller idea. Bajari, Benkard and Levin algorithm. Application: Technology adoption under direct network effects.

Reading

- Victor Aguirregabiria Pedro Mira (2008), "Dynamic Discrete Choice Structural Models: A Survey", forthcoming, Journal of Econometrics.
- Pat Bajari, Lanier Benkard and Jon Levin (2007)."Estimating Dynamic Models of Imperfect Competition", Econometrica, Vol. 75, No. 5, 1331–1370
- Ryan, S. and Tucker, C. (2006)."Heterogeneity and the Dynamics of Technology Adoption", working paper, MIT.

2.10 Week 10

Dynamics on both sides of the market - forward-looking consumers and firms. Applications: Durable good dynamic pricing; Pricing with network Effects.

Reading

- Harikesh Nair (2007). "Intertemporal Price Discrimination with Forward-looking Consumers: Application to the US Market for Console Video-Games" Quantitative Marketing and Economics, 5(3), 239-292
- Guenter Hitsch, Jean-Pierre Dube, Pradeep Chintagunta (2007). "Tipping And Concentration in Markets with Indirect Network Effects", working paper, University of Chicago.

2.11 Week 11

Projects due.

BLP | Pradeep Chintagunta | ①

$$P_{ijt} = \frac{e^{(\alpha_{ij} + x_{jt}\beta)}}{1+\sum_{k=1} e^{\alpha_{it}+x_{jt}\beta}}$$

household ↓ brand

observe aggregate share

$\alpha_{ij} = \alpha_j \quad \forall i \; j=1,\dots,J$

$\beta_i = \beta \; \forall i$ no hetrogentity

$$S_{jt} = \frac{\exp(\alpha_j + x_{jt}\beta)}{1+\sum^{J} \exp(\alpha_{jt} + x_{jt}\beta)}$$

$\boxed{\text{Quantity share}}$

Coke	0,33
pepsi	0,69
:	0,21
outside share	0,10

- why max likelihood works?
- model tells you P_{ij}

- aggregate data - observe share
- Gap prob model predict & observe data 0,1
- aggregate data no error
- predict share exactly
- structural Error term
- no Error in prediction

$S_{jt} \qquad 1-S_{jt}$

$\frac{S_{jt}(1-S_{jt})}{n} \xrightarrow{N\to\infty} 0$

- aggregate data no sampling Error with share
- what predict with what observe
- no variability when reconcile
- indiv. data there is variability in prediction
- ξ_{jt} is what brings variability to model

dummy

1000
0100
0010
0001

$$S_{jt} = \frac{\exp(\alpha_j + x_{jt}\beta + \xi_{jt})}{1+\sum \exp(\alpha_k + x_{kt}\beta + \xi_{kt})}$$

$$\ln\left(\frac{S_{jt}}{1-S_{jt}}\right) = \alpha_j + x_{jt}\beta + \xi_{jt}$$

Problem Correlation

Scanner data : ① price ②

② feature

③ Display

Macro level not tell

not observable — ① advertising manufact. level

② stores shelf location → store level

Question

- Correlated with price?
- Problem if firms price more adv more

- why critical src of correlation
  - ~~Sense~~ - to know some ways to find src of correlation
- Instrumental variable ① come from missing Adv or ② shelf space
  - Some instrument that capture advertising rather than price: Z_{it}
- no 2SLS rather than OLS
- Z_{it} - suck out part of x that is uncorrelated with ξ_{it}

INEVO → Cereal, everybody assume to use one bowl of cereal every day and do comparison

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when $\alpha_{ij} \neq \alpha_j$, $\beta_i \neq \beta$ → hetrogenity

$\{\alpha_{ij}, \beta_{ij}\}$ ↗ Discrete distribution ↘ Continuous distribution

Random Coefficient model

if indiv → MLE (repeated obsrvation from each household)

$$L_i = \prod_{t=1}^{T_i} \prod_{j=1}^{J} (P_{R\,ijt}|\theta_i)^{\delta_{ijt}} f(\theta_i)\, d\theta_i$$

$\delta_{ijt}=1$ if i buy j at t

all occasions of household

Conditional on random draw θ_i

estimate distrib.

$\theta_i \sim MVN(\theta, \Sigma)$ — ↓ mean, ↳ variance

unobservation → don't know same household or one buying multiple

- are you really estimating heterogeneity
- don't think at this as hetrogeneity
- You Can not estimate distribution the way you did likelihood
- aggregate

  various share in specific

  if no hetrogeneity

  iiA assump $\longrightarrow$ logit

- affect brands in specific way

  $e_{jj} + \beta(1-S_j)P_j$

  $\downarrow$

  elasticity respect own price

- if brand k change price, all other brand same pattern
- alternative $\begin{cases} \text{Probability free from IIA} \\ \text{Come from heterogenity} \end{cases}$
- with aggregate data you don't observe T_i
- no info identity of indiv

$$\int Pr_{ijt|\theta_i} * f(\theta_i)\, d\theta_i = S_{jt}$$

- You have to individually aggregate

$$\frac{S_{jt}}{S_{ot}} = \frac{\int \ldots}{\int \ldots}$$

- not nice form ratio two integral
- 1994

- previous α_j, β estimate

  here estimate $\begin{cases} \theta = \{\alpha_i, \beta\} \\ \Sigma \quad \text{Cover matrix} \end{cases}$

- ξ_{ijt} is inside Prob

  with hetrogeneity is hard

- how pull out? reduce proble you solved to use 2SLS

$$S_{it} = \int \frac{\overbrace{\exp(\alpha_j x_{jt}\beta + \xi_{it}}^{\delta_{jt}} + \overbrace{\Delta\alpha_j) + x_{jt}\Delta\beta_i}^{\Delta\mu_{ijt}}}{1 + \sum \exp(\underbrace{\alpha_k X_{kt}\beta + \xi_{kt}}_{\delta_{jt}} + \underbrace{\Delta\alpha_{ik} X_{kt}}_{\Delta\mu_{ikt}}}$$

term we had previously

$$S_{jt} = \int \frac{\exp(\delta_{jt} + \delta\mu_{ijt})}{1 + \sum_{k=1}^{K} \exp(\delta_{kt} + \Delta\mu_{ikt})} f(\theta_i) d\theta_i$$

- draw from distribution
- average over many draws

$$\Rightarrow S_{jt} = \frac{1}{D} \sum_{d=1}^{D} \frac{\exp(\delta_{jt} + \mu_{djt})}{1 + \sum_{k=1}^{K} \exp(\delta_{kt} + \Delta\mu_{dkt})}$$

as we know μ?

$\theta = MVN\{\alpha_i, \beta\} \longrightarrow D$ draws from

$\Delta\alpha_{dj} \quad j = 1, \ldots, J \quad \Delta\beta_d \sim MVN(0, \Sigma)$

$J+L$ dimensional draw

decompose sigma $\Gamma\Gamma' \longrightarrow$ choleski.

univariate draw multiply by choleski

positive semidefinite $(J+1)$ draw

take D of mv draws

we will know S_{jt}

- δ_j should be as much possible to shares of data
- big contribution: Simplity $\longrightarrow$ how to such out to become as close
- Contraction map

~~δ_j~~

- Start of with any choice of Δ - Zero
- $\delta_{jt}^{n+1} = \delta_{jt}^{n} + \ln(S_{jt}) - \ln(\hat{S}_{jt})$

  $\delta_{jt}^{1} = \delta_{jt}^{0} + \ln(S_{jt}) - \ln(\hat{S}_{jt} | \delta^{0})$

keep doing until the difference become small

$|\delta^{n+1} - \delta^{n}| < \varepsilon$

- ultimately we want to minimize ξ's

(*) outer loop: Guessing the value for Γ (lower triang. matrix)

inner loop:

1. Given $\Gamma \rightarrow$ compute δ using Contraction map

$J+L$

$\frac{(J+L)(J+L+1)}{2}$

2. Given δ run 2SLS
3. get ξ_{jt}

outer loop $\underline{\xi' Z(Z'Z)^{-1}Z'\xi}$

↓

solving correlation with instrument

not optimal weighting matrix (GMM)

for practical purpose it is good

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instrument: spot price of Coffee with lag

- replicate identity matrix (Dummy) fixed effect and stack on top of eachother

price = data

disp = data

feat = data

inst = data

** This procedure converges and we will have contraction

Structural model   March 02

(1)

10:37

- logit
- nested logit
- method of choice analysis (discrete choice)
- simulation: numerical approximation to integrals $\int$
- estimation of interactable models
- max likelihood: how works (computational perspective)
  - how code specific model
  - take existing code & change to rep. var in behavior
- use more avail code rather than write own code
- tailor-made models
- pedagogic value of programming (1) arbitrary (2) essential)

- Discrete vs. Contineous (extend)
- choice set

- behavioral process → choice
  Causal perspective
- observed factors: x
  unobserved factors: ε → density $f(\varepsilon)$
  agent's choice func: $y = h(x,\varepsilon)$
  deterministic
- Probability of particular outcome
  $P(y|x) = prob(\varepsilon \text{ s.t. } h(x,\varepsilon)=y)$

Dummy indicator: $I[h(x,\varepsilon)=y] = \begin{cases} 1 & \text{true} \\ 0 & \text{false} \end{cases}$

x & ε combine → result in y outcome

Probability of select y: $E(I)$ — Expected val of indicator over all possible values of unobserved factors:
$P(y|x) = P(I[h(x,\varepsilon)=y]=1) = \int I[h(x,\varepsilon)=y] f(\varepsilon)d\varepsilon$

Draw   Draw

(5) $\bar{t} = \int t(\varepsilon) f(\varepsilon) d\varepsilon$
expected value of t over all possible value of ε

(1) take draw ε from $f(\varepsilon)$ label ε^1
(2) check if $h(x,\varepsilon^1)=y$:
  → Yes: $I^1=1$
  → No: $I^1=0$
(3) repeat (1)(2), and cal I^r, $r=1\ldots R$
(4) Calc $\check{P}(y|x) = \frac{1}{R}\sum_{r=1}^{R} I^r$

$\check{P}$ = Proportion of times, draws of unobsrvd factors, when combined with observed factors x, results in outcome y

avg of various statistics

- Calculate choice probability from closed-form formula

take net benefit, or utility from action

$U = \beta' x + \varepsilon$ → indicator: if utility is positive
 → vector of variables
 → vector of parameters

probability of action $P = \int I[\beta' x + \varepsilon > 0] f(\varepsilon) d\varepsilon$

$f(\varepsilon) = \frac{e^{-\varepsilon}}{(1+e^{-\varepsilon})^2}$ logistic dist $F(\varepsilon) = \frac{1}{1+e^{-\varepsilon}}$

$P = \int I(\beta' x + \varepsilon > 0) f(\varepsilon) d\varepsilon = \int_{\varepsilon=-\beta' x}^{\infty} f(\varepsilon) d\varepsilon = 1 - F(-\beta' x) = 1 - \frac{1}{1+e^{\beta' x}} = \frac{e^{\beta' x}}{1+e^{\beta' x}}$

other closed form: (1) multinom logit (2) nested logit (3) ordered logit

partial simulation, partial closed form
$f(\varepsilon_1,\varepsilon_2) = f(\varepsilon_2|\varepsilon_1) \cdot f(\varepsilon_1)$ decomposition of random term
Convenient Error partitioning
analytic integral: (1) accurate (2) easier

eg mixed logit
analysis of ordered responses
binary probit

e.g. nested logit

Family of generalized extreme value models (GEV)

Discrete choice analysis:
(1) specification of behavioral model
(2) Estimation of parameters of model

data   unique setting   programming   goal

- Behavioral models
- choice probability
- utility: Constructed measure of well being

choice set
(1) mutually exclusive (not multi concurrent selections: A, B and A&B) (trick) kind of redefinition
(2) exhaustive (trick) none alternative
(3) finite # of alternatives ⇒ Restrictive
problem in Regression models

or Primary → helps release need for extra data
kind of Contiunity

RUM: Random utility model
known to decision maker
not known to researcher

V → estimate using parameters
 → Representative utility
x_{nj}: attributes of alternatives
s_n: attributes of decision maker

$V_{nj} \neq U_{nj}$ due to thing unobservable to researcher ⇒ $U_{nj} = V_{nj} + \varepsilon_{nj}$, $\forall j \neq i$

probability of choice { person: n, select alternative: i }
$P_{ni} = Prob(U_{ni} > U_{nj} \; \forall j \neq i) = Prob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj})$
$= prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall j \neq i)$

$P_{ni} = p(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \; \forall j \neq i) = \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \; \forall j \neq i) f(\varepsilon_n) d\varepsilon_n$

$I(w) = 1$ if true $= w$

P8

indogeneity (3.15) ②

① unobserved attrib of product affect price

(comfort of automobile, beauty, design) → affect price

② marketing effects can be related to prices

③ interrelated choices of decision makers

Compensate ① with price ⇒ price coeff downward bias

picks both price (neg)

& unobserved attrib (pos) ⇒ muting

① BLP

③

Iyengar 2012

Model Ram 1

Func form

$$C_{ijkst} \sim f_x(\beta_{ijkst} \sum_j \omega_{ijkst} Z_{jkst})$$

behavior or outcome

person, process, product, time

src

strength of conduit

susceptability

Bass

$$\frac{f(t)}{\bar F(t)} = p + qF(t)$$

internal force, External force

$$\simeq \frac{dN(t)}{dt} \simeq Mp + (\tilde Q - p)N(t)$$

potential MKT

cumulative # adopter @t

Jacob 2007

$$p = 1-(1-p)(1-q)^{\alpha(t)}$$

external (global)

WOM

potential adopter with x adopter neighbor

hazard rate difference

Dover 2008

$$\frac{dN(t)}{dt} = \sum_x H_x(t)\cdot(p+xq)$$

$$\Delta N_x(t) = H_x(t)(p+xq)\Delta t$$

$$\Delta H_{x\,x+1}(t) = (1-f_{x|x}(t))\,\omega(t) H_x(t)\Delta t$$

early stage:

$$\frac{dN(t)}{dt} = (M-N(t))p + qH_1(t) = Mp\left(1-\frac{k_{avg}q}{\tilde Q - 2p}\right)e^{-pt} + Mp\frac{k_{avg}q}{\tilde Q-2p}e^{(\tilde Q-3p)t}$$

$$\frac{df_{k|x}(t)}{dt} = \frac{H_{x-1}(t)}{H_x(t)}\,\omega(t)(1-f_{x-1|x}(t))(\tilde f_{k|x-1}(t) - f_{k|x}(t)) - \omega(t)(1-f_{x|x}(t))(\tilde f_{k|x}(t) - f_{k|x}(t))$$

$$\Delta H_x(t) = -\Delta N_x(t) - \Delta H_{x\,x+1}(t) + \Delta H_{x+x}(t)$$

$H_x(t)(p+xq)\Delta t$ potential adopters of order x → adopter within Δt

increase their potentiality to x+1

$$H_x(t)=0: f_{k|x}(t+\Delta t) = \frac{\Delta H_x^{(k)}(t)}{\Delta H_x(t)} = \frac{\Delta H^{(k)}_{x-1\,x}(t)}{\Delta H_{x-1\,x}(t)} = \hat f_{k|x-1}(t)$$

$$\Delta H_{x\,x+1}(t) = \frac{H_x(t)(1-f_{x|x}(t))}{\sum_z H_z(t)(1-f_{z|z}(t))}\cdot\sum_y \Delta N_y(t)\sum_k (k-y) f_{k|y}(t)$$

$$\Delta t\to 0:\ f_{k|x}(t=0) = \frac{(k-x+1)f_{k|x-1}(t=0)}{\sum_{k'}(k'-x+1)f_{k'|x-1}(t=0)}$$

AVGI $\sum_y \Delta N_y(t)\sum_k(k-y)f_{k|y}(t)$ → order y (adopter), degree k

total # potential adopters that increase their order by 1

single stage model: log likelihood

Allison 1992

$$LL = \sum_i\{c_i \ln\{Pr[T_i=t_i]\} + (1-c_i)\ln\{Pr[T_i>t_i]\}\}$$

t=1,...,T, i: actor

$$\Delta H_{x\,x+1}(t) = \frac{H_x(t)(1-f_{x|x}(t))}{\sum_z H_z(t)(1-f_{z|z}(t))}\cdot \boxed{\sum_y\Delta N_y(t)\sum_k(k-y)f_{k|y}(t)}$$ AVGI

hazard rate $P_{it} = Pr[T_i = t_i \mid T_i \ge t_i]$

$$\frac{dH_x(t)}{dt} = -(p+xq+(1-f_{x|x}(t))\,\omega(t))H_x(t) + (1-f_{x-1|x-1}(t))\,\omega(t)H_{x-1}(t)$$

y_{it}: dum{1: adopt(t), 0: otherwise}

d_{it}: dum{1: adopted, 0 « }

$$\omega(t) = \frac{\sum_y h_y(t)(p+yq)\sum_k(k-y)f_{k|y}(t)}{1-\sum_z h_z(t) f_{z|z}(t)}$$

BDM binary logit/prob (panel: i_t dependent)

$$LL = \sum_i\sum_t[1-d_{it}][y_{it}\ln\{P_{it}\} + (1-y_{it})\ln\{1-P_{it}\}]$$

$$h_y(t) = \frac{H_y(t)}{\sum_z H_z(t)},\quad f_{k|x}(t) = H_x^{(k)}(t)/H_x(t)$$ → # potential adopter of order x ntw deg k

U_{it}: eval of innov (actor i)

ϕ_{it}: utility threshold

$$f_{k|x}(t+\Delta t) = f_{k|x}(t) + \frac{\Delta H_x^{(k)}(t) - f_{k|x}(t)\Delta H_x(t)}{H_x(t)}$$

$U_{it} = V_{it} + \varepsilon_{ij}$ → Deterministic element, → stochastic element

$$\Delta H^{(k)}_{x\,x+1}(t) = \Delta H_{x\,x+1}\tilde f_{k|x}(t)$$

$$\tilde f_{k|x}(t) = \frac{(k-x)f_{k|x}(t)}{\sum_{k'}(k'-x)f_{k'|x}(t)}$$

x_{it} vector → all explanatory variables

$$\Delta N_x^{(k)}(t) = \Delta N_x(t) f_{k|x}(t)$$

α: vector of parameters to be estimated

$$P_{it} = [y_{it}=1|y_{it-1}=0] = pr[U_{it}>\phi_{it}] = pr[V_{it}-\phi_{it}\ge \varepsilon_{it}] = F(\mu\alpha x_{it})$$

positive scal parameter ~ var(ε)

ε ~ ~~Normal dis~~: probit; logistic: logit

F(u) = 1 − exp(−exp(u)) = Complementary log-log

estim indep length of time

(Nitzen et. al. 2011)

Model Ram 3

- Proportional hazard model → effect of vari. composing x_{it}

$h_i(t|x_{it}) = h_0(t) \cdot \exp(\beta' x_{it})$ → baseline hazard func

x_{it}: indiv char. @ defect t

→ hazard ratio

Variables: ① Exposure (previous defecter Existance) _ time varying (customer i @ month t) [basic & lagged]

defected, binary flag; not defected 0

$Exposure_{i,t} = \sum_{j \in SN_i} \delta_{j,t}$

immediate social network (neighbors)

② Tie Strength (volume of comm ($\sum$ sum (minutes talked, #text mssg)) 1 min of talk = 1; A or B party)

$TS_{i,j} = \frac{CommVol_{i,j}}{Total\_Comm_i}$, $j \in SN_i$

average tie strength with defecting neighbors:

$avgTS_{i,t} = \frac{\sum_{j \in SN_i} TS_{i,j} \times \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}}$, if $\sum_{j \in SN_i} \delta_{j,t} = 0 \Rightarrow avgTS = 0$

③ Homophily: percentage of similar charact. of connected

0.25 each (gender, age, segment, socio economic status)

{0, 1 less than 5 years

$avgH_{i,t} = \frac{\sum_{j \in SN_i} H_{i,j} \times \delta_{j,t}}{\sum_{j \in SN_{i,t}} \delta_{j,t}}$ focal cust i & Neighb. j

defected homophily

④ Degree: unique customers comm. with during 1st 3 month of data / average degree of defecting neighbors of focal

month t: $avgDEG_{i,t} = \frac{\sum_{j \in SN_i} DEG_j \times \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}}$

⑤ satisfaction — ① usage level change $\Delta Use_{i,t} = \frac{Use_{i,t}}{avg(Use_{i,t-1}, Use_{i,t-2}, Use_{i,t-3})}$

② # service records: total # records of problem or complaint at CR

⑥ Economic incentive (monthly): $EI_i = \frac{within\_Network\_MOU_i}{Total\_MOU_i}$

tenure: time from involvement

Model 1 (traditional)

$h_i(t|x_{it}) = f(ServiceRec_i, \Delta Use_{i,t}, avgEI_i, avgUsage_i, Tenure_i, Demography_i)$

Model 2 (social model)

$h_i(t|x_{it}) = f(Exposure_{i,t}, avgTS_{i,t}, avgH_{i,t}, avgDEG_{i,t}, Degree_i, ServiceRec_{i,t}, \Delta Use_{i,t}, avgEI_i, avgUsage_i, Tenure_i, Demography_i)$

Model 3 (lagged Exposure)

$h_i(t|x_{it}) = f(Exposure_{i,t}, Exposure_{i,t-1}, Exposure_{i,t-2}, Exposure_{i,t-3}, Exposure_{i,t-4}, avgEI_i, avgUsage_i, Tenure_i, Demography_i)$: ~~neighbors~~ previous period defected neighbor

bias overcome — demographic & usage (for intrinsic)

— time considering

— Response to external shock (environmental condition): time until event capture & not just whether event occured

— Competitive effect: advertising; Exposure to ad = monthly spending × age gender group (difference in viewership) ×16

Compare firm & Competitor

$h_i(t, x_{it}) = f(Exposure_{i,t}, avgTS_{i,t}, avgH_{i,t}, avgDEG_i, Degree_i, ServiceRec_{i,t}, \Delta Use_{i,t}, exp\_Ad\_Focal_{i,t}, exp\_Adv\_Comp_{i,t}, avgEI_i, avgUsage_i, Tenure_i, Demography_i)$

Varian 2009

lots of implication

interesting idea

③ idea: incumbent & Nesh on to learn

don't rush to literature

② you may have different approach

④ practice develop model

non Economist understand

your opportunity cost

→ Example

④ E: agents, same models

Consistent

① Constraint

② maximization

③ interaction

④ mutually Consistent

test case

utility

① 1 2 3

→ something interesting in examples?

may start from complex model

keep working until making simple

Keep it Simple Stupid

Varying parameter approach (model impact P.Struc on util.)

Model Ram 3

QTR_{jt} $(j=1,\dots,4)$ quarter dummy

$$V_{it} = \underbrace{\theta^u x_i}_{\text{tariff struc effect}} + \underbrace{\sum_{j=1}^{3} \mu_j^u QTR_{jt}}_{\text{Seasonality time effect}} + \underbrace{\sum_{j=1}^{3} \delta_j x_i \times QTR_{jt}}_{\text{how these effect vary across tariff conditions}} + \xi_i^u + \varepsilon_t^u$$

ξ_i^u: indiv specific unobserved influences $N(0, \sigma_u^2)$

ε_t^u: time specific unobserved temporal on cons pref.

New service → uncertainty about quality

Quality uncertainty & learning: $\varepsilon_t^u = \rho^u \varepsilon_{t-1}^u + \kappa_t^u$, $\kappa_t^u \sim N(0, \sigma_{\kappa u}^2)$

(Effect of past on current valu)

Satiation parameter

$$\underset{\geq 0}{\alpha_{it}} = \exp\big(\underbrace{\mu_0^c}_{\text{intercept}} + \underbrace{\theta^c x_i}_{\text{moderating}} + \lambda \log(\underbrace{q^{Actual}_{i,t-1}}_{\text{Effect of habit info}}) + \sum_{j=1}^{3} \mu_j^c QTR_{jt} + \xi_i^c\big)$$

moderating: Capture impact of tariff struct on utility TPT compared PPU

Effect of habit info: how update belief of how much to Consume in future month

ξ_i^c → indiv specific Rand Var. 4 unobserved heterogeneity

Churn help identify: intercept V_{it} & variance terms $(\sigma_{u1}^2, \sigma_{u2}^2)$

monthly churn & usage data → identify ① affected Consumption (α_{it})

② prop. income alloc telecom service (φ_{it})

Random assignment (TPT, PPU) → identify access fee effect by param θ^u, θ^c

unobserved heterogen ① repeated observation

② aided by changing price level during Experiment

state based error (keep & drop & usage decision) → Captured by time series nature of churn usage data

quarterly effects (μ's)

habit info params (λ)

- Robustness by other utility models

Vanden bult 2001 et al. (Cont.)

Spec.1: full observability (awareness & adoption)

state 0: $a_{it}=0$ no awrnss, no adpt

state 1: $a_{it}=1$ $e_{it}=0$ (awrnss, but no posit. eval no adopt)

state 2: $a_{it}=1$, $e_{it}=1$ (both awareness & positive eval. ⇒ adopt)

P_{sit} : prob i @ state(s) @ t

$$LL = \sum_j \sum_t [1-d_{it}][(a_{it}e_{it})\ln P_{2it} + a_{it}(1-e_{it})\ln P_{1it} + (1-a_{it})\ln P_{0it}]$$

assum $M_1 = M_2 = 1$: $P_{2it} = Pr[e_{it}=1, a_{it}=1 \mid y_{it-1}=0] = Pr[a_{it}=1 \mid y_{it}=0]\, Pr[e_{it}=1 \mid a_{it}=1, y_{it-1}=0]$

$= F_1(\alpha_1 x_{it1}) F_2(\alpha_2 x_{it2})$

$P_{1it} = Pr\{e_{it}=0, a_{it}=1 \mid y_{it-1}\} = Pr(a_{it}=1 \mid y_{it-1}=0]\, Pr(e_{it}=0 \mid a_{it}=1, y_{it-1}=0]$

$= F_1(\alpha_1 x_{it1})[1-F_2(\alpha_2 x_{it2})]$

$P_{0it} = Pr(a_{it}=0 \mid y_{it-1}=0] = 1-F_1(\alpha_1 x_{it1})$

$$\Rightarrow LL = \sum_i \sum_t [1-d_{it}]\big((a_{it}e_{it})\ln\{F_1(\alpha_1 x_{it1})F_2(\alpha_2 x_{it2})\} + a_{it}(1-e_{it})\ln\{F_1(\alpha_1 x_{it1})[1-F_2(\alpha_2 x_{it2})]\} + (1-a_{it})\ln\{1-F_1(\alpha_1 x_{it1})\}\big]$$

Spec2: partial observability without mem (no disting. b/w state 0 & 1) no sep. obs. e_{it}, a_{it} but only $a_{it} \times e_{it} = y_{it}$

applicant hiring (without memory) $LL = \sum_i \sum_t [1-d_{it}][y_{it}\ln\{F_1(\alpha_1 x_{it1})F_2(\alpha_2 x_{it2})\} + (1-y_{it})\ln\{1-F_1(\alpha_1 x_{it1})F_2(\alpha_2 x_{it2})\}]$

Spec3: part observ with mem (notation $F_m(\alpha_m x_{itm})$ as $F_m(t)$)

$Pr(T=1) = F_1(1)F_2(1)$, $Pr(T=2) = F_1(1)[1-F_2(1)]F_2(2) + [1-F_1(1)]F_1(2)F_2(2) = F_2(2)\{F_1(1)[1-F_2(1)] + [1-F_1(1)]F_1(2)\}$

↳ either aware 1st or second period

$$\Rightarrow Pr(T=t) = F_2(t)\sum_{s\leq t}\{\Pi_{k<s}[1-F_1(k)]\}F_1(s)\{\Pi_{s\leq q<t}[1-F_2(q)]\}$$

$$Pr(T>t) = \prod_{p\leq t}[1-F_1(p)] + [1-F_2(t)][\sum_{s\leq t}\{\Pi_{s\leq t}[1-F_1(k)]\}F_1(s)\{\Pi_{s\leq q\leq t}[1-F_2(q)]\}]$$

Model Ram 2

Vanden bult 2001

$pr[y_{it}=1 \mid y_{it-1}=0] = pr[e_{it}=1, a_{it}=1 \mid y_{it-1}=0] = pr[e_{it}=1 \mid a_{it}=1, y_{it-1}=0]\, pr[a_{it}=1 \mid y_{it-1}=0]$

a_{it}: binary indicator of whether perceptual aware @ t

e_{it}: binary indic of eval. highly?

I_{it}: amount of info exposed (media i) $= V_{it1} + \varepsilon_{it1}$ → Explanatory variables

Π_{it}: perceptual threshold $\quad V_{it1} - \Pi_{it} = \alpha_1 x_{it1}$

$Pr[a_{it}=1 \mid y_{it-1}=0] = Pr[I_{it} > \Pi_{it}] = Pr[V_{it1} - \Pi_{it} \geq \varepsilon_{it1}] = F_1(\mu_1 \alpha, x_{it1})$

$pr[e_{it}=1 \mid a_{it}=1, y_{it-1}=0] = Pr[V_{it} \geq \Phi_{it}] = Pr[V_{it2} - \Phi_{it} \geq \varepsilon_{it2}] = F_2(\mu_2 \alpha_2 x_{it2})$

---

permesh

$\frac{\partial u_i^t(n_p)}{\partial n_p} = V_i - C_t n_p = 0$

$n_{pi}^t = \frac{V_i}{c_i}, \quad i=\{L, \ell\}, \; t=\{H, L\}$

$u_i^t(n_p) = V_i n_p - \frac{1}{2} C_t (n_p)^2$

noise

$pr(k=\text{good}, n_p \mid c=l) = {}^{n_p}C_k (q_\ell)^k (1-q_\ell)^{n_p-k}$ ← being liked given it is leader

$pr(k=\text{good}, n_p \mid c=\ell) = {}^{n_p}C_k (q_\ell)^k (1-q_\ell)^{n_p-k}$

post ⓢ is good = like

Conditioning on anything variable

$\pi^{High}_{\ell\, euler} = \frac{\alpha \ell}{n_{p\ell}^{H*}+1} \sum_{k=0} P_k(n_{p\ell}^{H*})(v-c)$

Iyenger 2011 Iyenger (impact of tariff structure)

Y_{it} < 1 keep service, 0 drop

q_{it} usage here cons(i) per(t)

z_{it} all other telecom services

to identify α_{it} (no corner sol. but finite non zero slope @ axes) $F_{ik:1}$

allows indiff curves to intercept axes

translation params

$$V_{it}(Y_{it}=1, q_{it}, z_{it}) = V_{it} + \alpha_{it} \log(q_{it} + \tau^1) + \beta_{it} \log(z_{it} + \tau^0)$$

intercept ← ; $\boxed{>0}$ satiation params ; $\tau^0 = 0$ ensure existance of interior sol.

⇒ shows additional utility disutil of option to access service

if decide to drop service $U_{it}(Y_{it}=0, q_{it}=0, z_{it}) = \beta_{it} \log(z_{it})$

Capturing diminishing return (cell phone usage) → log

Stone Geary

I_i : cons(i)'s income

φ_i : I's prop. of telecom

$\varphi_i I_i$: Telecom budg

χ_i indic < 1 TPT, 0 PPU

F_{it} : Access fee

P_{it} : per min. usage

budg const: $P_{it} q_{it} + z_{it} + \chi_i F_{it} \leq \varphi_i I_i$

util. max: $z_{it} = \varphi_i I_i - \chi_i F_{it} - P_{it} q_{it}$

Util max (subj budg const): $q_{it}^* = \frac{\alpha_{it}}{\alpha_{it}+\beta_{it}} \frac{\varphi_i I_i - \chi_i F_i}{P_{it}} - \frac{\beta_{it}}{\alpha_{it}+\beta_{it}}$

$V_{it}^*(Y_{it}=1, P_{it}, F_{it}, I_i) = V_{it} + \alpha_{it} \log(q_{it}^* + 1) + \beta_{it} \log[\varphi_i I_i - \chi_i F_{it} - P_{it} q_{it}^*]$

indirect util of dropping: $V_{it}(Y_{it}=0, I_i) = \beta_{it} \log(\varphi_i I_i)$

indirect util (keep − drop) $= w_{it}(P_{it}, F_{it}, I_i) = V_{it} + \alpha_{it} \log(q_{it}^* + 1) + \beta_{it} \log\left(\frac{\varphi_i I_i - \chi_i F_{it} - P_{it} q_{it}^*}{\varphi_i I_i}\right)$

Rand util. keep/drop decision: $W_{it}(P_{it}, F_{it}, I_i) = w_{it}(P_{it}, F_{it}, I_i) + \vartheta_{it}$

ϑ_{it} < $N(0, \sigma_{u1}^2)$: PPU assigned ; $N(0, \sigma_{u2}^2)$: TPT assigned (different impact on constraints)

prob keep service: $p(Y_{it}=1 \mid P_{it}, F_{it}, I_i) = p(W_{it} > 0)$

— PPU condition $\Phi(w_{it}/\sigma_{u1})$

\ TPT condition $\Phi(w_{it}/\sigma_{u2})$

Φ cumul. Normal Dist

estimate: $\varphi_i = \frac{1}{1+e^{\pi + x_i}}$ → person specif Rand Effect

AVG Exp total income

$\log(Q_{it}) = \log(Q_{it}^*) + \eta_{it}$
$= \log\left(\frac{\alpha_{it}}{\alpha_{it}+1}\right) + \log(\varphi_i I_i - \chi_i F_{it} + P_{it}) - \log(P_{it}) + \eta_{it}$

temporal difference b/w: $Q_{it} = q_{it}^{Act} + 1$

(Skewed usage) (log − log) deci. time: $Q_{it}^* = q_{it}^* + 1$

time dependence $\eta_{it} = \varepsilon_t^q + w_{it}$ ← rand Error term

period speci. shock ; random white noise — σ_{q1}^2 PPU, σ_{q2}^2 TPT

time dependence (state based) stationary-autoreg $\varepsilon_t^q = \rho^q \varepsilon_{t-1}^q + k_t^q \quad k_t^q \sim N(0, \sigma_{kq}^2)$

Estimate from data

Dynamic Fw looking

Albuquerque 2012

$u_{ijpt} = \alpha_{0i} + \alpha_{ij} + \alpha_{2i} X_t$

heterogeneous intercept indiv ; Lifetime content unit ; Content specific intercept ; time specific occasion (Prod aging, Consumption) ; Intrinsic preference

$+ \beta Y_{it} + f(\beta_{ip}, \tau_{pt}) + g(I_j, I_{it}) + \delta_{2i} G_i$

State dependence or Cumulative

$\beta_{1ip} \tau_{pt} + \beta_{2ip} \tau_{pt}^2$ Novelty + satiation (how much played)

Content match (level of player & task) familiarity $\gamma[I_{it} - I_j]$

member ship 0/1

$+ h(I_{it}, \bar{I}_t) + \varepsilon_{ijt}$

Community Effect distance b/w people Communit AVG

$h(\bar{I}, I_{it}) \begin{cases} \delta_{1i}(E_{it} - \bar{I}_t) & \text{if } I_{it} > \bar{I}_t \\ \delta_{2i}(\bar{I}_t - I_{it}) & \text{if } I_{it} \leq \bar{I}_t \end{cases}$

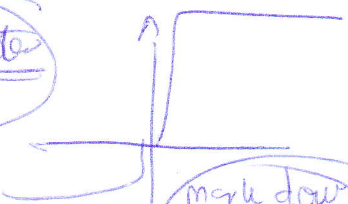
~~IX~~ $\boxed{\text{Structural models!}}$

- numerical integration → simulation
- Programming
- maximum likelihood computation

- choice probability & integration

$r = \dfrac{A}{(BC)^{1/2}}$ $\quad E(r) = \dfrac{E(A)}{\{E(B)E(C)\}^{1/2}} \left\{ 1 - \dfrac{\frac{1}{2}E(ab)}{E(A)E(B)} - \dfrac{\frac{1}{2}E(ac)}{E(A)E(B)} + \dfrac{\frac{1}{2}E(bc)}{E(B)E(C)} + \dfrac{\frac{3}{8}E(b^2)}{E^2(B)} + \dfrac{\frac{3}{8}E(c^2)}{E^2(C)} \right.$

two parameter



mark down

Variety seeking

not depend on policy

3 heterogeneity

desire

BLP

distribution

2 2SLS

1 logit

Consumer

Not see

Erdem & Keane

Bounded rationality

Dynamic → State dependence

1 Rationing

2 everyday low price

objective function

Control

utility

uncertainty

Guess → new thing

Search → $\sigma^2 \downarrow$

Learning

Brand attribute

Backward

Assumption?

Consideration set

Stage

1 Choice
2 timing

decay function

uncertainty quality

certain High price

Equilibrium

availability

marginal Cost

q: percieved prob avail 2nd period

Baysian learning

First period: $U_1(v, p_1) = (v - p_1) - \alpha q(p_1 - \delta p_1)$

high price regret

second period: $U_2(v, p_1) = q(v - \delta p_1) - \beta(1-q)\max\{(v - p_1), 0\}$

identification problem?

stock out regret

Expected Consumption utility of buying the product

marginal value

Baysian updating

$r \rightarrow$ actual period 2 fill rate

$\theta \rightarrow$ strength of deviation from real value

$\theta \rightarrow$ discounted

Probability

$q(r) = r^\theta$

available period 2

percieved period 2 fill rate

Convex

percieved

$\theta \geq 1$

$G = \dfrac{(1+\beta)(\bar{v} - p_1)}{(1+\beta)\bar{v} + (\alpha - \beta - (1+\alpha)\delta)p_1} < 1$ $\qquad v_1 = \dfrac{(1+\beta+(\alpha-\beta-(1+\alpha)\delta)q)p_1}{(1-q)(1+\beta)} \geq p_1$

cut off value

Stock that run out? → like Bass

→ = Constraints

$\alpha \leq \beta$

theory → direct

emperic → recover Backward

availability on Period 2 → period fill rate r

r → real fill rate probability

update of variance of probability of availability

Unknown? percieved value

↓

Erdem Quality match?

Cut off point

BLP:

- estimate param of company

choice specific

input bau

Bloom

① Random Coeff $\{\alpha_{ij}, \beta_j\}$

$\theta \sim MVN(\theta, \Sigma^{\sim/R\beta})$

param space

② $\prod(Pr \mid \theta_i)$ = likelihood

③ numerical integration ⇒ S_{jt}

$S_{jt}^{(n+1)} = \hat{S}_{jt} + \ln(S_{jt}) - \ln(\hat{S}_{jt})$

Given S → 2SLS → get ξ_{jt}

④ min $\xi' Z(Z'Z)^{-1}Z'\xi$

Instrument

— Software Eng → Reuse Component

Erdem (1)

(2) walstreet paper

※ → structured model ~~+ MKT Engineering~~ ⊙
→ ~~Analytical~~ ⊙ + (1) Demitri imperfect search + (3) Erdem (2001)
→ micro handouts

(4) Chapters of Economics of network
→ Coordin & Cooperatio
→ social barries

Hazard model

Erdem et al. 2002

$$U_{ijrt} = \beta_i(1 - e^{-\alpha G_{ijrt}}) + \gamma C_{ijrt} + \varepsilon_{ijrt}$$

Common across Consumers → unobserved by Econometrician, miscellaneous influence on Consumer

i.i.d. Capturing idiosyncratic taste

Consumer i

Product

time

1, 2 discrete amount of \$ willing to spend

$C_{ir} = I_i - P_r$

Income

Spending on P.C

$G_{ijRt} = \pi_{jt} P_r Q_j$

Efficiency unit of Computer purchased by P_r

index of efficiency

Capabilities per 1\$

Efficiency unit = Per \$ quality of Capabilities of technology j
Purchase j

assume Constant over time

X_i vector of

e.g.) Education (1), gender (2), age (3), income (4)

(5) Experience

individual specific

$$U_{ijrt} = \beta_i(1 - e^{-\alpha \pi_{jt} P_r Q_j}) - \gamma P_r + \varepsilon_{ijrt}$$

$\beta_i = \beta_0 + \beta X_i$

(1) unknown attribute = uncertainty about Q_j
(2) normal prior of Consumers (quality)
(3) recieve normally distributed noisy signals of quality

Consumer perception $E[Q_j \mid I_{it}] = Q_j + Z_{ijt}$

$Z_{ijt} \sim N(0, \sigma^2_{ijt})$

→ perception error Variance

⊕ Consumer Quality expectation

information set (Set of signal recieved)

$$E[U_{ijrt} \mid I_{it}] = \beta_i \{1 - e^{(-\alpha \pi_{jt} P_r E[Q_j \mid I_{it}] + (\alpha \pi_{jt} P_r)^2 \sigma^2_{ijt}/2)}\} - \gamma P_r + \varepsilon_{ijt}$$

→ degree of risk aversion $\alpha > 0$

→ property of Log normal distribution property

→ increased in Expected ~~utility~~ quality

decreasing in percieved variance

Assumption in Economy Standard

utility → linear in Consumption of outside good

Marginal utility Considering

Quality → person specific

process
(1) Preserve reduction in Price → π_{ij} grow over time ⟹ delay Purchase incentive
(2) begin Search with uncertainty — risk averse
uncertainty ↓ → utility ↑
→ delay Purchase to learn about quality
(3) opportunity Cost of delay

Utility of not purchase: $U_{i0}(x)$ depend
→ own Computer?
→ socio demographic

2 Erdem et al. 2003

distinguish Mechanism

price Expectation

into gathering

Learning Mechanism

identification

positive duration dependence

unobservable

1 just Expectation price data using choice data alone

2 Quality Perception each tech if changed price uncertainty not plausible

myopic agent

step

due to

price fall

elastisity

Main processes:

1. utility spec
2. Forecasting future price
3. Consumer learning about Quality
4. Consumer's Dynamic Optimization Problem
5. Consumer choice probabilities and the construction of likelihood function

non myopic

Even increase in price is the same substantially

Demand Elasticity

free to adjust

usually not flexibility

dependent

T

Quantity varies dependent

others Assumption of

1 Rational Expectation

Agents

Dynamic choice

*

$\ln \pi_{j,t+j} \sim N(E[\ln \pi_{j,t+j} | I_{it}], \sigma^2_{\pi})$

subjective of agents expectation

here use data to estimate Consumer process of price expectation future

2 Assuming stochastic process for price

Extrapolation of entire predictive distribution

point expectation Construction

Consumer were asked of perception

ask about familiar Brand

from previous period i.e. t-1 π_{jt}

Process assumption

Error term of Consumer answering

Isolate price

Quality bias avoidance $\pi/8$ = same

$E(\ln(\pi_{j,t+1}/\pi_{jt}) | I_{it}) = \theta_0 + \theta_1 \ln\left(\frac{\pi_{jt}}{\pi_{j,t-1}}\right) + \theta_2 \ln\left(\frac{\pi_{jt}}{\pi_{j,t-2}}\right)$

Consumer error term

$\Delta_{ij,t+1} = \pi^*_{j,t+1} / \pi^*_{jt}$

$\ln \Delta_{ij,t+1} = E\left[\ln\left(\frac{\pi_{j,t+1}}{\pi_{jt}}\right) | I_{jt}\right] + v_{ij,t+1}$

$v_{ij,t+1} \sim N(0, \sigma^2_{v})$

Measurement error

noisy measure of

acceleration/deceleration price change

Subjective expectation of log price change conditional on Information set I_{it}

Erden (3)

Learn about Quality

Prior uncertainity

assum Bayesian Customers

Prior $Q_j \sim N(Q_{j0}, \sigma^2_{j0})$

Learn $\Rightarrow$ reduce Variance

Source of learning

Focus group

(1) retail Store
(2) article in Specific publications
(3) article in general purpose
(4) advertising
(5) WOM

Decision of Customer

which Source info to visit

each visit

Recieve quality signal

Noisy signals

$S_{ikt} \sim N(Q_j, \sigma^2_k)$

Source

$S_{jkt} = Q_j + x_{ijkt} \quad x_{ijkt} \sim N(0, \sigma^2_{kt})$

$1/\sigma^2_k$

previously had: $E[Q_j | I_{it}] = Q_j + Z_{ijt}$

Quality Perception

$Z_{ijt} \sim N(0, \sigma^2_{ijt})$

true quality of tech (Apple, IBM

percision of information Contained in info Src

retain during updating Process

$\sigma^2_{ijt} = E[(Q_j - E[Q_j | I_{it}])^2 | I_{it}]$

two type Consumer ~ ~~Product~~ Quality level

L_{ikt} Dummy: Whether Src k visited

Bayesian

$\sigma^2_{ijt} = \left[\frac{1}{\sigma^2_{j0}} + \sum_{s=1}^{t} \sum_{k=1}^{5} \frac{L_{iks}}{\sigma^2_k}\right]^{-1}$

duration dependence

purchase hazard $\Downarrow$ $\sigma_{ijt} \downarrow$ over time @ acquire info

$Z_{ijt} = Z_{i,j,t-1} + \sum_{k=1}^{5} L_{ikt} \frac{\sigma^2_{ij,t-1}}{\sigma^2_{ij,t-1} + \sigma^2_k} \times (x_{ijkt} - Z_{i,j,t-1})$

evolution of accuracy of perception Error

increase utility

$Q_j \sim N(E(Q_j | I_{it}), \sigma^2_{ijt})$

Consumer subjective quality distribution

how perception Error themselves get updated

Kalman gain Coefficient

$\frac{\sigma^2_{ij,t-1}}{(\sigma^2_{ij,t-1} + \sigma^2_k)}$

Threshold parameters to be estimated

if info source very inaccurate $\Downarrow$ unlikely to update their quality perception substantially after visiting Src

Reported quality

$q_{ijt} = L$ if $E[Q_j | I_{it}] < \mu_{jL}$

$q_{ijt} = M$ if $E[Q_j | I_{it}] < \mu_{jH}$

$q_{ijt} = H$ if $E[Q_j | I_{it}] \geq \mu_{jH}$

Since # of signal Consumer recieved not actual Content but Random Variable due to normal distribution of $E[Q_j, I_{it}] \Rightarrow$ probit

Erdem (4)

$Pr(q_{ijt}=L) = \Phi_{\sigma_{ijt}}(\mu_{jL} - Q_j)$

$Pr(q_{ijt}=M) = \Phi_{\sigma_{ijt}}(\mu_{jH} - Q_j) - \Phi_{\sigma_{ijt}}(\mu_{jL} - Q_j)$

$Pr(q_{ijt}=H) = 1 - \Phi_{\sigma_{ijt}}(\mu_{jH} - Q_j)$

$\Phi_{\sigma_{ijt}} \rightarrow$ Normal distribution function with mean 0, variance σ^2_{ijt}

distribution variance of $E[Q_j | I_{it}]$

unobservables: percision of information sources → free to depart from real value → Representative heuristics not pure Bayesian = update too much recieving info

(*) The Consumer's Dynamic optimization problem

State of Consumer in a choice process → I_{it}

I_{it} Contains Complete set of signals recieved by consumer i until t

$I_{it} = \{ \{ \underbrace{E[Q_j | \tilde{x}_{it}]}_{E[Q_j | I_{it}]}, \sigma^2_{ijt}, \pi_{jt}, \pi_{j,t-1} \}_{j=IBM, Apple}, X_i, \tau \}$

vector of consumer characteristics

latent type

Subjective mean & variance of quality: $\tilde{x}_{it}$ → Current & lagged price indices

Current & Lagged inverse price indices

technologies ← 2·R → expenditure level

Buy choices

Choice set$_t$ = 2^5 = 32 (5 = Sources) → Buy / wait

option: m = 1–32 = 2^5

$V_{imt}(I_{it}) = -\sum_{k=1}^{5} d_{km} c_k + E \max\{ V^P_{it}(I_{it}, m), V^N_{it}(I_{it}, m) \} + \xi_{imt}$

parameter estimate

Cost of obtaining info from each k source

Indicator of whether source k is included in combination m

iid stochastic shock to the cost of using search option m at time t

Value of purchase option $U^P_{it}(I_{it}, m) = \max_{\{j, \tau\}} E[U_{ijt} | I_{it}, m]$

signals from these choices

Value function on grid of state point

Quality Perception Continuous

integration over distribution of signals recieved on search option m

Dynamic programming Recursion

Value of making no purchase at time t:

$U^N_{it} = U_{i0} + \delta E[\max_m V_{im,t+1}[I_{i,t+1}]] + \varepsilon_{i0}$

Discount rate

preperiod utility flow: $U_0(X_i) + \gamma_0 + \tilde{\gamma} X_i$

vector of indiv characteristics (have home computer?)

repeat decision of which info src visit

Shock to the value of no purchase option

known to consumer but unobserved to Econometrician

Consumer choice Probabilities & Construction of the likelihood function

Erdem(s)

2 decision

information gathering

Purchase/no purchase/ expenditure level

D_{ijrt} → Dummy of Purchase

@ descrette price set $\{P_1, P_2, \dots, P_R\}$

Compact expression

$$E[U_{ijrt} | I_{it}] = E[\bar{U}_{ijrt} | I_{it}] + \varepsilon_{ijrt}$$

$$\bar{U}_{ijrt} = \beta_i (1 - e^{-\alpha \pi_{ijrt} P_r (Q_j + Z_{ijt})} + (\alpha \pi_{it} P_r)^2 \frac{\sigma^2_{P_{ijt}}}{2})$$
$$- \gamma P_r$$

D_{iot} → dummy of not to make purchase at time t

$$U_{it}^N = \bar{V}_{it}^N + \varepsilon_{iot}$$

$$\bar{V}_{it}^N = U_{i0} + \delta E[\max_m V_{im,t+1} [I_{i,t+1}]]$$

Vector of stochastic terms $[2 \cdot R + 1] = \{\{\{\varepsilon_{ijrt}\}_{j = IBM, Apple}\}_{r=1,2}, \varepsilon_{iot}\}$

observable to Consumer

unobservable to econometrician

multinomial logit:

$$Pr(D_{ijrt} = 1 | \theta, Z_{it}, \tau) = \frac{\exp(E(\bar{U}_{ijrt} | I_i)}{\exp(\bar{V}_{it}^N) + \sum_{l=1}^{2} \sum_{q=1}^{R} \exp(E[\bar{U}_{ilqt} | I_{it}])} \quad j = IBM, Apple \quad r = 1, R$$

Complete set of model parameter

Vector of perception Error

Customer latent type

M_{imt} dummy variable equal to 1 if consumer i chooses info acquisition option m

$$Pr(D_{iot} = 1 | \theta, Z_{it}, \tau) = \frac{\exp(\bar{V}_{it}^N)}{\exp(\bar{V}_{it}^N) + \sum_{l=1}^{2} \sum_{q=1}^{R} \exp(E[\bar{U}_{ilqt} | I_{it}])}$$

$$V_{imt}(I_{it}) = \bar{V}_{imt}(I_{it}) + \xi_{imt}$$

$$= -\sum_{k=1}^{5} \lambda_{km} c_k + E\{\max\{V_{it}^P(I_{it}, m), V_{it}^N(I_{it}, m)\}\}$$

multinomial logit

$$Pr(M_{imt} = 1 | \theta, Z_{i,t+1}, \tau) = \frac{e^{\bar{V}_{imt}(I_{it})}}{\sum_{l=1}^{32} e^{\bar{V}_{ilt}(I_{it})}}$$

Vector: $(\xi_{i1t}, \dots, \xi_{i32t})$ → Revealed to Consumer unobserved by Econometrician

Likelihood Contribution for Consumer i @ t, Conditional on his/her quality perceptions and latent type:

$$L_{it}(\theta, Z_{it}, Z_{i,t-1}, \tau) = L_{1it}(\theta, Z_{i,t-1}, \tau) L_{2it}(\theta, Z_{it}, \tau) L_2(\theta, Z_{it}, \tau) \cdot L_{3it}(\theta, Z_{it}, \tau) L_{4it}(\theta)$$

info choices

purchase decisions

Reported Price Expectations

Reported quality ratings

$$L_{1it}(\theta, Z_{i,t-1}, \tau) = \prod_{m=1}^{32} Pr(M_{imt} = 1 | \theta, Z_{i,t-1}, \tau)^{M_{imt}}$$

$$L_{2it}(\theta, Z_{it}, \tau) = Pr(D_{iot} = 1 | \theta, Z_{it}, \tau)^{D_{iot}} \prod_{j=1}^{2} \prod_{r=1}^{R} Pr(D_{ijrt} = 1 | \theta, Z_{it}, \tau)^{D_{ijrt}}$$

$$L_{3it}(\theta, Z_{it}, \tau) = Pr(q_{ijt} = L)^{I[q_{ijt} = L]} Pr(q_{ijt} = M)^{I[q_{ijt} = M]} Pr(q_{ijt} = H)^{I[q_{ijt} = H]}$$

Erdem 6

$$L_{3it}(\theta) = \prod_{j=1}^{2} \frac{\exp(v_{ijt}^2 / 2\sigma_{v}^2)}{(2\pi)^{1/2}\sigma_v}$$

measurement error in price forecasting

Conditional likelihood (6 survey waves)

$$L_i(\theta, z_i, \tau) = \prod_{t=1}^{6} L_{it}(\theta, z_{it}, z_{i,t-1}, \tau)$$

$$L_i(\theta) = \sum_{\tau=1}^{2} \lambda_\tau \int_{z_i} L_i(\theta; z_i, \tau) f(z_i) dz_i$$

due to not observing z_i, or τ integrate

join density of perception error

multivariate normal

population type: Consumer type τ

Simulated maximum likelihood

12 Dimensional

BHHH algorithm to approximate the Hessian

14 Structural model (pradeep2008)

→ competition

→ better decision

→ Consumer choice effect on demand

→ usefulness ~~on~~ description

— Economic/Marketing behavior → Econometric spec (1)

Consumer/Firm

Utility Max by Consumer

Profit Max

Optimize behavior

— Assumption Validity test appropriatness

Variety seeking

— not dependent on policy parameters

— Consumer choice → demand → MKT competition

prediction

— Dynamic

description / Normative

(1) observe test the theories

(2) development to facilitate Estimation

(*) → Stated & revealed preference panel

@ indiv level

historical decision

data fitting

flexible

flexible functional

Psychology

Marketing

Economics

Reduced

easier

past behavior

Structural

predict

future behavior

Not Aggregate!

No

impose Structure

flexibility

let data speak

less predict

fit without response

Theory

~~Story~~

System Dynamic

policy Regieme shift

Structural model Pradeep 2008

Reduced
- theoritical use ~~the~~ fit data to reduced model
- statistical method ~~to explain~~ without theory for data fitting

time series to calibrate model (statistical / Econometric models)

Excellent validity of reduced, yet in similar domain of old strategies

not expansion!

But Structural model
interesting prediction
on Counter Factual

preference consumer etc
decision rules

Competitive vs. Collusive

Strategic interaction of agents

Change strategy

e.g promotional

parametrizition Econometrics

while econ focus on optimality constraint

Structured model

here: alleviate constraints

Bounded Rationality

Rational utility Maximization

assumption of optimality

facilitation

(a) Dynamic programing in Empirical Industrial organization

assumptions of microbehavior of agents

joint supply & demand

Weakness → Strong assumption

parameter Estimation

Reduced
- Exploratory analysis
- & testing theories

too much structure imposed ⇒ less useful for decision making purposes

e.g firm specific equilibrium

(a) Nash-Bertrand Price, Stackelberg

But

Not useful for pricing decision since we assumed it

e.g assumption of certain info available

Can be used for Counterfactual for different decision

No structure

too much structure constraint

~~Structured~~

Simultaneous Structured reduced

possible but evals
- plausibility
- interpretability
- fit
- Predictive Validity

P-4

logit

probit

Macfaden 1974

Recently

quantity & multiple discreteness

Structural interpretation

parametric representation of heterogeneity

individual level utility

previously aggregation based on representative Consumer assumption

Observable source

unobservable source

Distribution

Structural model pradeep 2006

3

- Structural demand only on contemporaneous factors ⟹ static-utility-maximizing

Dynamic

State dependence

choice of previous period

Causaly effect

Current utility + habit persistent

Random component of utility

forward looking Behavior

take into account impact of current action on future stream of utilities

Planning horizon rather than current utility

Dynamic response to exogeneous Variables

Reduced models

No explanation

Lagged choice Variable

Last purchase Dummy

Exponentially smoothed weighted avg

Backward looking

Forward looking

state dependency

Structal

Explain

Reference price

Learning

behavioral Source

Switching Cost

explain

Forward looking dynamic stuct. model features

1. time & uncertainty Explicitly treated
2. well define objective func of agents make decision sequentially based on current info
3. agents maximize multi period objective function

forward looking

about future price

Uncertainty

product quality

Price as signal of quality

alter purchase timing

brand choice

quantity Decision

impact of current choices on future expected utility when decision making rather than myopic process

Discrete decision

1. belief about nature
2. belief about competition
3. Dynamic model of belief about strategies of other players

Learning

1. Brand attributes on choice behavior

frequently purchased

1. informative role: signaling
2. direct impact on consumer utility = persuasive or prestige effect

advertising as a source of quality information

2. formation of consideration set

limit information search

Consumer price expectation affect

Purchase timing

Brand choice

Quantity decision

Structured model pradeep 2006

utility → betterprice

disutility → stock out

wrong elasticities of reduced models

price expectation

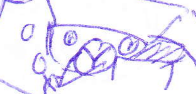
hig tech diffusion

mayopic bias exists in some cases

effect of accuracy of information on

1 info search

2 technology choice



need for multiple data source

relax & test some commonly made assumptions

e.g rational expectation

enhance behavioral richness & interpretation of these models

drivers of Consumer behavior

firm's cost function

Marginal cost considering advertising decisions

parameters of advertising cost function

estimate by advertising cost along with demand function

use in Estimation of Data

Profit maximizing

1 set by firm

prices

advertising level

parameters affecting consumer decision

V simultaneous optimization firm & consumer equilibrium

2 Rival firm Equilibrium

Resolve I

indogeneity bias

Supply side

II test competition theories

III measure & test nature of interaction among firms

IV policy analysis by simulating behavior under variety of mkt environment

firm forward looking

current period have effect on long run

next period profit of firm?

Dynamic oligopoly

appropriate: correlated with endogenous variable but uncorrelated with error term

Instrumental Variable IV

drawback: inefficient estimate

theoritical justification of validity of instrument

Different behavior regieme of firm interaction

marketing mix

Shock of environment on firm

e.g Regulatory

demand shock

Level of MKT activity

Error of demand function trem

endogeneity resolved by

account for different equation of

alivite it if not controled

supply

Demand

Consistency of Marketing theory with data e.g targetted coupon

horizontal vs. vertical differentiation

Competitive intensity *

Policy analysis

e.g price elasticity

1 parameters of demand model

2 Equation governing firm behavior

policies under various behavioral assumption

3 data on exogeneous variable on demand & supply side

impact on chain profit & customer welfare

price discrimination

pricing zone 3

uniform price 2

store specific price 1

Equilibrium Condition

Simulate price under Regiems

whole price

mark ups

For each category analysis

advertising effect

current period

future period

Dynamic advertising of Competitors

Equilibrium advertising

managerial input

Extra Condition of Equilibrium restrictions

Supply side

Price Coefficient *

2 Better describe market

3 input for managers

1 appropriate demand Estimate

4 firm may go for different Equilibrium

Correct equilibrium equation is Must

System of Equation substituting price demand in supply function

change of stochastic Process governing market *

assumption of size of market

incorrect estimation

Policy & strategy change

Economic

Structural model

Psychology

Quasi bayesian

Reference dependence

Focusing

Bracketing effect

Like Gary Bolton — Speculate model solution and check the result by math

Pricing Seminar of Professor Ozel and Profesor Moharram Oghli @ UTD: Twlefth session

Meisam Hejazinia

04/23/2013

1 Analytical and Behavioral Approaches: The Case of Forecast Information Sharing

Deterministic vs. Stochastic

Approach: Analytica vs. Behavioral

Foundation at least in one, and solve problem.

Not constraint by toolset, and not narrow minded look at the problem.

Analytical approah vs. Simulation as approaching a problem.

Things will evolve over time. Takes time to look at multiple angle. Research, reviewing and so on will be required.

Even full professor and think you are done and don't study anymore your skill begin to decade.

A complementary approach:

(i) Define problem. Why? Research question. Being curious about something. Important business relevant and pervasive. Is it relevant. Different industries interested in same question.

(ii) Analytical Approaches: Build mathematical descriptive models, stakeholders. Pecuniary objectives, payoffs, key tradeoffs. Decisions/actions, outcomes.

How to build analytica: (1) Identify stake holder. (2) Identify trade offs. (3) Identify most critical trade offs. Also you look at payoffs, objectives, and decision variables. There is a loop in this process.

Behavioral approach: (1)Bring the human perspective. Does it play a role. (2) What are non-pecuniary things that could affect. (3) When, how, and why?. Whether those affect decision. (4) Field study. Try the idea. How to change gift or donation policy. Buy back contracts. Are the effective or efficient. (5) Controlled lab experiment. Control is an important keyword here. Does not mean replicating exact business environment, but set up things in the way that you control everything. Change one thing at the time. Two by two design to understand impact of two variables. H: High, L: Low. (H,H), (H,L), (L,H), (L,L). (6) Theoretical underpinnings. Two ways: (a) Exploratory: too dark, and I start shooting. Shooting starts. Now maybe its going to give me some understanding of what may be happening. Today everything is not dark. You need to be exploring outer space. Today it does not exist. People are exploring and look at certaing aspect of problem, and know what is happening. Smack data to find some result out of. You don't want to be like that. (b) Theoretical underpining: You should have theoritical reason to know what is happening. Certain things is known that are well established to be certain theory. Individual (*)perference(prospect theory, risk aversion), (**)social perference (trust, fairness), (***)bounded rationality: complexity. You need to make sure that your result is robust to another experiment. Certain things in analytical model that does not capture and you use them to update your model. Don't shoot in the dark.

If the loop is for empirical and you start from analytical, and then behavioral approach, it will be called structural model estimation.

(iii) Goal: To understand, to build predictive model. To prescribe effective policies/strategies optimize (min/max) pecuniary payoffs. Decision support tools.

Don't be just analytica, empirical or behavioral, but try to do all of them.

Use research question to learn.

Co-author is like playing tennis, if they would be good, you will be good, if not, you would not be good either.

Sequence of reading papers.

The more fundamental courses you take, the easier for you to learn in future.

This is marathon, and not 100 meter run. You will run it for your whole time. This is life long. Don't be afraid to invest your time on learning.

During time things come back to you and you deeply understand it on the next time. You will suddenly understand that something is missing.

Discrete simulation versus Monte Carlo simulation.

In empirical approach you need to have theoretical reason to include variables that may affect the outcome.

PhD candidate appeal: creativity, research papers, recommendation that shows person can stand on his feet.

Person should also know area, and be able to say what happens if model elements modified, added, or removed.

Copy style of good papers, and then you will start to develop your sense of writing.

Any paper, even most technical, good presenter is able to present what is going on in there. Those who present and can not clarify it, shows the person does not know what they studied.

Trust and trustworthiness research just had its root in curiosity. They took the risk. Nothing has been done before.

If you are excited then who cares what would be end product. Product will become byproduct of your main product which is learning.

If you put your effort when your heart is not, when you don't get the job you will get misrable, but if you put your effort in where your heart is, at the end you will at least learn something, and would be happy at the end.

Funding as incentive for Health Care.

Research improvement is in the form of spike.

Credible forecast information sharing.

Assymetry of information.

Firms incentive to exagerate forecasts.

Principle agent model

Dynamic game of incomplete information

Heterogeneity in the distribution of sharing information.

You can close loop of analytical and behavioral model in one paper, or do it in multiple papers. You can do multiple iterations on each of the steps for different papers.

2 Experimental Study

Step 1: Set up your research question derieved from previous models. Theoretical guidance, set up. (Do not shoot in the dark and use current theories)

Step 2: Develop testable hypothesis based on well-established theories

Setep 3: Examine if, when, how and why actual behavior deviates?

Carefully controlled lab experiments

Step 4: Go to setp 2:

Validation is needed: Whether or not what I observe in the lab is replicatable. Control for culture for example.

Or test new hypothesis

Step5: Use the observations to build better predictive model.

Closing the model-exp-model loop

How to incorporate exp observation into the model?

(1) Start from original math model and add in behaviors observed in
Labratory experiment
studies from, soc., psyc., and decision theories.

(2) Use a minimalistic approach
Consider existing explanations and models
Add one piece at a time

(3) Check whether the resulting optimal decisions predicted by the new model

Have similar properties as those observed in the lab
Fits the data and makes accurate prediction?
Results in similar comparative statistics
Test for goodness of fit (such as, low AIC info criteria)

Does it match with the properties I observe in the data.
You want to make sure that properties of the model is similar to those visible in data.

Fit first half of data. Fit the model, and then use second half to check how your prediction compared to them.

If all are on 45 degree line shows that you have cheated.

Read the paper, and use the result to give managerial implication in MBA class.

Experiment

endowment effect

Status Quo bias

loss aversion

Assymetry

intersection indifference curve

Portfolio of cash and Securities

attractive option
Status Quo

Value function

Gain & LOSS

Califor pow
insurance new Jersey

trust

Reputation

Contractual precommitment

Punishment treat

Backward induction

join inprovement

History

what happened on previous
Experiment

Higher payoff on history for 10$

Lower Zero back