Learning Models and Experience Goods

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Grad IO

Introduction

Uncertainty and Learning

- We have already looked at models with forward looking consumers
- Consumers faced uncertainty about the price, but understood the characteristics and the utility received from the good up to the IID ϵ.
- In many cases, consumers do not fully understand their preferences over goods until they sample the goods themselves.
- Changes to brands, introduction of new brands, price cuts, coupons, or advertising may induce consumers to resample.
- We would like to incorporate persistence in brand choice but also experiential learning

Uncertainty and Learning

We examine three papers dealing with uncertainty and learning:

- Ackerberg (2001) looks at whether advertising lets consumers learn about new brands and distinguishes between informative and prestige effects
- Erdem and Keane (1996) extends models of brand choice to allow for Bayesian learning about experience goods
- Crawford and Shum (2005) look at how doctor's learn about patient's types as well as drug efficacy in a model of experiential learning.
- Dickstein (2018) studies adherence to anti-depressants and learning with Gittin's index.

Ackerberg

Ackerberg 2001: Advertising and Yoplait 150

- **Informative** about product existence and search characteristics. Stigler (1961), Butters (1977), Grossman Shapiro (1984) should not affect behavior of experienced users.
- **Signalling** Nelson (1974), Kihlstrom and Riordan (1984), Milgrom and Roberts (1986).
  1. If consumer perfectly learns about brand's experience characteristics after consumption $\rightarrow$ does not affect behavior of experienced users
  2. If consumer continues to learn about experience characteristics after consumption $\rightarrow$ should be decreasing in number of consumption experiences.
- **Prestige** Becker or Becker and Murphy (1993) does not depend on whether or not consumers have experienced the good but enters utility.

Ackerberg 2001: Advertising and Yoplait 150

- Ackerberg exploits panel data following advertising and grocery purchases over time.
- Hypothesis is that informative advertising has a larger effect on consumers with no brand experience.
- Prestige affects all consumers equally independent of experience.
- Looks at a new product introduction to get around initial conditions problem

Ackerberg 2001: Data

- AC Neilsen *Scanner Data* matched upw ith TV meters
- 1986-1989 covers 2000 households and 80% of area drugstores and supermarkets.
- Two cities: Sioux Falls, SD (SF) and Springfield, MO (SP)
- He chooses yogurt because it is not easily storable (Hendel Nevo 2007).
- Introduction of Yoplait 150 by the #2 manufacturer
- Heavily advertised, first low-fat, low-calorie yogurt by Yoplait!

Table 1: Descriptive Statistics

Variable	SF	SP
Households	950	825
Average shopping trips per household	70.58 (33.39)	65.82 (31.82)
Average price of Yoplait 150 (cents)	.645 (.060)	.663 (.079)
Shopping trips with Yoplait 150 purchase	302	656
Manufacturers' coupons redeemed for Yoplait 150	16	238
Shopping trips with other Yogurt purchase	5,432	3,863
Households trying Yoplait 150	123	184
Households trying other yogurts	648	512
Commercial exposures per household	13.60 (10.81)	15.22 (9.96)
Advertising share of Yoplait 150	.35	.37
Market share of Yoplait 150	.05	.14

Table 2: Descriptive Correlations

TABLE 2 **Weekly Correlations**

Variable	SF	SP
p_t, q_t	$-.326^{**}$	$-.499^{**}$
p_t, a_t	.106	$.285^{*}$
q_t, a_t	.122	.030
q_t, a_{t-1}	.028	.194
p_t, p_{t-1}	$.274^{*}$	$.744^{**}$
p_t, a_{t-1}	.141	.249
a_t, p_{t-1}	.216	.216
a_t, a_{t-1}	$.486^{**}$	$.387^{**}$

Table 3: Descriptive Results

	Dependent Variable: Initial Purchases				Dependent Variable: Repeat Purchases			
	1	2	3	4	1	2	3	4
N	918	918	678	918	918	918	678	918
R^2	.066	.085	.107	.066	.162	.149	.120	.162
Market	.222	.002	.224	.223	.700	.006	.832	.700
Dummy	(.062)	(.000)	(.069)	(.062)	(.089)	(.000)	(.111)	(.089)
Price	−5.298	−.038	−7.388	−5.354	−3.954	−.029	−5.512	−3.942
	(1.568)	(.013)	(1.726)	(1.585)	(1.829)	(.014)	(2.207)	(1.838)
Ads	.044	.030	.042	.044	.020	.014	.014	.016
	(.022)	(.015)	(.021)	(.022)	(.023)	(.017)	(.024)	(.024)
t-value	1.981	1.925	2.046	1.988	.873	.818	.596	.679

Notes: Unit of observation is a market day. Constant term and third-order polynomial in time not reported. SEs corrected for serial correlation using Newey-West.

Model

Reduced form for discrete choice that consumer i purchases Yoplait 150 on trip t

$$c_{it} = \begin{cases} 1 & \text{IFF } \alpha_i + X_{it}\beta_1 - \gamma p_{it} + \epsilon_{1it} > Z_{it}\beta_2 + \epsilon_{2it} \\ 0 & \text{o.w.} \end{cases}$$

- First term may proxy for static utility or choice specific value function of YP150 purchase
- Second term represents utility of outside option
- α_i is a random effect (persistent heterogeneity) for YP150.
- X_{it} contains advertising, household and consumer characteristics, and functions of previous purchases of YP150, coupon, time trend.
- Z_{it} contains an index of other competitors' prices

Likelihood

$$
\begin{aligned}
L_i(\theta) &= Pr[c_{i1}, \ldots, c_{iT_i} | W_i^t, Z_i^t, p_i^t; \theta] \\
&= \int Pr[c_{i1}, \ldots, c_{iT_i} | W_i^t, Z_i^t, p_i^t; a_i; \theta] f(d\alpha_i | \theta) \\
&= \int \prod_{t=1}^{T_i} Pr[c_{it} | X_{it}(c_i^{t-1}), Z_{it}, p_{it}; a_i; \theta] f(d\alpha_i | \theta)
\end{aligned}
$$

- c_i^{t-1} is your entire purchase history
- W_i^t is the subset of explanatory variables X_{it} that are completely exogenous
- Choice probabilities determined by ϵ IID logit.

Table 4: Parameter Estimates

Parameter	Simple Logit	Normal Random Effect	Simple Logit	Normal Random Effect	Flexible Ad Coefs	.5 Logit	With Mean Advertising	Extra Promotional Variables
Advertising *	2.04073	2.30566	—	—	2.32360	—	—	—
Inexperienced	(.72313)	(.77561)			(.78683)			
Advertising *	.90371	.43304	—	—	1.33200	—	—	—
Experienced	(.63504)	(1.21180)			(1.39850)			
t-statistic on diffference	1.47662	1.58703	—	—	—	—	—	—
Advertising	—	—	1.71550	2.01370	—	2.10570	1.73080	2.40619
			(.76392)	(.79037)		(.85627)	(.82047)	(.89738)
Advertising *	—	—	−.14812	−.35627	−.29487	−.27106	−.35253	−.39207
Num prev pur			(.06282)	(.10803)	(.12079)	(.14411)	(.10904)	(.11248)
Mean	—	—	—	—	—	—	2.48400	—
ads							(2.40050)	
Own price	−4.89980	−5.58440	−4.89500	−5.61630	−5.61890	−7.21680	−5.60710	−5.02189
	(.33114)	(.34993)	(.33501)	(.35604)	(.35541)	(.43486)	(.35583)	(.38633)
Store	2.72990	2.88690	2.73590	2.87050	2.88770	3.23160	2.88460	2.91887
coupon	(.74368)	(.85073)	(.74214)	(.85707)	(.85558)	(.95421)	(.86097)	(.86565)
Competitor	.76070	.76116	.76215	.76848	.76809	1.00150	.76963	.63461
price	(.19214)	(.21745)	(.19180)	(.21904)	(.21889)	(.24940)	(.21953)	(.23211)
Number prev	.10810	−.26717	.10314	−.27046	−.27303	−.55373	−.27129	−.27843
purchases	(.06370)	(.09312)	(.06227)	(.09152)	(.09235)	(.15038)	(.09161)	(.09715)
Number prev	−.00360	.00085	−.00340	.00110	.00117	.00019	.00119	.00130
purchases^2	(.00053)	(.00096)	(.00057)	(.00099)	(.00099)	(.00124)	(.00099)	(.00106)
Never	−2.78400	−.81135	−2.72150	−.58661	−.70453	−.22113	−.655 61	−.59998
purchased	(.11685)	(.22343)	(.11042)	(.21866)	(.22804)	(.29160)	(.21907)	(.22796)
Once	−.59088	−.08104	−.59857	.00169	−.06915	.11842	−.07050	−.03513
purchased	(.11515)	(.15986)	(.11430)	(.16046)	(.16103)	(.18864)	(.16181)	(.16683)
Prev purch/	.84429	.46907	.84135	.46784	.46557	0.85689	0.46457	0.46080
time	(.08562)	(.10757)	(.08571)	(.10882)	(.10903)	(.16457)	(.10940)	(.11785)
Purchased	.17144	.47774	.19047	.51778	.51009	1.12970	.51200	.51312
last s. trip	(.10042)	(.15667)	(.09691)	(.15421)	(.15550)	(.28121)	(.15559)	(.16910)
Days since	−.00577	−.00487	−.00582	−.00511	−.00499	−.00470	−.00504	−.00552
last purch	(.00072)	(.00091)	(.00073)	(.00092)	(.00092)	(.00103)	(.00092)	(.00096)
Time trend	−1.65580	−.36393	−1.64200	−.26339	−.30594	−.19387	−.28784	−.01729
	(.17406)	(.26303)	(.17325)	(.27417)	(.27314)	(.30920)	(.27332)	(.29203)

Discussion

- Adv*Exp insignificant image and prestige
- Adv*Inexp - Adv*Exp: significant informative
- 30-sec commercial each week is like 10 cent price decrease
- Adv*NPurch: decreasing returns to advertising

Erdem and Keane

- Many markets are characterized by lots of new brands, price changes, and brand repositioning (especially CPG).
- Nevo (2001) has hundreds of cereal brands enter and exit, similar in laundry detergent
- Consumers may spend time experimenting with different brands to learn about them.
- After learning takes place there may be state dependence until new brands are introduced or price cuts.

Guardini Little (Pre-Dynamics)

$$E[U_{ij}|I_i(t)] = a_j - w_P P_j + w_E \sum_{s=0}^{t} D_{1ijs} + w_{Ad} \sum_{s=t_0}^{t} D_{2ijs}$$

- a_j mean brand taste for j
- D_{1ijt}: dummy of whether consumer purchases brand j or not
- D_{2ijt}: dummy of whether consumers receives an advertising signal of brand j or not
- w are utility weights (Lancaster 1966)

- Consumer i chooses among J products in T periods of time.
- $d_{ij}(t) = 1$ if consumer chooses j (0 o.w.)
- Includes an *other brand* option
- $E[U_{ij}(t)|I_i(t)]$ is current period expected utility conditional on information set $I_i(t)$.

Consumers maximize a discounted stream of expected utilities producing the Bellman:

$$\begin{aligned} V_{ij}(I_i(t), t) &= E[U_{ij}(t)|I_i(t)] + \beta E[V(I(t+1), t+1)|I(t)] \\ V_i(I(t), t) &= \max_j V_j(I_j(t), t) \end{aligned}$$

Attribute Uncertainty

- $A_{ijt} = A_j + \xi_{ijt}$ with i.i.d. mean zero shock ξ_{ijt}
- Consumers don't immediately learn about attribute levels, instead:
- $A_{E_{ijt}} = A_{ijt} + \eta_{ijt}$ with mean zero i.i.d disturbance η_{ijt}.
- $A_{E_{ijt}} = A_j + \delta_{ijt}$ where $\delta_{ijt} = \xi_{ijt} + \eta_{ijt}$.
- Empirically can't differentiate between private value ξ_{ijt} and experience shock η_{ijt}.

Consumer Expected Utility

Additive Compensatory Multiattribute utility model. (Fishbein 1967) (Lancaster 1966)

$$\begin{aligned} U_{ijt} &= -w_p P_{ijt} + w_A A_{E_{ijt}} - w_A r A^2_{E_{ijt}} + e_{ijt} \\ E[U_{ijt}|I_i(t)] &= -w_j P_{ijt} + w_A E[A_{E_{ijt}}|I(t)] - w_A r E[A_{E_{ijt}}|I_i(t)]^2 \\ &\quad -w_A r E[A_{E_{ijt}} - E[A^2_{E_{ijt}}|I_i(t)]]^2 + e_{ijt} \end{aligned}$$

Where r is your risk parameter: $r > 0$ risk averse

$$\begin{aligned} EU_{i0t} &= \Phi_O + \Phi_{Ot} + \epsilon_{i0t} \\ EU_{iNPt} &= \Phi_{NP} + \Phi_{NPt} + \epsilon_{iNPt} \end{aligned}$$

For outside good or other good.

Bayesian Learning

With no experience initial variability δ_{ijt}, and advertising signal S_{ijt}

$$\delta_{ijt} \sim N(0, \sigma_\delta^2), \qquad A_j \sim N(A, \sigma_A^2(0))$$
$$S_{ijt} = A_j + \zeta_{ijt}, \qquad \zeta_{ijt} \sim N(0, \sigma_\zeta^2)$$

Consumers update:

$$\begin{aligned} E[A_{E_{ij,t+1}}|I_i(t)] &= E[A_{E_{ijt}}|I_i(t-1)] \\ &- D_{1ijt}\beta_{1ij}(t)[A_{E_{ijt}} - E[A_{E_{ijt}}|I_i(t-1)]] \\ &+ D_{2ijt}\beta_{2ij}(t)[S_{E_{ijt}} - E[S_{E_{ijt}}|I_i(t-1)]] \end{aligned}$$

Bayesian Learning

- D_{1ijt}: dummy of whether consumer purchases brand j or not
- D_{2ijt}: dummy of whether consumers receives an advertising signal of brand j or not
- Kalman Filter Update

$$\beta_{1ijt} = \frac{\sigma^2_{vij}(t)}{\sigma^2_{vij}(t) + \sigma^2_{\delta}}, \qquad \beta_{2ijt} = \frac{\sigma^2_{vij}(t)}{\sigma^2_{vij}(t) + \sigma^2_{\zeta}}$$

$$v_{ij} = E[A_{ij}|I_{ij}(t)] - A_j$$

- And

$$A_j = E[A_j|I_{ij}(t)] + v_{ij}(t)$$

$$A_{E_{ijt}} = A_j + \delta_{ijt}, \quad S_{ijt} = A_j + \zeta_{ijt}$$

$$
\begin{aligned}
v_{ijt}(t) &= v_{ij}(t-1) + D_{1ijt}\beta_{1ij}(t)[-v_{ij}(t-1) + \delta_{ijt}] \\
&+ D_{2ijt}\beta_{2ij}(t)[-v_{ij}(t-1) + \zeta_{jt}] \\
\sigma^2_{vij}(t) &= \frac{1}{\frac{1}{\sigma^2_v(0)} + \frac{\sum_{s=0}^{t} D_{1ijs}}{\sigma^2_\delta} + \frac{\sum_{s=0}^{t} D_{2ijs}}{\sigma^2_\zeta}}
\end{aligned}
$$

And expected utilities:

$$
\begin{aligned}
E[U_{ij}|I_i(t)] &= w_A A_j - w_A r A_j^2 - w_A r\sigma^2_\delta - w_P P_{ij} \\
&- -w_A r\sigma^2_{vij}(t) - w_A r v_{ij}(t)^2 - w_A v_{ij}(t) - 2w_A r A_j v_{ij}(t) \\
&+ e_{ijt} \\
E[V_{ij}|I_i(t)] &= E[U_{ij}|I_i(t)] + \beta E[V_{ij}|I_i(t+1)|d_{ijt} = 1, I_i(t)]
\end{aligned}
$$

Choice Probabilities

For the Static and Dynamic case:

$$P_i^s(I(t),t) = \int \frac{\exp[E[U_{ij}|I_i(t)]]}{\sum_k \exp[E[U_{ik}|I_i(t)]]} f(v)dv$$

$$P_i^d(I(t),t) = \int \frac{\exp[E[V_{ij}|I_i(t)]]}{\sum_k \exp[E[V_{ik}|I_i(t)]]} f(v)dv$$

- Static model allows choices to depend on current knowledge of attribute
- Static model does not incorporate value of learning for future consumption
- Logit choice probabilities but with time varying random coefficients
- Everything about learning in is in the distribution of v

Data

- Laundry detergent scanner data from 1986-1988.
- 3000 HH's w/ 20 purchases (7 liquid)
- Lots of advertising
- Only liquids (80% of market)
- Many new brands
- TVs measures ad exposure
  - Percentage of weeks household saw brand j's ad.
  - Saw at least one ad during that week

Table 2: Static Model No Learning

Table 2 GL Model Estimates

Parameter	Estimate	t-statistic
price coefficient ($-w_p$)	−1.077	−18.10
"brand loyalty" parameter (w_E)	3.363	53.18
advertising coefficient (w_{Ad})	0.144	0.31
brand intercepts (a_j):		
a_{Dash}	0.000	–
a_{Cheer}	1.115	8.87
a_{Solo}	0.917	7.22
a_{Surf}	1.382	14.43
a_{Era}	1.601	11.03
a_{Wisk}	1.102	6.78
a_{Tide}	1.700	12.29
"Other Brands" intercept (Φ_O)	−0.633	−2.98
"Other Brands" time trend (Ψ_O)	0.011	4.87
"No Purchase" intercept (Φ_{NP})	1.636	8.02
"No Purchase" time trend (Ψ_{NP})	0.005	1.35
"Brand Loyalty" smoothing coefficient (α_E)	0.770	50.62

Table 3: Dynamic Model

Table 3 Structural Model Estimates

Parameter	Immediate Utility Maximization[1] ($\gamma = 0$) Estimate	t-statistic	Forward-looking Dynamic Structural Model[2] ($\gamma = 0.995$) Estimate	t-statistic
price coefficient ($-w_p$)	−0.790	−12.26	−0.795	−12.31
utility weight (w_A)	28.356	1.73	34.785	1.84
risk coefficient (r)	3.625	2.08	4.171	2.25
initial variance ($\sigma_\chi^2(t)$)	0.053	4.64	0.040	4.21
mean attribute levels (A_j):				
A_{Dash}	0.049	0.74	0.040	0.74
A_{Cheer}	0.019	0.27	0.012	0.21
A_{Solo}	0.056	0.84	0.047	0.87
A_{Surf}	0.105	1.65	0.089	1.77
A_{Era}	0.137	2.41	0.120	2.64
A_{Wisk}	0.040	0.59	0.029	0.53
A_{Tide}	0.138	–	0.120	–
"Other Brands" intercept (Φ_O)	−17.657	−7.98	−17.267	−7.59
"Other Brands" time trend (Ψ_O)	0.018	8.53	0.018	8.91
"No Purchase" intercept (Φ_{NP})	−15.408	−6.99	−19.537	−8.55
"No Purchase" time trend (Ψ_{NP})	0.011	3.17	0.012	3.42
experience variability (σ_λ)	0.374	9.17	0.33	8.37
advertising variability (δ_ζ)	3.418	6.29	3.08	5.57

Results

- Static model has no effect of advertising (!)
- Consumers are risk averse
- Price coefficient negative and significant
- Utility weight is huge (latent attribute – cleaning power?)
- Attribute levels are not significant (maybe differences are?)
- Advertising more variable than experience
- relatively small initial variance
- Dynamic model shows more willingness to try new brands

Crawford and Shum

Uncertainty and Learning in Pharmaceutical Demand

Crawford and Shum (2005)

- Italian anti-ulcer data: 34,972 patients (and a total of 98,634 prescription episodes)
- Patients receive, on average, 2.8 prescriptions for 1.2 drugs over a period of just under 6 months.
- Break up data into *spells* or a sequence of one or more prescriptions of a single drug.
  - A patient has 1.2 spells on average
  - An average spell is around 2.37 prescriptions
- Probability of switching drugs is not constant over time
  1. Early Switching: Experimentation - about 10% after first prescription
  2. Late Switching: Learning rise in switching at the end, especially for long-treatment length patients

SWITCHING PROBABILITIES OVER THE COURSE OF TREATMENT[a]

Prescription Number	Total Treatment Length					
	5	6	7	8	9	10
2	14.3	13.6	10.9	10.0	7.8	9.2
3	11.6	11.6	6.3	8.8	7.8	6.6
4	8.9	5.6	5.4	3.1	7.8	3.9
5	13.4	7.9	10.0	8.8	4.9	5.3
6		11.3	6.3	5.7	2.9	5.3
7			9.5	10.0	7.8	11.8
8				8.1	4.9	11.8
9					7.8	5.3
10						11.8

[a]The (i, j)th entry is the percentage of treatment sequences of length j in which a switch was observed during the ith $(i \leq j)$ prescription.

Model Setup

- Patients, j. Drugs, $n = 5$, types $k = 4$ (known to doctor-patient but not econometrician).
- Treatment is characterized by two match values (μ_{jn}, ν_{jn}) and two corresponding signals (x_{jnt}, y_{jnt}) that correspond to the side-effects or curative probabilities respectively.
- Patient's utility $u(\cdot)$ depends on side effects x_{int}
- Cure probability $w(\cdot)$ depends on y_{jnt}
- Don't know your match value (μ_{jn}, ν_{jn}) only the signal (x_{jnt}, y_{jnt}), or treatment length $\tau = 1, \ldots, T$

Model Setup

- Consumers have both signals (x, y) and priors (μ, ν) about side effects and cure probability

$$\begin{pmatrix} x_{jnt} \\ y_{jnt} \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{jn} \\ \nu_{jnt} \end{pmatrix}, \begin{matrix} \sigma^2_{jn} \\ \tau^2_{jnt} \end{matrix} \right)$$
$$\begin{pmatrix} \mu_{jn} \\ \nu_{jn} \end{pmatrix} \sim N\left(\begin{pmatrix} \overline{\mu}_{nk} \\ \overline{\nu}_{nk} \end{pmatrix}, \begin{matrix} \overline{\sigma}^2_{n} \\ \overline{\tau}^2_{n} \end{matrix} \right)$$

- Where $k = 1, \ldots, 4$ indexes the type specific priors.

Model Setup

- Doctors (without incentive problems) solve:

$$\max_{D=\{(d_{jnt})_{n=1}^{N}\}_{t=1}^{\infty}} E_D \sum_{t=1}^{\infty} \beta^t d_{jnt} u_{jnt} (1 - w_{j,t-1})$$

- Patients have CARA utility

$$u(x_{jnt}, p_n, \epsilon_{jnt}) = -\exp(r * x_{jnt}) - \alpha p_n + \epsilon_{jnt}$$

- Derive the expected utility as:

$$\begin{aligned} \tilde{EU}(\mu_{jn}(t), \nu_{jn}(t), p_n, \epsilon_{jnt}) &= -\exp(r * \mu_{jn}(t) + \frac{1}{2} r^2(\sigma)(\sigma_n^2 + V_{jn}(t))) \\ &\quad -\alpha p_n + \epsilon_{jnt} \\ &= EU(\mu_{jn}(t), V_{jn}(t), p_n) + \epsilon_{jnt} \end{aligned}$$

State Space

- State Variables S_t:
  - $(\mu_{jnt}, \nu_{jnt}), I_{jnt}$ for $n = 1, \ldots, 5$ drugs.
  - $h_{j,t-1}$ (cure probability)
  - ϵ_{jnt}
- Recovery probability follows a Markov Process:

$$h_{jt}(h_{j,t-1}, y_{jnt}) = \frac{\left(\frac{h_{j,t-1}}{1-h_{j,t-1}}\right) + d_{jnt}y_{jnt}}{1 + \left(\frac{h_{j,t-1}}{1-h_{j,t-1}}\right) + d_{jnt}y_{jnt}}$$

- Beliefs follow Bayesian updating depending on I_{jnt} the number of times patient j takes drug n at time t.

Dynamic Decision Problem (DDP)

Doctors face choice specific value function (infinite horizon, recovery state absorbing):

$$
\begin{aligned}
W(S_t) &= \max_n [\exp(-r\mu_{jnt} + 0.5r^2(\sigma_n^2 + V_{jnt})) - \alpha p_n + \epsilon_{jnt} \\
&\quad + \beta E[(1 - h_{jt}(h_{j,t-1}, y_{jnt}) E[W(S_{t+1}) | x_{jnt}, y_{jnt}, d_n = 1] | S_t] \\
&= \log[\sum_n \exp[\tilde{EU}(s) + \beta E[(1 - h(s'))W(s') | d_n = 1] | S_t] \\
&= \max_n \{W_n(S_t)\}
\end{aligned}
$$

Value Function

$$
\begin{aligned}
W(S_t) &= \max_n [\exp(-r\mu_{jnt} + 0.5r^2(\sigma_n^2 + V_{jnt})) - \alpha p_n + \epsilon_{jnt} \\
&\quad + \beta E[(1 - h_{jt}(h_{j,t-1}, y_{jnt}) E[W(S_{t+1})|x_{jnt}, y_{jnt}, d_n = 1]|S_t] \\
&= \log[\sum_n \exp[\tilde{EU}(s) + \beta E[(1 - h(s'))W(s')|d_n = 1]|S_t] \\
&= \max_n \{W_n(S_t)\}
\end{aligned}
$$

VFI + Simulate + Interpolate: (Keane Wolpin 1994):

1. Define discrete grid $S^* \in S$
2. For each state $s \in S^*$ make an initial guess at the value function $W^0(s)$.
3. Run regression $W^0(s) = G(s)'\theta^0 + \varepsilon$
4. Draw the M random signals $\{x_{jn}^m, y_{jn}^m\}$
5. Compute the expected value of choosing drug n for each $s \in S^*S$, where s^m is state corresponding to random draw m and drug n being chosen.

$$E[W(s|d_n = 1, s)] = \frac{1}{M} \sum_m (1 - h(s^m)) W^0(s^m)$$

6. Update the value function for each $s \in S^*$
7. Iterate until convergence

Likelihood

For $I_{=}0$ and $I_j = 1$ censored and uncensored observations for patient j.

$$\sum_{k=1}^{K} p_k E_{\overline{x}_{jnT_j},k|h_{0,j,k}} \left[\prod_{t=1}^{T_j-1} \left((1 - h_{jt,k}) \prod_n \lambda_{jnt,k}^{d_{jnt}} \right) \right] \cdot h_{jT_j,k} \prod_n \lambda_{jnt,k}^{d_{jnt}}$$

$$\sum_{k=1}^{K} p_k E_{\overline{x}_{jnT_j},k|h_{0,j,k}} \left[\prod_{t=1}^{T_j-1} \left((1 - h_{jt,k}) \prod_n \lambda_{jnt,k}^{d_{jnt}} \right) \right] \cdot \prod_n \lambda_{jnt,k}^{d_{jnt}}$$

(λ is logit choice probability)

We need to calculate expectations of joint distribution of $(\overline{x}, h)$ by drawing $S = 30$ sequences per patient.

Identification

- Key restrictions
  - drug's symptomatic effects only impact a patient's utility
  - curative effects only influence the recovery probabilities
- For $(\underline{\mu}_j, \underline{\sigma}_j^2, \sigma_j, r)$
  - enter per period utility expression
  - $\underline{\mu}_j$ comes from initial prescription shares across patients
  - Difference in drug choice probabilities early vs. late in sequence help identify $\underline{\sigma}_j^2$
  - r vs. σ_j
    - persistence in drug choices gives r
    - extent to which rate of switching varies with l_{ij}^t identifies σ_j

Identification

- For $(\underline{\nu}_j, \underline{\tau}_j^2, \tau_j, h_{0i})$
  - enters dynamic choice problem through expected recovery probability
  - h_{0i} identified separately because it only enters healing probability; other 3 enter posterior mean and variance for curative match value
- Can identify $\underline{\mu}_j$ separately from price coefficient, α, because of functional form assumption; $\underline{\mu}_j$ enters per period utility nonlinearly and α enters linearly.

Dynamic Model Parameters: Sick vs. Not so Sick

Parameter	Est.	Std. Err.	Est.	Std. Err.
Illness heterogeneity distribution	Recovery Probability		Type Probability	
θ_1 (Type 1)	0.433	0.003	0.593	0.006
θ_2 (Type 2)	0.127	0.003	0.335	0.006
θ_3 (Type 3)	0.199	0.007	0.043	0.001
θ_4 (Type 4)	0.432	0.011	0.029	0.002
Means, symptom match values[b]	Type 1		Type 2	
$\underline{\mu}_1$	0.927	0.282	1.195	0.369
$\underline{\mu}_2$[c]	0.928	0.287	0.428	0.166
$\underline{\mu}_3$	0.481	0.197	−0.028	0.178
$\underline{\mu}_4$	0.335	0.161	−0.145	0.079
$\underline{\mu}_5$	0.451	0.174	−0.483	0.137
Means, curative match values[b]	Type 1		Type 2	
$\underline{\nu}_1$	0.014	0.003	0.006	0.000
$\underline{\nu}_2$[c]	0.015	0.005	0.006	0.001
$\underline{\nu}_3$	0.013	0.030	0.006	0.095
$\underline{\nu}_4$	0.013	0.084	0.014	0.009
$\underline{\nu}_5$	−0.034	0.000	−0.038	0.000
Std. dev., symptom match values				
$\underline{\sigma}$	1.574	0.448		
Std. devs., symptom signals				
σ_1	0.998	0.287		
σ_2	1.134	0.326		
σ_3	1.375	0.395		
σ_4	1.159	0.333		
σ_5	0.931	0.268		
Std. dev., curative match values				
$\underline{\tau}$	0.007	0.000		
Std. dev., curative signals				
τ	0.007	0.001		
Price coefficient, α[a]	1.080	0.091		
Risk-aversion parameter, r	0.990	0.274		
Discount rate, β	0.950	Fixed		
Number of observations	34,972			
Number of similar draws	30			

Dynamic Model Parameters: Omeprazole (All types)

	Type 1		Type 2		Type 3		Type 4	
Parameter	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
Match values, all types								
Symptom match values								
$\underline{\mu}_1$	0.927	0.282	1.195	0.369	0.489	0.163	0.151	0.091
$\underline{\mu}_2$[a]	0.928	0.287	0.428	0.166	0.577	0.198	0.573	0.199
$\underline{\mu}_3$	0.481	0.197	−0.028	0.178	1.762	0.531	0.013	0.167
$\underline{\mu}_4$	0.335	0.161	−0.145	0.079	−0.111	0.305	0.504	0.184
$\underline{\mu}_5$	0.451	0.174	−0.483	0.137	−0.113	0.125	−0.561	0.220
Curative match values								
$\underline{\nu}_1$	0.014	0.003	0.006	0.000	0.011	0.002	0.014	0.010
$\underline{\nu}_2$[a]	0.015	0.005	0.006	0.001	0.011	0.006	0.015	0.003
$\underline{\nu}_3$	0.013	0.030	0.006	0.095	0.004	0.001	0.013	0.329
$\underline{\nu}_4$	0.013	0.084	0.014	0.009	−0.035	0.214	0.012	0.003
$\underline{\nu}_5$	−0.034	0.000	−0.038	0.000	−0.037	0.054	−0.034	0.409
Time-varying priors for omeprazole								
Symptom match value, $\underline{\mu}_2$								
Period 1	0.805	0.258	0.306	0.140	0.454	0.171	0.451	0.172
Period 2	0.910	0.285	0.411	0.166	0.560	0.197	0.556	0.198
Period 3	0.722	0.237	0.223	0.122	0.371	0.151	0.368	0.152
Period 4	0.979	0.301	0.480	0.181	0.628	0.212	0.625	0.214
Period 5[a]	0.928	0.287	0.428	0.166	0.577	0.198	0.573	0.199
Curative match value, $\underline{\nu}_2$								
Period 1	−0.007	0.011	−0.016	0.010	−0.011	0.011	−0.007	0.010
Period 2	−0.001	0.012	−0.011	0.011	−0.006	0.012	−0.001	0.011
Period 3	0.015	0.016	0.005	0.015	0.011	0.016	0.015	0.016
Period 4	0.013	0.017	0.004	0.016	0.009	0.017	0.013	0.017
Period 5[a]	0.015	0.005	0.015	0.001	0.011	0.006	0.015	0.003

Results

- Coefficient of risk aversion is high (switching costs?)
- Learning happens very fast (variance falls from 2.48 to 0.7 after only one prescription).
- Learning slows after first prescription
- Counterfactual (Complete Information): You know your match values which you draw from the same distribution but your perceived variance $V_{jn}^t = R_{jn}^= 0$.
  - Leads to more drugs 1.9 instead of 1.4.
  - Substitution away from market leader (no reason to stay with first drug). Lower HHI
  - Welfare up 9%. Treatment up 80%, cost up 60%.
- Counterfactual (Ban Experimenting): You are stuck with your first drug forever.
  - Utility down 6% but treatment length and costs about the same.
  - Wasn't much experimentation to begin with
- Counterfactual (No Diagnostic Matching): Doctors can't learn types.
  - Utility down 11% and costs and length up 30-40%.

Results

- Counterfactual 1: patients have complete info about match values (set perceived variances, $(V_{ij}^t, R_{ij}^t) = 0$)
  - discounted expected utility increases (though by small amount)
  - average number of drugs used increases
- Counterfactual 2: constrain patients to take the first drug they're prescribed
  - shuts down learning after 1st prescription
  - does not change simulated treatment lengths
  - lowers avg utility 6%
- Counterfactual 3: no diagnostic matching to patient "type"
  - expected utility decreases 11%, costs 40% higher than baseline
  - diagnostic matching at least as important as idiosyncratic learning

Dickstein: Efficient Provision of Experience Goods: Evidence from Antidepressant Choice

Goals and RQ

Goals of Paper

- Theory Testing
- Measurement
- Methodology

Goals of the Paper

- Theory Testing
  - Do the pricing schemes of Shapiro (1983), Bergemann and Valimaki (2006) appear in markets in which consumer perceptions change with experience?
  - Can adherence information in observational data provide a measure of treatment effectiveness?
- Measurement
  - Identify the elasticity of patients/physicians with respect drug copayments and wholesale prices
  - Measure the dynamic response of patients and physicians to prices/promotion, in both costs and health.
  - Provide average adherence information by drug compound

Goals of the Paper (continued)

- Methodology
  - Provide feasible estimation approach for dynamic discrete choice problems with large choice sets, given correlation in outcomes across alternatives.

Research Questions

What policies can improve the efficiency of drug choice, maximizing adherence and patient health while minimizing the costs of treatment?

- Copayment schemes
  - Tiered policy
  - Uniform pricing
  - “Value-based" design (Chernew et al. (2007))
- Informational campaigns
  - Discourage use of “me-too" branded drugs
  - Endow general practitioners with psychiatrists’ preferences

Research Questions (Continued)

- What information can observational studies contribute— beyond results from randomized trials— to judge the efficacy of different treatments?
  - Philipson and Hedges (1998) provide theoretical justification
  - Chan and Hamilton (2006) measure the benefits in the clinical trial setting
- With 20 products available, what assumptions permit estimation of the agent's learning process over this choice set?

Data

Market for Depression Care

- Major depression affects 6.5% of adults in the US annually
- US antidepressant market sales in 2008
  - $9.6 Billion
  - 164 million monthly prescriptions (3rd ranked class)

Six subclasses: differ in their effect on serotonin, norepinephrine, or dopamine in the brain.

"First Generation"	"Second Generation"
TCAs	SSRIs, SNRIs, NDRIs, NaSSAs, SARIs

- Choice set: 13 compounds, 20 unique products

Data

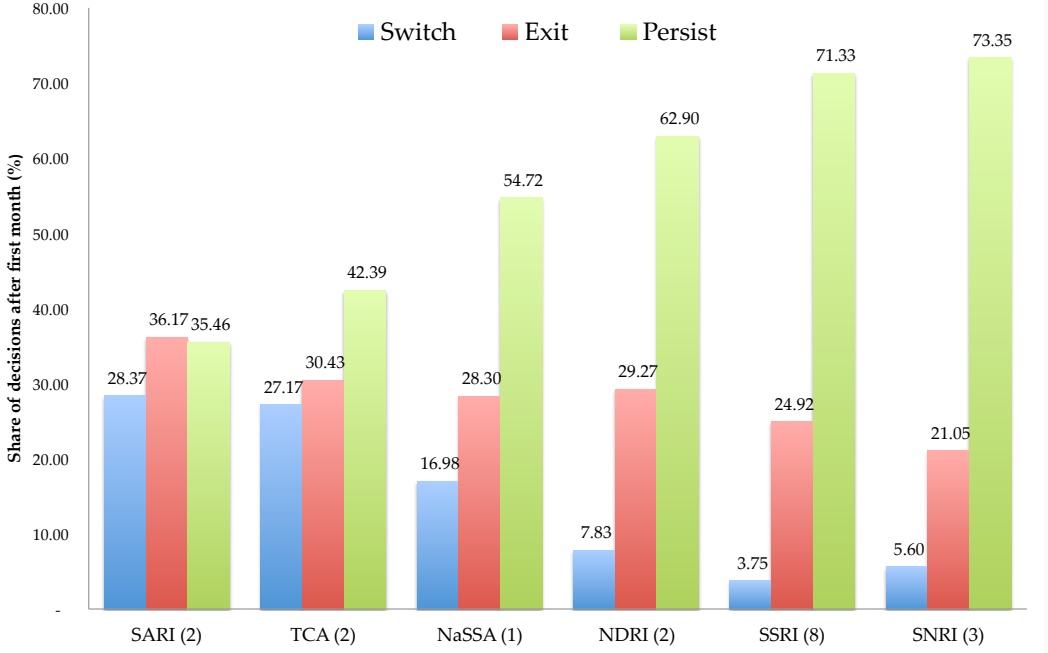
Source: Thomson Medstat Marketscan databases, 2003-2005.

- Includes active employees (and dependents) of large self-insured firms that contribute claims to the Marketscan database

Requirements for inclusion in sample

- Patients newly diagnosed in an outpatient visit with: major depression (296.2-3), related depression conditions (300.4, 309.0-1, 311)
- No concurrent diagnosis of manic disorders (296.0-1, 296.4-8) or schizophrenic disorders (295.0-9)
- Age between 18 and 64
- Visits a health professional with prescribing ability
- Not pregnant

Product Name	Subclass	Brand?	Daily dosing	Market Share (%) 2003	2004	2005
None	None	-	-	35.2	39.3	34.2
Citalopram HBr	SSRI	No	1	-	0.2	4.2
Celexa	SSRI	Yes	1	4.1	2.7	0.1
Lexapro	SSRI	Yes	1	13.8	13.0	12.0
Fluoxetine HCL	SSRI	No	1-2	7.3	11.5	10.6
Paroxetine HCL	SSRI	No	1	1.7	4.3	4.4
Paxil CR	SSRI	Yes	1	6.4	3.6	1.6
Zoloft	SSRI	Yes	1	12.5	10.6	9.6
Cymbalta	SNRI	Yes	1-2	-	0.5	2.4
Effexor-XR	SNRI	Yes	1	8.6	7.5	7.0
Bupropion HCL	NDRI	No	3	0.3	3.4	4.5
Wellbutrin XL	NDRI	Yes	1	6.5	5.7	5.1
Amitriptyline HCL	TCA	No	1	0.7	0.9	0.7
Mirtazapine	NaSSA	No	1	0.5	0.7	0.6
Trazodone HCL	SM	No	3	1.3	1.8	1.6
			Total # unique patients:			102,780
			Total # of observations:			267,390
			Total # unique plans:			307


Switch
Exit
Persist
Share of decisions after first month (%)
80.00
70.00
60.00
50.00
40.00
30.00
20.00
10.00
-
28.37
36.17
35.46
27.17
30.43
42.39
16.98
28.30
54.72
7.83
29.27
62.90
3.75
24.92
71.33
5.60
21.05
73.35
SARI (2)
TCA (2)
NaSSA (1)
NDRI (2)
SSRI (8)
SNRI (3)

Timing of Switches

Prescription count in episode	Length of Treatment Episode (# monthly prescriptions dispensed)							
	1	2	3	4	5	6	7	8
1	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
2		85.1	86.8	88.9	89.4	89.6	90.4	91.4
3			84.4	84.2	84.7	85.8	86.4	88.2
4				82.3	82.0	83.0	83.9	86.4
5					80.2	81.0	82.2	84.4
6						79.6	80.1	82.6
7							79.3	80.7
8								79.9
Share of dataset	56.7%	12.9%	9.3%	6.4%	4.4%	3.1%	2.1%	1.7%

Hazard of switching

- Interpret as probability of finding a drug “ineffective"
- Condition on patient costs, doses/day, rate of side effects, patient diagnosis
- Find range of predicted prob of effectiveness

	Periods since the patient's initial diagnosis		
Class	Period 1	Period 2	Period 3
TCA	52.4	62.7	68.7
SSRI	66.1	74.2	78.6
SNRI	66.2	74.3	78.7
NDRI	61.1	70.2	75.1
NaSSA	59.2	68.5	73.7
SARI	43.7	55.1	61.8

Learning Model

Learning Model

Goal:

Estimate parameters of the agent's learning process using the timing and identity of observed switch/persist decisions

Requires:

Predicted choice probabilities to match to observed choices

- (1) Discrete outcomes
- (2) Patient and physician priors
- (3) Updating process
- (4) Decision rule
  - myopic vs. forward-looking
  - independent vs. correlated choices

(1) Discrete outcomes

- Patient and physician (i) observe a discrete outcome, Y_{ijt}, under treatment j at time t
- "Outcome" includes efficacy, price, side effects, ease of use, ...

(1) Discrete outcomes

- Patient and physician (i) observe a discrete outcome, Y_{ijt}, under treatment j at time t
- "Outcome" includes efficacy, price, side effects, ease of use, ...
- Y_{ijt} drawn from a Bernoulli distribution
- Probability of a successful outcome equals p_j:

$$Y_{ijt} \backsim p_j^k(1-p_j)^{1-k}, k \in \{0,1\}$$

where $k = 1$ if drug j proves effective in period t

(1) Discrete outcomes (continued)

Prior on p_j

- Beta distribution with parameters $(a_{j,0}, b_{j,0})$
- Mean and variance of Beta distribution:

$$\begin{aligned} \mu_{j,0} &= \frac{a_{j,0}}{a_{j,0} + b_{j,0}} \\ v_{j,0} &= \frac{a_{j,0} b_{j,0}}{(a_{j,0} + b_{j,0})^2 (a_{j,0} + b_{j,0} + 1)} \end{aligned}$$

where $a_{j,0} > 0$ and $b_{j,0} > 0$.

(2) Updating process

After t trials of treatment j:

- add to $a_{j,0}$ the number of successes observed
- add to $b_{j,0}$ the number of failures observed

Why?

- Beta is conjugate prior for Bernoulli likelihood. So, posterior distribution of p_j is Beta.

Caveat

- In the application, successes and failures not observed; I integrate over the discrete number of possible realizations.

(3) Decision Rule: Options

(1) 'Bayesian Myopic' at $(T+1)$ after updating using $\widehat{Y}_{ij}$:

$$\max_{j \in 1,...,J} E(p_{i,j,T+1}|a_0, b_0, \widehat{Y}_{ij}) + \varepsilon_{ijt} = \mu_{j,T+1} + \varepsilon_{ijt}$$

- Experience on j for periods $t = 1, ..., T$ in vector $\widehat{Y}_{ij}$
- Choose what to consume at $T+1$
- ε_{ijt} represents idiosyncratic tastes for j at t

(3) Decision Rule: Options

(2) 'Forward-Looking' at $(T+1)$ after updating using $\widehat{Y}_{ij}$:

$$\max_{j \in 1,\ldots,J} \mu_{j,T+1} + h(V(p_{i,j,T+1}|a_0, b_0, \widehat{Y}_{ij})) + \varepsilon_{ijt}$$

(3) Decision Rule: Forward-Looking Problem

The physician and patient choose a sequence of drugs to maximize the expected discounted sum of outcomes, Y_t:

$$\int ... \int E_{p_1,...,p_J} \left(\sum_{t=1}^{\infty} \delta^{t-1} Y_t \right) d\Pi^{(1)}(p_1) \cdots d\Pi^{(J)}(p_J) \tag{1}$$

- δ is given and $p = (p_1, ..., p_J)$ is the unknown vector of probabilities that a drug $j \in 1, ..., J$ is effective.
- the agent forms independent priors, Π, on the elements of p
- The state variables include the number of successes and failures under each choice

(3) Decision Rule: Forward-Looking Solutions

Solutions:

- Dynamic Programming, via Rust (1987) and Hotz and Miller (1993)
- Keane and Wolpin (1984), simulation and interpolation
- Gittins' (1979) index rule: Break J-dimensional problem into J continue-quit decisions, one for each choice
  - Inner maximization: solve 1-dim optimal stopping problem for each j. Save discounted expected value, the "index"
  - Outer maximization: choose j with the maximal index value

(3) Decision Rule: Forward-Looking Solutions

Requirements for Gittins' Index:

1. the decision-maker selects only one option at t
2. options not chosen remain in their initial state
3. each option is independent
4. options not selected do not contribute to the individual's outcome

More on Gittins

(3) Decision Rule: Forward-Looking Solutions

My approach (computable via forward induction):

- Use index rule, treating each drug compound choice as independent
  - unobservables not correlated across drug choices
- Use index rule with explicit nesting structure
  - use drug classes as nests, within which choices may be correlated
  - unobservables not correlated across drug classes

(3) Decision Rule: Index Rule form

Apply forward induction rule

$$G(\Pi_t^{(j)}) = \mu_{j,t} + \sqrt{v_{j,t}} * \left[\psi \left(\frac{v_{j,t}}{h(\delta) * \sigma^2(\mu_{j,t})} \right) \right]$$

- $(\mu_{j,t}, v_{j,t})$, are the mean and variance of the posterior beta distribution for p_j, the probability that drug j is effective.
- $\psi(.)$ represents the closed-form numerical approximation to the boundary of the one-dimensional optimal stopping problem for each drug (Chang and Lai (1987))

(3) Decision Rule: Index Rule form

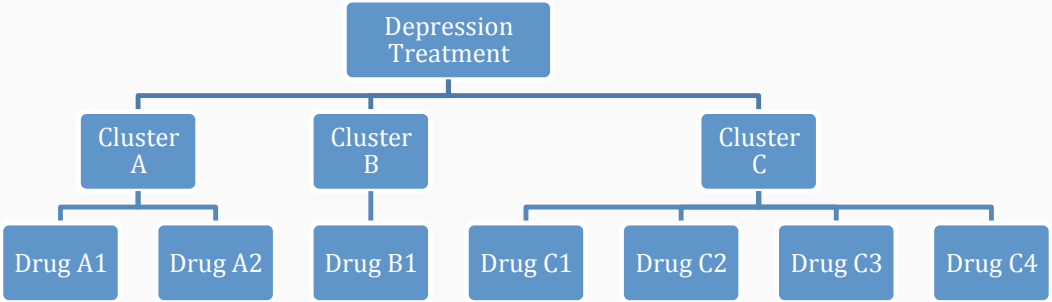
$$G(\Pi_t^{(j)}) = \mu_{j,t} + \sqrt{v_{j,t}} * \left[\psi \left(\frac{v_{j,t}}{h(\delta) * \sigma^2(\mu_{j,t})} \right) \right]$$

$$\begin{aligned} \mu_{j,t} &= \frac{a_{j,t}}{a_{j,t} + b_{j,t}} \\ v_{j,t} &= \frac{a_{j,t} b_{j,t}}{(a_{j,t} + b_{j,t})^2 (a_{j,t} + b_{j,t} + 1)} \\ \sigma^2(\mu_{j,t}) &= \mu_{j,t} * (1 - \mu_{j,t}) \end{aligned}$$

Experimentation incentive diminishes when:

- δ is small, $h(\delta)$ is large
- when past experience diminishes $v_{j,t}$

(3) Decision Rule: Index Rule with Correlation



- Cluster by drug class
- Sum outcomes over all trials of drugs within the class

$$a_{c,t} = \sum_{j} 1\{j \in c\} * a_{j,t}$$

$$b_{c,t} = \sum_{j} 1\{j \in c\} * b_{j,t}$$

(3) Decision Rule: Index Rule with Correlation

- Index rule for the class

$$G(\Pi_t^{(c)}) = \mu_{c,t} + \sqrt{v_{c,t}} * \left[\psi \left(\frac{v_{c,t}}{h(\delta) * \sigma^2(\mu_{c,t})} \right) \right]$$

- Drug class choice probability

$$\text{Prob}_{c,t} = \frac{\exp(G(\Pi_t^{(c)}))}{1 + \sum_{s=1}^{C-1} \exp(G(\Pi_t^{(s)}))}$$

- Drug compound choice probability

$$\begin{aligned} \text{Prob}_{j \in c,t} &= \text{Prob}_{c,t}(\text{Prob}_{j,t} | 1\{\text{c chosen}\}) \\ &= \text{Prob}_{c,t} * \frac{\exp(G(\Pi_t^{(j)}))}{\sum_{k \in c} \exp(G(\Pi_t^{(k)}))} \end{aligned}$$

Estimates and Fit

Econometric Model

- Parameterize p_j using beta regression model

$$\begin{aligned} p_j|X_{ij} &\backsim Beta(a_0, b_0) \\ \mu(X_{ij};\gamma_1) &= \frac{a_o}{a_0+b_0} = \frac{\exp(X_{ij}\gamma_1)}{1+\exp(X_{ij}\gamma_1)} \\ \phi(\gamma_2) &= a_0+b_0 = \exp(\gamma_2) \end{aligned}$$

  where μ is prior mean, ϕ is the prior precision of p_j
- The prior variance of p_j is:

$$V(p_j|X_{ij}) = \frac{\mu(1-\mu)}{1+\phi}$$

- For a fixed μ, the larger the value of ϕ, the smaller the variance in p_j.

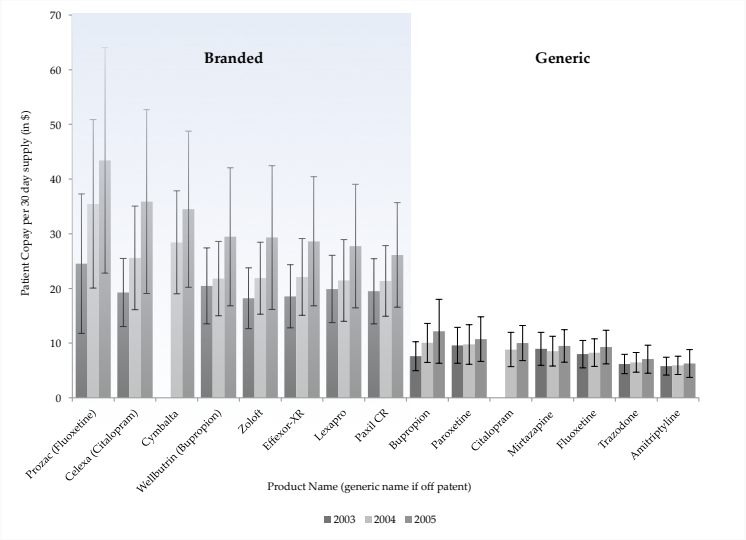


Figure 1: Patient Copayments by Product and Year (standard deviation across insurance plans shown)

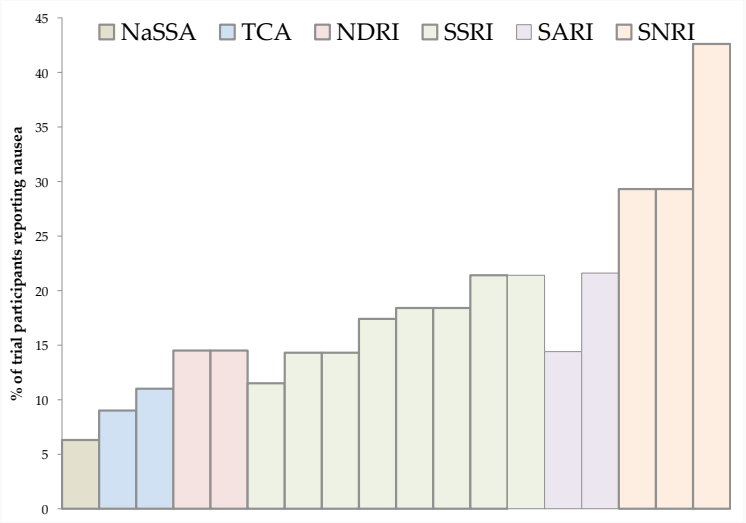


Figure 2: Nausea Side Effects in Clinical Trials

Identification

Goal: recover $\gamma = (\gamma_1, \gamma_2)$, in the mean and precision of p_j

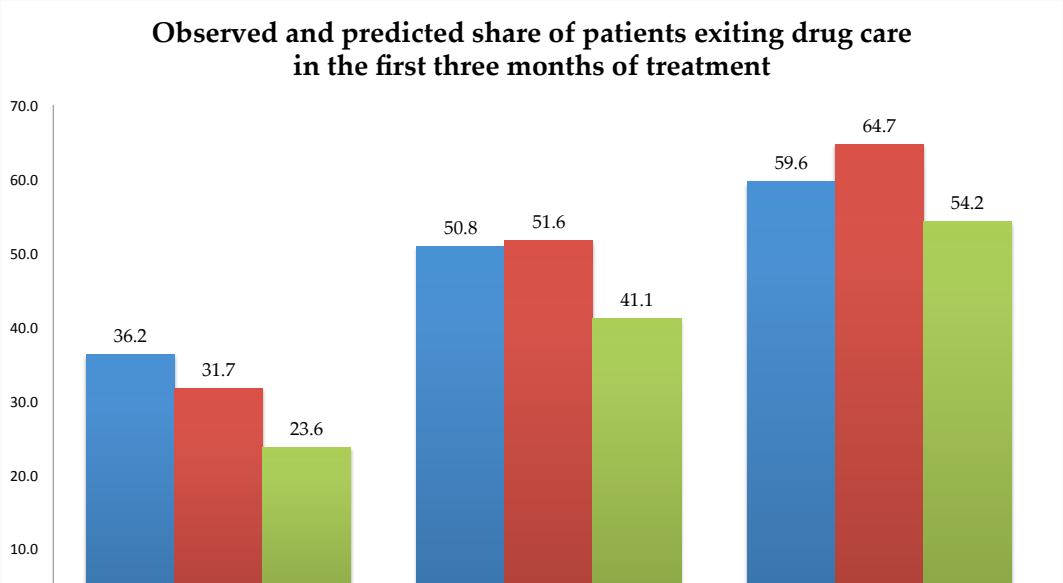
1. Identity of choice throughout the sequence of treatments
   - Identifies expected mean outcome under available choices following standard arguments
2. Information on drug characteristics from clinical trial data, external sources
3. Timing of observed switches
   - Identifies precision of the agents' priors
   - Slowing switching, condition on μ, higher uncertainty in agents' priors
   - Errors assumed idiosyncratic

Results, via maximum likelihood

	(1) Two-Level Gittins Index Model		(2) Two-level Bayesian-Myopic Model	
Covariates in prior mean	Est	Std. Err	Est	Std. Err
1{SSRI}	99.16	8.72	-0.84	6.75
1{SNRI}	-22.58	2.23	-69.23	10.74
1{NDRI}	-43.09	5.77	-73.38	7.33
1{NaSSA}	-35.36	8.47	-15.08	3.24
1{SARI}	-40.03	2.04	-7.62	18.92
1{TCA}	-72.44	4.36	-13.72	8.88
1{more than 1 dose needed per day}	-76.77	3.66	-20.69	18.94
pecentage of nausea reports in trials	-15.62	5.20	9.23	47.77
1{reformulation}	13.91	15.96	70.17	2.99
1{branded}	-9.80	4.93	3.23	1.54
copayment, in $/day	-81.58	19.58	-3.42	2.26
log(precision)	-3.28	2.61	-32.06	0.02

*Includes interactions between speciality and drug class, diagnosis severity

Fit - Adherence Rate



Fit: Predicted Choices by Individual

Panel A: Percentage of patients who have exited care in the first three months of treatment			
Model	t=1	t=2	t=3
Raw data	36.2	50.8	59.6
Dynamic model, clustered by type	31.7	51.6	64.7
Bayesian myopic model, clustered by type	23.6	41.1	54.2
Panel B: Percentage of patients for whom the obs choice equals the model's top predictions			
Examination	t=1	t=2	t=3
Compare to top 3 ranked by dynamic model	44.9	62.7	74.3
Compare to top 3 ranked by Bayesian-myopic model	48.5	65.7	76.7
Compare to top 5 ranked by dynamic model	70.8	72.8	78.9
Compare to top 5 ranked by Bayesian-myopic model	66.3	74.6	79.0

- Kullback-Leibler Information Criterion: 11.95
- At the 95% critical value, the data favors the two-level dynamic model over the one-level model.

Counterfactuals

Counterfactuals: Shares in the First Month

Counterfactual policies	None	TCA	NDRI	SSRI	SNRI	NaSSA	SARI
Pricing							
Baseline	31.7	4.9	12.1	31.9	12.1	2.4	4.9
All copayments set to $5	31.1	4.8	11.9	33.1	11.9	2.4	4.8
Value-based design	16.5	6.6	16.5	34.1	16.5	3.3	6.6
Informational campaigns							
Baseline	31.7	4.9	12.1	31.9	12.1	2.4	4.9
Discourage use of reformulations	31.8	4.9	12.2	31.7	12.2	2.4	4.9
Psychiatrists' priors	31.6	4.8	12.1	32.2	12.1	2.4	4.8

Counterfactuals: Calculating dollar value of health

- Berndt et al. (2002) provides recovery rates of first 16 weeks of care (via expert panel)
  - e.g. Patient on SSRI for > 30 days has $.28$ rate of recovery, $.60$ rate of partial recovery
- Convert each individual's choice to an expected number of weeks with full/partial symptoms over first 16 weeks

Treatment	Full (wks)	Partial (wks)
No Drug Care	11.9	2.8
SSRI, ≤ 30 days	10.3	3.9
SSRI, > 30 days	7.3	5.9

- Lave et al. (1998): disutility from full depression, -.41
- Covert utility change (in weeks) to dollars using \$100,000 value of year of life (Cutler (2004))

Counterfactuals: Cost and health comparison

	Three month drug costs per patient (in $)	Value of utility gain from symptomatic recovery (in $)
Baseline	67.25	929.90
Effects of copayment policies		
	Change in three month drug costs per patient (in $)	Change in symptomatic recovery (in $)
All copayments set to $5	30.28	10.42
Value-based design	3.13	193.35
Effects of informational campaigns		
	Change in three month drug costs per patient (in $)	Change in symptomatic recovery (in $)
Discourage use of reformulation products	(0.04)	(1.85)
Endow all physicians with psychiatrists' priors	0.65	2.18

Counterfactuals: New Protocol

				(1)	(2)	(3)	(4)	(5)
Product	Class	Prob drug is effective, hazard model	Prob drug is effective, dynamic model	Texas Medication Algorithm Project (1998)	APA Guidelines, Second Edition (2000,2005)	Comparative effectiveness review; AHRQ (2007)	Hazard Model	Dynamic Model
Amitriptyline	TCA	51.7	0.0		X			
Bupropion	NDRI	60.5	0.0	X	X	X	X	
Wellbutrin XL	NDRI	61.8	0.0	X	X	X	X	
Citalopram	SSRI	72.0	55.7	X	X	X	X	X
Celexa	SSRI	66.1	59.4	X	X	X	X	X
Cymbalta	SNRI	67.4	0.0		X	X	X	
Lexapro	SSRI	64.6	81.1	X	X	X	X	X
Fluoxetine	SSRI	70.6	100.0	X	X	X	X	X
Prozac	SSRI	65.5	50.6	X	X	X	X	
Mirtazapine	NaSSA	59.2	0.0			X	X	
Nefazodone	SARI	41.7	0.0	X				
Nortriptyline	TCA	53.0	0.0		X			

Estimation: Likelihood form

When we assume independent products, the likelihood for individual i in period t is:

$$\prod_{j=1}^{J} E_{\varepsilon_{i1t},...,\varepsilon_{iJt}}(1\{G_{ijt}(\Pi_t^{(j)}) + \varepsilon_{ijt} > G_{ikt}(\Pi_t^{(k)}) + \varepsilon_{ikt} \text{ for all } k \neq j\}^{d_{ijt}})$$

$$= \prod_{j=1}^{J} \left(\frac{\exp(G_{ijt}(X_{ij}, \widehat{Y}_{i,j,t-1}; \gamma))}{1 + \sum_k \exp(G_{ikt}(X_{ik}, \widehat{Y}_{i,k,t-1}; \gamma)} \right)^{d_{ijt}}$$

- G_{ijt} is the index rule
- $d_{ijt} = 1$ if i chooses drug j in period t
- $\widehat{Y}_{i,l,t-1}$ is a vector of realized outcomes under treatments $l = 1, ..., J$ during the previous $(t-1)$ periods
- ε_{ijt} follow an extreme value distribution

Estimation: Likelihood form

- $(\widehat{Y}_{i,1,t-1}, ..., \widehat{Y}_{i,J,t-1})$ are latent
- Sum over the possible sequences of outcomes, weighting by the probability of observing those sequences

$$\sum_s \omega_{i,s} \prod_{j=1}^{J} \left(\frac{\exp(G_{ijt}(X_{ij}, \widehat{Y}^s_{i,j,t-1}; \gamma))}{1 + \sum_k \exp(G_{ikt}(X_{ik}, \widehat{Y}^s_{i,k,t-1}; \gamma)} \right)^{d_{ijt}}$$

- $\omega_{i,s}$ is the probability of observing one of $s \in S$ possible sequences; follows a discrete binomial distribution
- $\widehat{Y}^s_{i,j,t-1}$ represents discrete counts of successes and failures realized over $(t-1)$ periods.
- Under rational expectations, the parameters that underlie $\omega_{i,s}$ equal the parameters of the agents' priors.

Estimation: Likelihood form

$$\sum_s \omega_{i,s} \prod_{c=1}^{C} \left[\left(\frac{\exp(G_{ict}(\Pi_t^{(c),s}))}{1 + \sum_m^{C-1} \exp(G_{imt}(\Pi_t^{(m),s})} \right)^{d_{ict}} \prod_{j \in c}^{J_c} \left(\frac{\exp(G_{ijt}(\Pi_t^{(j),s}))}{\sum_k^{J_c} \exp(G_{ikt}(\Pi_t^{(k),s})} \right)^{d_{ijt}} \right]$$

where drug j is a choice contained in class c.

- Calculate the choice probabilities at two levels:
  1. the probability of a class being chosen
  2. the conditional probability of a drug being chosen, conditional on the class choice

Return to Results

Decision Rule: Index Solution

- $X_k(t)$ - the state variables of the choice problem at t (depends on $\widehat{Y}_{t-1}$)
- At t, the agent chooses j if and only if:

$$G_j(X_j(t)) = \max_{k \in \{1,\ldots,J\}} G_k(X_k(t))$$

$$G_j(x_j(t)) = \sup_{\tau \geq t} \left\{ \frac{E_t\left[\sum_{r=t}^{\tau} \beta^{r-t} R_j(X_j(r)) | x_j(t)\right]}{E_t\left[\sum_{r=t}^{\tau} \beta^{r-t} | x_j(t)\right]} \right\}$$

- $R_j(X_j(r))$ - the returns from option j given the state variables at time r

Return to Decision Rule