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Learning in Drug Choice

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Crawford and Shum (2005)

Uncertainty and Learning in Pharmaceutical Demand

Model

- Forward-looking physician maximizes patient's present-discounted expected utility

$$\max_{D \equiv \left\{ \{d_{ijt}\}_{j=1}^{J} \right\}_{t=1}^{\infty}} E_D \sum_{t=1}^{\infty} \beta^t d_{ijt} u_{ijt} (1 - \omega_{i,t-1})$$

- For patient i, drug j characterized by two time-invariant match values:
  - μ_{ij} - symptomatic effect
  - ν_{ij} - curative effect
- Each prescription yields two signals
  - $x_{ijt} \sim F(\mu_{ij}, .)$ - symptomatic signal
  - $y_{ijt} \sim F(\nu_{ij}, .)$ - curative signal

Model

- Length of treatment unknown; prob of recovery endogenizes length
- Priors
  - Unobserved to econometrician
  - Diagnosis falls into one of K latent types

$$
\begin{aligned}
h_{oi} &= \theta_k \text{ with probability } p_k \\
h_{it}(h_{i,t-1}, y_{ijt}) &= \frac{\left(\frac{h_{i,t-1}}{1-h_{i,t-1}}\right) + d_{ijt}y_{ijt}}{1 + \left(\left(\frac{h_{i,t-1}}{1-h_{i,t-1}}\right) + d_{ijt}y_{ijt}\right)}
\end{aligned}
$$

- Preferences

$$u(x_{ijt}, p_j, \varepsilon_{ijt}) = -\exp(-r * x_{ijt}) - \alpha p_j + \varepsilon_{ijt}$$

  - Quasi-linear utility, CARA specification

Learning

- Prior means

$$\begin{pmatrix} \mu_{ij} \\ \nu_{ij} \end{pmatrix} \sim N\left(\begin{pmatrix} \underline{\mu}_{ij} \\ \underline{\nu}_{ij} \end{pmatrix}, \begin{pmatrix} \underline{\sigma}_j^2 & 0 \\ 0 & \underline{\tau}_j^2 \end{pmatrix} \right)$$

- Distribution of signals, conditional on priors

$$\begin{pmatrix} x_{ijt} \\ y_{ij}t \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{ij} \\ \nu_{ij} \end{pmatrix}, \begin{pmatrix} \sigma_j^2 & 0 \\ 0 & \tau_j^2 \end{pmatrix} \right)$$

Model

- Rational expectations - prior beliefs correspond to actual distribution of idiosyncratic match values
- Updating: (similar for posterior beliefs on curative match value)

$$\mu_{ij}^{t+1} = \frac{\frac{\mu_{ij}^{t}}{V_{ij}^{t}} + \frac{x_{ij,t+1}}{\sigma_j^2}}{\frac{1}{V_{ij}^{t}} + \frac{1}{\sigma_j^2}} \text{ or } \mu_{ij}^{t}$$

$$V_{ij}^{t+1} = \frac{1}{\frac{1}{\sigma_j^2} + \frac{I_{ij}^{t+1}}{\sigma_j^2}} \text{ or } V_{ij}^{t}$$

Model

- State variables
  - i's posterior mean match values, μ_{ij}^t, ν_{ij}^t for $j = 1, ..., 5$
  - counts of no. of times tried a drug, l_{ij}^t, $j = 1, ..., 5$
  - recovery probability for patient i at period t, h_{it}
  - ε_{ijt}, $j = 1, ..., 5$
- Dynamic problem - solve via Bellman Equation
  - Policy: in period t, i chooses j with highest value function
  - Approximate via variant of Keane and Wolpin (1994)

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 I_{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.

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

Efficient Provision of Experience Goods: Evidence from Antidepressant Choice

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 Question

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?

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

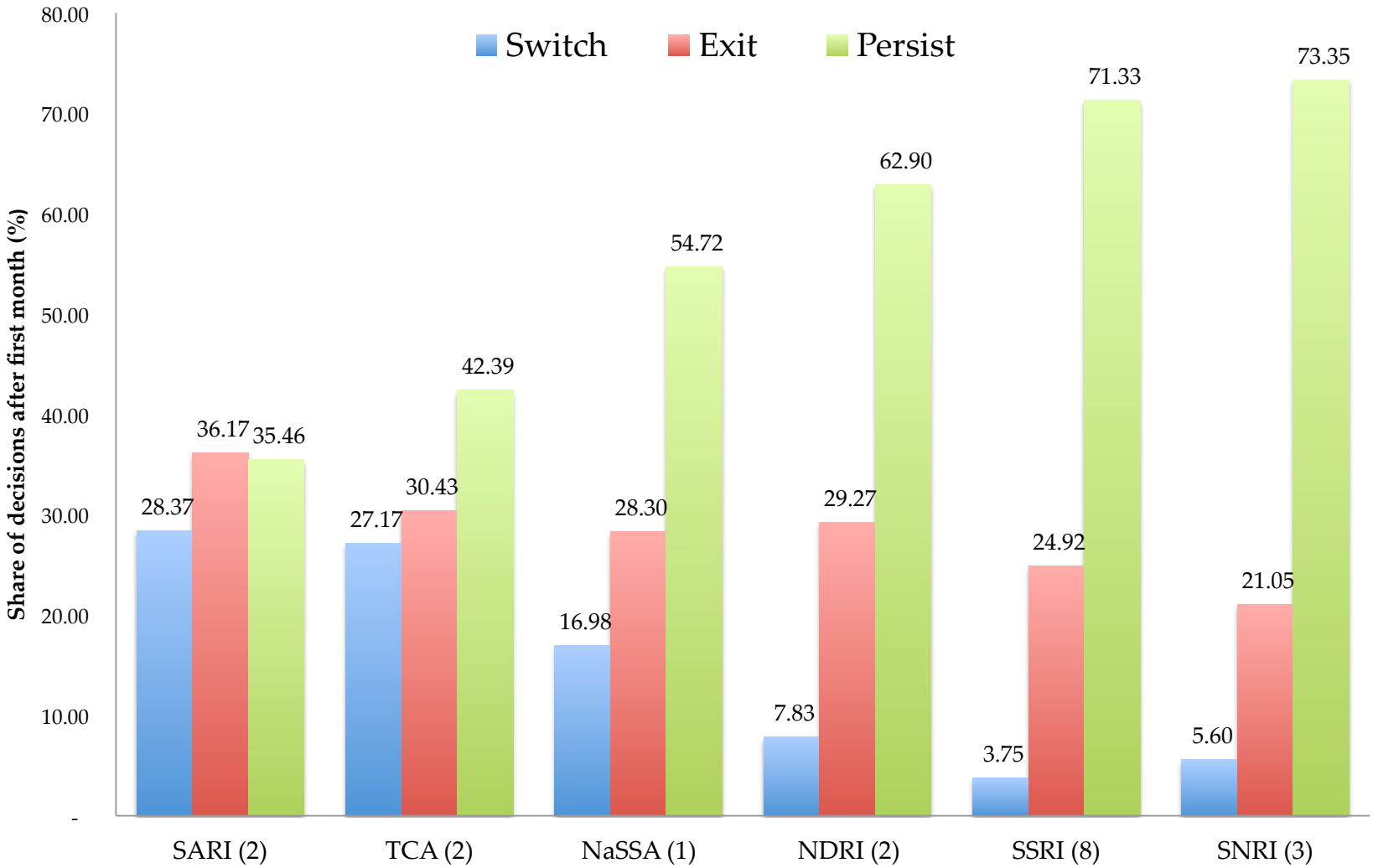
Source: Thomson Medstat Marketscan databases, 2003-2005.

- 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/Quit/Persist across Classes after First Month

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

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:

$$\mu_{j,0} = \frac{a_{j,0}}{a_{j,0} + b_{j,0}}$$

$$v_{j,0} = \frac{a_{j,0} b_{j,0}}{(a_{j,0} + b_{j,0})^2 (a_{j,0} + b_{j,0} + 1)}$$

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 $\widehat{Y}_{ij}$:

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

- 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:

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

- 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

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

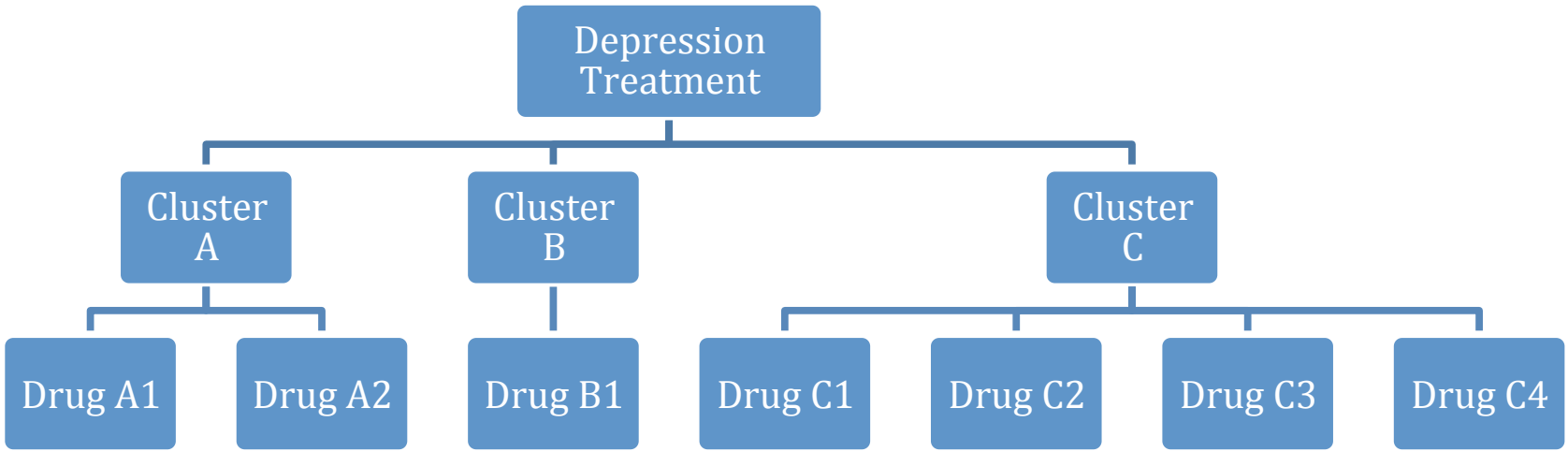
$$\begin{aligned} \mu_{j,t} &= \frac{a_{j,t}}{a_{j,t} + b_{j,t}} \\ v_{j,t} &= \frac{a_{j,t} b_{j,t}}{(a_{j,t} + b_{j,t})^2 (a_{j,t} + b_{j,t} + 1)} \\ \sigma^2(\mu_{j,t}) &= \mu_{j,t} * (1 - \mu_{j,t}) \end{aligned}$$

Experimentation incentive diminishes when:

- δ is small, $h(\delta)$ is large
- when past experience diminishes $v_{j,t}$
- when $\sigma^2(\mu_{j,t})$ is large

(3) Decision Rule: Index Rule with Correlation

via Pandey et al. (2007)



- 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

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

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.

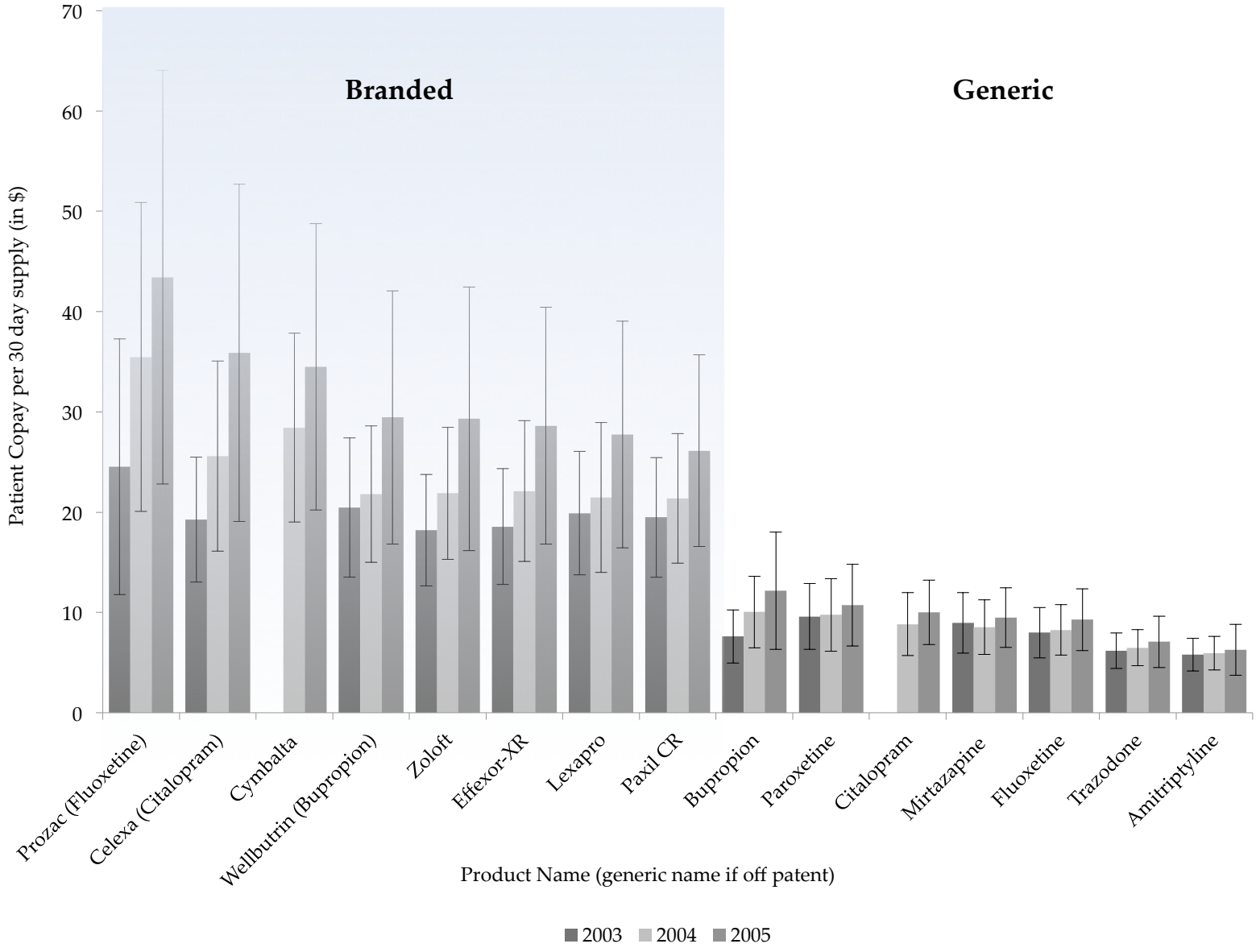


Figure 1: Patient Copayments by Product and Year (standard deviation across insurance plans shown)

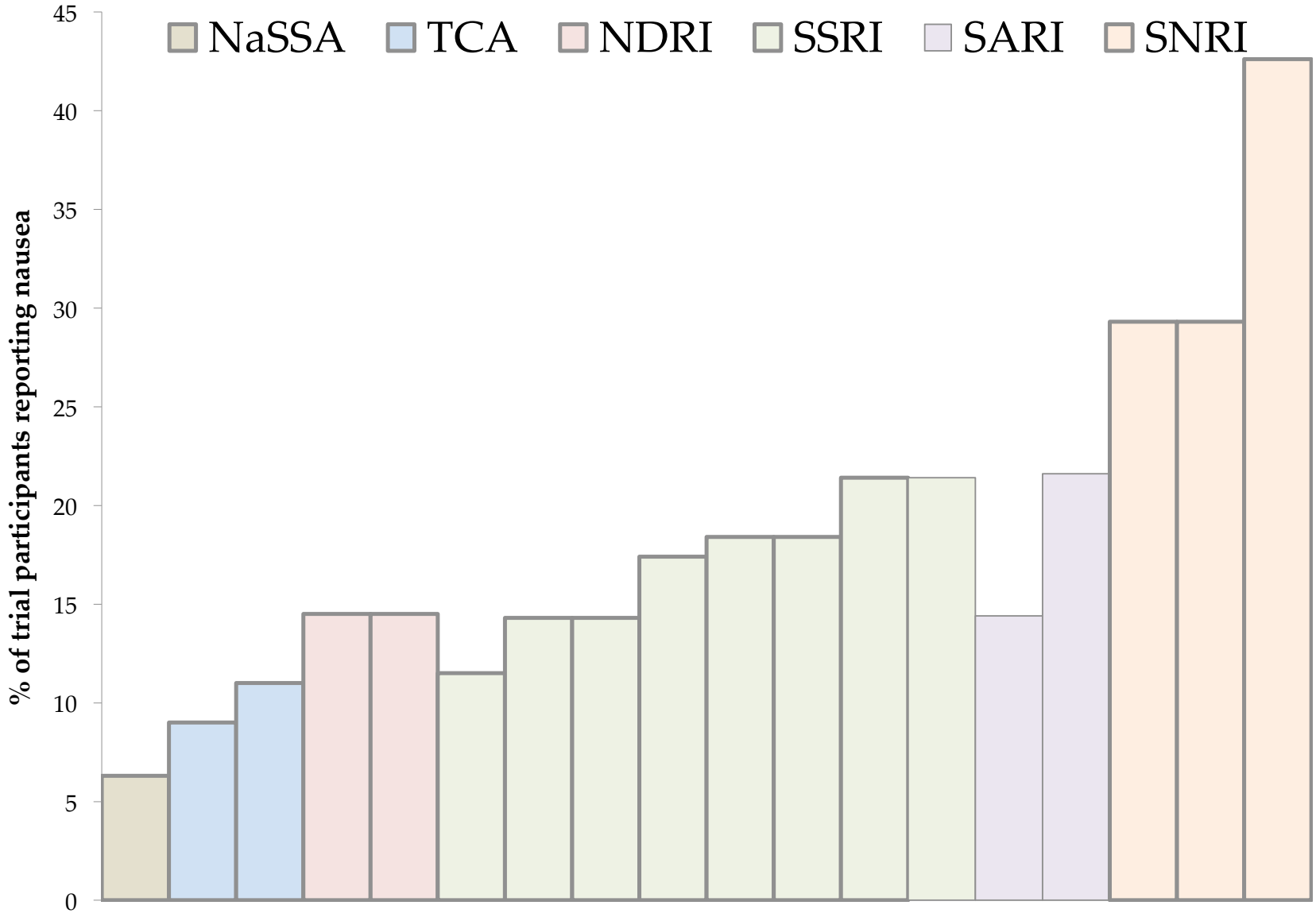


Figure 2: Nausea Side Effects in Clinical Trials

Identification

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

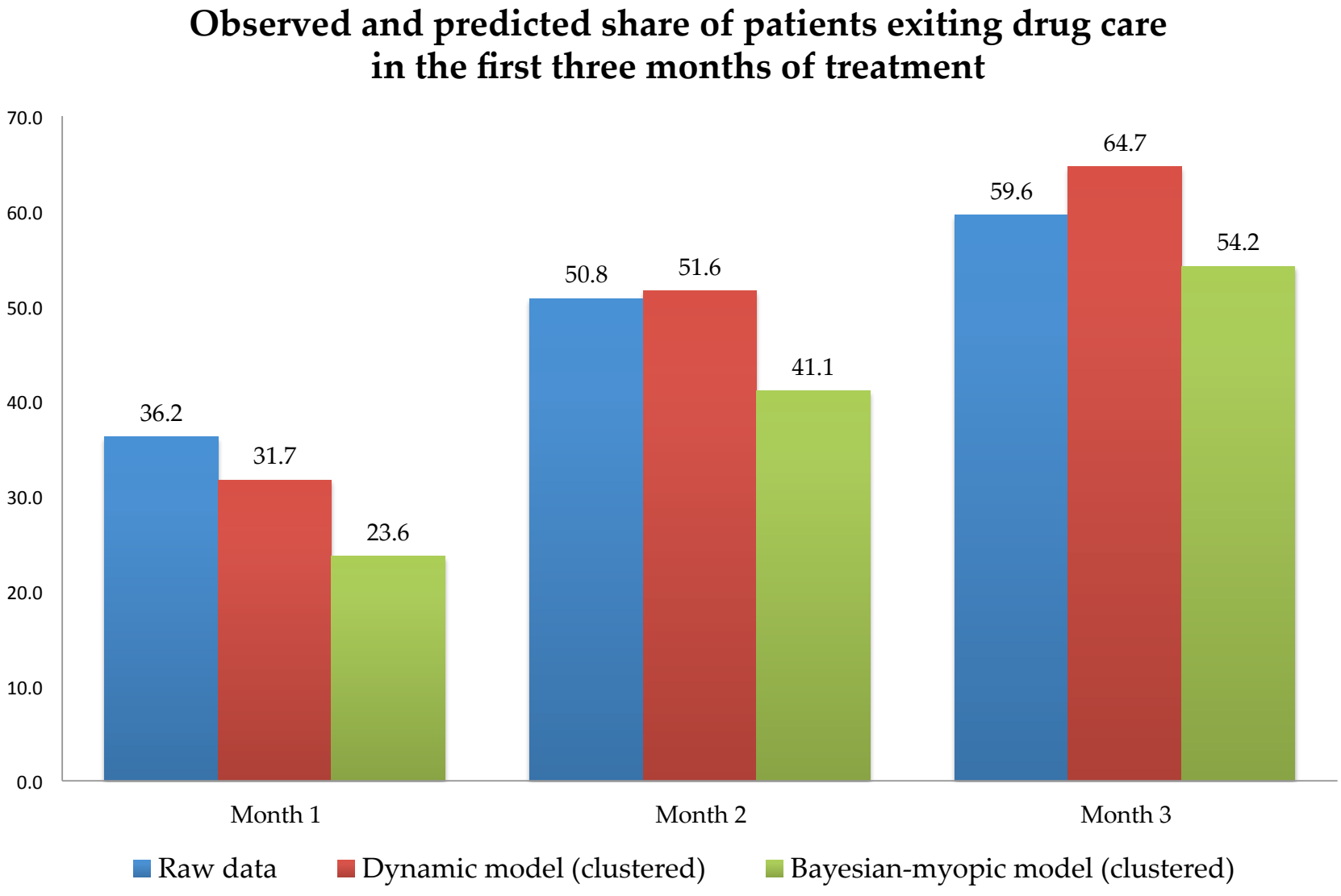
1. Identity of choice throughout the sequence of treatments
   - Identifies expected mean outcome under available choices following standard arguments
2. Information on drug characteristics from clinical trial data, external sources
3. Timing of observed switches
   - Identifies precision of the agents' 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 and drug class

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: 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, $\leq$ 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			
Paroxetine	SSRI	69.3	97.0	X	X	X	X	X
Paxil CR	SSRI	58.3	97.9	X	X	X	X	X
Zoloft	SSRI	62.4	77.2	X	X	X	X	X
Trazodone	SARI	45.7	0.0					
Effexor	SNRI	60.2	0.0	X	X	X	X	
Effexor-XR	SNRI	71.1	0.0	X	X	X	X	

Estimation: Likelihood form

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

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

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

- 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 $l = 1, \ldots, J$ 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.

Return to Results

Estimation: Likelihood form

With dependency across the drugs via clusters

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

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