Uncertainty and Learning in Pharmaceutical Demand

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Econometrica, 2005

presented by Jonathan Elliott

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Outline

Introduction

Model

Empirical Setup

Results & Counterfactuals

Motivation

- What is the impact of uncertainty on consumers' decisions in experience good markets?
- To what extent can learning counteract the effect of uncertainty?
- In medicine, heterogeneity in effectiveness of drugs across patients

  this paper: anti-ulcer drugs
- Doctors uncertain about patient-drug match quality, but can learn about match quality through prescribing
- **This paper**: drugs have both curative and symptomatic effects, patients/doctors can learn about these effects through noisy signals and optimally prescribe drugs

Industry Background

- Anti-ulcer market "almost entirely drug-based"
- Drugs mostly distinguished by active ingredient (or molecule)
- Drug prices set by regulatory agent
    - same active ingredient, same route of administration $\Rightarrow$ same price
- No differences in insurance status
    - patients pay 50% copay

Drugs in Market

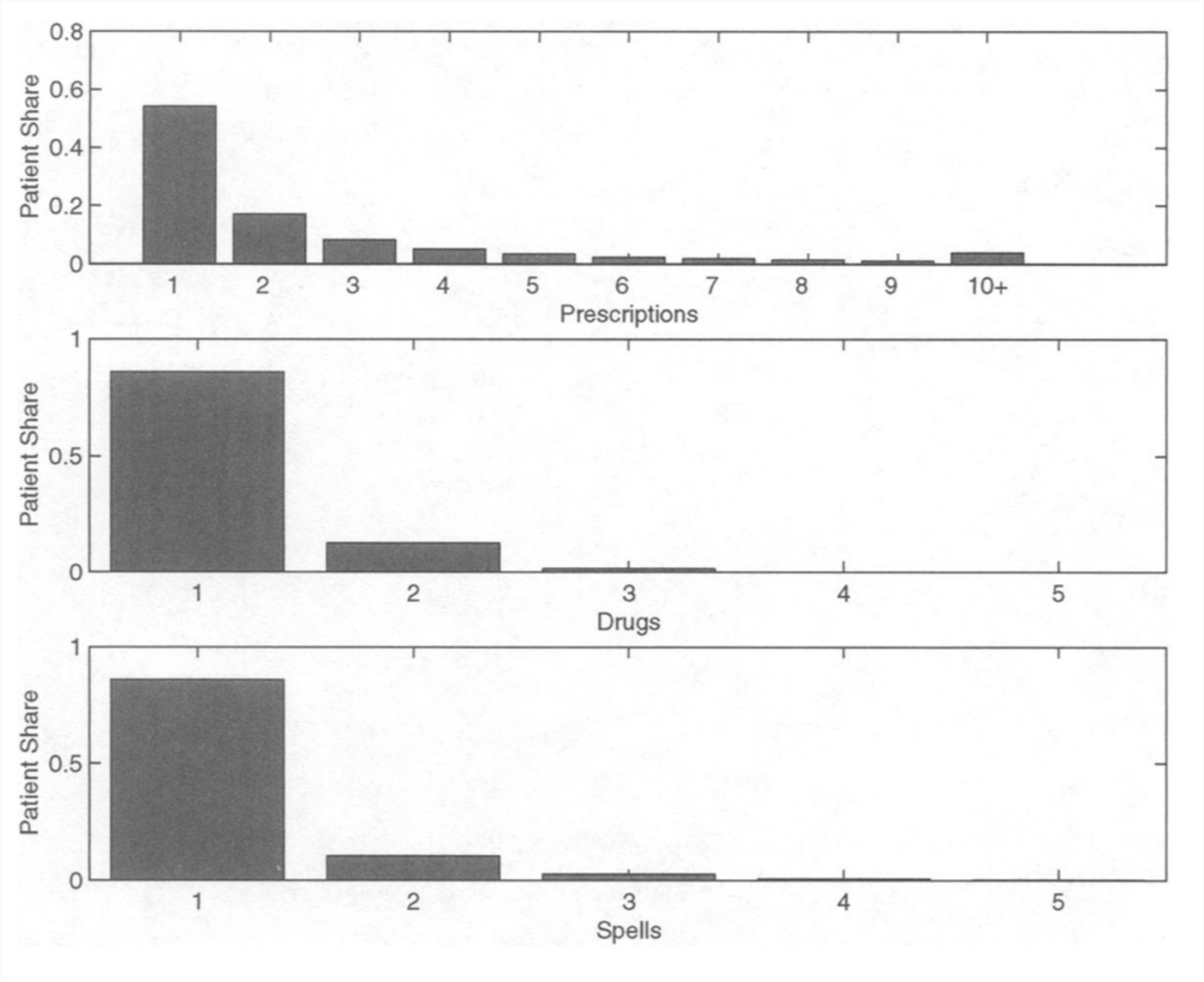
Summary Statistics from the Data

#	Molecule	Patent-Holder	In-Sample Mkt. Share[c]	Major Brands[a] in Italian Mkt.	Date of Entry	Avg.[b] Price
1	Ranitidine	Glaxo	64.4	Zantac*, Ranidil	1981	$2.90
2	Omeprazole	Astra	11.0	Losec*, Omeprazen	1990	$3.14
3	Famotidine	Merck	6.8	Pepcid*, Famodil	1986	$2.59
4	Nizatidine	Lilly	3.2	Axid*, Zanizal	1988	$2.74
5	19 others	—	14.6	Various	<1981	$1.42[d]

Data

- All anti-ulcer prescriptions of 10% sample of patients ages 15–85 in Rome from 1990 – 1992
  - 55,000 patients
  - observe the sequence of prescriptions over time period
- Aggregate by active ingredient (molecule)
- **Left censoring**: Drop patients first observed before the sixth month
- **Right censoring**: Patients with last in-sample prescription within final six months (don't drop, but deal with differently)

Data


Patient Share
0.8
0.6
0.4
0.2
0
1
2
3
4
5
6
7
8
9
10+
Prescriptions
Patient Share
1
0.5
0
1
2
3
4
5
Drugs
Patient Share
1
0.5
0
1
2
3
4
5
Spells

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Overview

- Patient arrives and doctor diagnoses illness
- Doctor selects initial drug treatment
- Patient completes initial drug treatment and returns if not healed
- Doctor prescribes same drug or different drug
- Forward-looking and risk aversion work in opposite directions for prescription decisions
    - **forward-looking**: want to experiment using several drugs to learn about match quality
    - **risk aversion**: want to stay with current drug if working pretty well (functions kind of like switching cost)

Doctor's Problem

- Select sequence of drugs that maximize patient's expected utility

$$\max_{D \equiv \left\{ \{d_{jnt}\}_{n=1}^{N} \right\}_{t=1}^{\infty}} \mathbb{E}\left[\sum_{t=1}^{\infty} \beta^t \left(1 - w_{j,t-1}\right) d_{jnt} u_{jnt} \right]$$

  - d_{jnt} indicator $= 1$ if patient j takes n in t
  - w_{jt} indicator for whether j recovers after period t
- Uncertainty over (1) match value
  - μ_{jn} symptomatic effect of n on j
  - ν_{jn} curative effect of n on j
- and (2) patient's length of treatment
  - prescriptions continue until recovery ($w_{jt} = 1$)

Patient Types

- Econometrician doesn't know patient's diagnosis or doctor's beliefs
- **Assume**: Patient conditions fall into one of K types
  - let h_{0j} denote probability j can be healed without treatment
  - can take one of K values

$$h_{0j} = \theta_k \text{ with probability } p_k, \quad k = 1, \ldots, K$$

where

$$0 < p_i < 1, \quad \sum_i p_i = 1, \quad 0 \leq \theta_1, \ldots, \theta_K \leq 1$$

- Doctor's prior beliefs allowed to differ across patient types
  - but conditional on patient type, doctors have rational expectations

Preferences

- Linear utility specification too restrictive because implies risk neutrality
- Constant Absolute Risk Aversion specification:

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

  - x_{jnt} is patient j's symptomatic signal from taking drug n in period t
  - $r > 0$ measures degree of risk aversion

Recovery Probabilities

- Let h_{jt} be probability that j recovers by the end of t
- Sequence of recovery probabilities

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

  - y_{jnt} is curative signal for drug n prescribed to j in t

Learning Process

- Doctor's prior beliefs

$$\begin{pmatrix} \mu_{jn} \\ \nu_{jn} \end{pmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \underline{\mu}_{nk} \\ \underline{\nu}_{nk} \end{bmatrix}, \begin{bmatrix} \underline{\sigma}_n^2 & 0 \\ 0 & \underline{\tau}_n^2 \end{bmatrix} \right)$$

- Doctor does not know (μ_{jn}, ν_{jn}) but receives i.i.d. signals (x_{jnt}, y_{jnt})

$$\begin{pmatrix} x_{jnt} \\ y_{jnt} \end{pmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_{jn} \\ \nu_{jn} \end{bmatrix}, \begin{bmatrix} \sigma_n^2 & 0 \\ 0 & \tau_n^2 \end{bmatrix} \right)$$

Learning Process

- Let I_{jn}^t denote number of times j has taken n up to and including period t
- Initial values $\mu_{jn}^0 = \underline{\mu}_{nk}$, $V_{jn}^0 = \underline{\sigma}_n$ (rational expectations)
- Posterior symptomatic mean and variance

$$\mu_{jn}^{t+1} = \begin{cases} \frac{\sigma_n^2 \mu_{jn}^t + V_{jn}^t x_{jnt+1}}{\sigma_n^2 + V_{jn}^t} & \text{if drug } n \text{ taken in period } t+1, \\ \mu_{jn}^t & \text{otherwise} \end{cases}$$

$$V_{jn}^{t+1} = \begin{cases} \frac{\sigma_n^2 \underline{\sigma}_n^2}{\sigma_n^2 + I_{jn}^{t+1} \underline{\sigma}_n^2} & \text{if drug } n \text{ taken in period } t+1, \\ V_{jn}^t & \text{otherwise} \end{cases}$$

- Analogous for curative posteriors ν_{jn}^{t+1}, R_{jn}^{t+1}

Dynamic Problem

- State variable

$$\mathcal{S}_t \equiv \left(\mu_{j1}^t, \ldots, \mu_{j5}^t, \nu_{j1}^t, \ldots, \nu_{j5}^t, I_{j1}^t, \ldots, I_{jn}^t, h_{jt}, \epsilon_{j1t}, \ldots, \epsilon_{j5t}\right)$$

- Value function $W\left(\mathcal{S}_t\right)$

$$= \max_n \left\{\mathbb{E}\left[u\left(x_{jnt}, p_n, \epsilon_{jnt}\right) + \beta\left(1 - w_{jt}\right)\mathbb{E}\left[W\left(\mathcal{S}_{t+1}\right)\middle| x_{jnt}, y_{jnt}, n\right]\middle|\mathcal{S}_t\right]\right\}$$

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Likelihood Function

- Observe $d_{j1t}, \ldots, d_{jNt}$ and treatment length T_j
- Likelihood

$$\begin{array}{ll} \prod_n \mathbb{E}\left[\mathbf{1}\left\{W_{jn1,k} > W_{jn'1k}, n' \neq n\right\}^{d_{jn1}}\right] & t = 1 \\ \mathbb{E}\left[(1 - h_{jt-1k})\left(\prod_n \mathbb{E}\left[\mathbf{1}\left\{W_{jntk} > W_{jn'tk}, n' \neq n\right\}^{d_{jnt}}\right]\right)\right] & 1 < t < T_j \\ \mathbb{E}\left[(1 - l_j)\, h_{jT_jk}\right] & t = T_j \end{array}$$

where l_j indicator $= 1$ if j's treatment length censored by end of sample period

  - we don't know whether or not those patients healed after period T_j

Likelihood Function

- Assume type 1 extreme value errors

$$\mathbb{E}\left[\mathbf{1}\left\{W_{jnt,k} > W_{kn't,k}, n \neq n'\right\}\right] = \frac{\exp\left(W_{jnt,k}\right)}{\sum_{n'=1}^{5}\exp\left(W_{jn't,k}\right)} \equiv \lambda_{jnt,k}$$

- Likelihood (for uncensored)

$$\sum_{k=1}^{K} p_k \cdot \mathbb{E}\left[\prod_{t=1}^{T_j-1}\left((1-h_{jt,k})\prod_{n}\lambda_{jnt,k}^{d_{jnt}}\right)\right] \cdot h_{jT_j,k}\prod_{n}\lambda_{jnT_j,k}^{d_{jnT_j}}$$

- Expectations approximated by simulation

Identification

- **Symptomatic match value distribution**: variation in drug choices across patients and prescriptions
- **Curative match value and illness heterogeneity distributions**: variation in recovery frequencies conditional on different sequences of drug choices

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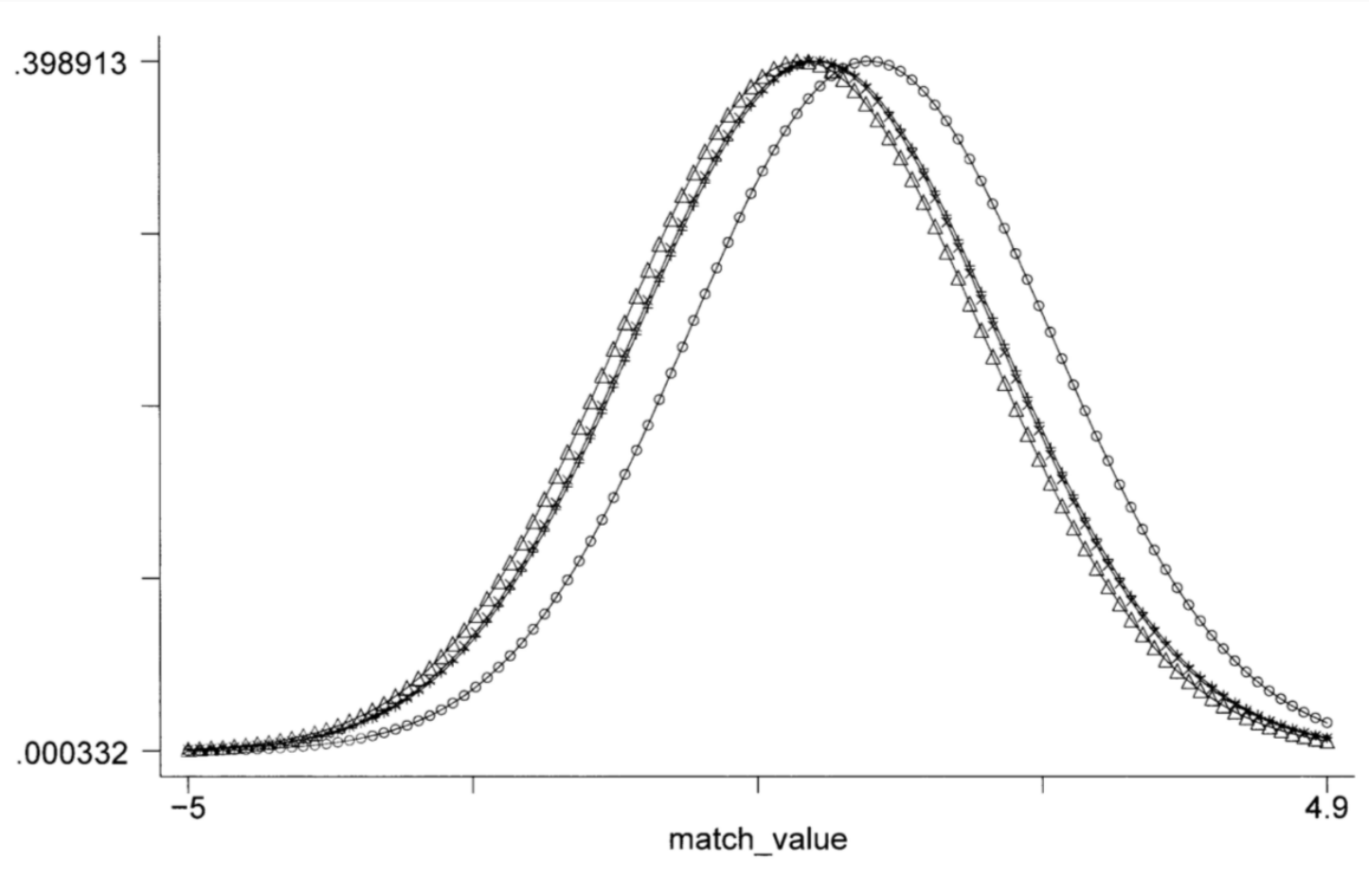
Types

- How many types?
  - Start at $K = 2$ and increase until negligible changes in results

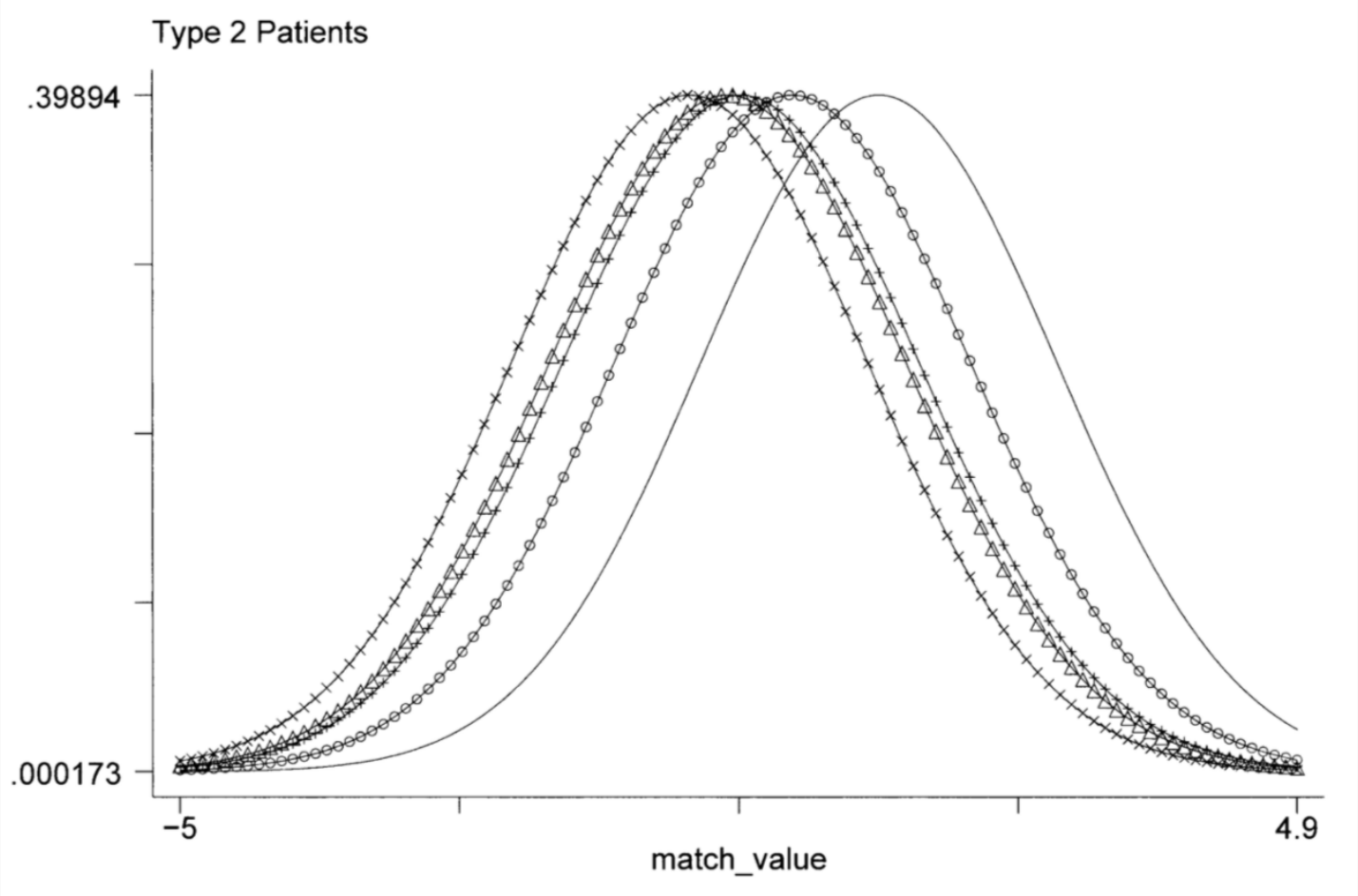
$$\Rightarrow K = 4$$

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

Symptomatic Match Values: Type 1



Symptomatic Match Values: Type 2



Match Values

- Overlap in support of density function implies drugs are horizontally differentiated
- Symptomatic ranking for Type 1: $(2, 1, 3, 5, 4)$
- Symptomatic ranking for Type 2: $(1, 2, 3, 4, 5)$
- Curative ranking for Type 1: $(2, 1, 3, 4, 5)$
- Curative ranking for Type 2: $(4, 1, 2, 3, 5)$
- Significant learning: for Type 1, perceived variance for symptomatic relief falls 70% after single prescription
    - majority of uncertainty reduction comes with first use

Counterfactuals

- What is the cost of uncertainty in anti-ulcer market?
- **Counterfactual #1**: Drug choice in world where patients have complete information about match values
  - Patients draw symptomatic and curative match values drawn from population distributions $\mathcal{N}(\underline{\mu}_{nk}, \underline{\sigma}_{nk})$ and $\mathcal{N}(\underline{\nu}_{nk}, \underline{\tau}_{nk})$
  - Perceived variances, V_{jn}^t and R_{jn}^t, set to zero
- **Counterfactual #2**: Drug choice in world where unable to switch after first drug prescribed (shutting down learning)
- Counterfactuals isolate effects of uncertainty and experimentation

Counterfactual Results

Baseline Specification[a]	
Avg. discounted utility	−28.7
Avg. treatment length	4.8
Avg. treatment cost	245
Avg. number of different drugs	1.4
Counterfactual I: Complete Information[b]	
Avg. discounted utility	−26.4
Avg. treatment length	8.8
Avg. treatment cost	385
Avg. number of different drugs	1.9
Counterfactual II: No Experimentation[c]	
Avg. discounted utility	−30.6
Avg. treatment length	4.8
Avg. treatment cost	248

Counterfactual Results

- Number of drugs and treatment length actually *increase* under complete information
    - patients optimize choice of drugs over course of treatment
- Treatment length stays the same under no experimentation
- Discounted utility increase in complete information larger than discounted utility decrease in no experimentation
    - learning enables patients to realize discounted utility levels closer to those under first-best

Conclusion

- **Advantages**
  - Neat structural model of learning in dynamic setting
  - Evidence of importance of learning in specific medical setting
- **Disadvantages**
  - Don't allow for doctors learning across patients they treat
  - No agency problems that might exist