Self-selection: The Roy model

Heidi L. Williams

MIT 14.662

Spring 2015

Roy model: Physician practice patterns

Despite its origin in labor economics, the Roy model has been applied across a wide range of fields in economics

Chandra and Staiger (2007): one of the most important papers in health economics in recent years, and one that has really changed how people think about a variety of issues

Geographic variation in medical expenditures

- Earliest work I'm aware of: Glover (1938)
  - England and Wales: variation in small-area tonsillectomy rates
  - Looked for correlations with "any factor which might have some ætiological bearing on chronic tonsillitis and adenoidal growths - such factors for example as overcrowding...not the slightest suggestion of correlation has been obtained."
  - Maybe not the regressions we would estimate, but the start of a puzzle!

- Skinner (2012) *Handbook* chapter provides overview of this literature
  - Adjusting for prices doesn't really matter (Gottlieb *et al.* 2010)
  - Debate over relative importance of supply vs. demand

Geographic variation in medical expenditures (continued)

- "Fact" #1: geographic variation in health spending is not associated with improved satisfaction, outcomes, or survival
  - Consensus view from Dartmouth Atlas
  - Caveats: Cutler (2005), Joe Doyle's line of research
- Surprising in light of Fact #2: many technologies shown to be associated with improved survival in randomized clinical trials
- Facts #1, 2 often reconciled by "flat of the curve" argument
  - RCTs run on patients most likely to benefit
  - Physicians may treat until marginal return is zero

Three problems with "flat of the curve" argument

1. No explanation of why we observe geographic variation
2. Still predicts positive relationship between spending, outcomes unless all areas in range of zero or negative marginal benefits
    - Has never been documented in the literature
3. Predicts marginal benefit from more intensive treatment should be lower in areas that treat more aggressively
    - Available US-Canada comparisons suggest the opposite: US treats heart attacks more intensively, yet marginal benefit from intensive heart attack treatments appears to be larger in US

Chandra and Staiger (2007)

Chandra and Staiger present a Roy model with productivity spillovers that can reconcile these facts.

Their paper is an excellent illustration of how a set of facts can motivate a (relatively simple) theoretical framework producing testable implications that can then be taken back to the data.

What motivates a model with productivity spillovers?

- Patients receive either of two treatments:
  1. Nonintensive management (medical management; subscript 1)
  2. Intensive intervention (surgery; subscript 2)
- Physicians choose treatment to maximize utility over expected survival (Survival_1, Survival_2) and cost (Cost_1, Cost_2)
- Productivity spillovers: survival, cost positively related to share of patients receiving same treatment $(P_1, P_2 = 1 - P_1)$
  - As in Katz and Shapiro's (1985) model of network externalities (telephones, hardware-software, foreign auto firms)

What motivates a model with productivity spillovers?

Why would this productivity spillovers assumption be plausible? Chandra and Staiger focus on three possible explanations:

1. Knowledge spillovers. Physicians may learn about new surgical techniques and procedures from direct contact with other physicians ("see one, do one, teach one")
2. Availability of support services. Some places have cardiac catheterization labs whereas other don't (choice variable)
3. Selective migration. Physicians more skilled at the intensive treatment may self-select into areas that treat more intensively

Model

To the basic framework outlined above, add heterogeneity across patients that affects expected survival and cost

- Some heterogeneity captured by observable characteristics (Z)
- Other factors (ϵ) known to patient and physician at the time of choosing treatment, but not observed by econometrician

This is the Roy model component of the model: patients are sorted into the two treatments based on expected returns

Model (continued)

For treatments $i \in \{\text{nonintensive, intensive}\}$, denote the survival rate and cost for each treatment as:

$$\text{Survival}_i = \beta_i^s Z + \alpha_i^s P_i + \epsilon_i^s \text{ for } i = 1, 2$$
$$\text{Cost}_i = \beta_i^c Z + \alpha_i^c P_i + \epsilon_i^c \text{ for } i = 1, 2$$

Denoting value of life ($\frac{\text{survival}}{\$}$) by λ, patient's indirect utility U is:

$$U_i = \text{Survival}_i - \lambda \text{Cost}_i = \beta_i Z + \alpha_i P_i + \epsilon_i \text{ for } i = 1, 2$$

where $\beta_i = \beta_i^s - \lambda\beta_i^c$, $\alpha_i = \alpha_i^s - \lambda\alpha_i^c$, and $\epsilon_i = \epsilon_i^s - \lambda\epsilon_i^c$

- $\beta_i Z$: index of patient appropriateness for each treatment (e.g. age)
- $\alpha_i P_i$: productivity spillover (α could be zero)
- ϵ_i: unobservables that influence survival and cost
- Note λ could be 0 due to insurance

Model (continued)

An individual is treated intensively ($i = 2$) if $U_2 > U_1$ (treatment maximizes patient U, not accounting for externalities). Recall $P_1 = 1 - P_2$:

$$\begin{aligned}
\Pr\{\text{intensive}\} &= \Pr\{i = 2\} \\
&= \Pr\{U_2 - U_1 > 0\} \\
&= \Pr\{\beta_2 Z + \alpha_2 P_2 + \epsilon_2 - \beta_1 Z - \alpha_1(1 - P_2) - \epsilon_1 > 0\} \\
&= \Pr\{P_2(\alpha_1 + \alpha_2) - \alpha_1 + (\beta_2 - \beta_1)Z > \epsilon_1 - \epsilon_2\} \\
&= \Pr\{\alpha P_2 - \alpha_1 + \beta Z > \epsilon\}
\end{aligned}$$

where $\alpha = \alpha_1 + \alpha_2$, $\beta = \beta_2 - \beta_1$, and $\epsilon = \epsilon_1 - \epsilon_2$

Model (continued)

Among the patients who choose the intensive treatment, the expected utility gain is:

$$E[U_2 - U_1 | U_2 - U_1 > 0] = \beta Z + \alpha P_2 - \alpha_1 + E[\epsilon | U_2 - U_1 > 0]$$

$\Rightarrow$ patients receiving treat$_2$ have higher expected utility gain if:

1. More appropriate (higher βZ)
2. Live in a more intensive region (higher αP_2)

Intuition: patients are given the best care conditional on where they live, but marginal patients would be better off in area with other specialization.

Equilibrium (fixed point) condition

Let $f(Z)$ denote distribution of Z. In equilibrium, fraction of patients choosing intensive treatment (P_2) must match demand equation for Pr{intensive treatment}.

That is, proportion of patients choosing intensive treatments must generate benefits (with productivity spillovers) consistent with proportion.

$$\begin{aligned} P_2 &= \int_Z \Pr\{\alpha P_2 - \alpha_1 + \beta Z > \epsilon\} f(Z) dZ \\ &= G(P_2) \end{aligned}$$

Variation across areas in use of intensive treatment can arise for two reasons: multiple equilibria, or single equilibrium determined by small differences in patient characteristics

Equilibrium

Variation across areas in treat_2 can arise for two reasons:

1(A): Multiple (here: two) stable equilibria: intensive (high returns to treat_2) and non-intensive (low returns to treat_2); no prediction on choice

1(B): Single equilibrium determined by small differences in patient characteristics: productivity spillovers can magnify small differences

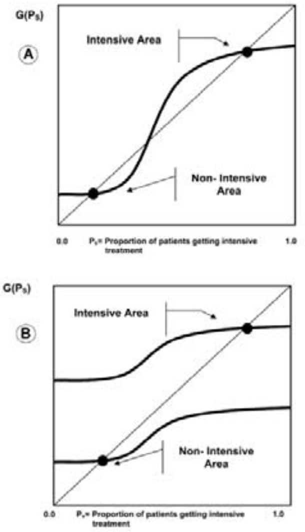


Fig. 1.—Characterizations of area variations: A, multiple equilibrium; B, single equilibrium.

Equilibrium: Key figure

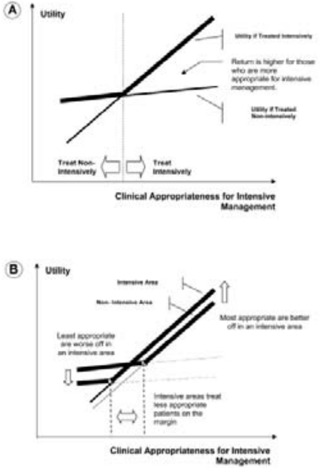


Fig. 2.—Graphical illustration of the Roy model with productivity spillovers. *A*, Relationship between two alternative ways to treat patients within an area. The production possibilities frontier describes the best treatment for a patient of given clinical appropriateness. The model predicts that the returns to intensive management are increasing in patients' appropriateness for such interventions. *B*, Contrasts the care across two areas that differ in their surgical intensity. As a result of the productivity spillover, patients appropriate for intensive management are better off in the surgically intensive areas, whereas patients appropriate for nonintensive management are worse off in such areas.

Ignore ϵ, plot U against Z

Think of Z as propensity score of appropriateness for treat$_2$ (age, comorbidities)

Equilibrium: Key figure

Figure 2(a): within-area, gap between $treat_1$ and $treat_2$ larger for more appropriate patients ($\Rightarrow$ returns are higher for these patients)

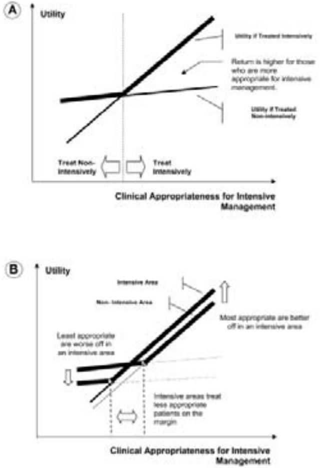


Fig. 2.—Graphical illustration of the Roy model with productivity spillovers. *A*, Relationship between two alternative ways to treat patients within an area. The production possibilities frontier describes the best treatment for a patient of given clinical appropriateness. The model predicts that the returns to intensive management are increasing in patients' appropriateness for such interventions. *B*, Contrasts the care across two areas that differ in their surgical intensity. As a result of the productivity spillover, patients appropriate for intensive management are better off in the surgically intensive areas, whereas patients appropriate for nonintensive management are worse off in such areas.

Equilibrium: Key figure

Figure 2(b):

1. Less appropriate patients worse off in intensive areas
2. Marginal patient less appropriate in intensive areas
3. More appropriate patients better off in intensive areas

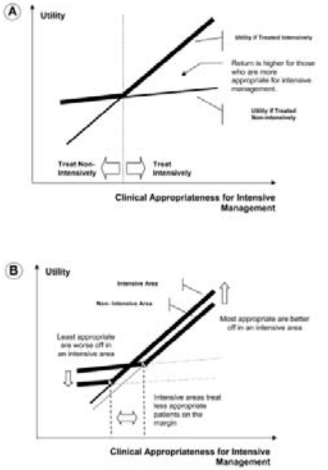


FIG. 2.—Graphical illustration of the Roy model with productivity spillovers. *A*, Relationship between two alternative ways to treat patients within an area. The production possibilities frontier describes the best treatment for a patient of given clinical appropriateness. The model predicts that the returns to intensive management are increasing in patients' appropriateness for such interventions. *B*, Contrasts the care across two areas that differ in their surgical intensity. As a result of the productivity spillover, patients appropriate for intensive management are better off in the surgically intensive areas, whereas patients appropriate for nonintensive management are worse off in such areas.

Welfare

- Spillovers $\Rightarrow$ increase in P_2 has positive externality on some patients, negative externality on others
- Unsurprisingly, externalities $\Rightarrow$ equilibrium may not be optimal
- Single vs. multiple equilibrium cases matter for welfare
    - Multiple: "area approach" can determine optimal P_2
    - Single: *too little* area variation in treatment as long as marginal patient ignores externality she imposes

Data

- Context: heart attacks ('acute myocardial infarctions')
  - Common condition
  - Extensive data (Medicare claims + CCP chart data)
  - Relatively high mortality rate
  - Limited role for patients to select providers
- Treatments:
  - Non-intensive: beta blockers (note: should be prescribed to all)
  - Intensive: cardiac catheterization
- 'Standard' market definitions: 306 'hospital referral regions'
- Assign patients to HRR of residence, not treatment

Estimation

Partition patients into groups (k) based on appropriateness for treat$_2$

For Outcome$_{ijk} \in \{\text{Survival}_{ijk}, \text{Cost}_{ijk}\}$ for patient i in HRR j and group k, key estimating equation is:

$$\text{Outcome}_{ijk} = \beta_{0k} + \beta_{1k}\text{Intensive Treatment}_i + \mathbf{X}_i \Pi_k + u_{ijk}$$

- What is the potential problem with this OLS regression?
- IV: 'differential distance' (McClellan *et al.* 1994)
  - Distance to nearest cath hospital minus distance to nearest noncath hospital (negative $\Rightarrow$ nearest hospital is cath hospital)
- Appropriateness measure: $\Pr(\text{Cardiac Cath}_{ij}) = \hat{G}(\theta_0 + \mathbf{X}_i \Phi)$

Results

Two sets of results:

- Testing implications of the Roy model
  1. Returns to intensive treatment increase in appropriateness
  2. Marginal patient less appropriate in intensive areas
- Testing implications of productivity spillovers
  1. Quality of medical management worse in intensive areas
  2. Characteristics of other patients influence treatment
  3. Returns to intensive treatment higher in intensive areas
  4. Most appropriate patients better off in intensive areas
  5. Least appropriate patients worse off in intensive areas

Results: Table 1

- IV: outcome = f(cath), survival = f(spending)
- More appropriate patients benefit more from treat_2: 0.038 vs. 0.002 in Column 3; higher survival, lower costs
- Similar results with age
- Consistent with Roy model

TABLE 1
INSTRUMENTAL VARIABLE ESTIMATES OF INTENSIVE MANAGEMENT AND SPENDING ON ONE-YEAR SURVIVAL BY CLINICAL APPROPRIATENESS OF PATIENT

	INSTRUMENTAL VARIABLE ESTIMATES OF		
	Impact of Cath		
SAMPLE	On One-Year Survival (1)	On One-Year Cost ($1,000s) (2)	Impact of $1,000 on One-Year Survival (3)
A. All patients (N = 129,895)	.142	9.086	.016
	(.036)	(1.810)	(.005)
B. By cath propensity:			
Above the median (N = 64,799)	.184	4.793	.038
	(.034)	(1.997)	(.017)
Below the median (N = 65,096)	.035	17.183	.002
	(.083)	(3.204)	(.005)
Difference	.149	−12.39	.036
	(.090)	(3.775)	(.018)
C. By age:			
65–80 (N = 89,947)	.171	6.993	.024
	(.037)	(1.993)	(.009)
Over 80 (N = 39,948)	.016	16.026	.001
	(.108)	(2.967)	(.007)
Difference	.155	−9.033	.023
	(.114)	(3.574)	(.011)

NOTE.—Cath propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk adjusters. Differential distance (measured as the distance between the patient's zip code of residence and the nearest catheterization hospital minus the distance to the nearest hospital) is the instrument. Each model includes all the CCP risk adjusters, and the standard errors are clustered at the level of each HRR.

Results: Table 2

Split the sample by above/below median values of instrument

1. Predicts cath (first stage, 48.9 - 42.8 = 6.1pp)
2. Predicts survival (reduced form, 67.6 - 66.7 = 0.9pp)
3. *Doesn't* predict 'predicted survival' (67.5 - 67.2 = 0.3pp)
4. Columns (7) and (8) argue marginal patients similar to average

TABLE 2

RELATIONSHIP BETWEEN DIFFERENTIAL DISTANCE (DD) AND PROBABILITY OF CATHETERIZATION AND SURVIVAL, AND DIFFERENTIAL DISTANCE AND OBSERVABLE CHARACTERISTICS (%)

	30-DAY CATH RATE		ONE-YEAR SURVIVAL		ONE-YEAR PREDICTED SURVIVAL		30-DAY PREDICTED CATH RATE FOR PATIENTS GETTING CATH	
SAMPLE	DD Below Median (1)	DD Above Median (2)	DD Below Median (3)	DD Above Median (4)	DD Below Median (5)	DD Above Median (6)	DD Below Median (7)	DD Above Median (8)
All patients (N = 129,997)	48.9	42.8	67.6	66.7	67.5	67.2	63.3	63.2
By cath propensity:								
Above the median (N = 64,733)	74.0	67.1	84.6	83.8	83.4	83.5	72.6	72.6
Below the median (N = 65,244)	22.9	19.5	50.1	50.4	51.1	51.6	32.3	32.5
By age:								
65–80 (N = 90,016)	61.1	54.9	74.3	73.5	73.9	73.9	67.4	67.3
Over 80 (N = 39,961)	20.3	16.5	52.1	52.1	52.6	52.7	34.6	34.1

NOTE.—Cath propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk adjusters. Differential distance is measured as the distance between the patient's zip code of residence and the nearest catheterization hospital minus the distance to the nearest hospital.

Results: Figure 3

Test in the spirit of Gruber *et al.* (1999)

- Sample: patients receiving cath
- Patient appropriateness = f(log, risk-adjusted HRR cath rate)
- Negative: average patient appropriateness lower in more intensive areas
- Consistent with Roy model

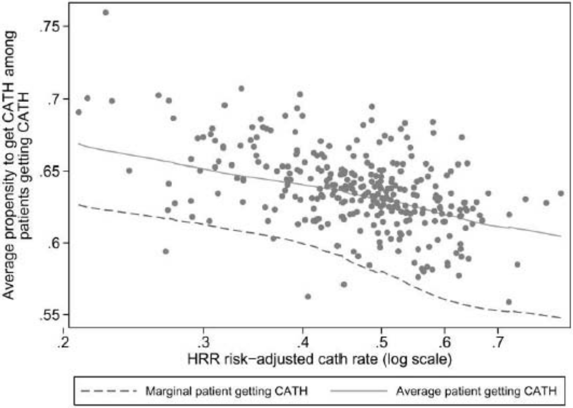


FIG. 3.—Relation between average patient and marginal patient receiving cardiac catheterization. For each of the 306 HRRs we graph the average propensity to receive cardiac catheterization (among patients who actually received it) against the log of the area risk-adjusted cath rate. Using local regression, we estimated the relationship between the average propensity and the risk-adjusted cath rate and the slope of this line at each point. These estimates were then used to plot the average (upper line) and marginal patient (lower line and estimated as the local difference in the average) receiving treatment.

Results: Table 4

- Quality of non-intensive treatment (beta blockers) worse in intensive areas: -0.31
- Consistent with productivity spillovers

TABLE 4
HRR-Level Measures of Intensive Treatment, Medical Management, Support of Medical Treatment, and Demographic Characteristics

HRR Indicator	Mean	Standard Deviation	10th Percentile	90th Percentile	Correlation with HRR Cath Rate
Measures of intensive treatment:					
Risk-adjusted 30-day cath rate	46.3%	9.1%	34.5%	58.3%	1.00
Risk-adjusted 30-day PTCA rate	17.7%	5.1%	11.3%	23.6%	.81
Risk-adjusted 30-day CABG rate	13.4%	2.9%	10.2%	16.9%	.51
Risk-adjusted 12-hour PTCA rate	2.7%	2.6%	.6%	5.8%	.52
Measures of quality of medical management:					
Risk-adjusted beta-blocker rate	45.6%	9.5%	34.2%	58.3%	−.31
Support for intensive treatment:					
Cardiovascular surgeons per 100,000	1.06	.27	.70	1.40	.33
Cath labs per 10,000	2.40	.76	1.50	3.30	.39
Demographic characteristics:					
Log of resident population	13.96	.89	12.72	15.18	−.05
Log of per capita income	9.55	.20	9.31	9.85	.02
Percent college graduates	19.3%	5.5%	13.1%	26.6%	−.05

Note.—HRR surgical and medical intensity rates are computed as the risk-adjusted fixed effects from a patient-level regression of the receipt of cath or beta-blockers on HRR fixed effects and CCP risk adjusters.

Results: Table 5

- Cath = f(average appropriateness of patients in your HRR)
- 1pp increase in average propensity of patients in your HRR $\Rightarrow$ 0.53pp increase in the probability you receive cath
- Consistent with productivity spillovers

TABLE 5

OLS RESTIMATES OF THE RELATIONSHIP BETWEEN PROBABILITY OF RECEIVING CATHETERIZATION AND HRR PATIENT CHARACTERISTICS (N = 138,873)

HRR-LEVEL INDEPENDENT VARIABLE	PROBABILITY OF RECEIVING CATHETERIZATION (1)	(2)
Average propensity to get cath	.529	.575
	(.172)	(.167)
Percent under age 65		.150
		(.135)
Log of resident population		−.003
		(.005)
Log of per capita income		.024
		(.024)

NOTE.—The table reports OLS estimates of the relationship between a patient receiving catheterization and the average appropriateness for catheterization in an HRR. Regressions control for patient risk adjusters, and standard errors are clustered at the level of HRRs.

Results: Table 6

- IV: outcome = f(cath), survival = f(spending) (like Table 1, but area)
- Returns to treat_2 higher in intensive areas (0.038 vs. 0.009); opposite prediction from "flat of the curve" model
- Difference in IV from survival, not costs
- Consistent with productivity spillovers

TABLE 6
INSTRUMENTAL VARIABLE ESTIMATES OF INTENSIVE MANAGEMENT AND SPENDING ON SURVIVAL, BY SURGICAL INTENSITY OF HOSPITAL REFERRAL REGION

	Instrumental Variable Estimates of		
	Impact of Cath		
Sample	On One-Year Survival (1)	On One-Year Cost ($1,000s) (2)	Impact of $1,000 on One-Year Survival (3)
A. All patients:			
HRR risk-adjusted cath rate:			
Above the median (*N* = 63,771)	.256	6.691	.038
	(.061)	(3.510)	(.021)
Below the median (*N* = 66,124)	.09	9.835	.009
	(.059)	(3.155)	(.007)
Difference	.166	−3.144	.029
	(.085)	(4.720)	(.022)
B. Patients above the median cath propensity:			
HRR risk-adjusted cath rate:			
Above the median (*N* = 32,388)	.271	.347	.78
	(.064)	(4.370)	(9.820)
Below the median (*N* = 32,411)	.168	4.962	.034
	(.046)	(2.890)	(.021)
C. Patients below the median cath propensity:			
HRR risk-adjusted cath rate:			
Above the median (*N* = 31,383)	.206	16.21	.013
	(.129)	(5.130)	(.009)
Below the median (*N* = 33,713)	−.139	22.064	−.006
	(.165)	(6.870)	(.007)

NOTE.—HRR intensity rates are computed as the risk-adjusted fixed effects from a patient-level regression of the receipt of cath on HRR fixed effects and CCP risk adjusters. Differential distance (measured as the distance between the patient's zip code of residence and the nearest catheterization hospital minus the distance to the nearest hospital) is the instrument. Each model includes all the CCP risk adjusters, and the standard errors are clustered at the level of each HRR.

Results: Table 7

- OLS: outcome = f(HRR-level cath rate)
- On average, no return to spending; hides important heterogeneity
- Intensive areas: appropriate patients better off (0.052), less appropriate patients worse off (-0.075)
- REALLY striking
- Consistent with productivity spillovers

TABLE 7
RELATIONSHIP BETWEEN HRR CATHETERIZATION RATE, SURVIVAL, AND COSTS, BY CLINICAL APPROPRIATENESS FOR INTENSIVE MANAGEMENT

	OLS ESTIMATES OF THE RELATIONSHIP BETWEEN HRR RISK-ADJUSTED CATH RATE AND			
SAMPLE	One-Year Survival (1)	One-Year Cost ($1,000s) (2)	Beta-Blocker in Hospital (3)	Catheterization within 30 Days (4)
A. All patients (N = 138,873)	.007	8.093	−.28	.702
	(.019)	(1.410)	(.073)	(.004)
B. By cath propensity:				
Top tercile (N = 46,287)	.052	10.012	−.366	.802
	(.019)	(1.439)	(.073)	(.032)
Middle tercile (N = 46,295)	.03	11.154	−.271	.906
	(.030)	(1.784)	(.082)	(.021)
Bottom tercile (N = 46,291)	−.075	2.763	−.209	.369
	(.028)	(1.612)	(.073)	(.021)
Difference (top − bottom)	.127	7.249	−.157	.433
	(.034)	(2.161)	(.103)	(.038)
C. By age:				
65–80 (N = 96,093)	.023	9.616	−.311	.775
	(.021)	(1.448)	(.072)	(.012)
Over 80 (N = 42,780)	−.031	4.738	−.215	.531
	(.028)	(1.603)	(.080)	(.022)
Difference (top − bottom)	.054	4.878	−.096	.244
	(.035)	(2.160)	(.108)	(.025)
D. By AHA/ACC criterion:				
Ideal (N = 89,569)	.027	9.845	−.302	.769
	(.023)	(1.599)	(.076)	(.010)
Appropriate (N = 31,800)	−.002	6.174	−.282	.752
	(.024)	(1.537)	(.080)	(.026)
Not appropriate (N = 17,504)	−.08	2.958	−.177	.264
	(.040)	(1.511)	(.065)	(.021)
Difference (top − bottom)	.107	6.887	−.125	.505
	(.046)	(2.200)	(.100)	(.023)

NOTE.—Cath propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk adjusters. HRR surgical and medical intensity rates are computed as the risk-adjusted fixed effects from a patient-level regression of the receipt of cath or beta-blockers on HRR fixed effects and CCP risk adjusters.

Take-aways

- 'Facts' of geographic variation have been around a long time
  - Health economists' favorite puzzle: tremendous variation in medical spending across observationally similar patients
  - Caveat: other industries...
- High impact paper: simple model, careful empirics
- Not your 'standard' IV paper
- Not much on mechanisms for productivity spillovers
- Very policy relevant, but pretty silent on welfare
  - Is high spending evidence of overuse?
  - Can't infer overuse if productivity is heterogeneous
  - Chandra-Staiger (2011):
    "Expertise, overuse, and underuse in health care"

Expertise, overuse, and underuse in health care

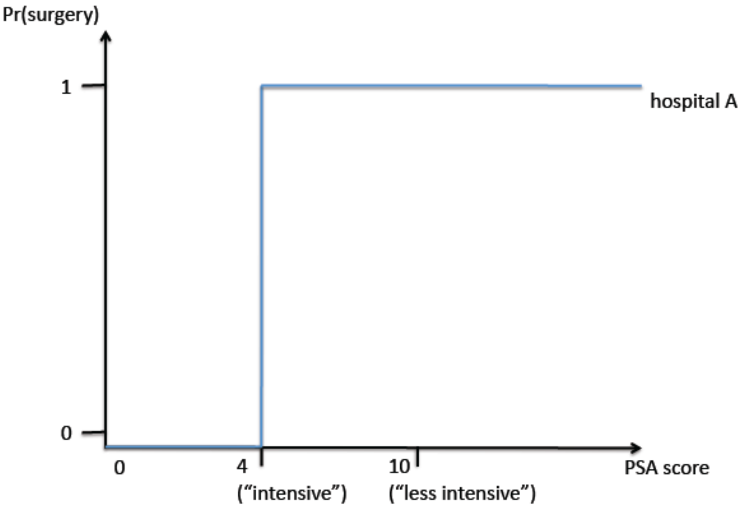
- Variation in treatment intensity across hospitals due to:
  1. Greater benefits of treatment ("expertise")
  2. Withholding of treatment ("underuse")
  3. Providing harmful treatment ("overuse")
- Model:
  - Expected benefit from treatment: $B_{ih} = \alpha_h + X_{ih}\beta + \epsilon_{ih}$
  - Expertise: α_h
  - Hospital treats if B_{ih} exceeds hospital-specific threshold τ_h
  - $E(B_{ih}|\text{treat}_{ih} = 1) = \alpha_h + X_{ih}\beta + E(\epsilon_{ih}| - \epsilon_{ih} < X_{ih}\beta + \alpha_h - \tau_h)$
- Tentative conclusion: Expertise varies widely, lots of overuse
- Won't go through empirics, just an example

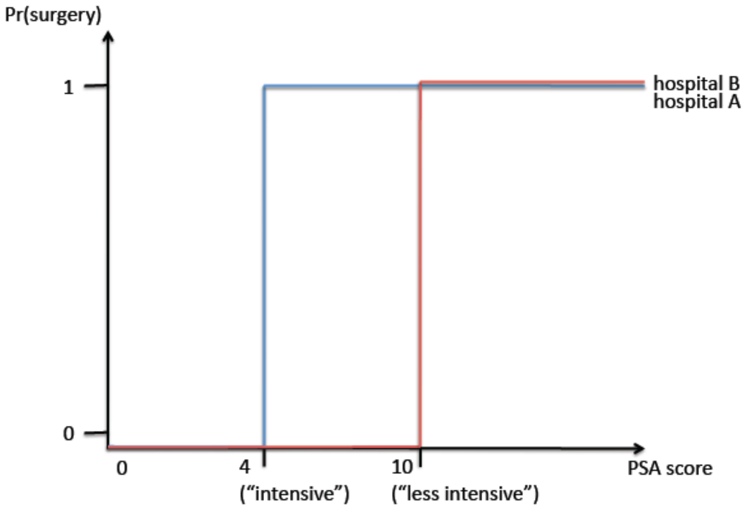
Different model/example: Prostate cancer

- Two treatment options: surgery, watchful waiting
- Assume PSA score is a perfect risk adjuster
  - Different from Chandra-Staiger: No uncertainty
- Patients as good as randomly allocated to providers
- Providers use a threshold rule

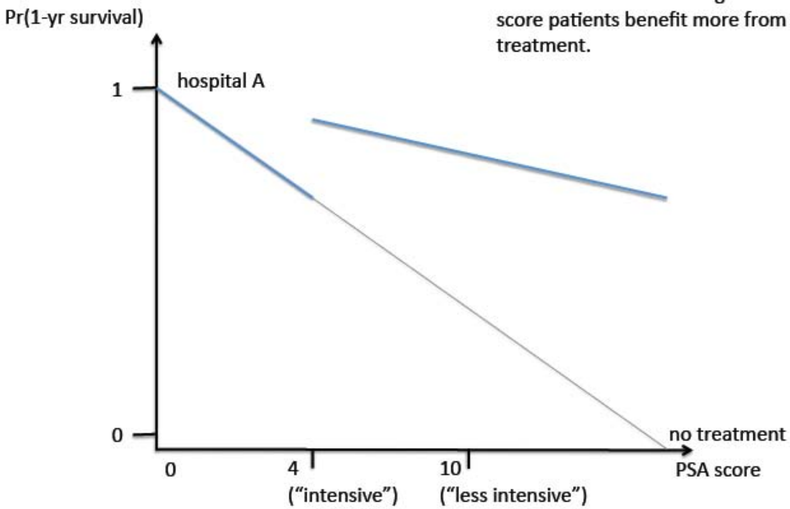
- Frame as a regression discontinuity (RD) framework
  - Goal: Clarify how parameters are identified in the data

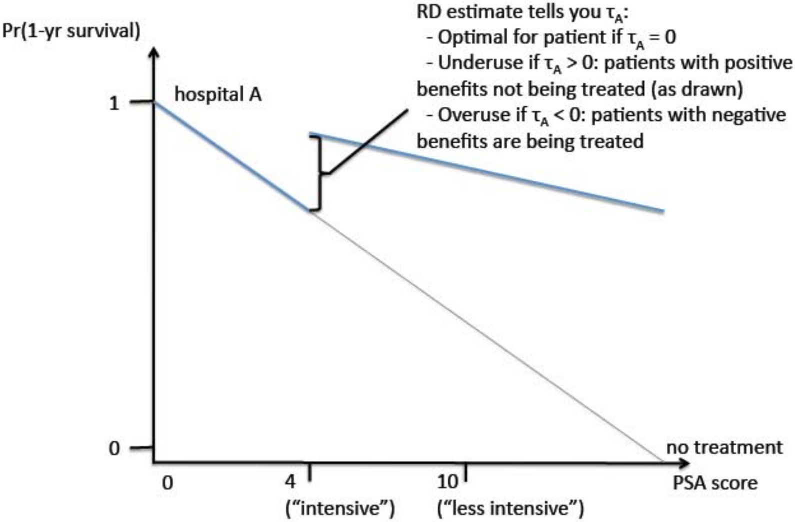
- Want to identify:
  - α_h: Hospital "expertise"
  - τ_h: Look for evidence of overuse/underuse ($\tau_h \gtrless 0$)


Pr(surgery)
1
0
hospital A
0
4
("intensive")
10
("less intensive")
PSA score


Pr(surgery)
1
0
0
4
("intensive")
10
("less intensive")
PSA score
hospital B
hospital A

Note: Drawn such that higher PSA score patients benefit more from the treatment.



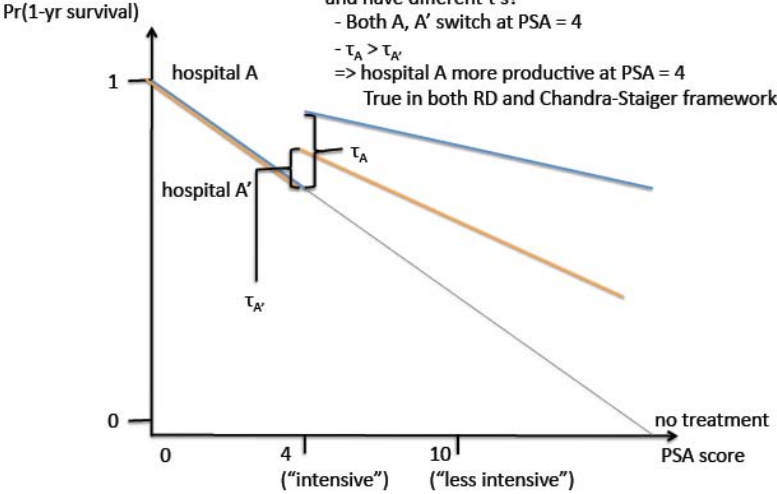

RD estimate tells you τ_A:
- Optimal for patient if $\tau_A = 0$
- Underuse if $\tau_A > 0$: patients with positive benefits not being treated (as drawn)
- Overuse if $\tau_A < 0$: patients with negative benefits are being treated
Pr(1-yr survival)
1
hospital A
0
no treatment
0
4
("intensive")
10
("less intensive")
PSA score

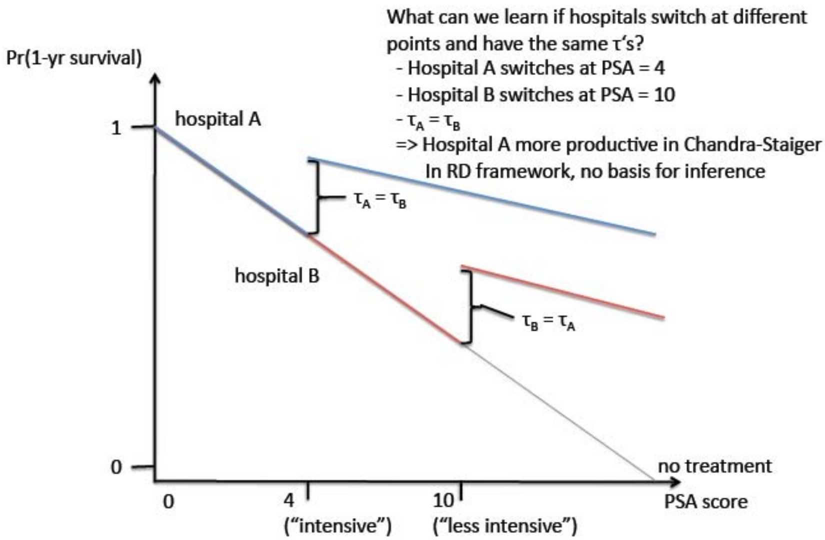
What can we learn if hospitals switch at the same point and have different τ's?

- Both A, A' switch at PSA = 4
- $\tau_A > \tau_{A'}$

=> hospital A more productive at PSA = 4

True in both RD and Chandra-Staiger frameworks





Same tau, less appropriate X's $\Rightarrow$ higher α_h

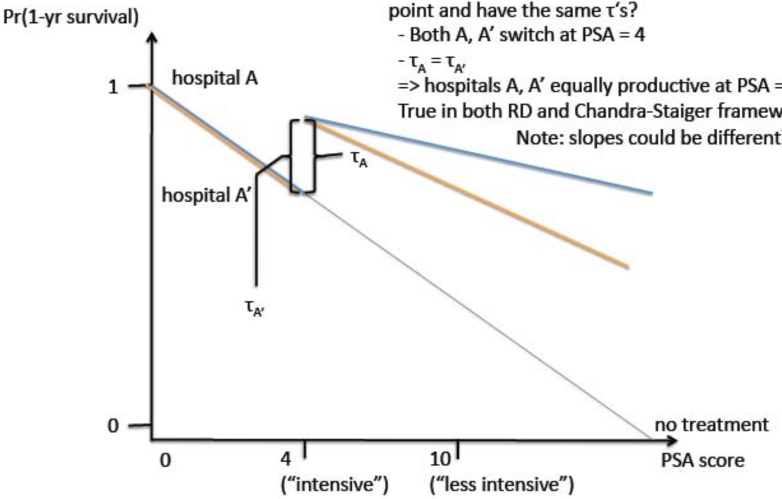
What can we learn if hospitals switch at the same point and have the same τ's?

- Both A, A' switch at PSA = 4
- $\tau_A = \tau_{A'}$

=> hospitals A, A' equally productive at PSA = 4

True in both RD and Chandra-Staiger frameworks

Note: slopes could be different?



Connecting this to the Chandra-Staiger model

- Identification of τ_h is clearer than is identification of α_h
- In RD framework, α_h is identified by comparing realized returns across hospitals using the same threshold
- How is α_h identified in Chandra-Staiger?
  - Component of treatment returns common across patients in h
  - Is this how we would ideally model expertise?
    - What if good at treating easy but not complicated patients?
    - Does this complicate decomposition exercise?
  - Estimation of α_h is very important, because α_h pins down where hospital A's optimal threshold *is* if currently $\tau_A \neq 0$
    - Key input into welfare analysis with counterfactuals
    - Exactly what RD *can't* tell us: Almond *et al.* (2010) example

Add'l application: Welfare effects of fixed thresholds

- Treatment guidelines based only on patient characteristics
  - Care for newborns: *e.g.* birthweight $\leq$ 1250g
  - Prostate cancer antigen (PSA) score: *e.g.* PSA $=$ 4
  - Hypertension: *e.g.* systolic blood pressure $\geq$ 160mm
- Implicit assumption: all variation is driven by τ_h, not α_h
- Criticisms of guidelines usually focus on patient heterogeneity
- But: heterogenous productivity $\Rightarrow$ different optimal thresholds

- Chandra-Staiger model could be applied to estimate the welfare gains and losses from uniform treatment guidelines
  - Net welfare effect ambiguous
    - Welfare gain from limiting overuse or avoiding underuse
    - Welfare loss from heterogeneous hospitals using fixed threshold
  - Could estimate policy counterfactuals, conduct welfare analysis

1. Roy model application #1: Health care
2. Roy model application #2: Redistribution
3. Looking ahead

Abramitsky (2009)

- Series of papers - and a book (in progress) - investigating the equality-incentives trade-off in the context of the Israeli kibbutz
- Key features:
  1. Equal sharing in the distribution of income
  2. No private property
  3. Non-cash economy
- PF literature: expect mobility in response to redistributive policies
- Roy model:
  - Positive self-selection of migrants expected when place of origin has lower returns to skill (more redistribution) than destination
  - Negative self-selection of migrants expected when place of origin has higher returns to skill (less redistribution) than destination
- Abramitsky (2009) tests these ideas in context of Israeli kibbutzim
  - As in work on US immigration, takes advantage of a new longitudinal data set of individuals linked across population censuses

Data

- Random representative sample of individuals linked between 1983 and 1995 Israeli Censuses of Population
  - Censuses identify individuals who life in "a cooperative rural settlement, in which production, marketing, and consumption are organized in a cooperative manner" (kibbutz members)
- Focuses on Jewish individuals between the ages of 21 and 54 in 1983 (ages of 33 and 66 in 1995)

Three subsamples

1. 1983 kibbutz members and other rural residents also observed in 1995
   - Compare kibbutz-to-city migrants both with kibbutz members who stayed in their kibbutz and with other rural-to-city migrants
2. City residents observed in 1995, including individuals who migrated from the kibbutz and from other rural areas between 1983 and 1995
   - Analyze earnings of kibbutz-to-city migrants in the city labor market compared with earnings of city natives and other rural-to-city migrants
3. City residents observed in 1983, including individuals who would migrant to kibbutz or other rural localities between 1983 and 1995
   - Compare the pre-entry earnings of city-to-kibbutz migrants with the earnings of city stayers and city-to-other rural migrants

Summary statistics on entry and exit

- A total of 343 out of the 1577 individuals in the sample who lived in a kibbutz in 1983 left the kibbutz between 1983 and 1995, over 20%
- A total of 90 out of the 16,789 individuals in the sample who lived outside of kibbutzim in 1983 (with non-missing earnings) entered a kibbutz in this period, around 0.5%
  - Note: low in part because screening mitigates adverse selection
  - Makes it harder to document negative selection

Testing for positive selection in exit

More educated members and those with higher skilled occupations are more likely to leave kibbutzim, and this skill bias in out-migration is stronger in kibbutzim than in other rural localities. These results suggest a positive selection away from redistribution.

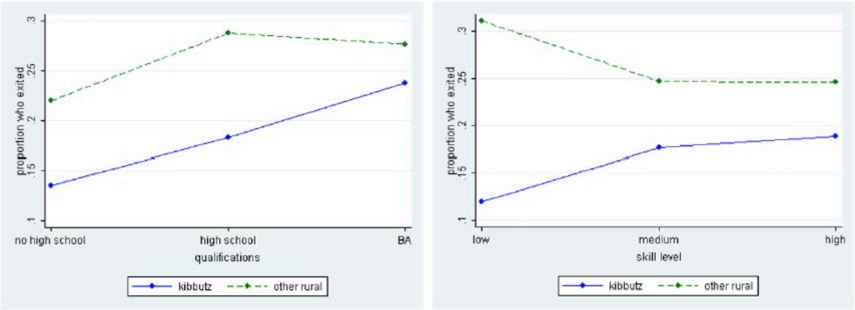


Fig. 1. Exit from kibbutzim and other rural areas, 1983–1995. Notes: The left hand panel shows the proportion of kibbutz members (solid line) and individuals from other rural areas (dashed line) who moved to the city between 1983 and 1995 by level of qualifications in 1983. The right hand panel shows the same, but broken down by the skill level of the member's occupation in 1983.

Testing for negative selection in entry

Individuals with lower wages are more likely to enter a kibbutz.

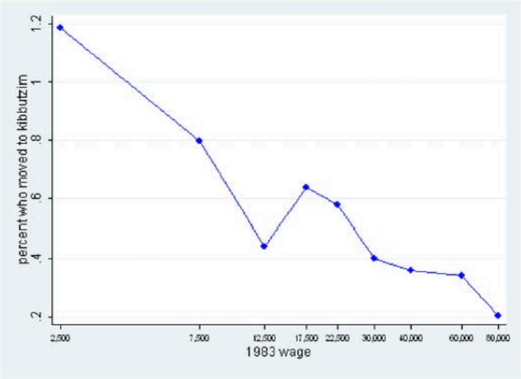


Fig. 3. Entry to kibbutzim from cities by wages. Notes: This figure shows the proportion of people living in cities in 1983 who entered kibbutzim between 1983 and 1995, broken down by wage categories in 1983. The numbers on the *x*-axis are plotted on a log scale.

Take-aways

- Paper formalizes these results, but I like that the key ideas are clearly illustrated in these two simple figures
- Broader research agenda uses the kibbutz as a laboratory for understanding how one form of intensive redistribution was able to survive over time; many kibbutzim eventually moved away from full equal sharing to something closer to capitalism and taxation

1. Roy model application #1: Health care
2. Roy model application #2: Redistribution
3. **Looking ahead**

Looking ahead

Equalizing wage differentials

For next Wednesday: Please read Goldin-Katz (forthcoming, JOLE)