Sources of Geographic Variation in Health Care: Evidence From Patient Migration

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Motivation

- Wide variation of health care utilization across the US
  - Miami ($\$14,423$) vs. Minneapolis ($\$7,819$)
  - McAllen ($\$13,648$) vs. El Paso ($\$8,714$)

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- Higher utilization not correlated with better health outcomes- Skinner (2011)
- Important for policy makers to understand what drives the variation: patient or place?

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Place Specific: **Supply**

- Doctor's incentives/beliefs (aggressive care)
- hospital market structure
- endowments

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Patient Specific: **Demand**

- Health level
- Preference of care

Preview

We'll look at event study and main model estimations.

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Contribution: Using migration of patients allows separation of this variation without depending solely on observables.

Building Model & Assumptions

Patient:

$$\max_{y} u_i(y|h_{it}, \eta_i) = \max_{y} -\frac{1}{2}(y - h_{it})^2 + \eta_i y$$

- $\mathbf{h_{it}}$: health status, (higher means worse)
- $\eta_{\mathbf{i}}$: preferences, (higher means prefers more aggressive)

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Assumption: Expectation of y^* can be written as addition of patient fixed effect and data observed by econometrician.

$$E[y^*_{it}|i, j, t, x_{it}] = \alpha_i + x_{it}\beta$$

Theory & Assumptions

Physician:

$$\max_y \tilde{u}_j(y|h_{it}, \eta_i) - \mathrm{PC}_{jt}(y)$$

- **j**: geographic area
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- $\tilde{\mathbf{u}}_{\mathbf{j}}(\mathbf{y}|\mathbf{h}_{\mathbf{it}}, \eta_{\mathbf{i}}) = u_i(y|h_{it}, \eta_i) + \lambda_j y$
  - Perceived utility
  - λ_j represents practice style (higher means more aggressive)
  - captures heterogeneity in physician beliefs

Theory & Assumptions

Putting It Together:

Max physician problem and write in terms of fixed effects:

$$y_{ijt} = \alpha_i + \gamma_j + \tau_t + x_{it}\beta + \epsilon_{ijt}$$

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- τ_t: time fixed effect
- x_{it}: dummies for age (in 5-year bins) and relative year fixed effects

Theory & Assumptions

Decomposing Variation:

- $\overline{y_{jt}}$: avg utilization across patients in area j in year t
- $\overline{y_j}$: avg of $\overline{y_{jt}}$ across t
- $\overline{y_{jt}^*}$ and $\overline{y_j^*}$ same but for patient optimal care utilization level

Then

$$\overline{y_j} - \overline{y_{j'}} = \underbrace{(\gamma_j - \gamma_{j'})}_{place} + \underbrace{(\overline{y_j^*} - \overline{y_{j'}^*})}_{patient}$$

$$1 = \underbrace{\frac{(\gamma_j - \gamma_{j'})}{\overline{y_j} - \overline{y_{j'}}}}_{S_{place}(j,j')} + \underbrace{\frac{(\overline{y_j^*} - \overline{y_{j'}^*})}{\overline{y_j} - \overline{y_{j'}}}}_{S_{pat}(j,j')}$$

Identification

- Need movers
- Assume utilization shocks do not coincide directly with the time of the move
- Assume α_i amd λ_j are additively separable
  -
  - Assume similar patients do not seek out different types of providers
- Assume λ_j that are relevant for movers are also relevant for nonmovers
- No habit formation

Data

Claims Data- 20% random sample of Medicare patients (65+) from 1998 to 2008

- Utilization is adjusted for regional price differences
- Use log utilization+1 in regressions
- Geographic regions defined by HRRs

TABLE I

SUMMARY STATISTICS

	(1) Nonmovers	(2) Movers
Female	0.57	0.60
White	0.86	0.88
Age first observed:		
65–74	0.67	0.59
75–84	0.24	0.31
≥85	0.09	0.09
First observed residence:		
Northeast	0.20	0.17
South	0.39	0.41
Midwest	0.26	0.19
West	0.16	0.23
Annual utilization:		
Mean	$7,796	$7,399
Std. dev.	$12,690	$9,567
Share of patient-years with zero	0.06	0.06
Number of chronic conditions:		
Mean	2.98	3.30
Std. dev.	2.15	2.06
Share of patient-years with zero	0.18	0.15
Average # of years observed	6.26	7.45
Share who die during sample	0.35	0.32
Share of patient-years excluded because patient is in Medicare Advantage that year	0.18	0.20
# of patients	2,033,096	497,097
# of patient-years	12,730,766	3,702,189

Event Study

Preliminary:

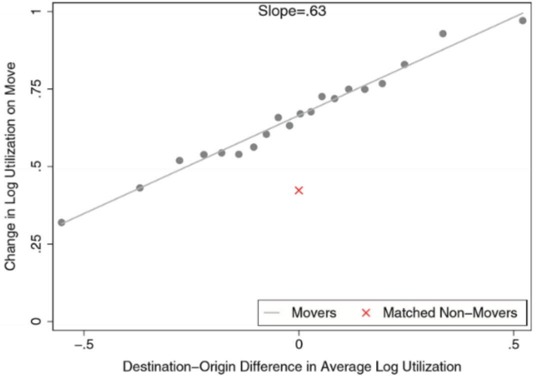

FIGURE IV

Event Study

$$y_{it} = \alpha_i + \theta_{r(i,t)}\hat{\delta}_i + \tau_t + x_{it}\beta + \epsilon_{it}$$

- $\hat{\delta}_i$: difference in sample means of log utilization between origin and destination
- $\theta_{r(i,t)}$: coefficient of interest
  - Measure changes in log utilization around the move, scaled relative to $\hat{\delta}_i$

Event Study

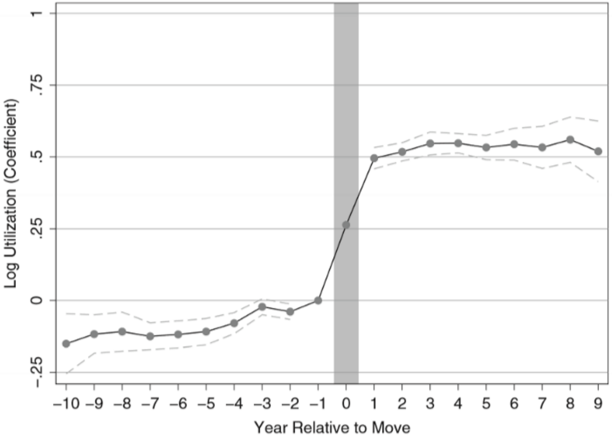

FIGURE VI

Main Model

Recall,

$$y_{ijt} = \alpha_i + \gamma_j + \tau_t + x_{it}\beta + \epsilon_{ijt}$$

TABLE II

ADDITIVE DECOMPOSITION OF LOG UTILIZATION

	(1) Above/ below median	(2) Top & bottom 25%	(3) Top & bottom 10%	(4) Top & bottom 5%	(5) McAllen & El Paso	(6) Miami & Minneapolis
Difference in average log utilization						
Overall	0.283	0.456	0.664	0.817	0.587	0.667
Due to place	0.151	0.271	0.406	0.461	0.374	0.466
Due to patients	0.132	0.185	0.258	0.356	0.213	0.200
Share of difference due to						
Patients	0.465	0.405	0.388	0.435	0.363	0.300
	(0.027)	(0.029)	(0.026)	(0.025)	(0.161)	(0.088)
Place	0.535	0.595	0.612	0.565	0.638	0.700

Extra Analysis

TABLE IV

COMPONENTS OF UTILIZATION

	Utilization measure	(1) Mean of utilization measure	(2) Above/below median difference in utilization measure	(3) Share due to patients	
(1)	Baseline: log(utilization)	7.193	0.283	0.465	(0.027)
(2)	Seen a primary care physician	0.884	0.042	0.452	(0.027)
(3)	Seen a specialist	0.815	0.051	0.322	(0.024)
(4)	Any hospitalization	0.226	0.037	0.410	(0.034)
(5)	Any emergency room visit	0.346	0.045	0.714	(0.031)
(6)	Log(# of diagnostic tests)	1.449	0.550	0.092	(0.008)
(7)	Log(# of imaging tests)	0.842	0.220	0.142	(0.014)
(8)	Log(# of preventive care measures)[a]	1.376	0.098	0.611	(0.018)
(9)	Log(# of different doctors seen)	1.525	0.113	0.392	(0.016)
(10)	Log(inpatient utilization)[b]	2.004	0.340	0.242	(0.035)
(11)	Log(outpatient utilization)[b]	6.890	0.193	0.358	(0.031)
(12)	Log(emergency room utilization)[b]	2.296	0.352	0.639	(0.031)
(13)	Log(other utilization)[b]	3.430	0.957	0.124	(0.010)

Robustness

- Robust to limiting the window of time before and after move
- Robust to allowing place effects for each quartile of patient age
- Robust to excluding patients who enter/exit the sample
- Robust to different definitions of movers

Threats

- Assumption of no habit formation
- Limited to short run supply side
- Would be troublesome to extend to different population