Input Regulation and the Production of Hospital Quality

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- Approach: Estimate model of quality in hospital productivity + labor inputs

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- 0.7 pct. increase in 30-day non-readmission rate but heterogeneous

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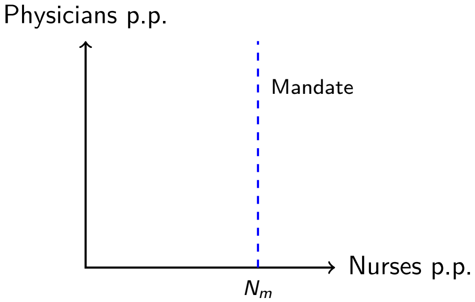

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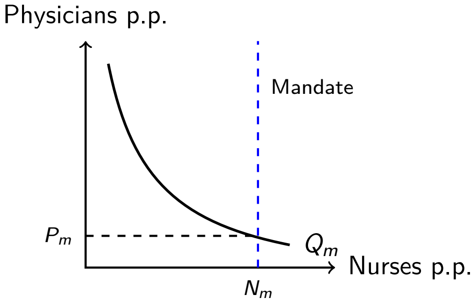

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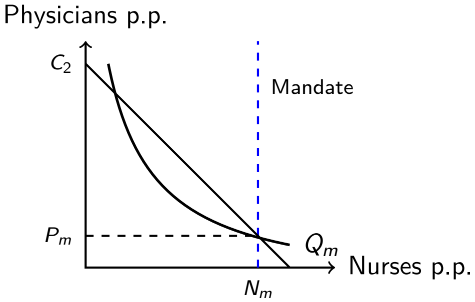

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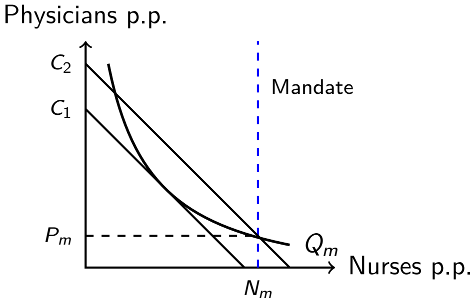

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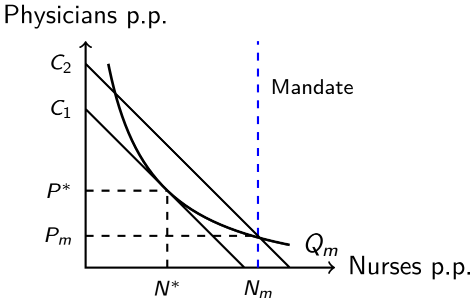

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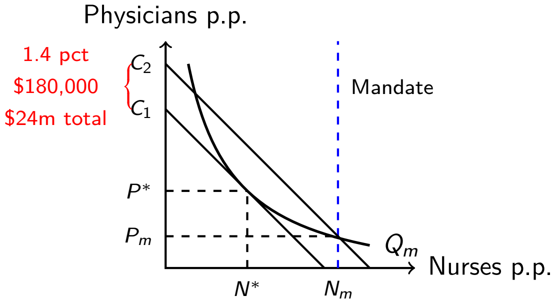

Results:

- Ratios raise healthcare costs by 1.4 pct on average holding quality constant
- $24m in aggregate across treated hospitals
- Efficient solution is to use nurses and physicians in near fixed-proportion

leontief

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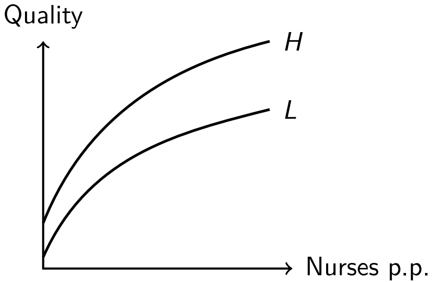

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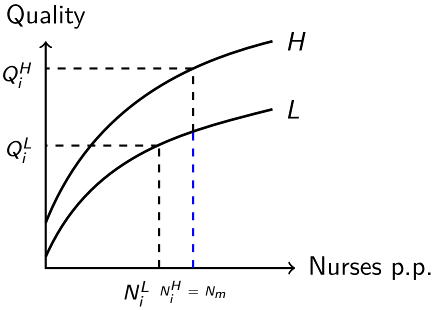

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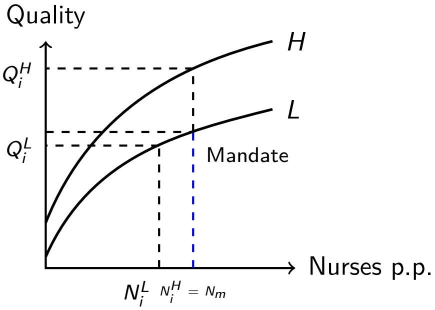

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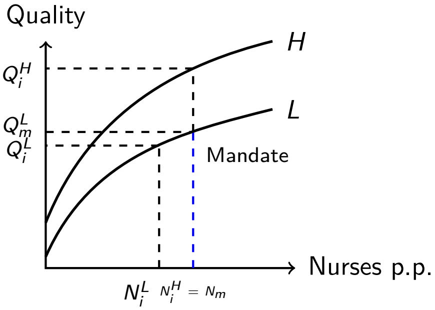

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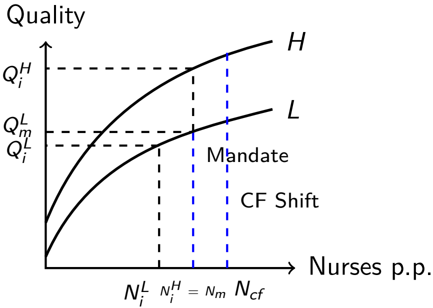

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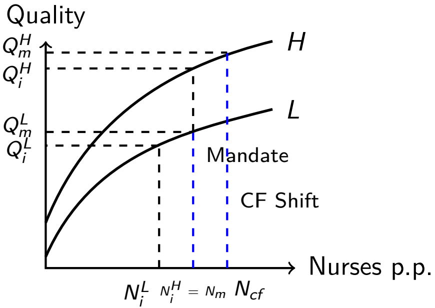

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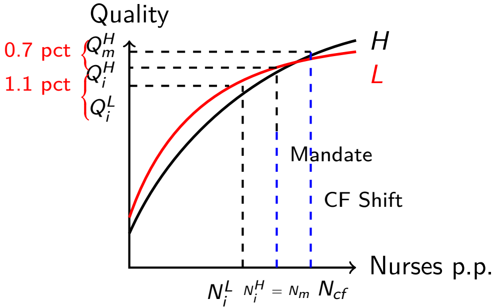

Results:

- No across-hospital misallocation on average due to the mandate
- Low staffing hospitals are equally productive with less severe patients
- Relative to crude mandate, efficiency gains from accounting for patient severity

Contribution to the Literature

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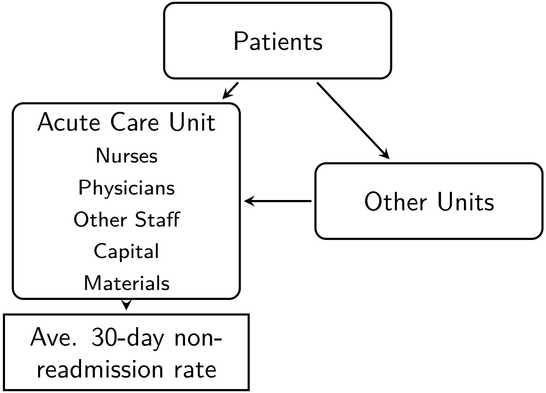
Roadmap of Talk

1. Introduction
2. Setting and Reduced-Form
3. Model
4. Identification and Estimation
5. PF Results
6. Policy Counterfactuals
7. Conclusion

Hospital Production



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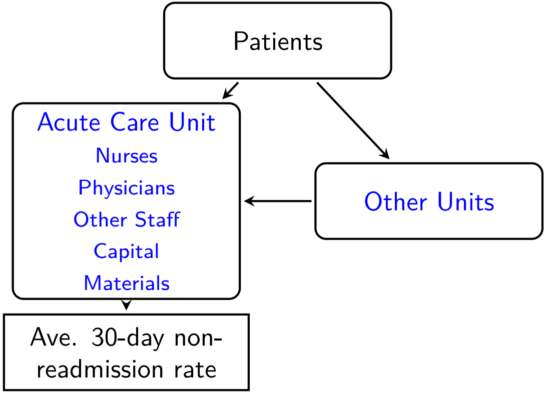

Data from CA Health Dept. (1995-2008):

- Financial records (hospital-year)
  - Nurses: unit-level licensed nursing hours
  - Physicians: hospital-level affiliated medical staff physician counts
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  - Sample: universe of encounters
  - Risks: patient characteristics + identifier

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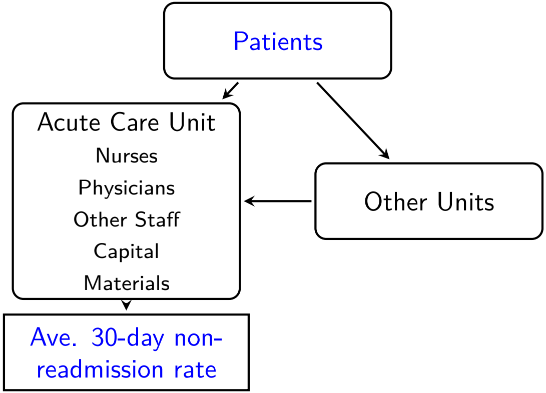

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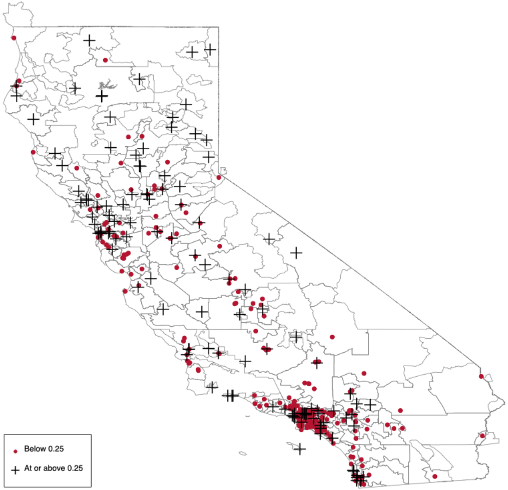
risk-adjustment why readmission?

Identifying Variation from 1999 Nurse Staffing Mandate



Notes: This figure shows the locations of hospitals in the balanced panel based on their pre-mandate nurse staffing levels in the Acute Care Unit.

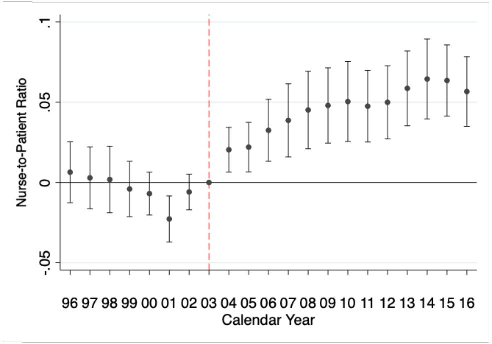
- Nurse-to-patient ratios set at unit level
    - Legislated Dec. 1999
    - Ratios announced Jan. 2003
    - Implementation Jan. 2004 + Jan. 2005
- Acute Care Unit threshold binding for ∼ half of hospitals
- Homogeneous threshold for all hospitals
- Compare hospitals below and above the threshold in DiD + event study

hospital stats

Mandate Shifts Nurse Labor

Figure 1: Effect of Mandate on Nurse-to-Patient Ratio from Raja (2023)

$$y_{ht} = \beta_0 + \sum_{t \neq 2003} \beta_t \{YEAR_t = t\} * BELOW_h + \gamma_h + \xi_t + \epsilon_{ht}$$

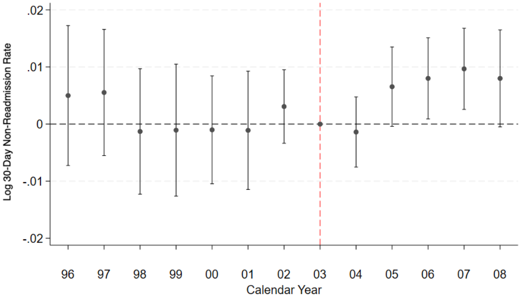


Notes: This figure plots β_t and 95 percent confidence intervals for the risk-adjusted nurse-to-patient ratio. Standard errors are clustered at the hospital level.

Quality Gains

Figure 2: Effect of Mandate on Log 30-Day Non-Readmission

$$y_{ht} = \beta_0 + \sum_{t \neq 2003} \beta_t \{YEAR_t = t\} * BELOW_h + \gamma_h + \xi_t + \epsilon_{ht}$$



Notes: This figure plots coefficients β_t and 95 percent confidence intervals for the log of the non-readmission rate. Standard errors are clustered at the hospital level.

heterogeneity

Roadmap of Talk

1. Introduction
2. Setting and Reduced-Form
3. Model
4. Identification and Estimation
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Model

$$
\begin{aligned}
Q_{ht} &= e^{\omega_{ht}+\epsilon_{ht}} F(x_{ht}^{h}, x_{ht}^{n}, x_{ht}^{p}) \\
&\equiv e^{\omega_{ht}+\epsilon_{ht}} \prod_{i\in\{h,n,p\}} (x_{ht}^{i})^{\beta_i} \prod_{i\in\{h,n,p\}} (x_{ht}^{i})^{\frac{1}{2}\left(\sum_{j\in\{h,n,p\}} \beta_{ij}\ln(x_{ht}^{j})\right)}
\end{aligned}
$$

Taking log of both sides leads to linear-in-parameters expression

$$
\ln(Q_{ht}) = \sum_{i\in\{h,n,p\}} \beta_i \ln(x_{ht}^{i}) + \frac{1}{2} \sum_{i\in\{h,n,p\}} \sum_{j\in\{h,n,p\}} \beta_{ij} \ln(x_{ht}^{i}) \ln(x_{ht}^{j}) + \omega_{ht} + \epsilon_{ht}
$$

- Quality Q, Nurses per patient x^n, Physicians per patient x^p, Patient case mix x^h
- Productivity ω, Measurement error ϵ

Model Features

$$\ln(Q_{ht}) = \sum_{i\in\{h,n,p\}} \beta_i \ln(x^i_{ht}) + \frac{1}{2} \sum_{i\in\{h,n,p\}} \sum_{j\in\{h,n,p\}} \beta_{ij} \ln(x^i_{ht}) \ln(x^j_{ht}) + \omega_{ht} + \epsilon_{ht}$$

- Structural value-added model in Acute Care nurse and physician labor assumptions

Model Features

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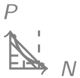
- Structural value-added model in Acute Care nurse and physician labor assumptions
- Allow elasticity of substitution to vary with x^n, x^p, x^h Shape of the isoquant curves



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  - Enables study of efficient allocation within hospitals

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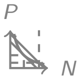

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- Allow labor productivity to vary flexibly with x^h, ω Shape of the production curves

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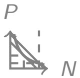

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  - Reflects heterogeneity in x^h, ω across hospitals
  - Enables study of efficient allocation across hospitals
- Allow ω to vary flexibly across hospitals and over time

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Identification

Challenges: (Marschak and Andrews, 1944)

- Hospitals observe ω before choosing to enter or remain in market
- Hospitals observe ω before choosing x^n, x^p
- Patients x^h observe ω before choosing hospital

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- Patients x^h observe ω before choosing hospital

Empirical Strategy:

1. Economic assumptions:
    - Abstract from entry and exit
    - Assume Hicks-neutral productivity
2. Statistical assumptions:
    - $\omega_{ht} = \omega_h + \gamma_t + \xi_{ht}$
    - Use hospital and year fixed effects to address endogeneity of ω_h, γ_t
    - Assume instruments Z excluded from ξ (no serial correlation in ξ) overidentifying restrictions test
    - Assume instruments Z are relevant first-stage f-statistics

PF Identification: Comparison to Prior Approaches

- Control Function (Olley and Pakes, 1996; Levinsohn and Petrin (2009); Ackerberg, Caves, and Fraser (2015))
  - Behavioral assumption on input demand to construct CF for ω
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  - Use timing assumptions over fixed inputs + instruments Z for flexible inputs
  - This Paper: Leverages external mandate and lags (Lee et al., 2013)

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Production Function Estimates

	Translog			
	(1) OLS	(2) FE	(3) IVFE	(4) IVFE
Log nurses per patient	0.026	0.035**	-0.028	
	(0.020)	(0.015)	(0.055)	
Log physicians per patient	-0.004	-0.014**	0.110***	0.103***
	(0.005)	(0.006)	(0.042)	(0.032)
Log patient health	0.054***	0.040*	0.227***	0.197***
	(0.020)	(0.021)	(0.065)	(0.053)
Log nurses squared	-0.014	-0.021***	-0.038*	-0.052***
	(0.010)	(0.007)	(0.022)	(0.011)
Log physicians squared	-0.000	0.001	-0.055***	-0.053***
	(0.001)	(0.002)	(0.018)	(0.013)
Log patient health squared	-0.012	-0.012	-0.104	
	(0.015)	(0.025)	(0.145)	
Log nurses x Log physicians	0.009**	0.013***	0.053***	0.056***
	(0.004)	(0.004)	(0.016)	(0.011)
Log nurses x Log patient health	-0.037**	-0.047***	-0.122**	-0.100***
	(0.017)	(0.014)	(0.049)	(0.027)
Log physicians x Log patient health	-0.006	-0.007	-0.060***	-0.047***
	(0.006)	(0.007)	(0.022)	(0.018)
Observations	2,704	2,704	2,496	2,496
R^2	0.018	0.518	-	-
Hospital Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓

Notes: This table reports the production function estimates. Standard errors are not clustered.

- IVFE is the preferred model

hausman test

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Derivation of Structural Objects from β

- Elasticity of substitution (Sargan (1971); Sato and Koizumi (1973); Boisvert (1974))

$$\sigma_{np} = \frac{\mathrm{d}\ln\left(\frac{x_n}{x_p}\right)}{\mathrm{d}\ln\left(\frac{\frac{\partial Q}{\partial x_p}}{\frac{\partial Q}{\partial x_n}}\right)} = f(x_n, x_p, x_h, \beta)$$

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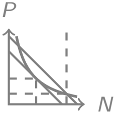
Shape of the isoquant curves 

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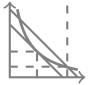

- Marginal product of nurse labor

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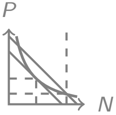

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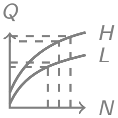

Nurses and Physicians are Highly Complementary

	Percentiles of Elasticity of Substitution				
Nurses per 1,000 Patient Days	10th	25th	50th	75th	90th
1.5	0.020	0.049	0.091	0.132	0.168
2	0.012	0.031	0.062	0.106	0.135
2.5	0.009	0.023	0.043	0.078	0.102
3	0.013	0.026	0.051	0.085	0.132
3.5	0.012	0.024	0.058	0.096	0.112
4	0.002	0.010	0.044	0.075	0.086

Notes: In this table, I present the percentiles of the distribution of elasticities of substitution derived for each hospital-year in my sample with positive marginal products for nurses and physicians. The near zero elasticities of substitution indicate strong complementarities in quality production between nurses and physicians. Nurses and physicians are more substitutable at low levels of the two inputs i.e. when hospitals are relatively understaffed.

- Ranges from 0-0.2

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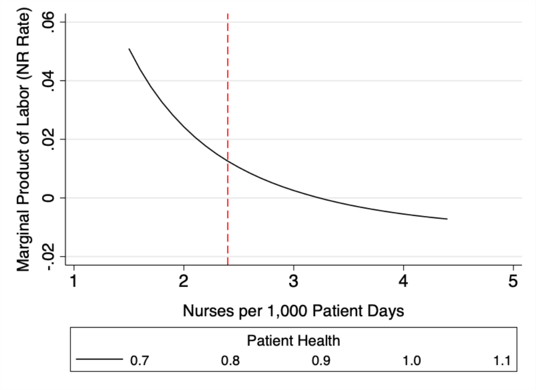
- More substitutable when patients are less severe
- Lower severity patients have needs better met independently by nurses consistent with reduced-form work

Labor is More Valuable in High Severity Settings



Notes: This figure plots the median value of the marginal product of nurse labor across the hospital-years in my sample at each level of nurse staffing shown on the x-axis and each level of patient health shown in the legend. The levels of physicians and productivities are allowed to vary across hospital-years as in the data or estimates, respectively.

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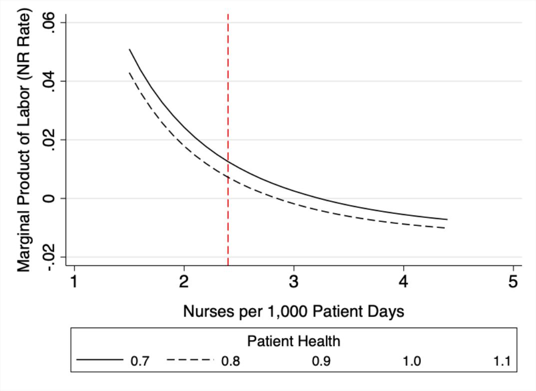

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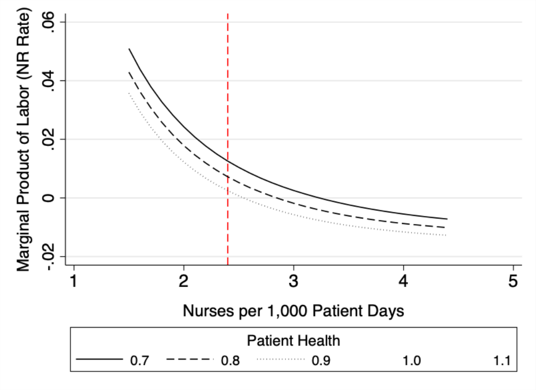

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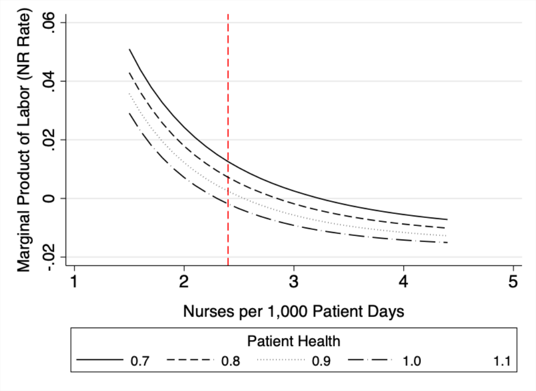

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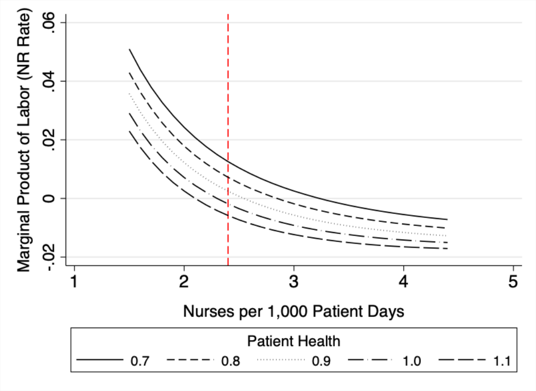

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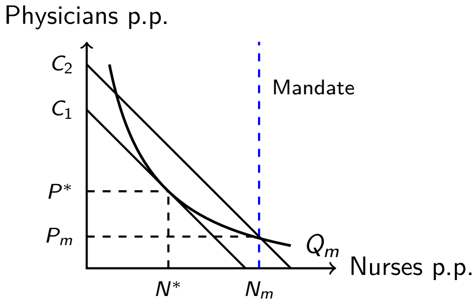
Question: What are the efficiency implications of minimum nurse-to-patient ratios?

Within-Hospital Misallocation: Nurse mandate vs. cost-minimizing, direct quality mandate



Within-Hospital Misallocation Exercise

Solve the hospital's cost-minimization problem for each of the 208 hospitals in sample:

$$\min_{x^n_{ht}, x^p_{ht}} \{x^n_{ht} * w^n_{ht} + x^p_{ht} * w^p_{ht}\}$$
$$\text{s.t.} \;\; e^{\hat{\omega_{ht}} + \hat{\epsilon_{ht}}} \hat{F}(x^h_{ht}, x^n_{ht}, x^p_{ht}) \geq Q_{ht}$$

3 scenarios

1. Solve problem subject to quality constraint (Q_{ht} = pre-mandate observed)
2. Solve problem subject to quality constraint (Q_{ht} = pre-mandate observed * 1.005)

Within-Hospital Misallocation Exercise

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$$\begin{aligned} \min_{x^n_{ht}, x^p_{ht}} & \{x^n_{ht} * w^n_{ht} + x^p_{ht} * w^p_{ht}\} \\ \text{s.t. } & e^{\hat{\omega_{ht}} + \hat{\epsilon_{ht}}} \hat{F}(x^h_{ht}, x^n_{ht}, x^p_{ht}) \geq Q_{ht} \\ & x^n_{ht} \geq x^n_{min} \end{aligned}$$

3 scenarios

3. Solve problem subject to quality constraint in (2) and staffing constraint (x^n_{min} = median of model prediction in (1))

Within-Hospital Misallocation Results

	Cost-Minimization Scenario				
Quartile	Nurses	Phys.	Nurse-Phys.	Costs p.p.d.	Quality
Top 25	2.28	0.81	2.83	508	0.987
50-75	1.56	0.58	2.70	359	0.980
25-50	1.18	0.44	2.71	248	0.976
Bottom 25	0.77	0.28	2.76	159	0.981
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25-50	1.41	0.42	3.31	258	0.976
Bottom 25	1.41	0.28	5.06	203	0.981
	Misallocation				
	% Incidence	% Diff. Costs	% Diff. Nurses	% Diff. Phys.	Diff. Ratio
Top 25	–26.53	0.00	0.00	–0.00	0.00
50-75	1.94	0.03	0.46	–0.15	0.02
25-50	31.97	4.57	19.15	–2.60	0.61
Bottom 25	106.48	32.83	83.69	0.38	2.29

Notes: In the top panel, this table shows the cost-minimizing allocations of nurses and physicians. The ratio of nurses to physicians is roughly 2.70-2.90. In the second panel, I show the allocations under the mandate. The last panel shows the within-hospital misallocation between the two scenarios.

- For one-fifth of hospitals, even a nurse + physician staffing mandate is misallocative
- For the other four-fifths: prefer a nurse-to-physician ratio around 2.70-2.90 when cost-minimizing

aggregate nurse-phys statistics

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Bottom 25	1.41	0.28	5.06	203	0.981
	Misallocation				
	% Incidence	% Diff. Costs	% Diff. Nurses	% Diff. Phys.	Diff. Ratio
Top 25	–26.53	0.00	0.00	–0.00	0.00
50-75	1.94	0.03	0.46	–0.15	0.02
25-50	31.97	4.57	19.15	–2.60	0.61
Bottom 25	106.48	32.83	83.69	0.38	2.29

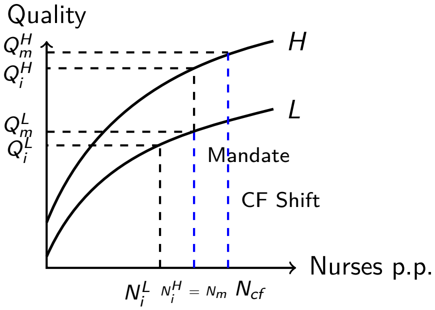
Notes: In the top panel, this table shows the cost-minimizing allocations of nurses and physicians. The ratio of nurses to physicians is roughly 2.70-2.90. In the second panel, I show the allocations under the mandate. The last panel shows the within-hospital misallocation between the two scenarios.

- For the hospital with average incidence (12 pct.): mandate increases labor costs by 1.4 pct holding quality constant
- Depends on labor supply assumption
- Distributional consequences depend on pre-mandate nurse-to-physician ratio: Mean 3.12, IQR 1.51-4.02

distortions in input use

Question: What are the efficiency implications of minimum nurse-to-patient ratios?

Across-Hospital Misallocation: Allocate nurses + patients to treated vs. control hospitals



Across-Hospital Misallocation Results

- If we hold fixed the number of nurses per patient added due to the regulation and change their allocation across hospitals could we produce higher quality of care?

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$$Q_{h,pre} = Q(x^n_{h,2002}, x^p_{h,2002}, x^h_{h,2002}, \hat{\beta}, \widehat{\omega_{h,2002}})$$
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- **Results:** 1.1 percent gain in quality for treated vs. 0.7 percent for control
  - Low staffing hospitals are equally productive
  - Relative to a crude mandate, efficiency gains from accounting for patient severity: densely populated counties where untreated hospitals admit higher severity patients

This Paper: Conclusion

- **Reduced-form:** Back-of-the-envelope costs vs. benefits

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  - Hospital production is organizationally complex
  - Add more physicians or change production primitive (σ_{np})
  - Account for patient severity when allocating labor
  - Pre-existing variation in labor use is not driven by productivity differences; worthwhile to regulate low performers vs. transfer patients

Published and Work-in-Progress

1. Raja, 2023. “How Do Hospitals Respond to Input Regulation? Evidence from the California Nurse Staffing Mandate." *Journal of Health Economics*.
2. JMP “Input Regulation and the Production of Hospital Quality."

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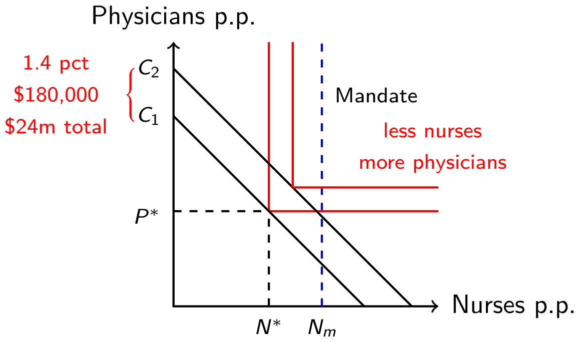
Leontief Implications



Go back

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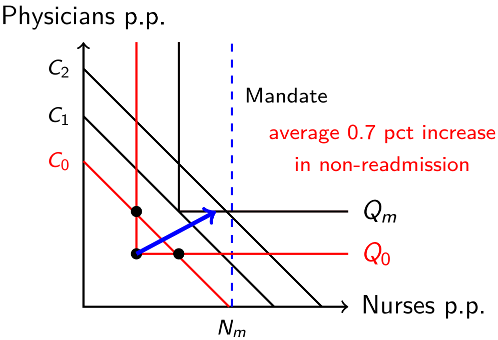

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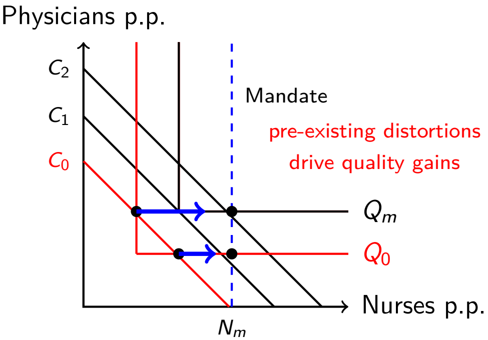


Go back

Pre-Existing Distortions in Labor Use

		Nurse-Phys - 2.8
Investor owned		−0.105
		(0.170)
Government owned		1.027***
		(0.164)
Teaching hospital		−0.773***
		(0.128)
Small/rural hospital		0.500***
		(0.167)
Observations	1,456	1,456
R^2		0.065

Geographic maldistribution of health care providers and service is one of the most persistent characteristics of the American health care system. Even as an oversupply of some physician specialties is apparent in many urban health care service areas across the country, many inner city and rural communities still struggle to attract an adequate number of health professionals to provide high-quality care to local people. This is the central paradox of the American health care system: shortages amid surplus.

Council on Graduate Medical Education, 1998 Go back

Heterogeneity in Quality Gains

	Log Non-Readmission Rate	
	(1)	(2)
Treat x Post	-0.003	0.004
	(0.006)	(0.004)
Treat x Post x Log physicians per patient	0.006*	
		(0.003)
Log physicians per patient	-0.000	
	(0.003)	
Treat x Post x Log patient health		-0.027**
		(0.011)
Log patient health		-0.009
		(0.019)
Observations	2,704	2,704
R^2	0.531	0.533
Mean	0.970	0.970
Hospital Fixed Effects	✓	✓
Year Fixed Effects	✓	✓

Notes: This table presents estimates of the difference-in-differences treatment effect of the mandate on quality with heterogeneity along the physician and patient health dimensions.

Effect sizes by level

- Phys. = 1: -0.3 pct
- Average Phys.: 0.6 pct
- Health = 1: 0.4 pct
- Average Health: 0.6 pct

Go back

Construction of Risk-Adjusted 30-Day Non-Readmission Rate

1. Identify index admissions according to CMS methodology report (Horwitz et al., 2012)
   - Exclude patients that died in hospital
   - Exclude patients that were discharged to another acute care hospital
   - Exclude patients that were discharged against medical advice
2. Exclude patients with an inpatient stay within the prior year for risk-adjustment consistent with prior work (Chandra et al., 2016a; Friedrich and Hackmann, 2021; Gupta, 2021)
3. Compute 30-day non-readmission rate for patient sample
   - Following Horwitz et al., 2012 exclude readmissions for diagnoses and clinical procedures designated as likely to be planned
4. Regress the 30-day non-readmission rate on granular gender-age-race interaction terms and obtain the constant + residual from regression (Grieco and McDevitt, 2017)

Go back

Why Readmission?

1. Consequential to regulators
   - “Costly and preventable event": 20 pct Medicare patients re-hospitalized within 30 days and $17 billion annual readmission payments (Horwitz et al., 2012; Jencks et al., 2009)
   - Target of CMS regulation: Public reporting of quality measures (HIQPR), Medicare value-based purchasing program (HRRP)
2. Frequently studied in the literature (Friedrich and Hackmann (2021); Chandra et al. (2016b); Gupta (2021))
3. Positively correlated with process of care measures (Chandra et al. (2016b)
4. Sensitive to acute care input use (vs. mortality measures)
   - Emergency / intensive care stabilize patients prior to transfer to lower level of care
   - Extremely low rate of in-hospital mortality in acute care
   - End of the inpatient stay is a critical period to avoid readmission and most often spent in acute care (93 pct of discharges from the two main units are made from acute care)

Go back

Healthcare Practitioner Labor Share in U.S. Hospitals

Occupational Category	Employment	Share
Healthcare practitioners and technical	2,574,190	52.67
Office and administrative support occupations	746,270	15.27
Healthcare support	626,950	12.83
Building and grounds cleaning and maintenance occupations	178,580	3.65
Management occupations	165,770	3.39
Food preparation and serving related occupations	137,270	2.81
Community and social services occupations	91,090	1.86
Business and financial operations occupations	84,330	1.73
Installation, maintenance, and repair occupations	50,730	1.04
Computer and mathematical occupations	47,620	.97
Protective service occupations	38,010	.78
Production occupations	24,750	.51
Personal care and service occupations	22,510	.46
Life, physical, and social science occupations	22,040	.45
Education, training, and library occupations	20,100	.41
Transportation and material moving occupations	15,540	.32
Construction and extraction occupations	13,490	.28
Sales and related occupations	12,960	.27
Arts, design, entertainment, sports, and media occupations	8,900	.18
Architecture and engineering occupations	4,910	.1
Legal occupations	1,120	.02

Notes: This table presents the employment shares by occupational category for U.S. General Medical and Surgical Hospitals (NAICS 622100) published by the Bureau of Labor Statistics for 2006. Physicians that are not directly employed by hospitals may not be included in the healthcare practitioner employment share. Go back

Nurses vs. Other Practitioners and Healthcare Support

Occupational Category	Detail	Employment	Share
Healthcare practitioners and technical	Registered nurses	1,373,610	42.91
Healthcare practitioners and technical	Physicians	172,490	5.38
Healthcare practitioners and technical	Physician assistants	14,530	0.45
Healthcare practitioners and technical	Other healthcare diagnosis or treating practitioners	191,760	5.99
Healthcare practitioners and technical	Health technologists and technicians	797,820	24.92
Healthcare practitioners and technical	Other healthcare practitioners and technical occupations	23,920	0.75
Healthcare support	Nursing aides, orderlies, and attendants	382,940	11.96
Healthcare support	Other aides	20,330	0.64
Healthcare support	Occupational therapy and physical therapist assistants and aides	35,050	1.09
Healthcare support	Other healthcare support occupations	188,630	5.89

Notes: This table presents the employment shares for two occupational categories (Healthcare practitioners and technical support occupations; Healthcare support occupations) for U.S. General Medical and Surgical Hospitals (NAICS 622100) published by the Bureau of Labor Statistics for 2006. Physicians that are not directly employed by hospitals may not be included in the healthcare practitioner employment share. This table indicates that the non-physician medical practitioner share (Physician Assistant, Nurse Practitioner) is low – a fact that is corroborated by the HCAI financial reporting data for California hospitals in the early 2000s. Aides on the other hand make up a significant share of hospital employment but are not healthcare practitioners and are not licensed to perform medical care.

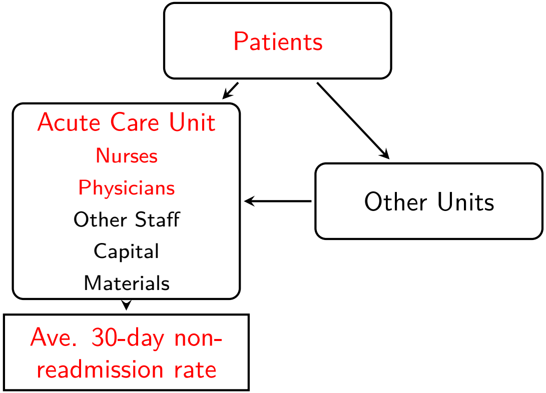
Descriptive Statistics for California Hospitals from 1996-2002

	Nurse-to-Patient Ratio Distribution			
	Bottom 25	25-50	50-75	Top 25
Hospitals	52	52	52	52
Annual discharges	9,367	10,368	10,993	9,433
Annual inpatient revenue ($)	60,769,720	78,174,402	77,836,713	77,893,051
Acute share of revenue	0.366	0.401	0.417	0.448
Case Mix Index	1.03	1.08	1.10	1.14
Hospital-wide discharges				
30-day non-readmission rate	0.902	0.897	0.887	0.897
Risk-adjusted 30-day non-readmission rate	0.970	0.968	0.966	0.973
Length of stay	3.407	3.510	3.496	3.544
Inputs in acute care				
Nurses per 1,000 patient days	2.196	2.443	2.725	3.230
Physicians per 1,000 patient days	1.091	1.289	1.295	1.233
Materials expenditures per 1,000 patient days ($)	4,403	3,531	3,872	4,120
Capital expenditures per 1,000 patient days ($)	433,019	468,360	541,930	580,107
Patient care costs per 1,000 patient days ($)	399,171	473,644	547,243	626,019
Hospital characteristics				
Share church or non-profit	0.654	0.596	0.692	0.731
Share investor-owned	0.115	0.192	0.154	0.096
Share teaching hospitals	0.038	0.096	0.115	0.154
Share small/rural hospitals	0.173	0.115	0.135	0.212

Notes: This table presents the descriptive statistics for a balanced panel of 208 California hospitals. The nurse staffing mandate was set at approximately 2.4 nurses per 1,000 patient days (0.2 nurse-to-patient ratio or 1 nurse per 5 patients).

Go back

Value-Added Production



- "Structural value-added" (Diewert (1978); Gandhi et al. (2017))
- Technological assumption of Leontief

$$\begin{aligned} Q_{ht} &= e^{\omega_{ht}+\epsilon_{ht}} g(x_{ht}^n, x_{ht}^p, x_{ht}^h, x_{ht}^m) \\ &= e^{\omega_{ht}+\epsilon_{ht}} \min[F(x_{ht}^n, x_{ht}^p, x_{ht}^h), s(x_{ht}^m)] \end{aligned}$$

- Behavioral assumption on input usage

$$\text{where: } F(x_{ht}^n, x_{ht}^p, x_{ht}^h) = s(x_{ht}^m)$$

- Supporting evidence
  - Cross-sectional input use
  - Mandate effects on other input use
  - Gupta (2021) findings on HRRP

Go back

Estimation: Moment Conditions

$$\mathbb{E}\{\xi_{ht}(\beta_n, \beta_p, \beta_h, \beta_{nn}, \beta_{pp}, \beta_{hh}, \beta_{np}, \beta_{nh}, \beta_{ph}) \begin{pmatrix} x^n_{ht-1} \\ x^p_{ht-1} \\ x^h_{ht-1} \\ x^n_{ht-1}x^p_{ht-1} \\ x^n_{ht-1}x^h_{ht-1} \\ x^p_{ht-1}x^h_{ht-1} \\ M_h \times \mathbb{1}\{\text{Post}\} \\ x^p_{ht-1}M_h \times \mathbb{1}\{\text{Post}\} \\ x^h_{ht-1}M_h \times \mathbb{1}\{\text{Post}\} \\ \mathbb{1}\{\text{CAH}_h\} \times \mathbb{1}\{\text{Post}\} \end{pmatrix} \} = 0$$

First-Stage and Specification Tests

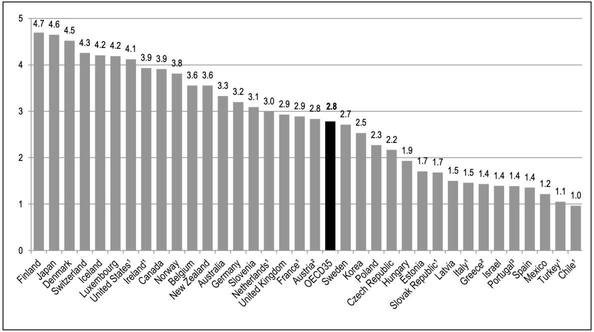
Hausman χ^2	33.05
Hausman p-value	0.0001
Sargan χ^2	1.883
Sargan p-value	0.1700
1st Stage F-stats	91.41, 125.47, 260.47, 86.22, 103.05, 94.95, 107.71, 306.92, 210.58
Sanderson-Windmeijer F-stats	31.91, 14.77, 105.85, 179.11, 13.90, 34.54, 19.35, 51.06, 88.22

Notes: This table presents the test statistics from the first-stage and specification tests. The null hypothesis of the Hausman (1978) specification test is that both OLS and IVFE estimates are consistent and OLS is more efficient. I reject the null hypothesis with a p-value of 0.0001. The null hypothesis of the Sargan overidentifying restrictions test is that the instruments are valid and excluded. I cannot reject the null hypothesis with a p-value of 0.1700. The first-stage F-statistics from Sanderson-Windmeijer are compared to the Stock-Yogo (2005) weak identification F-test critical values. Of the nine F-statistics, the statistics associated with three instruments are within the lowest 5 percent maximal IV relative bias critical value (20.74). The remainder have F-statistics higher than the highest critical value.

Go back

Nurse-to-Physician Ratios

Figure 1. Ratio of Nurses per Physician in OECD countries, 2014 (or nearest year)



Notes: 1. For those countries which have not provided data for practising nurses and/or practising physicians, the numbers relate to the "professionally active" concept for both nurses and physicians. 2. For Austria and Greece, the data refer only to nurses and physicians employed in hospitals. 3. The ratio for Portugal is underestimated because the numerator refers to professionally active nurses while the denominator includes all physicians licensed to practice.

Source: OECD Health Statistics 2016, http://dx.doi.org/10.1787/health-data-en

Source: Maier, C., L. Aiken and R. Busse (2017), "Nurses in advanced roles in primary care: Policy levers for implementation", OECD Health Working Papers, No. 98, OECD Publishing, Paris. Go back