I. Supplemental Appendix

A. Data and Measurement Details

A..1 The hospital's organization of medical care

Hospitals organize inpatient medical care into acute and intensive care hospital units. Examples of acute care units include Medical/Surgical Acute Care, Definitive Observation, and Obstetrics Acute. Examples of intensive care units include Coronary Care and Medical/Surgical Intensive Care. Intensive care units are used for treating patients of higher severity relative to acute care units. Most GAC hospitals in my sample (97 percent) have at minimum a Medical/Surgical Acute Care unit and a Medical/Surgical Intensive Care unit. Patient days in intensive care patient made up 8 percent of the total inpatient days with the interquartile range falling between 5 and 10 percent. It should be noted that the share of total inpatient days associated with each hospital unit is close but not equivalent to the revenue share of each unit. In the average hospital-year, acute care revenues made up 40 percent of total revenue (interquartile range of 29-54 percent) whereas intensive care revenues made up 16 percent of total revenue (interquartile range of 12-20 percent). Given the majority of payments are made prospectively rather than on a cost-basis, the mismatch likely reflects the fact that the average patient in intensive care is higher severity and therefore the payor pays higher reimbursement for this patient's inpatient stay relative to the average patient in acute care. Beyond these two units the service line offerings vary across hospitals. The other units with the highest likelihoods of being offered are Definitive Observation (42 percent of hospitals) and Coronary Care (28 percent of hospitals).

A..2 Choice of acute care

I focus on the inputs in the acute care unit rather than hospital level inputs. This is for a few reasons. First, every GAC hospital has an acute care unit which is not the case for any other unit except the Medical/Surgical Intensive Care unit (hereafter "intensive care"). Focusing on acute care or intensive care therefore allows me to use a wide and representative sample. Second, the acute care unit has the largest share of total inpatient days of any unit [1] with most patients' pathways through the hospital including time in acute care prior to discharge. Staffing shocks in acute care are therefore likely to impact hospital level quality. Third, I use quasi-experimental variation for identification from nurse staffing regulation which targeted and has been shown to have a large effect on acute care staffing levels and no effect on intensive care staffing levels (Raja, 2023). Intensive care nurse-to-patient ratios have been in place in California beginning in the 1976-1977 fiscal year whereas ratios for acute care were established by the 1999 California nurse staffing mandate and implemented in 2003. Note that the parameters of interest to the audience may differ relative to the ones estimated in this paper if the policy of interest aims to increase nursing in intensive care units.

[1] 48 percent on average and an interquartile range of 34-63 percent.

A..3 Choice of output

I focus on non-readmission and survival as my quality measures for a few reasons. First, non-readmission and survival are standard, widely-studied measures of hospital quality. Non-readmission and survival are standard measures of hospital quality studied by regulators, healthcare professionals, and economists (Friedrich and Hackmann, 2021, Chandra et al., 2016, Gupta, 2021). By using them I can benchmark my findings to prior work and construct quality indicators according to methods standardized across academic and regulatory contexts.

Furthermore, both institutional knowledge and prior work on heart attack patients (Raja, 2023) indicates that non-readmission is sensitive to acute care staffing. Most patients spend significant time in acute care with patient days in acute care making up 85 percent of the patient days shared by the acute and intensive care units. Patients that spend time in multiple units are discharged from the hospital from acute care with discharges from acute care making up 93 percent of hospital discharges made from one of the two units. According to practitioners, the end of the inpatient stay is a particularly critical time for monitoring and discharge planning to avoid readmission. Nurses in particular play a well-documented role in preventing readmission (Needleman and Hassmiller, 2009).

Finally, readmission is consequential to regulators and targeted by large-scale federal programs beginning in the mid-2010s. Readmission is considered a "costly and often preventable event" with one-fifth of Medicare beneficiaries re-hospitalized within 30 days of discharge in 2003-2004 and one estimate that CMS spent more than $17 billion on payments for readmissions made within 30 days of discharge in 2004 (Horwitz et al., 2012). As a result, CMS has several programs aimed to lower hospital readmission rates. For example, as a part of the Hospital Inpatient Quality Reporting Program, CMS publicly reports hospital level risk-adjusted readmission rates for several diagnosis cohorts on its Hospital Care Compare website. Additionally, the Affordable Care Act of 2012 established several Medicare value-based purchasing programs including the Hospital Readmissions Reductions Program (HRRP) which ties hospitals' Medicare reimbursements to their readmission rates for specific diagnosis cohorts.

A..4 Measurement of physicians

In California, regulation prohibits the majority of hospitals from directly employing physicians. The exceptions are county hospitals and teaching hospitals. Most physicians are organized in physician practice groups that contract with hospitals. Consequently, hospitals are not required to report these expenditures directly in the hospital reporting form. It is only specific types of physician contract arrangements (reported on Page 2 of the hospital reporting form) that require physician fees to be reported as expenditures to contractors. Given that these are not observed it is not known what proportion of physician fees are being reported by the hospital and therefore cannot be relied upon for measurement. The reported numbers of active medical staff on the other hand include all physicians regardless of whether they are employed directly by the hospital or not. Active medical staff refer to hospital-based and non-hospital-based physicians that are voting members of and can hold office in the Medical Staff organization of the hospital (HCAI, 2003). Of the five categories of physicians who work in a hospital (attending, associate, house staff, courtesy, and consulting), only courtesy and consulting staff are excluded from the active medical staff category. The number of active medical staff therefore reasonably captures physician labor employed in patient care.

The measure of the number of physicians affiliated with a hospital is not directly comparable in terms of time spent on patient care to the measure of the number of nurses employed by a hospital without making two adjustments. First, physicians do not necessarily work full-time in the hospitals with which they are affiliated as active medical staff but the number of nurses is constructed under the assumption of full-time equivalent hours. Several California hospital bylaws indicate that active medical staff must have "regular involvement in patient care" but these requirements are far below full-time. My data report 124,542 active medical staff physicians in 2006 across the hospital-years of the unbalanced sample which still excludes Kaiser and federal hospital physicians. I compare this to aggregate data on the number of licensed physicians actively involved in patient care in California in the same year (49,753) from the California Health Care Foundation to obtain the number of full-time equivalent physicians represented by one affiliation (0.40). Second, while the nursing hours are comprised of only clinical hours not all physician time spent in the hospital is spent on direct patient care. I therefore apply the reported share of patient care from the external source (0.56) to the physician FTEs. For benchmarking, the HCAI hospital financial reporting form has a section that requires the reporting of physicians' time spent on various activities for hospitals that employ salaried physicians. The average time spent on direct patient care as a function of the total is around 80 percent for salaried physicians.

The California financial reporting data are appealing because, as far as I am aware, there is a lack of data available to researchers on physician time at the hospital and year level. [2] We may be concerned, however, that hours worked by the average active medical staff physician varies across hospitals in systematic ways. This would lead to non-classical measurement error in the independent variable if the model used across-hospital variation for identification. I have two comments here: first, my model relies solely on within-hospital variation for identification and consequently the concern over retrieving consistent estimates depends only on the gap between the proxy and true physician time being correlated with time-varying unobservables within the hospital. Second, the financial reporting data have the granularity for robustness checks on this dimension. For each hospital and year, I can observe the number of physicians by hospital- vs. non hospital-based vs. resident vs. fellow, board certification status (board-certified, board-eligible, other), and each of 42 specializations which would allow me to link these figures with external data on physician hours worked at the board certification and specialization level (Leigh et al., 2010). The breakdowns by all categories other than specialization are shown in Appendix Table A.1.

A..5 Measurement of nurses

Reported hours for nurses are total paid hours including overtime less hours not on the job (vacation, sick leave, holidays, and other paid time-off). In California and most other U.S. states, there are two types of licensed nurses (Registered Nurses and Licensed Vocational Nurses) where RNs are the

[2] Survey data from the American Medical Association and proprietary data sources with physician hours are generally not linked to hospitals and the latter are furthermore available beginning only in the mid-2000s. Other papers that have used measures of physician time rely on the Veteran's Affairs hospitals.

higher-skilled and higher-licensed nurse.

I aggregate RN and LVN labor in my analysis given that the majority of nurse labor in the hospital comes from RNs and their share of total nursing hours has only grown over time. In Appendix Table A.1, I present the average numbers of physicians and nurses for hospitals according to their location in the staffing distribution. Over 85 percent of nurses employed in the California hospital setting between 1996-2002 (prior to the mandate) were RNs.[3] By 2019, 90 percent were RNs indicating that the presence of vocational nurses is small.[4]

Table A.1: Physicians and Nurses at California Hospitals from 1996-2002

	Bottom 25	25-50	50-75	Top 25
Physicians (total, part-time)	261	309	401	376
Hospital-based, board-certified	0.15	0.15	0.24	0.33
Hospital-based, board-eligible	0.01	0.02	0.04	0.01
Hospital-based, other	0.01	0.02	0.01	0.02
Non-HB, board-certified	0.59	0.59	0.51	0.41
Non-HB, board-eligible	0.07	0.07	0.06	0.03
Non-HB, other	0.10	0.08	0.08	0.05
Residents	0.06	0.06	0.05	0.15
Fellows	0.01	0.01	0.01	0.01
Nurses (total, full-time)	142	156	208	197
Registered Nurses	0.85	0.88	0.89	0.90
Vocational Nurses	0.15	0.12	0.11	0.10
Nurses per 1,000 patient days	2.19	2.46	2.72	3.27
Physicians per 1,000 patient days	1.16	1.37	1.25	1.27
Nurse to physician ratio	1.88	1.79	2.17	2.57

Notes: This table includes the 208 hospitals in my balanced panel sample from 1996-2008. The number of physicians is reported as the number of active medical staff and delineated into hospital-based, non-hospital-based, and residents and fellows.

A..6 Measurement of the Case Mix Index

The CMI is calculated by the California Health Department. Patients are assigned to one of hundreds of diagnosis-related groups (DRGs) based on their primary and secondary diagnoses, comorbidities, procedures performed, and age and gender and each of these DRGs is assigned a weight according to CMS that reflects the average resource consumption of the DRG relative to the average resource consumption of all patients (HCAI, 2023). For example, a patient that undergoes knee replacement surgery would be assigned "DRG 469 – Major joint replacement or reattachment of lower extremity

[3] RNs may be more useful than LVNs in hospitals due to a better match between the higher training their receive and the higher severity of the inpatient hospital setting relative to home health or nursing home settings which also employ licensed nurses. The fact that the highest staffing hospitals (also the highest patient severity hospitals) in Table A.1 have the highest RN share of total nursing staff is supportive of this match effect.

[4] Depending on the setting there may be a need to study the quality returns to the two types of nurses separately. For example, states where licensing restrictions are less stringent and/or lower-skilled nurses make up a larger part of the hospital workforce.

with MCC (Major Complication or Comorbidity)". The CMI is calculated as the average of the DRG weights across all patients discharged in the calendar year. [5] A higher CMI therefore reflects a case mix that requires greater resource intensity to improve the patient's health. According to HCAI: "CMI is the average relative DRQ weight of a hospital's inpatient discharges, calculating by summing the Medicare Severity-Diagnosis Related Group (MS-DRG) weight for each discharge and dividing the total by the number of discharges. The CMI reflects the diversity, clinical complexity, and resource needs of all the patients in the hospital. A higher CMI indicates a more complex and resource-intensive case load."

Government payors reimburse the majority of hospitals based on Prospective Payment System (PPS) which sets a prospective price for each patient's treatment based on the average resource use required to treat an average patient with the same diagnosis-related group or DRG and adjusts the price based on local input costs and the severity of the patient mix. Hospitals with more severe patients are reimbursed at higher rates per patient. Small and rural hospitals are eligible for reimbursement on a cost basis rather than PPS through the Critical Access Hospital (CAH) program.

A..7 Measurement of the 30-day, hospital-wide non-readmission rate

I construct the readmission rate from the patient level discharge data by identifying index admissions according to the methodology report for 30-day all-cause readmission published by CMS (Horwitz et al., 2012). Consistent with the CMS exclusion criteria, I exclude patients who died during hospitalization, patients who were transferred to another acute care hospital upon discharge, and patients who were discharged against medical advice. Relative to CMS, I use the full sample of payors rather than restrict to Medicare patients again to reflect the entire patient population. I identify patients that were readmitted to any hospital within 30 days of their discharge date as readmitted and I exclude planned readmissions for diagnoses and clinical procedures that have been designated by CMS as likely to be planned readmissions (Horwitz et al., 2012).

B. Institutional Context

B..1 Timing assumptions in healthcare labor markets

Many examples in the literature impose timing assumptions over the factors of production which eliminate the endogeneity problem for inputs for whom choice over the input is assumed to be made prior to the realization of the productivity shock in the period ("fixed" inputs). I argue that these timing assumptions are unreasonable in my setting and I consider all three inputs to be "flexible" and chosen in the same period in which they are used. Separately, I assume that nurse and physician labor are "dynamic" but patient severity is "nondynamic" implying that there are no fixed costs of changing the Case Mix Index but there can be fixed hiring or firing costs of labor.

The market for healthcare professionals is notably rigid relative to other sectors with the fill rate in healthcare and education services – the ratio of hires to job vacancies – remaining stable around 0.7 during the early 2000s compared to 1.3 over the same period for total nonfarm occupations (noa,

[5] Note that CMS also calculates a version of the CMI that limits the sample to Medicare patients because their index is used to adjust Medicare reimbursement rates upwards for hospitals with more severe case loads.

2019). Furthermore, significant rigidities may exist due to unionization – fifty percent of nurses employed in a California hospital during the sample period reported being unionized (Raja, 2023).

The low fill rate in the industry and documented search costs in the market for healthcare professionals suggest non-negligible fixed costs of hiring. Significant unionization among nurses and the complexity of hospital-physician group contracting suggests that there may be additional fixed costs associated with termination. These features of the input markets indicate the presence of adjustment costs. Prior work in this literature has also accounted for the adjustment costs in hiring healthcare workers when modeling production (Lee et al., 2013, Grieco and McDevitt, 2017).

Yet even in this relatively rigid labor market the "time-to-hire" from the initial search to the contract date falls well below the one year mark indicating that nurses and physicians should be considered flexibly chosen at t.[6] Recent survey evidence from organizations participating in physician search suggests that the upper bound on time from search to contract signing was slightly under one year for the longest specialties (urology, neurology) with the average time to fill a physician vacancy being four months (Gradney, 2023). The nursing labor market is less rigid than the physician market with time-to-hire periods for hospital nurses ranging from two-and-a-half months for the labor and delivery unit to just over three months for the medical/surgical unit (noa, 2024).

B..2 Threats to identification from external instruments

In Section 3, I show the relevance of the mandate as a shifter of nurse labor. I argue that CAH conversion is relevant because it limited the participant hospitals' length of stay and consequently case mix. Prior work has shown that CAH conversion did not change the composition of inpatient services but participant hospitals were incentivized to engage in selective admissions or transfer severe patients to other hospitals leading to changes in case mix (Schoenman and Sutton, 2008). Participant hospitals may "make more strategic admission decisions in order to ensure that they remain within the program limits on average length of stay (i.e., they would be less likely to admit a patient whose LOS is expected to be much longer than the average target LOS)" (Schoenman and Sutton, 2008). I corroborate the reduction in length of stay and increase in the patient health index in my sample.

I investigate threats to identification from the mandate and CAH conversion events whereby the events may have affected hospital productivity independently of their effects on input use and case mix. Raja (2023) finds that the mandate led to reduced capacity, increased bed utilization rates, increased share of lower-licensed nurses, and a reduction in length of stay at treated hospitals. Raja (2023) does not find any effects on input use in the intensive care unit or on the number of admissions.

I argue that it is unlikely for increased bed utilization to impact quality conditional on per patient resource use. Given that the mandate led to an increase in lower-licensed and younger nurses, the quality effects estimated based on the mandate period may underestimate the effect of nurse additions made in other periods and overestimate the within-hospital misallocation. The endogeneity issue with length of stay is when there is evidence of premature discharge – patients being discharged "quicker and sicker" to the detriment of their health – in which case the mandate leading to lower length of stay may affect quality directly rather than through labor or case mix.

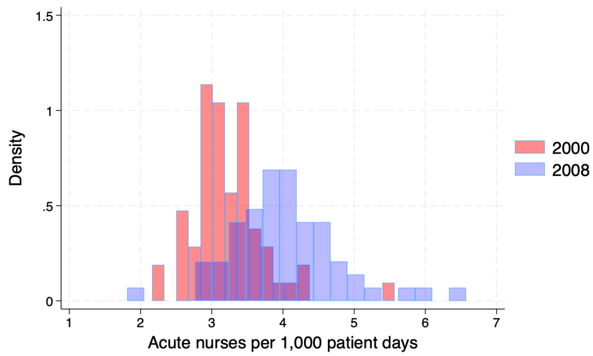
[6] While there are some exceptions among physicians – for example, teaching hospitals must determined the numbers of residents and fellows at least one year in advance – this is not true for the average physician.

Schoenman and Sutton (2008) document the effects of hospital enrollment in the CAH program finding that it led to reductions in the capacity, number of discharges, length of stay, and number of personnel in addition to changes in the DRGs of admitted patients. Reductions in capacity or number of personnel are unlikely to impact quality conditional on the per patient resource use. Length of stay is an issue for the same reason as under the nurse staffing mandate. The number of discharges may also be an issue if there are unmeasured quality returns to scale as found in Dingel et al. (2023).

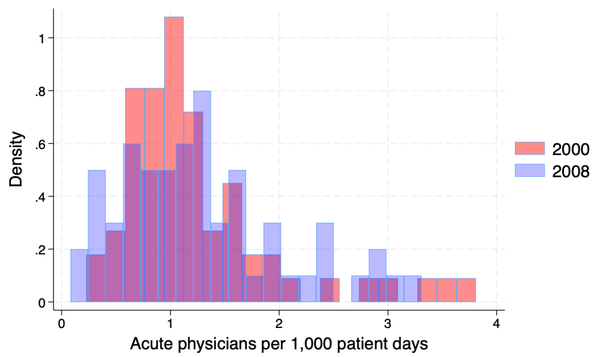
To address the possibilities that length of stay or patient volumes are omitted variables, I estimate first-stage regressions with length of stay and number of discharges as dependent variables to determine whether they are shifted by the instrument vector. These are shown in Appendix Table A.5. The F-statistics indicate a weak first-stage but to follow-through with the possibility I estimate versions of the model that make average length of stay and number of discharges observable. I find that neither length of stay nor patient discharges are statistically significant at the ten percent level and that the coefficients on the other inputs remain statistically significant and similar in magnitude to the model without length of stay or patient discharges. [7]

[7] These findings are not inconsistent with Dingel et al. (2023): first, the instruments that I use are weak shifters of patient discharges in the first-stage because the focus of my empirical strategy is not in estimating returns to scale; second, there are differences in setting: I focus solely on acute inpatient care, which relative to outpatient services has a larger share of emergency rather than elective procedures and I aggregate across rare and common procedures. Returns to scale are larger for rare procedures which can be scheduled in advance.

C. Additional Results



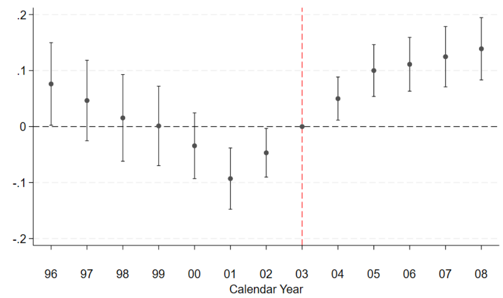
(a) Nurses Per Patient in 2000 vs. 2008



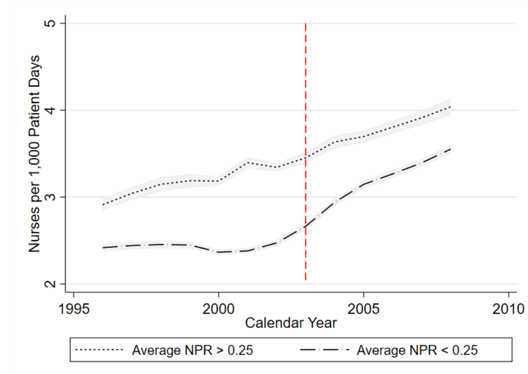
(b) Physicians Per Patient in 2000 vs. 2008

Figure A.1: Input Use in 2000 vs. 2008 for Control Hospitals

Notes: In panel (a), this figure shows the histogram of control hospitals according to the number of nurses per 1,000 patient days prior to the mandate in 2000 (red) and after the mandate in 2008 (blue). In panel (b), I do the same for physicians per 1,000 patient days.



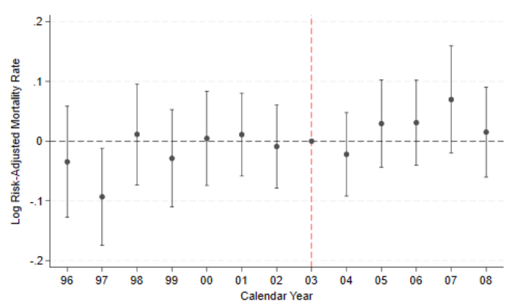
(a) Event-Study Estimates



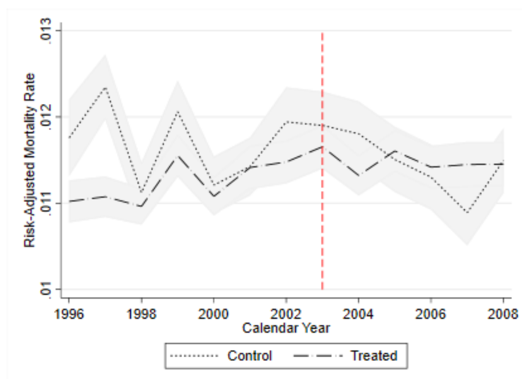
(b) Raw Means

Figure A.2: Event-Study Estimates of the Effect of Mandate on Log Nurses

Notes: In panel (a), this figure plots coefficients β_t and 95 percent confidence intervals from Equation (4) with the log of nurses per 1,000 patient days as dependent variable. Standard errors are clustered at the hospital level. In Panel (b), this figure plots average values and standard error bands of the nurses per 1,000 patient days by group.



(a) Event-Study Estimates



(b) Raw Means

Figure A.3: Event-Study Estimates of the Effect of the Mandate on Log Mortality

Notes: In panel (a), this figure plots coefficients β_t and 95 percent confidence intervals from Equation (4) with the log of the risk-adjusted 30-day mortality rate as the outcome variable. Standard errors are clustered at the hospital level. The mandate has no significant effect on mortality rates. In Panel (b), this figure plots average values and standard error bands of the rate by group.

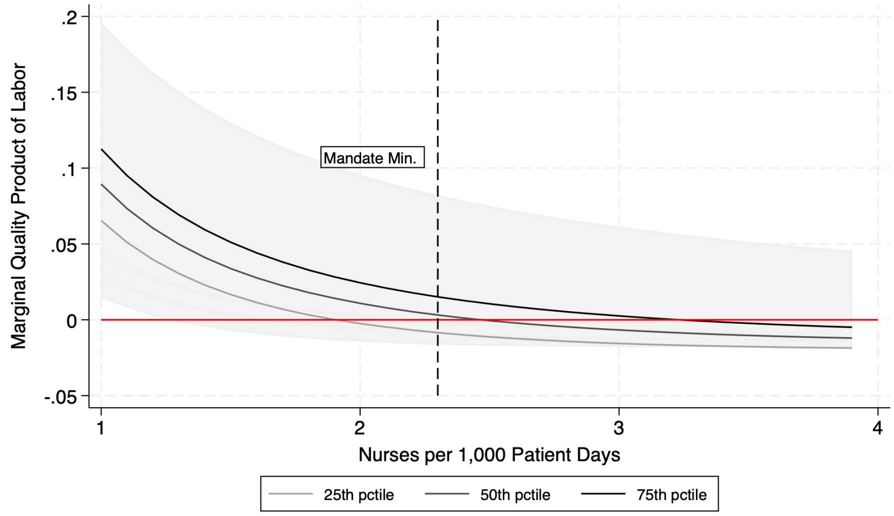


Figure A.4: 25, 50, and 75th Percentiles of Nurse Marginal Product

Notes: This figure plots the distribution of the variance of the marginal products of nurse labor for markets with treated hospitals separately from those without treated hospitals. The markets with treated hospitals are driving the results.

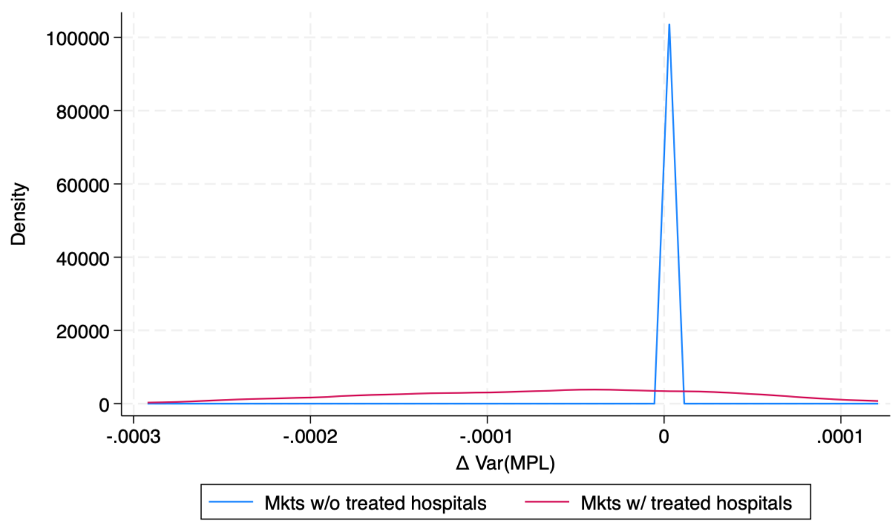


Figure A.5: Distribution of Δ Var(MPL) Across Markets, By Market Type

Notes: This figure plots the distribution of the variance of the marginal products of nurse labor for markets with treated hospitals separately from those without treated hospitals. The markets with treated hospitals are driving the results.

Table A.2: First-Stage – Log Inputs

	(1) Log nurses	(2) Log physicians	(3) Log patient health
L1 Log nurses per patient	0.512***	0.199**	0.009
	(0.035)	(0.079)	(0.011)
L1 Log physicians per patient	0.034*	0.713***	0.007
	(0.020)	(0.044)	(0.006)
L1 Log patient health	-0.213*	0.106	0.781***
	(0.116)	(0.260)	(0.036)
L1 Log nurses x L1 Log patient health	0.061	-0.094	-0.018
	(0.077)	(0.172)	(0.024)
L1 Log nurses x L1 Log physicians	-0.008	-0.041***	-0.003
	(0.007)	(0.015)	(0.002)
L1 Log physicians x L1 Log patient health	0.037	0.058	-0.025**
	(0.039)	(0.086)	(0.012)
Log (0.25 - pre-mandate ratio) x Post-mandate	0.942***	0.883	0.216**
	(0.320)	(0.715)	(0.099)
L1 Log physicians x Mandate interact	0.353*	-0.712	0.007
	(0.194)	(0.434)	(0.060)
L1 Log patient health x Mandate interact	0.589	-1.840	0.250
	(0.786)	(1.757)	(0.244)
Critical Access Hospital x Post-enrollment	0.023	-0.072	0.016**
	(0.025)	(0.056)	(0.008)
Observations	2,496	2,496	2,496
R^2	0.778	0.829	0.959
Within R^2	0.286	0.355	0.555
Mean	2.916	4.613	0.921
F-Statistic	90.758	124.737	282.398
Sanderson-Windmeijer F-Statistic	31.91	14.77	105.85
Hospital Fixed Effects	✓	✓	✓
Year Fixed Effects	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: First-Stage – Log Inputs Squared

	(1) Log nurses sq.	(2) Log physicians sq.	(3) Log health sq.
L1 Log nurses per patient	0.954***	-0.222	0.008
	(0.077)	(0.263)	(0.006)
L1 Log physicians per patient	-0.022	1.756***	-0.000
	(0.043)	(0.147)	(0.003)
L1 Log patient health	-0.305	1.338	0.020
	(0.254)	(0.863)	(0.018)
L1 Log nurses x L1 Log patient health	0.016	-0.523	-0.129***
	(0.168)	(0.569)	(0.012)
L1 Log nurses x L1 Log physicians	0.016	0.013	-0.002*
	(0.015)	(0.051)	(0.001)
L1 Log physicians x L1 Log patient health	0.072	-0.300	-0.035***
	(0.084)	(0.286)	(0.006)
Log (0.25 - pre-mandate ratio) x Post-mandate	0.308	1.729	0.036
	(0.698)	(2.367)	(0.051)
L1 Log physicians x Mandate interact	0.701*	-1.542	-0.040
	(0.424)	(1.438)	(0.031)
L1 Log patient health x Mandate interact	0.940	-3.361	0.578***
	(1.715)	(5.820)	(0.125)
Critical Access Hospital x Post-enrollment	0.115**	0.085	0.004
	(0.054)	(0.184)	(0.004)
Observations	2,496	2,496	2,496
R^2	0.770	0.806	0.916
Within R^2	0.259	0.313	0.245
Mean	3.330	15.035	1.037
F-Statistic	79.383	103.277	73.654
Sanderson-Windmeijer F-Statistic	179.11	13.90	34.54
Hospital Fixed Effects	✓	✓	✓
Year Fixed Effects	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: First-Stage – Log Inputs Interacted

	(1) Nur. x Phys.	(2) Nur. x Patient health	(3) Phys. x Patient health
L1 Log nurses per patient	0.260**	0.023	0.055**
	(0.109)	(0.014)	(0.024)
L1 Log physicians per patient	0.311***	0.016**	0.040***
	(0.061)	(0.008)	(0.013)
L1 Log patient health	0.031	0.285***	0.342***
	(0.356)	(0.047)	(0.078)
L1 Log nurses x L1 Log patient health	-0.086	0.541***	-0.148***
	(0.235)	(0.031)	(0.051)
L1 Log nurses x L1 Log physicians	0.103***	-0.006**	-0.018***
	(0.021)	(0.003)	(0.005)
L1 Log physicians x L1 Log patient health	-0.032	-0.028*	0.592***
	(0.118)	(0.016)	(0.026)
Log (0.25 - pre-mandate ratio) x Post-mandate	-1.050	0.395***	0.110
	(0.978)	(0.130)	(0.214)
L1 Log physicians x Mandate interact	2.132***	-0.009	0.171
	(0.594)	(0.079)	(0.130)
L1 Log patient health x Mandate interact	-1.504	2.322***	0.963*
	(2.405)	(0.320)	(0.526)
Critical Access Hospital x Post-enrollment	-0.076	0.022**	0.027*
	(0.076)	(0.010)	(0.017)
Observations	2,496	2,496	2,496
R^2	0.810	0.949	0.940
Within R^2	0.322	0.580	0.483
Mean	5.252	0.908	0.865
F-Statistic	107.472	313.348	211.926
Sanderson-Windmeijer F-Statistic	19.35	51.06	88.22
Hospital Fixed Effects	✓	✓	✓
Year Fixed Effects	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: First-Stage – Other Inputs

	(1) Log discharges	(2) Log length of stay
L1 Log nurses per patient	0.012	0.012
	(0.054)	(0.019)
L1 Log physicians per patient	-0.021	0.012
	(0.029)	(0.010)
L1 Log patient health	0.100	-0.380***
	(0.169)	(0.060)
L1 Log nurses x L1 Log patient health	-0.327***	0.094**
	(0.112)	(0.040)
L1 Log nurses x L1 Log physicians	-0.007	-0.002
	(0.010)	(0.004)
L1 Log physicians x L1 Log patient health	0.051	0.022
	(0.057)	(0.020)
Log (0.25 - pre-mandate ratio) x Post-mandate	-0.270	0.449***
	(0.491)	(0.174)
L1 Log physicians x Mandate interact	0.512*	-0.245**
	(0.291)	(0.103)
L1 Log patient health x Mandate interact	5.457***	1.357***
	(1.158)	(0.409)
Critical Access Hospital x Post-enrollment	-0.112***	-0.020
	(0.040)	(0.014)
Observations	2,431	2,431
R^2	0.958	0.833
Within R^2	0.023	0.053
Mean	4462.990	3.490
F-Statistic	5.138	12.440
Hospital Fixed Effects	✓	✓
Year Fixed Effects	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D. Additional Derivations

D..1 Elasticities of Substitution and Marginal Products of Labor for Three-Factor Translog

For clarity of notation, I have omitted the subscript from earlier notation that references the hospital-year (ht) and moved the superscript referencing the input ($i \in \{h, n, p\}$) to a subscript. [8]

$$\sigma_{np} = \frac{\mathrm{dln}\left(\frac{x_n}{x_p}\right)}{\mathrm{dln}\left(\frac{\frac{\partial Q}{\partial x_p}}{\frac{\partial Q}{\partial x_n}}\right)}$$

In the three-factor translog model, the elasticity of substitution between nurses and physicians, σ_{np}, is a complex function of the levels of the inputs (x_n, x_p, x_h) and the production parameters (β) given by[9]

$$\sigma_{np} = \frac{x_p e_n \left\{-\frac{1}{x_p}\frac{x_p e_n}{x_n e_p} - \frac{1}{x_n}\right\}}{\left\{(e_n + \beta_{np}) - \frac{x_p e_n}{x_n e_p}\frac{x_n \beta_{pp}}{x_p}\right\}\left\{-\frac{x_p e_n}{x_n e_p}\right\} + \left\{\frac{x_p \beta_{nn}}{x_n} - \frac{x_p e_n}{x_n e_p}(e_p + \beta_{np})\right\}} \tag{1}$$

where the output elasticities are equal to

$$e_n = \frac{\partial \ln(Q)}{\partial \ln(x_n)} = \beta_n + \beta_{nn}\ln(x_n) + \beta_{np}\ln(x_p) + \beta_{nh}\ln(x_h)$$
$$e_p = \frac{\partial \ln(Q)}{\partial \ln(x_p)} = \beta_p + \beta_{pp}\ln(x_p) + \beta_{np}\ln(x_n) + \beta_{ph}\ln(x_h)$$

The marginal product of nurse labor is equal to

$$\frac{\partial Q}{\partial (x_n)} = \left[\frac{\partial \ln(Q)}{\partial \ln(x_n)}\right]\left[\frac{Q}{x_n}\right] = (\beta_n + \beta_{nn}\ln(x_n) + \beta_{np}\ln(x_p) + \beta_{nh}\ln(x_h))(\frac{Q}{x_n}) \tag{2}$$

[8]While the translog can be interpreted as a Taylor approximation of the CES production function, the original result in Kmenta (1967) is for two factors and limited work has been done to show the extension to the n factor case (Hoff, 2004) much less the extension to the nested n factor case. Most importantly, the Taylor approximation is a reasonable approximation of CES around the point of the approximation which is when the elasticity of substitution is close to unity (the Cobb-Douglas case) which I show is not the case in my setting.

[9]See Boisvert (1982), Appendix C for the derivation. Note that the coefficients on the squared terms in Table **??** should be multiplied by two to recover the corresponding parameters β_{nn}, β_{pp}, and β_{hh} in Equation 6.

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