Recent Trends in Rural Hospitals: Shifting Service Lines and Artificial Intelligence Use

Brian Whitacre

Professor and Neustadt Chair

DEPARTMENT OF
AGRICULTURAL ECONOMICS

University of Vermont

Rural Development Series Seminar
University of Vermont
Department of Community Development and Applied Economics
Oct. 13, 2025

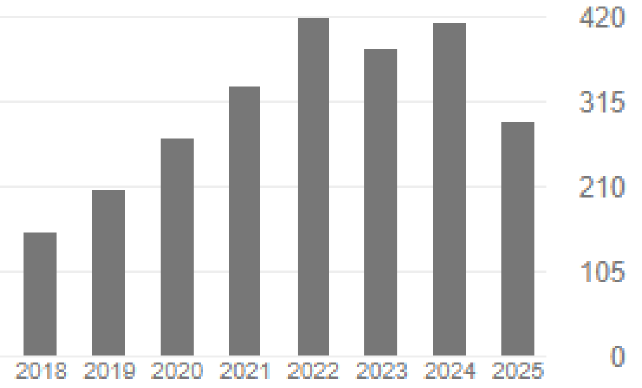
About Me

- Ph.D. Virginia Tech (2005)
- Assistant / Associate / Full Professor, Oklahoma State
- 65% Extension / 25% Research / 10% Teaching
  - Rural Economic Development (undergrad)
  - Spatial Econometrics (graduate)

Google Scholar Profile

Cited by VIEW ALL

	All	Since 2020
Citations	3339	2117
h-index	30	25
i10-index	61	47



Broadband' s contribution to economic growth in rural areas: Moving towards a causal relationship B Whitacre, R Gallardo, S Strover Telecommunications Policy 38 (11), 1011-1023	387	2014
Infrastructure and the rural—urban divide in high-speed residential Internet access BE Whitacre, BF Mills International Regional Science Review 30 (3), 249-273	208	2007
Does rural broadband impact jobs and income? Evidence from spatial and first-differenced regressions B Whitacre, R Gallardo, S Strover The Annals of Regional Science 53 (3), 649-670	201	2014
Understanding the Non-Metropolitan—Metropolitan Digital Divide BF Mills, BE Whitacre Growth and Change 34 (2), 219-243	183	2003

Mostly Focused on Broadband!

So Why Rural Hospital Trends??

- Rural health an important topic in the general regional science / ag econ field
- Ties in with my broader focus on technology / policy evaluation
- Good fit with land-grant mission

Early adoption of telehealth/remote patient monitoring and hospital revenue changes during COVID-19

Claudia A Rhoades[1], Brian E Whitacre[2] and Alison F Davis[1]

The Influence of the Degree of Rurality on EMR Adoption, by Physician Specialty

Brian E. Whitacre

Higher Electronic Health Record Functionality Is Associated with Lower Operating Costs in Urban—but Not Rural—Hospitals

Claudia A. Rhoades[1] Brian E. Whitacre[1] Alison F. Davis[2]

Community sociodemographics and rural hospital survival

Claudia A. Rhoades PhD[1] | Brian E. Whitacre PhD[1] | Alison F. Davis PhD[2]

Agenda: 2 Topics

Recently-published paper on shifting “service lines” among rural hospitals and the resulting impact on profitability

- What changes make economic sense?

Ongoing project related to Artificial Intelligence use by hospitals

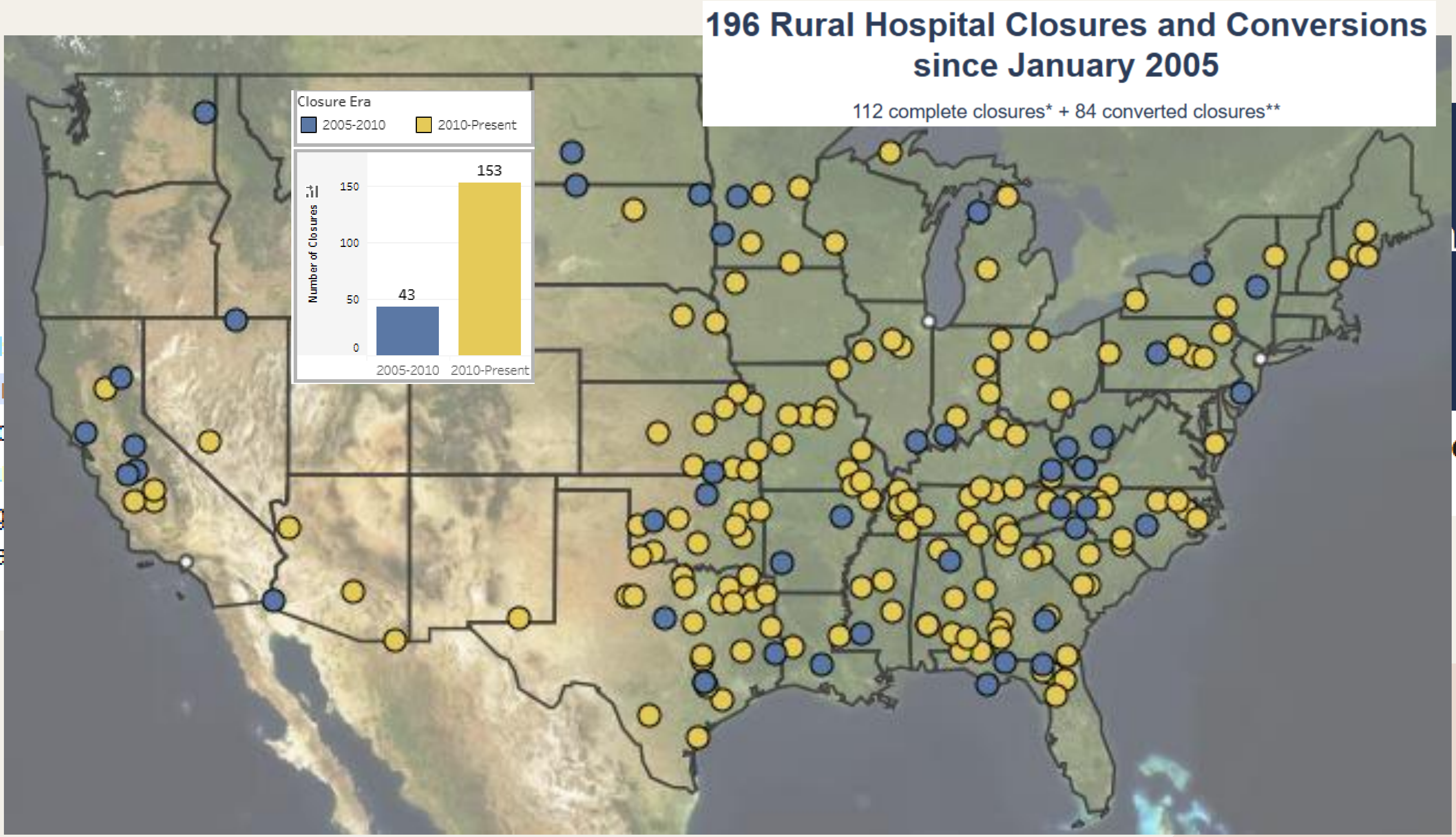
- Rural – urban differences in specific tasks?
- Determinants of AI adoption in rural hospitals
- Potential impacts of AI use by rural hospitals

Broader Rural Hospital Landscape

AI summary:

AI Overview

The current rural hospital land
hospitals operating at a loss a
factors like declining patient vo
from cyber threats. These fina
healthcare deserts and forcing
health outcomes. Efforts to sta
advocacy for rural needs, and



Current Policy Environment

American Hospital Association™
Advancing Health in America

Rural Hospitals at Risk: Cuts to Medicaid Would Further Threaten Access

- Significant cuts to Medicaid in "One Big Beautiful Bill"

The One Big Beautiful Bill Act (H.R. 1) would result in 1.8 million individuals in rural communities losing their Medicaid coverage by 2034. In addition, select Medicaid provisions in H.R. 1 would result in a $50.4 billion reduction in federal Medicaid spending on rural hospitals over 10 years.[1]

- Rural Health Transformation Fund dramatically changes funding process
  - $50 Billion awarded to states over 5 years
  - Base allotment of $500 million / state (same for VT / TX!)

The 'One Big Beautiful Bill,' Now Law, Does Not Protect Rural Hospitals

HealthAffairs

No Guarantees For Rural Hospitals; Fast And Steep Funding Cliffs

Funding To States Not Hospitals

The Notice of Funding Opportunity (NOFO) for the RHTP was posted on September 15th.

Rural Hospital Service Lines: Changes Over Time and Impacts on Profitability

- Background & Recent Literature
- Data & Methods
  - Medicare Cost Reports, 2010 – 2021
  - Panel Event Study
- Results & Robustness Checks
- Conclusion

Full paper available: http://dx.doi.org/10.1097/JHM-D-24-00012

Rural Hospital Service Lines: Changes Over Time and Impacts on Profitability

Brian E. Whitacre, PhD, Department of Agricultural Economics, Oklahoma State University, Stillwater, Oklahoma; and Claudia A. Rhoades, PhD and Alison F. Davis, PhD, Center for Economic Analysis of Rural Health, Department of Agricultural Economics, University of Kentucky, Lexington, Kentucky

SUMMARY

Goal: To document shifts in rural hospital service line offerings between 2010 and 2021 and to assess the resulting impacts on hospital profitability.

Methods: We used annual Medicare cost report data for all rural hospitals that did not change payment classifications between 2010 and 2021. We documented changes in the percentages of hospitals offering each of the 37 inpatient or ancillary service lines included in the data. We then used panel event studies to assess effects on hospital operating margin for specific service lines that changed most prominently during this period.

Principal Findings: Twelve service lines changed by more than 5% during our period of analysis. These are highlighted by hospitals adding rural health clinics (+32%) and CT scans (+20%) and removing delivery rooms (−21%) and skilled nursing facilities (−19%). Panel event studies demonstrated that the addition or subtraction of most services did not have statistically significant impacts on future hospital operating margins. Notable exceptions were the addition of rural health clinics and the removal of delivery services, both of which positively affected future operating margins. The addition of occupational therapy services had a positive effect on operating margin in the near term, but adding MRI services had a negative effect.

Practical Applications: The finding that only a select few service line changes resulted in meaningful impacts to hospital operating margins suggests that hospital leaders should be wary of implementing such changes as a means of improving financial viability.

Journal of Healthcare Management

Background

2016 **Predicting Financial Distress and Closure in Rural Hospitals**

George M. Holmes PhD, Brystana G. Kaufman MSPH, George H. Pink PhD

2018 GAO Highlights

Highlights of GAO-18-634, a report to congressional requesters

August 2018

RURAL HOSPITAL CLOSURES

Number and Characteristics of Affected Hospitals and Contributing Factors

2021 Impact of Rural Hospital Closures on Health-Care Access

Sean McCarthy MD [a], Dylana Moore BS [a b], W. Andrew Smedley BS [a b], Brandon M. Crowley BS [a b],

- Existing literature largely focuses on survival / closure of rural hospitals and resulting impact on healthcare access
- Recognition that financial pressures impact hospital's ability to provide *specific types of hospital services*

2009 **Hospital Financial Conditions and the Provision of Unprofitable Services**

2025
- Rural hospitals lose money on several **critical service lines**, including behavioral health, pulmonology, obstetrics, and burns and wounds.[4]

- Clear patterns for rural hospitals over past several decades:
  - Reduction in inpatient volume
  - Changes in revenue sources (growing outpatient share)
  - Affiliation with larger health systems

Escalating Pressure to Control Costs / Maximize Revenue

Shifting Service Lines

- Shifts documented by John et al. (2022) and Oyeka et al. (2023)
  - 2009 – 2017: More cardiology, pain management but less skilled nursing, birthing
  - 2008 – 2020: Service **additions** more frequent in hospitals that <u>left</u> health care systems. Majority of service **losses** occurred in hospitals that <u>joined</u> systems.

No peer reviewed studies on IMPACT of these shifts on hospital finances

NC RHRP

Findings Brief
NC Rural Health Research Program

August 2022

Changes in the Provision of Health Care Services by Rural Critical Access Hospitals and Prospective Payment System Hospitals in 2009 compared to 2017

Randall John, BSPH; Kathleen Knocke, MSPH, PhD; Sharita Thomas, MPP; Kristie Thompson, MA; Mark Holmes, PhD; George Pink, PhD

RUPRI Center for Rural Health Policy Analysis

Rural Policy Brief

Brief No. 2023-2 JANUARY 2023 http://www.public-health.uiowa.edu/rupri/

Changes in Service Offerings Post-System Affiliation in Rural Hospitals

Onyinye Oyeka, MPH, PhD; Fred Ullrich, BA; Dan Shane, PhD; Keith J. Mueller, PhD

Data

RAND HOSPITAL DATA

CMS Hospital Cost Report Data Made Easy

We Process the Data, You Do the Analysis

RAND Hospital Data enhances CMS hospital cost report data and makes it more accessible. We download the publicly available data from CMS, process it into panel datasets, and add key metrics.

https://www.hospitaldatasets.org/

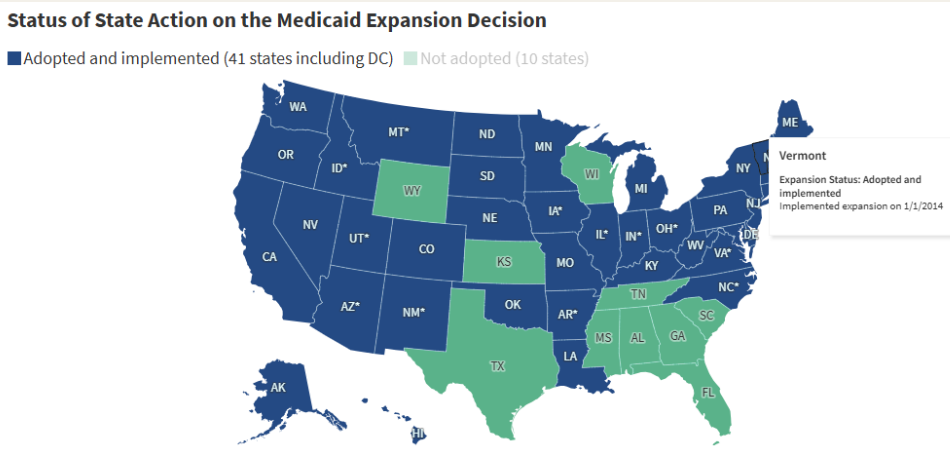
- Center for Medicare and Medicaid Service (CMS) Healthcare Cost Report Information System (HCRIS)
  - Medicare Cost Reports compiled by each individual hospital
  - Compiled by RAND Corporation for 1996-2021
  - Include larger share of rural hospitals than voluntary AHA annual surveys
- Limited analysis to subset of all hospitals:
  - Only hospitals with complete annual data for 2010 – 2021
  - Only hospitals defined as "rural" by Federal Office of Rural Health Policy
    - RUCA codes ranging from 4-10 OR
    - RUCA codes 2-3 with population density < 35 people / square mile
  - Only hospitals that did not switch payment classifications during this period

Critical Access Hospital
Medicare Dependent Hospital
Sole Community Hospital
Prospective Payment System
Rural Referral Center

Data (cont'd)

Only from patient care;
not cafeterias / gift shops

- Dependent variable: Operating Margin $= \frac{\textit{net income}}{\textit{revenue}}$
  - Commonly used to assess profitability in rural hospitals
  - Strong predictor of hospital closure BUT useful to assess trends over time
- Control variables:
  - Occupancy rates
  - Medicare charge-to-cost ratio (inpatient, outpatient)
  - Healthcare system affiliation (dummy)
  - State participation in Medicaid Expansion (dummy)
    - Kaiser Family Foundation
    - Time of entry important



FINAL DATASET:

1,901 hospitals
12-year period of analysis
22,812 observations

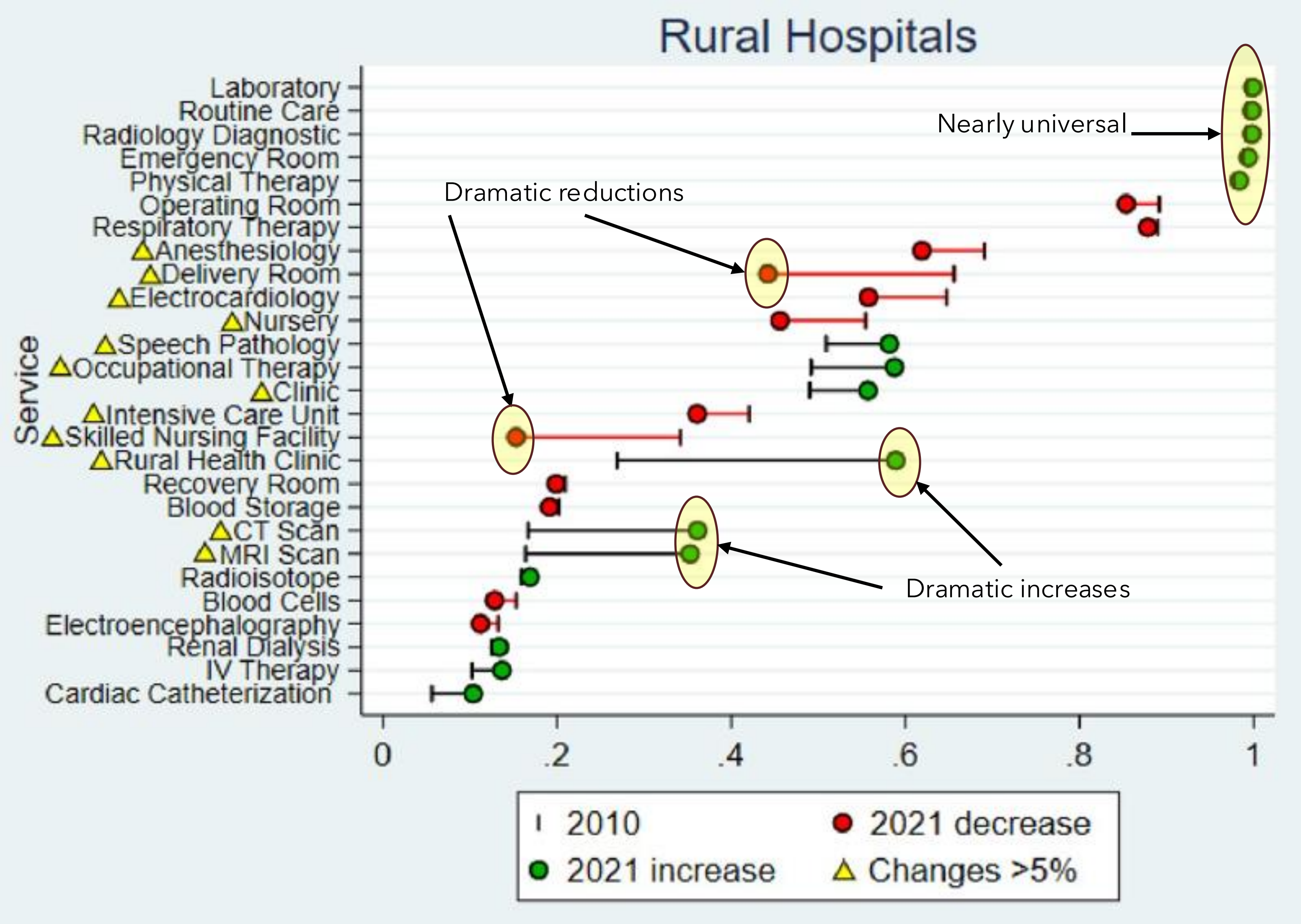
Hospital Summary Statistics

	M	*SD*	Min	Max
Operating margin	0.015	0.130	−0.561	0.522
Occupancy rate	0.350	0.186	0.000	3.620
Inpatient charge-to-cost ratio	2.101	1.565	0.100	13.710
Outpatient charge-to-cost ratio	3.352	2.234	0.237	24.600
System affiliation (0/1)	0.385	0.487	0	1
Medicaid expansion (0/1)	0.361	0.480	0	1
Payment classification:				
Critical access hospital	0.624	0.484	0	1
Medicare-dependent hospital	0.042	0.200	0	1
Prospective payment system hospital	0.120	0.326	0	1
Rural referral center	0.097	0.296	0	1
Sole community hospital	0.117	0.322	0	1
No. of observations	22,812			

What Service Lines to Consider?

- HCRIS contains data on 37 inpatient or ancillary “cost centers”
- Documented changes in % of rural hospitals offering each service
- Limited analysis to those that appeared in at least 10% of rural hospitals (any year)
- Service lines of interest defined as those that were added or removed by at least 5% of hospitals over the analysis period.
- Used those services in the panel event study analysis

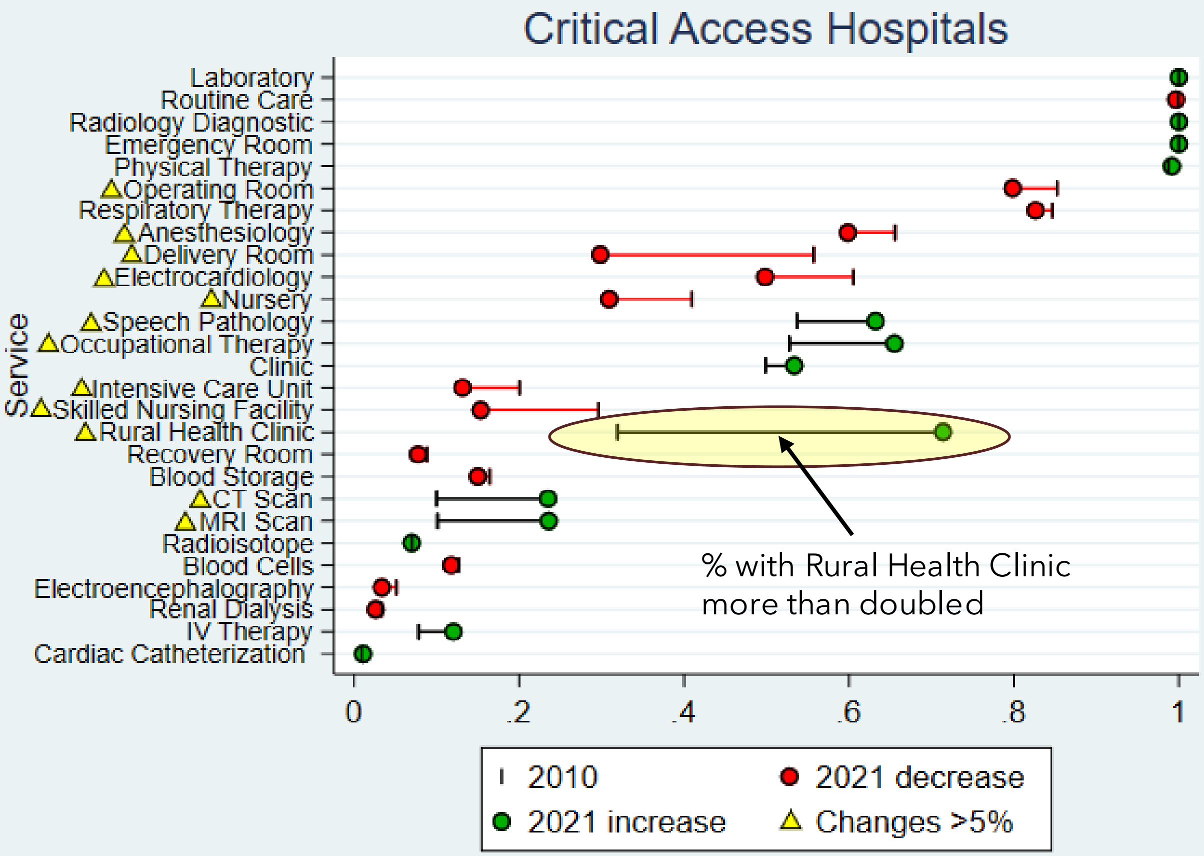
Changes in Rural Hospital Service Lines, 2010-2021

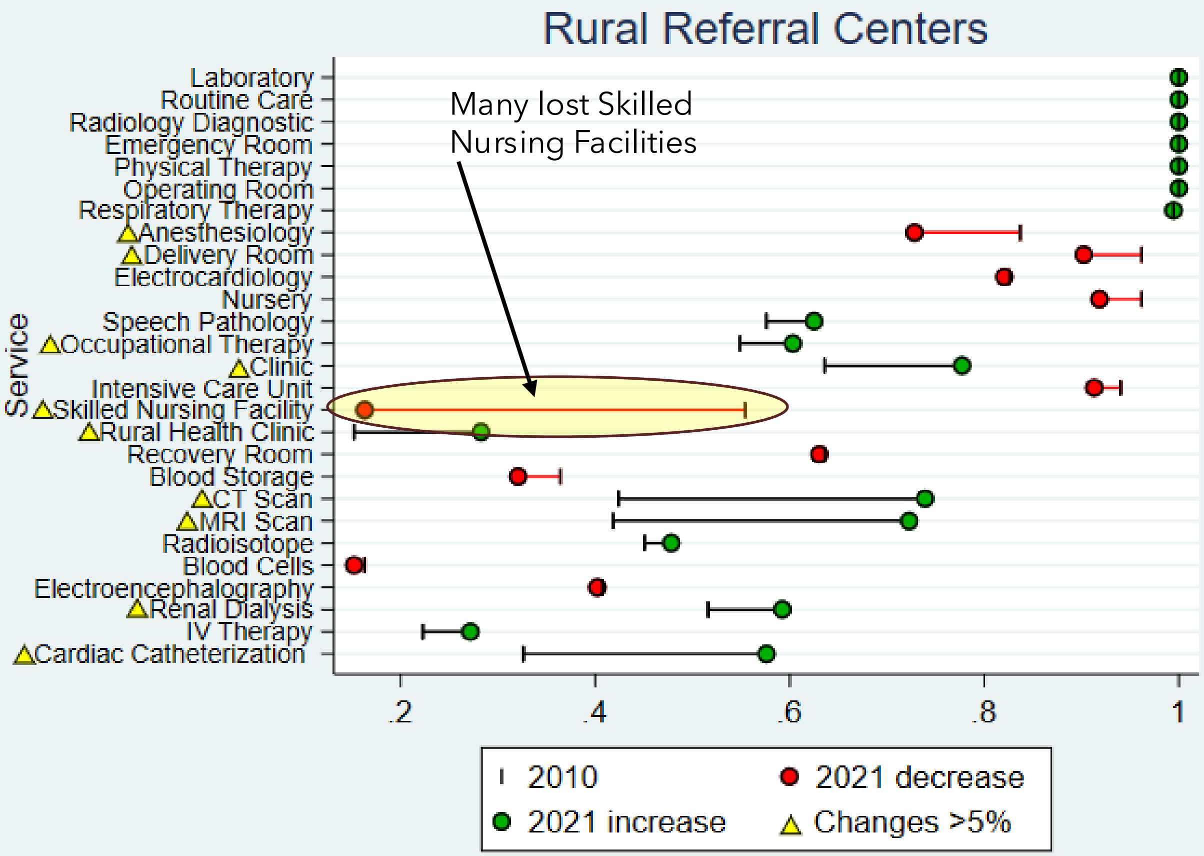


12 service lines of interest

△ Changes >5%

Rural Hospital Service Line Changes Across Payment Classifications





A Problem…Adding / Removing Multiple Service Lines

Number of Service Lines Added and Removed Across Rural Hospitals

# Service Lines Added		# Service Lines Removed								
		0	1	2	3	4	5	6	Total #	%
	0	259	194	99	30	9	4	0	595	0.31
	1	217	158	94	32	6	1	0	508	0.27
	2	151	111	75	26	15	3	0	381	0.20
	3	97	92	44	23	2	2	0	260	0.14
	4	33	32	13	5	3	0	0	86	0.05
	5	16	17	8	1	1	0	1	44	0.02
	6	9	11	4	2	1	0	0	27	0.01
	Total #	782	615	337	119	37	10	1	1,901	1.00
	%	0.41	0.32	0.18	0.06	0.02	0.01	0.00	1.00	

Note. Highlighted cells contain 1,358 hospitals (71%) that had no more than two service lines added and no more than two service lines removed. These hospitals are used in the panel event-study regressions that follow.

Methods

Treated: Hospitals that added (removed) service line of interest

Control: Only hospitals NEVER offering service (for additions); Only hospitals ALWAYS offering service (for removals)

- Panel Event Study (Clarke and Tapia-Schythe, 2022):

Year fixed effect

$$y_{ht} = \alpha + \sum_{j=2}^{J} \beta_j (Lead\ j)_{ht} + \sum_{k=1}^{K} \gamma_k (Lag\ k)_{ht} + \theta_h + \delta_t + \rho X_{ht} + \varepsilon_{ht}$$

Operating margin for hospital *h* in year *t*

Dummies for years **leading up to** addition / removal of line

Dummies for years **after** addition / removal of line

Hospital fixed effect

Time-varying control vector *X* (occupancy rate, system affiliation, etc.)

Event takes place in final "lead" (j = 1)

Should all be 0 if there are no differences between treated / control before change!

Results – ADDED Service Lines (6)

	Rural Health Clinic			Traditional Clinic			CT Scan			MRI Scan			Occup. Therapy			Speech Path.		
	Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.	
Occupancy Rate	0.082	0.017	***	0.050	0.028	*	0.053	0.025	**	0.052	0.024	**	0.050	0.027	*	0.048	0.027	*
Inpatient Charge-Cost Ratio	-0.004	0.004		-0.007	0.005		-0.001	0.003		-0.004	0.004		-0.007	0.005		-0.009	0.005	*
Outpatient Charge-Cost Ratio	0.012	0.003	***	0.013	0.003	***	0.011	0.003	***	0.013	0.003	***	0.012	0.003	***	0.012	0.003	***
System Affiliation	0.006	0.006		0.012	0.009		0.006	0.006		0.011	0.006	**	0.012	0.009		0.018	0.009	**
Medicaid Expansion	0.014	0.005	***	0.023	0.006	***	0.014	0.004	***	0.014	0.004	***	0.014	0.006	**	0.014	0.006	***
Adj. R2	0.595			0.583			0.585			0.585			0.610			0.601		
# Obs		11,256			8,196			13,044			13,128			7,692			7,644	
# Treated Hospitals (added service)		366			232			146			138			103			98	
# Control Hospitals (never had)		572			451			941			956			538			539	
Wald test (all Leads=0), p-value	0.568			0.109			0.345			0.710			0.171			0.747		
Wald test (Signif. Lags are =), p-value	0.000			0.852			0.087			0.313			0.194			.		

Note: *, **, and *** denote statistical significance at the *p*<0.10, 0.05, and 0.01 levels, respectively

Control variables behave as expected:

- (+) impact of higher occupancy rates
- (+) impact of outpatient charge – cost ratio
- (+) impact of state Medicaid Expansion

Results – ADDED Service Lines (6)

	Rural Health Clinic			Traditional Clinic			CT Scan			MRI Scan			Occup. Therapy			Speech Path.		
	Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.	
Occupancy Rate	0.082	0.017	***	0.050	0.028	*	0.053	0.025	**	0.052	0.024	**	0.050	0.027	*	0.048	0.027	*
Inpatient Charge-Cost Ratio	-0.004	0.004		-0.007	0.005		-0.001	0.003		-0.004	0.004		-0.007	0.005		-0.009	0.005	*
Outpatient Charge-Cost Ratio	0.012	0.003	***	0.013	0.003	***	0.011	0.003	***	0.013	0.003	***	0.012	0.003	***	0.012	0.003	***
System Affiliation	0.006	0.006		0.012	0.009		0.006	0.006		0.011	0.006	**	0.012	0.009		0.018	0.009	**
Medicaid Expansion	0.014	0.005	***	0.023	0.006	***	0.014	0.004	***	0.014	0.004	***	0.014	0.006	**	0.014	0.006	***
Lead10	-0.014	0.016		-0.011	0.026		0.018	0.022		0.012	0.033		0.007	0.023		-0.007	0.020	
Lead9	0.004	0.013		0.004	0.019		0.031	0.016	*	-0.019	0.041		-0.013	0.025		0.000	0.021	
Lead8	0.007	0.012		0.012	0.017		0.034	0.020	*	0.013	0.016	**	-0.070	0.019		-0.001	0.017	
Lead7	0.004	0.011		-0.007	0.018		0.049	0.029	*	0.014	0.026	*	-0.001	0.021		-0.005	0.019	
Lead6	0.016	0.010	*	-0.014	0.011		0.016	0.018		0.005	0.018		-0.018	0.022		0.017	0.020	
Lead5	0.006	0.010		0.000	0.009		0.019	0.020		0.017	0.013		-0.008	0.014		-0.005	0.015	
Lead4	-0.003	0.009		0.002	0.009		-0.002	0.012		0.019	0.013		-0.021	0.013	*	-0.015	0.014	
Lead3	-0.005	0.008		-0.004	0.008		0.010	0.012		0.022	0.011	**	-0.038	0.012	***	-0.010	0.011	
Lead2	-0.004	0.007		-0.009	0.008		0.005	0.009		0.010	0.008		-0.014	0.008		-0.005	0.009	
Lag0	0.002	0.005		-0.006	0.005		0.001	0.007		-0.012	0.005	**	0.008	0.007		-0.009	0.010	
Lag1	-0.009	0.006		-0.020	0.009	**	0.004	0.009		-0.017	0.009	*	0.016	0.009	*	0.003	0.013	
Lag2	-0.009	0.007		-0.022	0.009	**	0.007	0.010		-0.011	0.010		0.031	0.014	**	0.021	0.015	
Lag3	0.002	0.008		-0.013	0.009		-0.009	0.010		-0.018	0.012		0.030	0.015	**	0.017	0.016	
Lag4	0.011	0.007		-0.020	0.009	**	-0.006	0.011		-0.030	0.012	**	0.003	0.015		0.007	0.015	
Lag5	0.002	0.008		-0.024	0.010	**	-0.010	0.014		-0.034	0.011	***	-0.007	0.014		0.003	0.018	
Lag6	0.014	0.009	*	-0.030	0.010	***	-0.007	0.012		-0.029	0.010	***	-0.011	0.016		-0.010	0.019	
Lag7	0.016	0.010		-0.026	0.013	**	-0.016	0.011		-0.026	0.010	**	-0.023	0.019		-0.013	0.019	
Lag8	0.032	0.011	***	-0.025	0.015	*	-0.014	0.013		-0.032	0.012	***	-0.009	0.017		0.029	0.018	
Lag9	0.028	0.012	**	-0.074	0.022	***	-0.047	0.015	***	-0.049	0.011	***	0.033	0.016	**	0.017	0.023	
Lag10	0.055	0.014	***	-0.020	0.021		-0.069	0.019	***	-0.063	0.016	***	0.056	0.023	**	-0.008	0.038	
Constant	-0.047	0.010	***	-0.041	0.013	***	-0.040	0.011	***	0.041	0.011	***	-0.041	0.013	***	-0.037	0.012	***
Adj. R2	0.595			0.583			0.585			0.585			0.610			0.601		
# Obs		11,256			8,196			13,044			13,128			7,692			7,644	
# Treated Hospitals (added service)		366			232			146			138			103			98	
# Control Hospitals (never had)		572			451			941			956			538			539	
Wald test (all Leads=0), p-value	0.568			0.109			0.345			0.710			0.171			0.747		
Wald test (Signif. Lags are =), p-value	0.000			0.852			0.087			0.313			0.194			.		

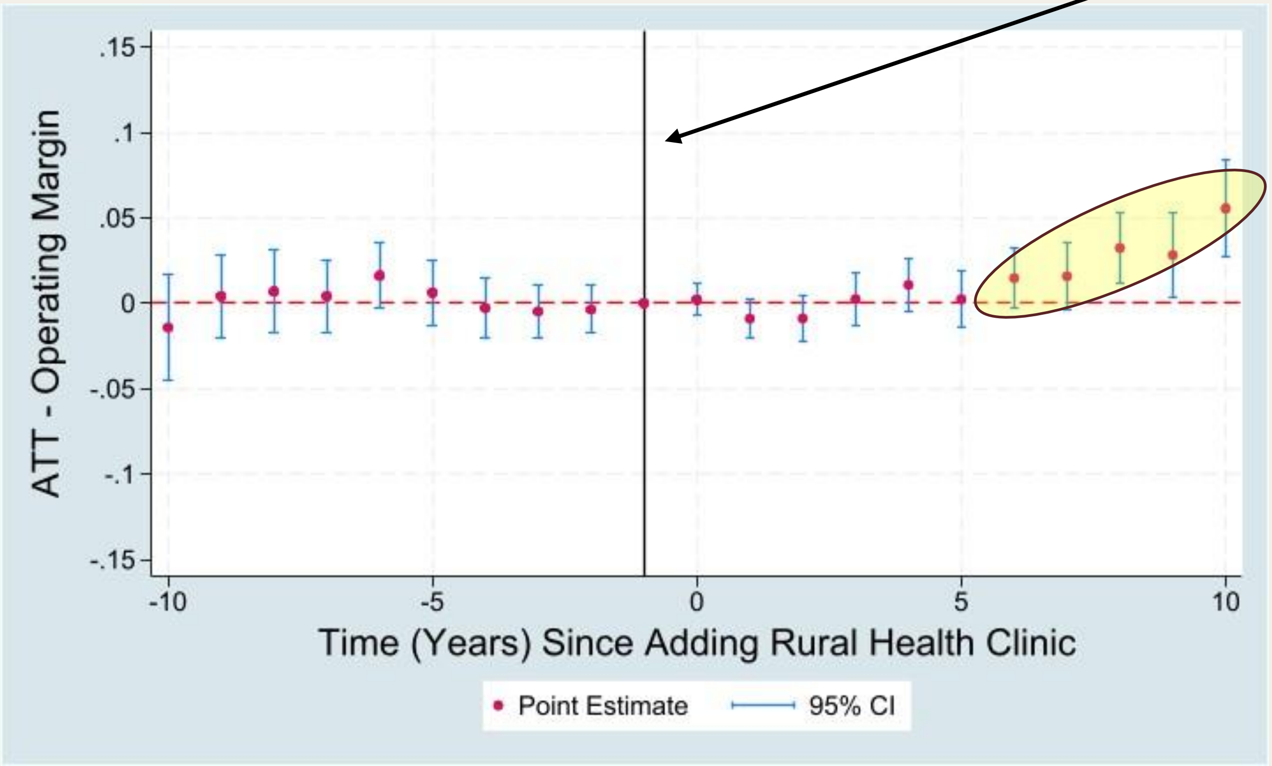
Note: *, **, and *** denote statistical significance at the p<0.10, 0.05, and 0.01 levels, respectively
Grey cells denote lag coefficients with statistical significance for more than 1 consecutive period at the p<0.05 level

Lead coefficients largely insignificant

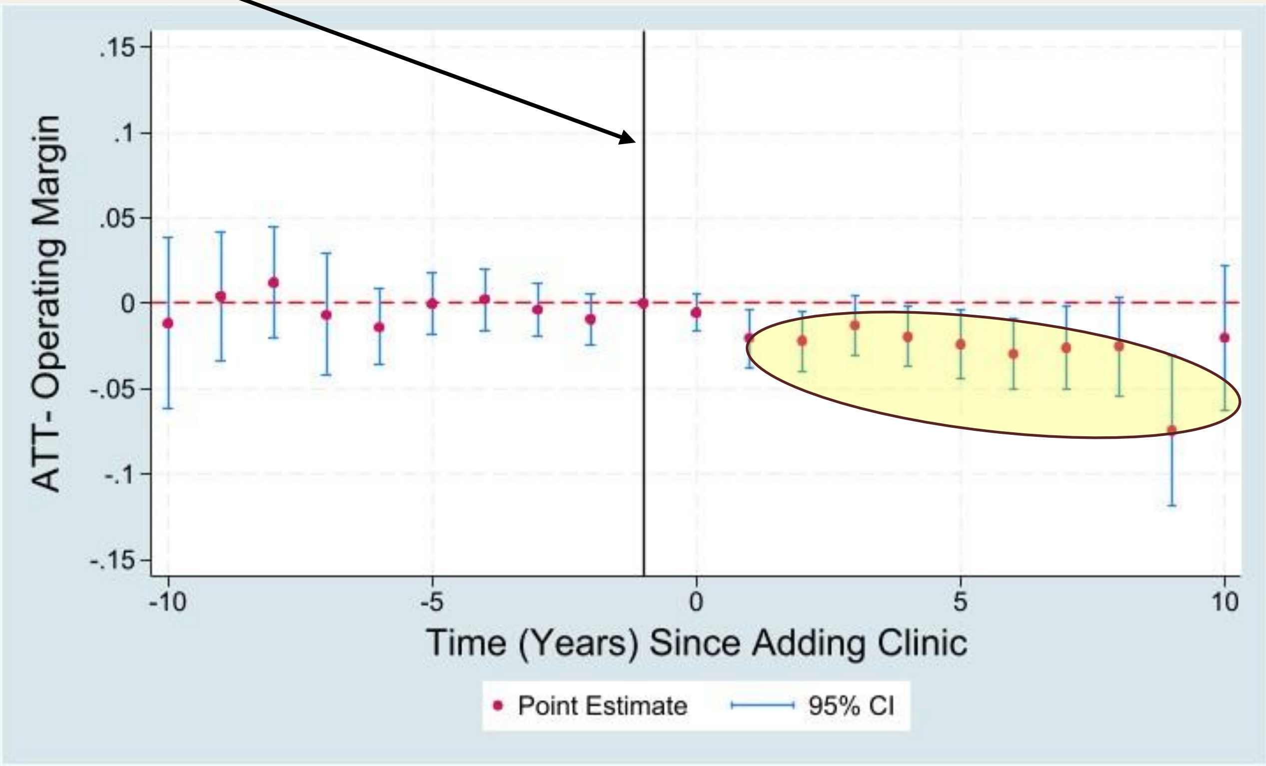
Some positive (and negative!) impacts after addition

Results – ADDED Service Line Event-Study Plots

Year prior to change



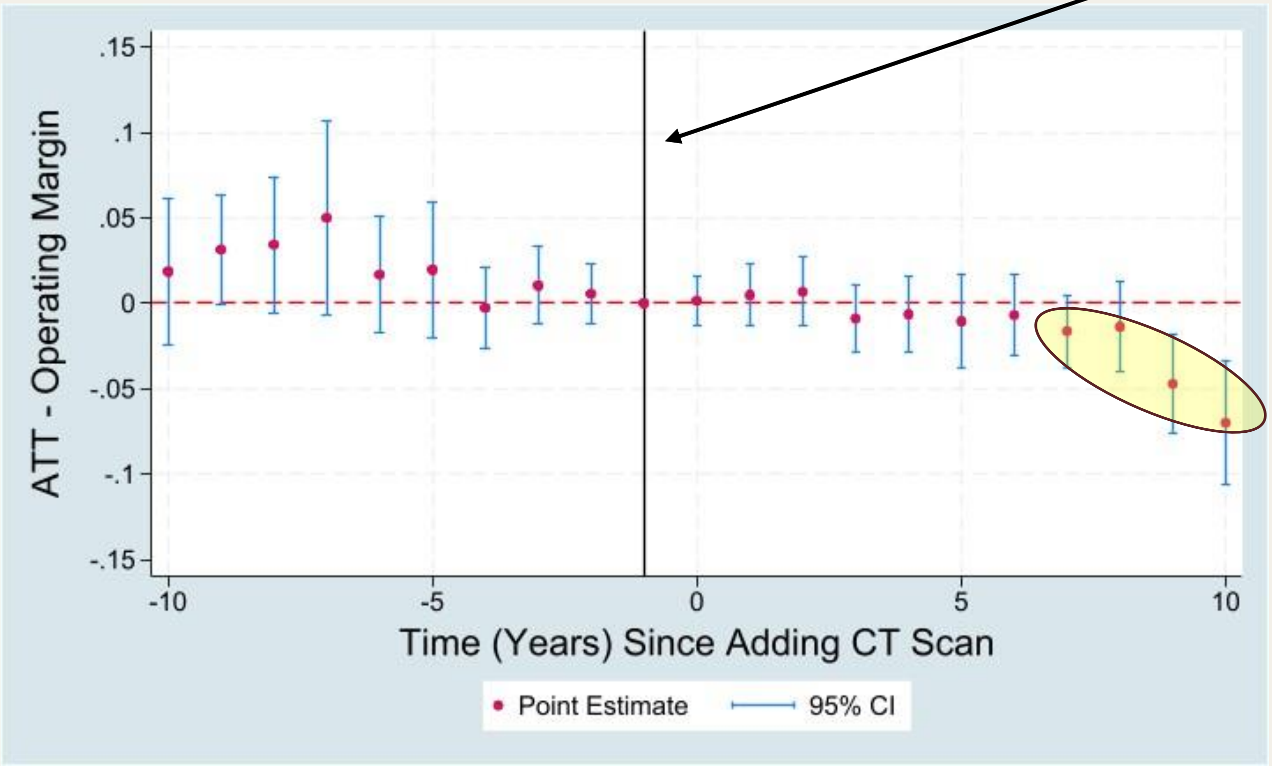
Rural Health Clinic



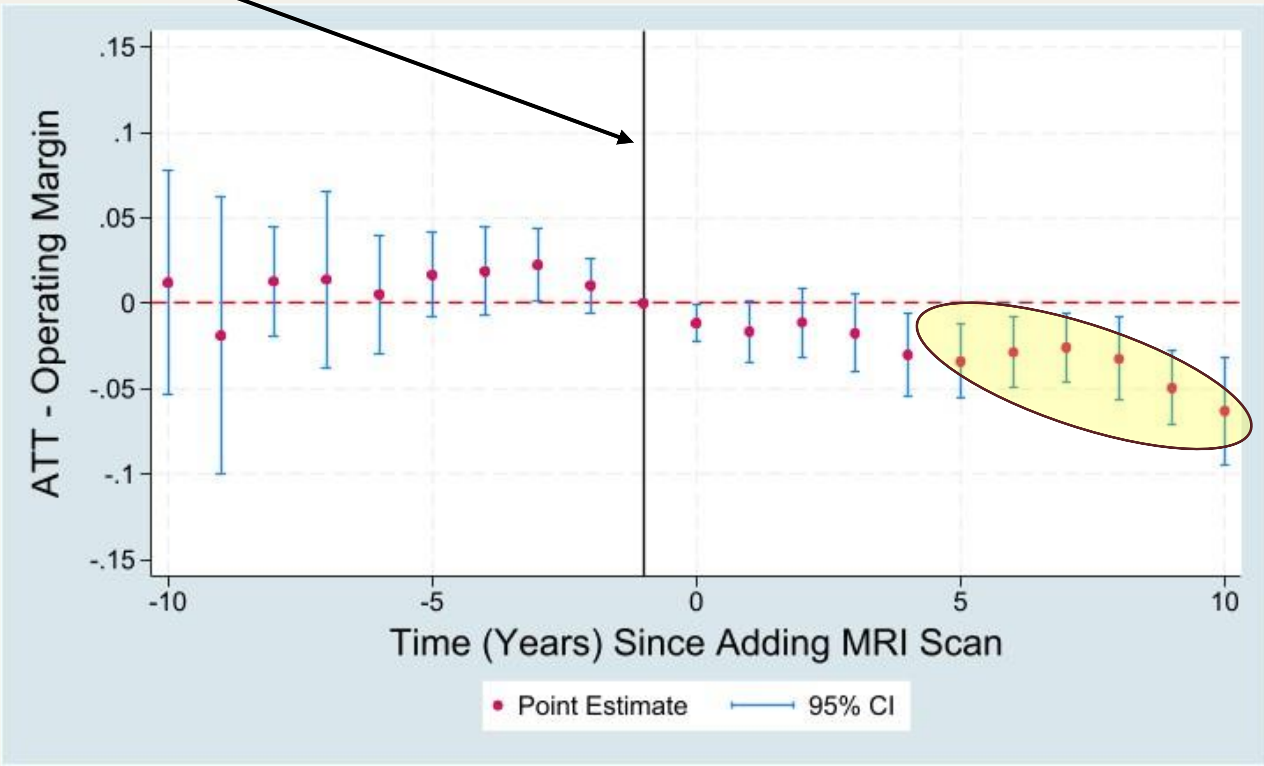
Traditional Clinic

Results – ADDED Service Line Event-Study Plots

Year prior to change



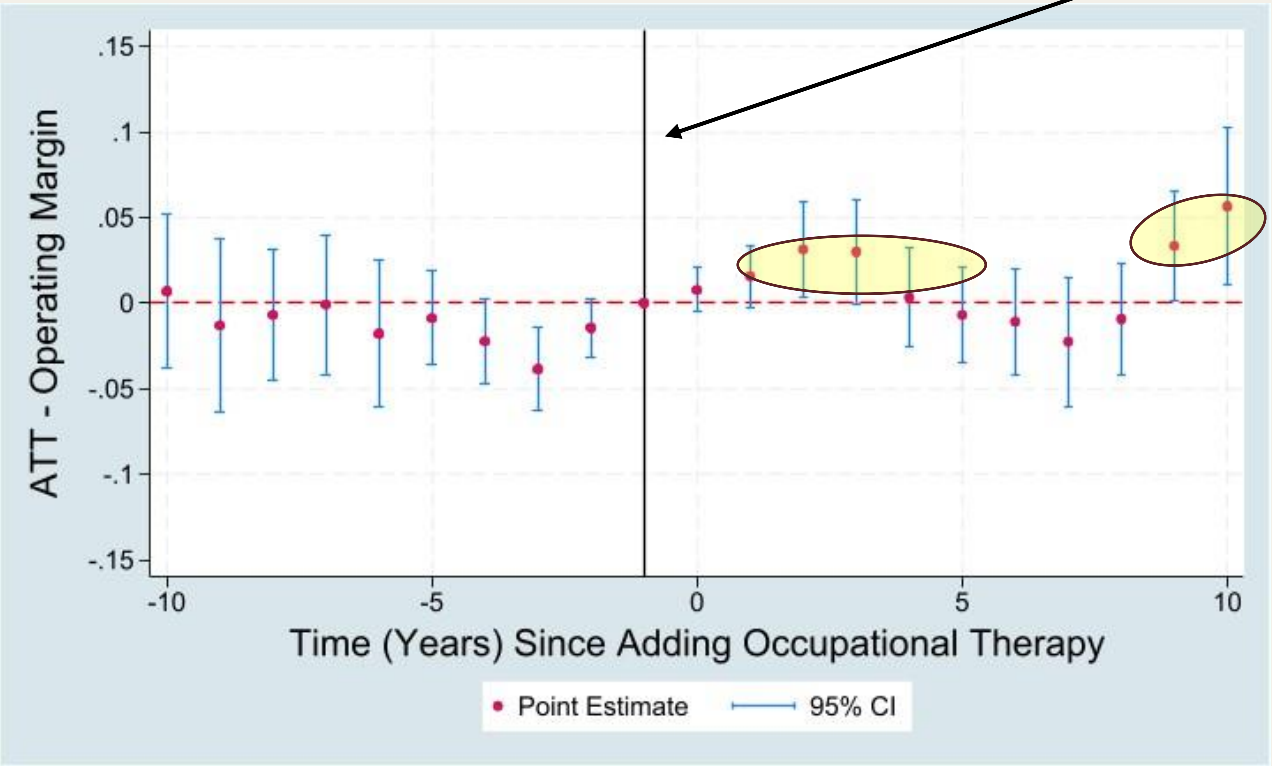
CT Scan

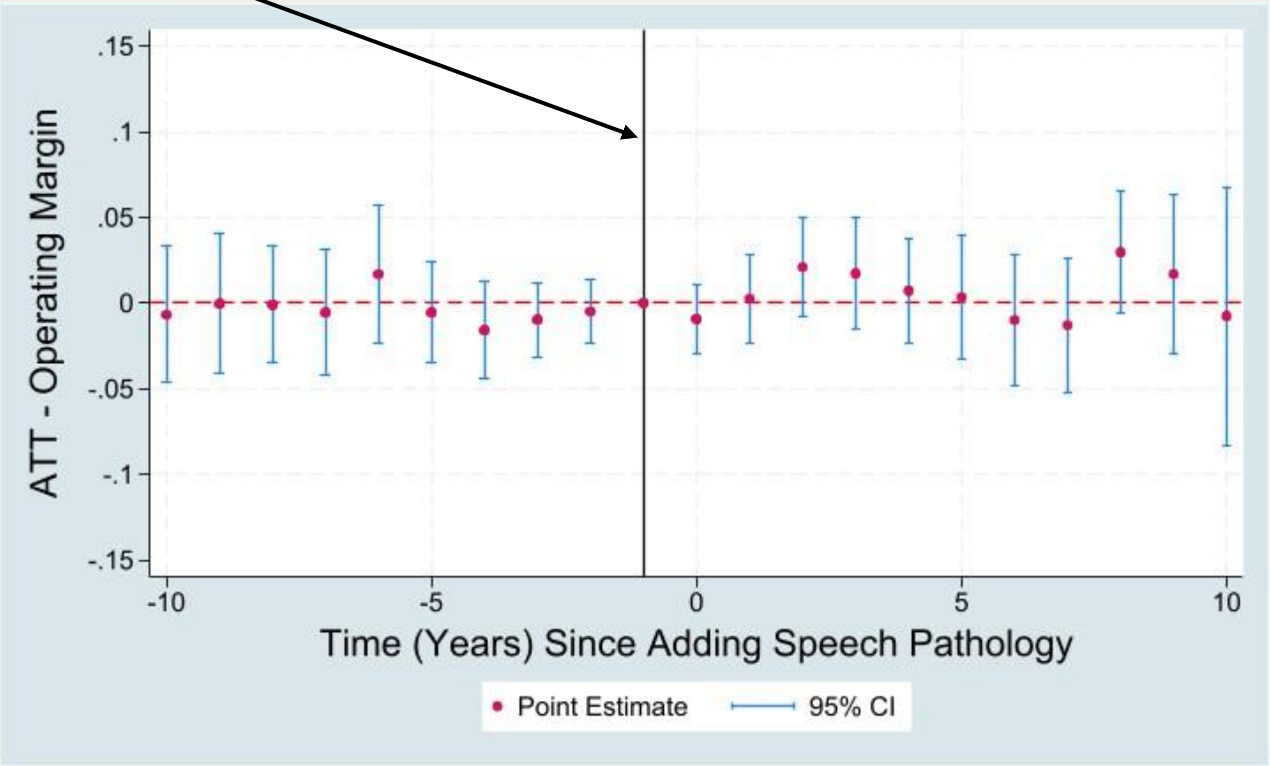


MRI Scan

Results – ADDED Service Line Event-Study Plots

Year prior to change





Occupational Therapy

Speech Pathology

Results – REMOVED Service Lines (6)

	Delivery Room			Nursery			Anesthesiology			Electrocardiology			ICU			Skilled Nursing		
	Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.	
Occupancy Rate	0.058	0.019	***	0.060	0.021	***	0.036	0.017	**	0.044	0.028		0.039	0.022	*	0.016	0.030	
Inpatient Charge-Cost Ratio	0.005	0.006		0.013	0.005	***	-0.001	0.008		-0.004	0.005		0.009	0.004	**	0.001	0.003	
Outpatient Charge-Cost Ratio	0.009	0.003	***	0.006	0.003	**	0.009	0.004	**	0.011	0.003	***	0.005	0.003	*	0.007	0.030	**
System Affiliation	0.005	0.006		0.001	0.006		-0.003	0.005		0.003	0.006		0.008	0.007		-0.006	0.008	
Medicaid Expansion	0.013	0.004	***	0.013	0.004	***	0.012	0.004	***	0.014	0.005	***	0.004	0.005		0.019	0.006	***
Adj. R2	0.581			0.560			0.521			0.552			0.594			0.534		
# Obs		10,284			9,216			10,776			10,644			6,432			5,460	
# Treated Hospitals (removed service)		244			88			149			167			70			237	
# Control Hospitals (always had)		613			680			749			720			466			218	
Wald test (all Leads=0), p-value	0.121			0.656			0.203			0.519			0.166			0.033		
Wald test (Signif. Lags are =), p-value	0.000			.			.			.			.			.		

Note: *, **, and *** denote statistical significance at the *p*<0.10, 0.05, and 0.01 levels, respectively

Control variables still behave as expected:

- (+) impact of higher occupancy rates
- (+) impact of outpatient charge – cost ratio
- (+) impact of state Medicaid Expansion

Results – ADDED Service Lines (6)

	Delivery Room			Nursery			Anesthesiology			Electrocardiology			ICU			Skilled Nursing		
	Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.		Coeff	S.E.	
Occupancy Rate	0.058	0.019	***	0.060	0.021	***	0.036	0.017	**	0.044	0.028		0.039	0.022	*	0.016	0.030	
Inpatient Charge-Cost Ratio	0.005	0.006		0.013	0.005	***	-0.001	0.008		-0.004	0.005		0.009	0.004	**	0.001	0.003	
Outpatient Charge-Cost Ratio	0.009	0.003	***	0.006	0.003	**	0.009	0.004	**	0.011	0.003	***	0.005	0.003	*	0.007	0.030	**
System Affiliation	0.005	0.006		0.001	0.006		-0.003	0.005		0.003	0.006		0.008	0.007		-0.006	0.008	
Medicaid Expansion	0.013	0.004	***	0.013	0.004	***	0.012	0.004	***	0.014	0.005	***	0.004	0.005		0.019	0.006	***
Lead10	-0.040	0.018	**	-0.041	0.020	**	-0.007	0.019		-0.026	0.025		-0.023	0.019		0.006	0.024	
Lead9	-0.016	0.016		-0.026	0.018		0.010	0.018		0.018	0.015		-0.031	0.025		-0.006	0.027	
Lead8	-0.005	0.015		-0.015	0.017		0.015	0.018		0.021	0.017		-0.041	0.024	*	0.026	0.020	*
Lead7	-0.009	0.016		-0.013	0.018		-0.001	0.018		0.006	0.015		0.001	0.230		0.034	0.015	**
Lead6	-0.009	0.015		0.009	0.016		-0.002	0.014		0.007	0.012		0.008	0.020		0.024	0.017	*
Lead5	0.004	0.017		0.000	0.019		0.012	0.010		0.013	0.012		-0.016	0.013		0.009	0.013	
Lead4	0.012	0.013		0.001	0.014		0.012	0.011		0.013	0.010		-0.007	0.017		0.016	0.012	
Lead3	-0.001	0.012		-0.007	0.014		-0.005	0.009		0.003	0.010		-0.010	0.013		0.004	0.009	
Lead2	-0.009	0.011		-0.011	0.010		-0.010	0.007		-0.009	0.008		-0.014	0.011		-0.014	0.010	
Lag0	0.004	0.005		-0.009	0.007		0.010	0.008		0.007	0.006		0.012	0.011		0.004	0.006	
Lag1	0.003	0.006		-0.006	0.009		-0.003	0.010		0.001	0.007		0.004	0.014		0.004	0.007	
Lag2	0.007	0.007		0.000	0.011		-0.012	0.013		0.002	0.008		-0.010	0.019		0.006	0.008	
Lag3	0.014	0.008	*	0.011	0.014		0.002	0.011		0.010	0.009		0.006	0.019		0.010	0.008	
Lag4	0.017	0.009	*	-0.001	0.018		0.002	0.013		0.015	0.009		0.017	0.022		0.012	0.088	
Lag5	0.023	0.009	**	0.006	0.017		-0.008	0.013		0.019	0.012		0.032	0.023		0.012	0.009	
Lag6	0.021	0.010	**	-0.003	0.016		-0.017	0.012		0.034	0.018	*	0.015	0.025		0.008	0.011	
Lag7	0.025	0.009	***	0.018	0.022		0.002	0.016		0.020	0.015		0.052	0.029	*	0.009	0.011	
Lag8	0.035	0.011	***	0.007	0.023		-0.012	0.019		0.006	0.019		0.047	0.027	*	0.014	0.013	
Lag9	0.059	0.012	***	0.012	0.024		0.002	0.024		-0.009	0.026		0.057	0.039		0.014	0.014	
Lag10	0.066	0.013	***	0.078	0.038	**	0.002	0.039		0.011	0.042		0.078	0.052		0.003	0.016	
Constant	-0.048	0.011	***	-0.049	0.012		-0.021	0.009	**	-0.032	0.012	***	-0.039	0.013	***	-0.029	0.016	*
Adj. R2	0.581			0.560			0.521			0.552			0.594			0.534		
# Obs		10,284			9,216			10,776			10,644			6,432			5,460	
# Treated Hospitals (removed service)		244			88			149			167			70			237	
# Control Hospitals (always had)		613			680			749			720			466			218	
Wald test (all Leads=0), p-value	0.121			0.656			0.203			0.519			0.166			0.033		
Wald test (Signif. Lags are =), p-value	0.000			.			.			.			.			.		

Note: *, **, and *** denote statistical significance at the $p<0.10$, 0.05, and 0.01 levels, respectively

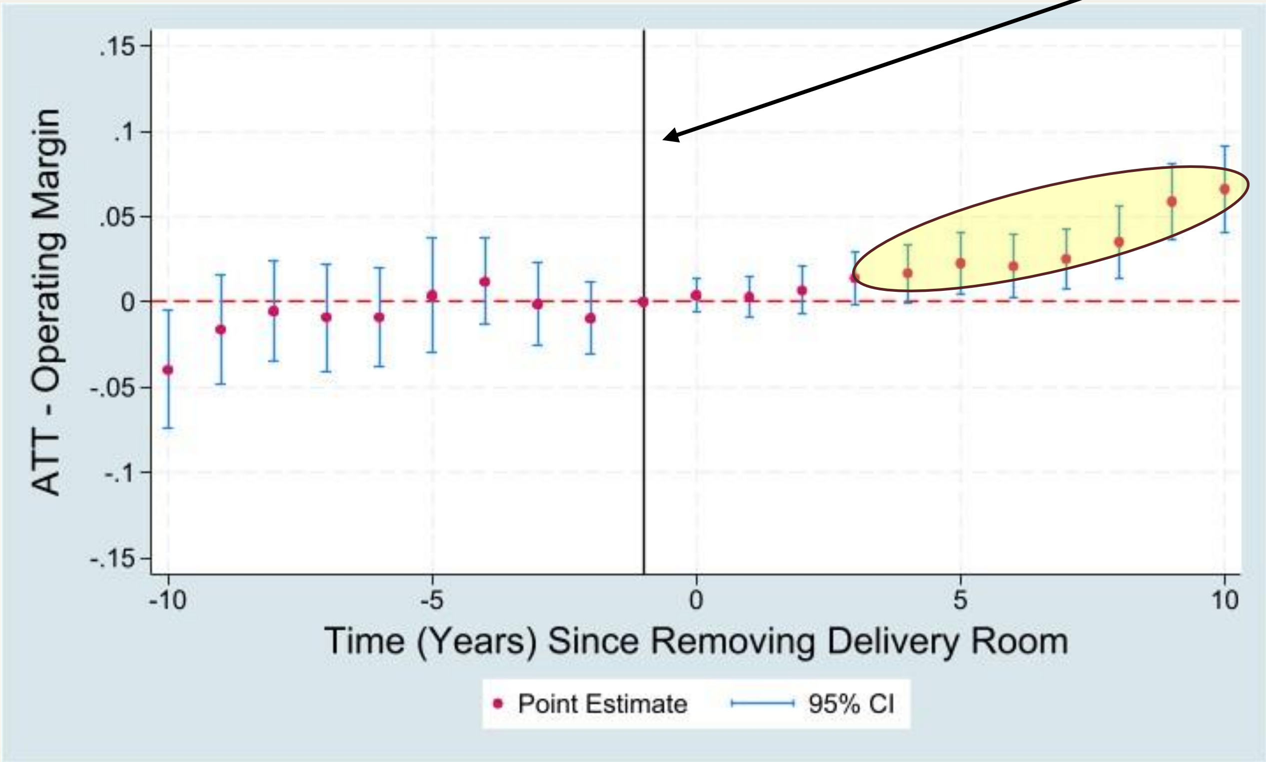
Grey cells denote lag coefficients with statistical significance for more than 1 consecutive period at the $p<0.05$ level

Lead coefficients largely insignificant

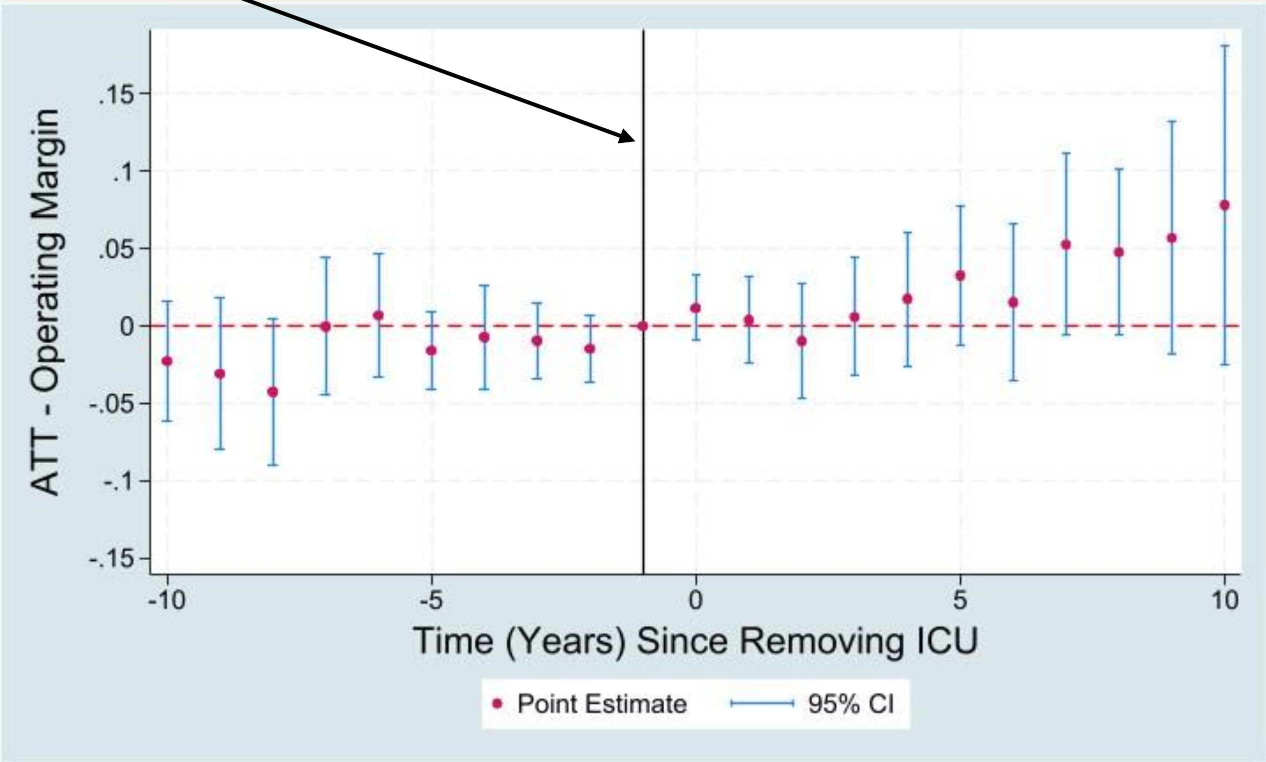
Only removal of Delivery Room has any impact

Results – REMOVED Service Line Event-Study Plots

Year prior to change



Delivery Room

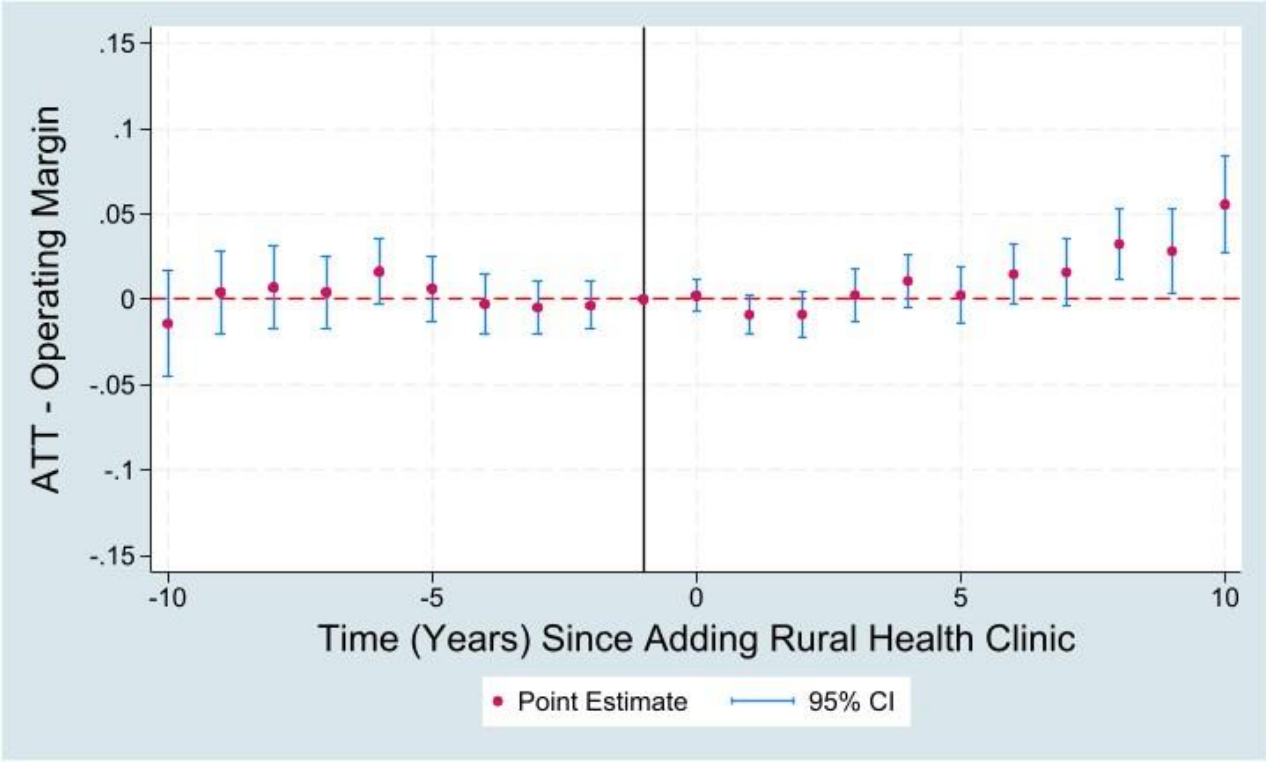


Intensive Care Unit

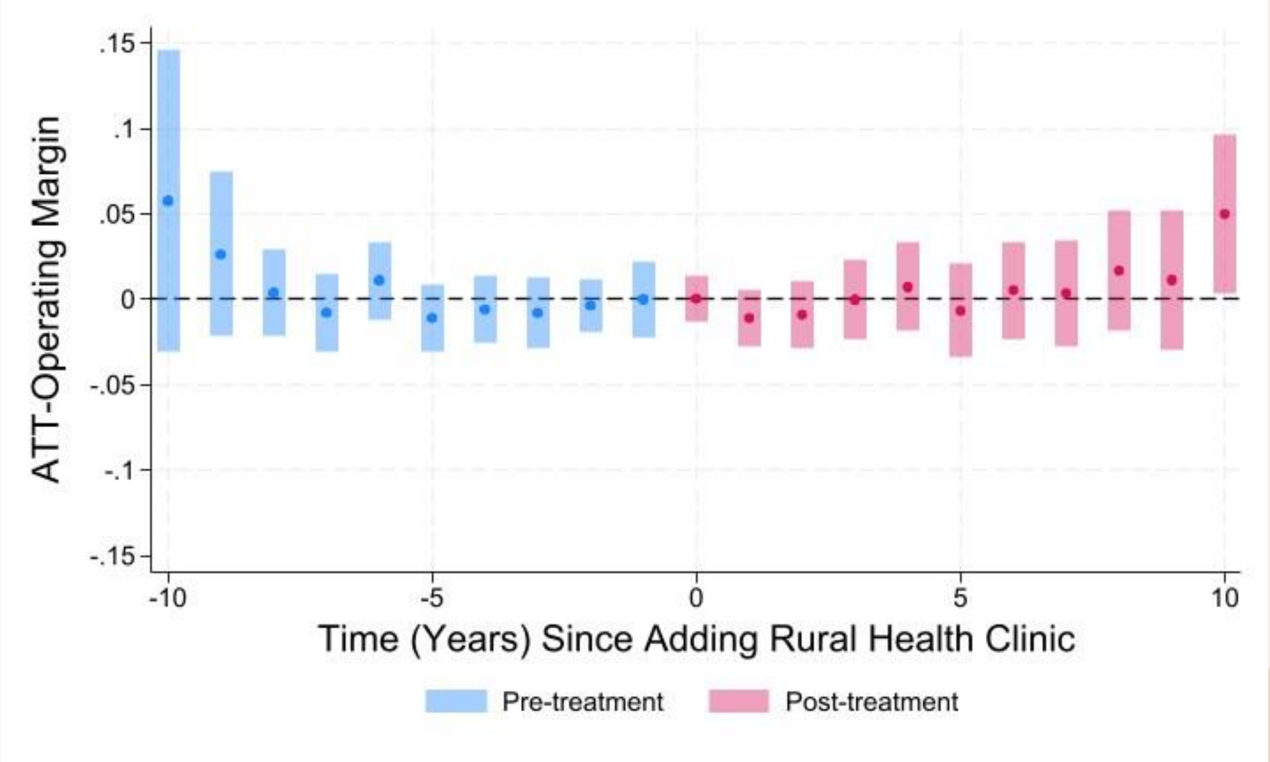
Robustness Checks

Comparison with Callaway and Sant-Anna (2021) correcting for problematic variation in treatment timing (“forbidden comparisons)

Rural Health Clinic



Clarke and Tapia-Schythe

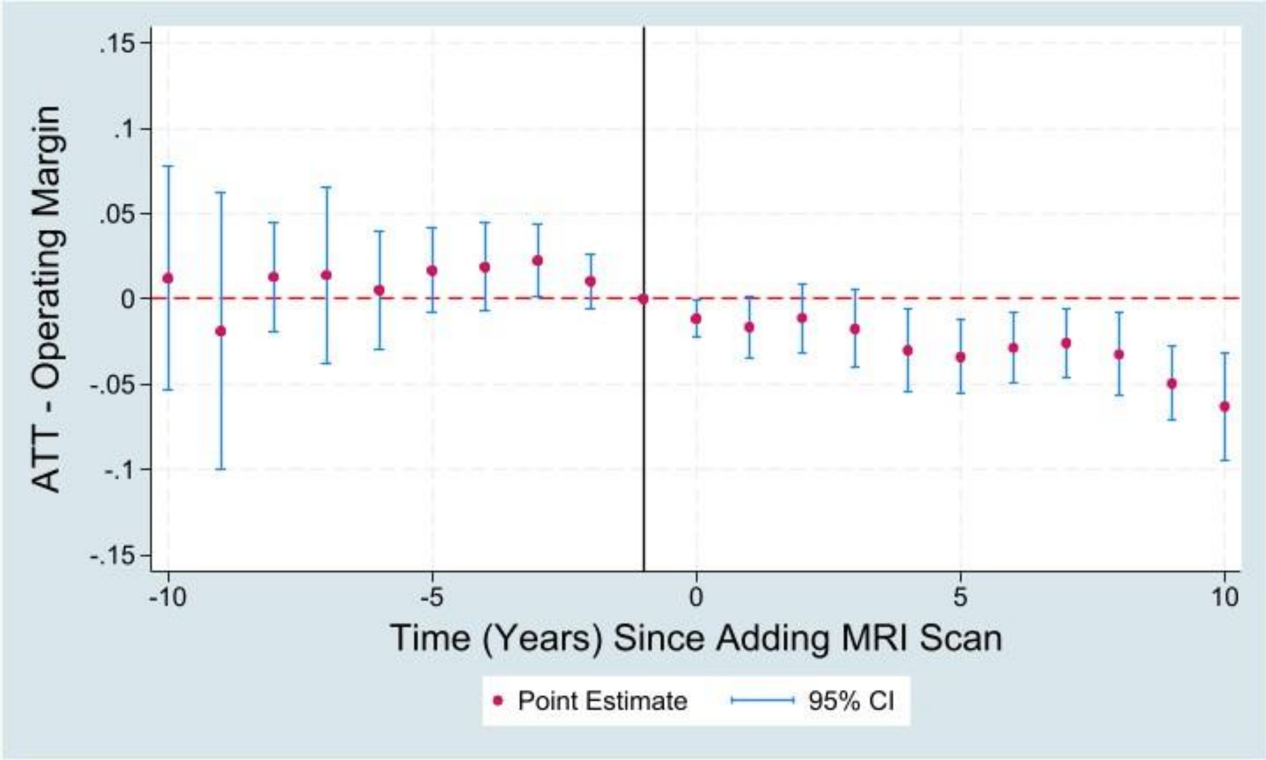


Callaway and Sant-Anna

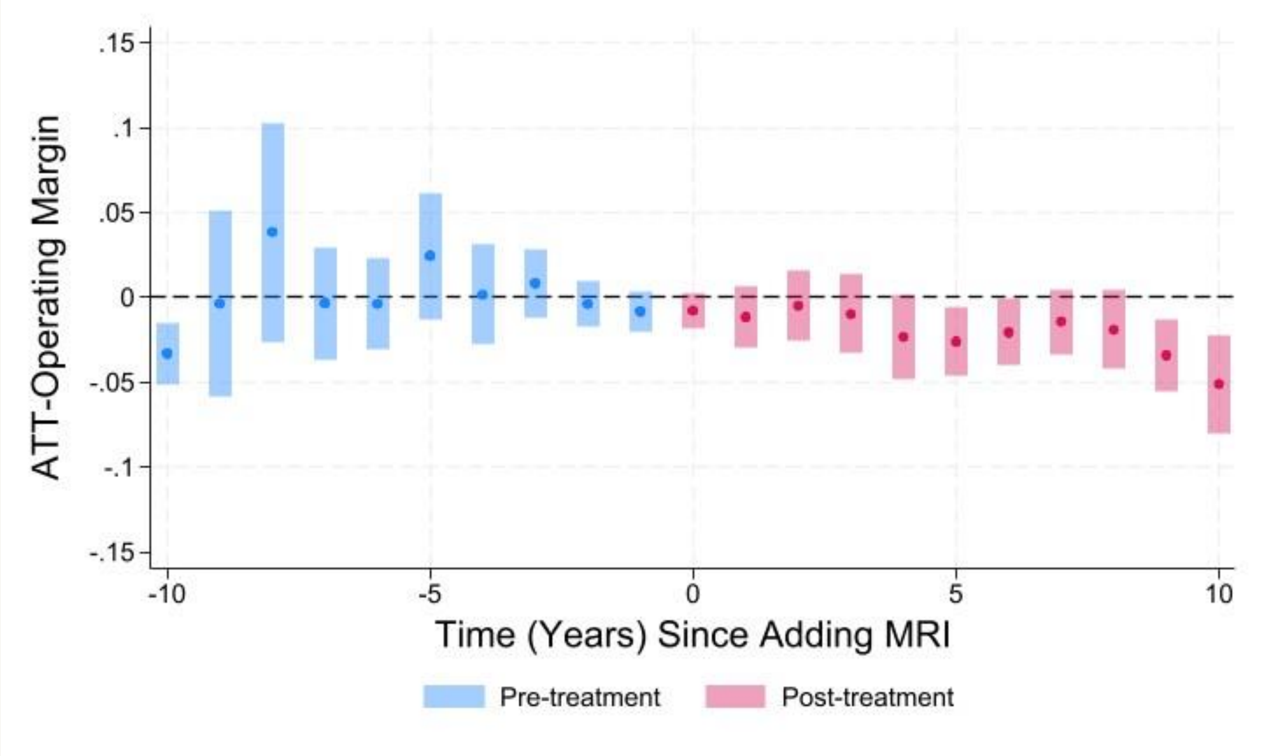
Robustness Checks

Comparison with Callaway and Sant-Anna (2021) correcting for problematic variation in treatment timing (“forbidden comparisons)

MRI Scan



Clarke and Tapia-Schythe

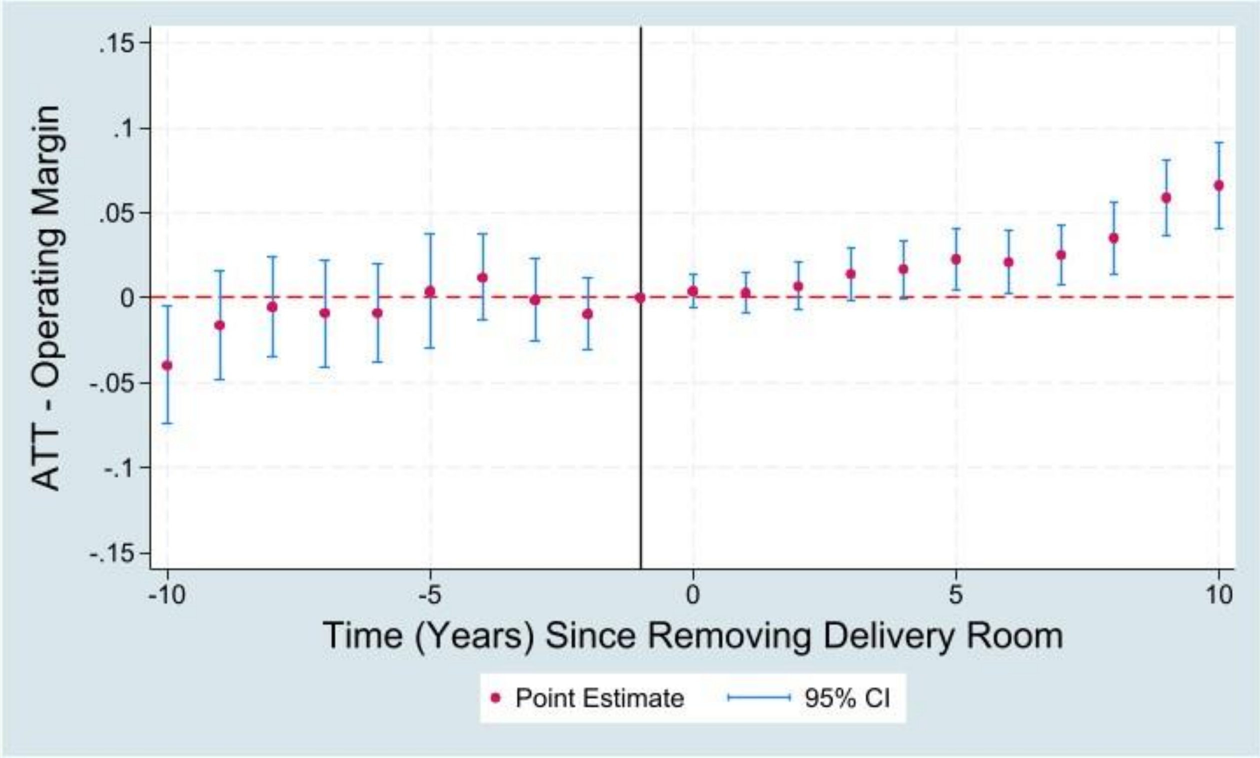


Callaway and Sant-Anna

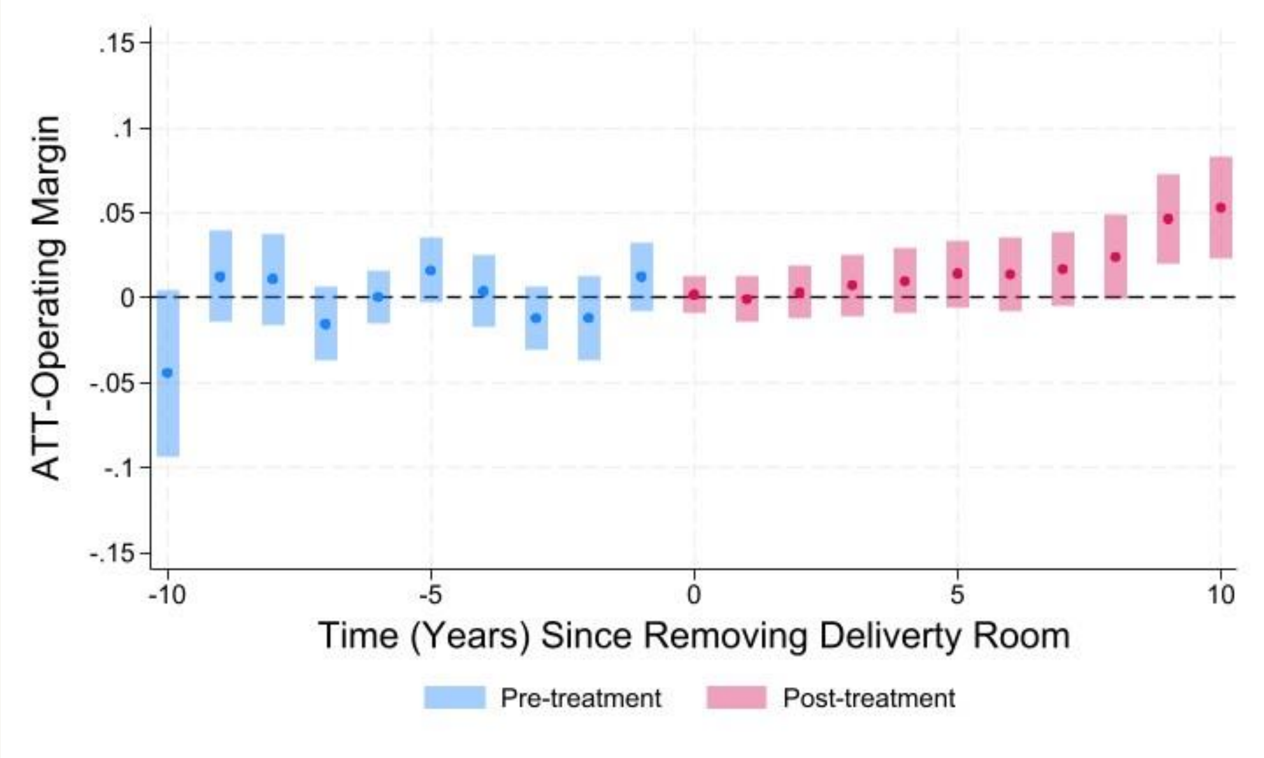
Robustness Checks

Comparison with Callaway and Sant-Anna (2021) correcting for problematic variation in treatment timing ("forbidden comparisons")

Delivery Room



Clarke and Tapia-Schythe



Callaway and Sant-Anna

Other Robustness Checks

- Common combinations of service changes
  - MRI and CT scans: operating losses similar to those for each service individually
  - Delivery rooms and Nurseries: operating margin increases by year 6-7
- Shortened period of analysis to 2010 – 2019
  - Avoid overlap with COVID-19 (some geographies hit harder)
  - Largely similar results
- Restrictions to system affiliated vs. independent rural hospitals
  - Impact of line changes more pronounced for independent hospitals
- Alternative control groups:
  - Hospitals adding service lines vs. those that always had it
  - Hospitals removing service lines vs. those that never had it

More likely to be different *prior to* treatment but converge after

Conclusion

- Service line changes are common across rural U.S. hospitals
  - 6 services added / 6 removed by more than 5% of hospitals during 2010-2021 period
  - Most frequently added: rural health clinics
  - Most frequently removed: delivery rooms
- Addition / subtraction of most of these services did not have meaningful impact on hospital operating margins!
  - May be disappointing for hospital administrators looking for “quick fix”
  - Only rural health clinic addition / delivery room removal had positive effect on operating margin
  - Some had negative impacts! High cost of MRI / CT equipment may be to blame
- Not able to assess drivers of these findings (capital or labor categories) given data constraints

Rural Hospital AI Use & Evaluation

- Background
- AI & Healthcare in the press
- AI Definition
- Current Literature
- Results
- "So what?"

hospitals use of AI

AI Mode | All | Images | News | Videos | Short videos | Shopping | More | Tools

AI Overview

Hospitals are increasingly using Artificial Intelligence (AI) to improve patient care, operational efficiency, and administrative tasks through applications like predictive modeling for patient demand and health trajectories, diagnostic assistance in medical imaging, and automating back-office tasks such as prior authorizations and billing. While AI-driven clinical decision support is still in its early stages, its potential to augment staff knowledge and improve patient outcomes is growing, with the ultimate goal of delivering more accurate, efficient, and equitable healthcare.

Background

- Summer of 1956
    - Dartmouth Conference on Artificial Intelligence hosted first formal discussions on AI

    - Framingham Heart study laid a foundation for predictive models in healthcare

The researchers recruited 5,209 men and women between the ages of 30 and 62 from the town of Framingham, Massachusetts, and began the first round of extensive physical examinations and lifestyle interviews that they would later analyze for common patterns related to CVD

Dartmouth Conference participants; many referred to as “founding fathers” of AI

Framingham, MA around the time the study began

Bill Knaus, APACHE inventor

- Acute Physiology and Chronic Health Evaluation (APACHE)
    - 1981: APACHE I, 1985: APACHE II, 1991: APACHE III, 2006: APACHE IV
    - Estimates illness severity/mortality among Intensive Care Unit patients
    - Initially hard to implement with different health recordkeeping systems.
- 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act
    - Provided incentive payments for hospitals that used electronic health records
    - Established 62 Regional Extension Centers to train hospital staff
    - A year before passing the act 4.6% of rural hospitals used EHRs, 3 years after a third did
- Advance Alert Monitor (AAM)
    - Created by Kaiser Permanente in 2013, uses machine learning
    - Over 500 deaths per year prevented

KAISER PERMANENTE

AI & Healthcare in the Press

HARVARD MEDICAL SCHOOL | BLAVATNIK INSTITUTE BIOMEDICAL INFORMATICS

Donate DBMI People Directory Harvard M

AI is Making Medical Decisions — But For Whom?

Doctors warn that without an ethical framework, patients could be left behind.

Olivia Farrar | Harvard Magazine | May 23, 2025

AXIOS

Sep 30, 2025 - Health

Trump orders $50M for AI in pediatric cancer research

Tina Reed

AP

WORLD U.S. POLITICS SPORTS ENTERTAINMENT BUSINESS SCIENCE FACT CHECK ODDITIES MORE

LIVE: Federal shutdown Lisa Cook Bronx building collapse Stock markets today Jane Goodall

HEALTH

Regulators struggle to keep up with the fast-moving and complicated landscape of AI therapy apps

Forbes

The Accelerating State Of AI Health In Hospitals And Homes

By Gil Press, Senior Contributor. ⓘ Gil Press writes about technology, entrepr...

Follow Author

Published Apr 27, 2025 at 09:00am EDT, Updated Apr 28, 2025 at 02:25pm EDT

FINANCIAL TIMES

Microsoft claims AI diagnostic tool can outperform doctors

AI Defined

- According to the European Commission (2018), AI “refers to systems that display intelligent behavior by analyzing their environment and acting, with some degree of autonomy, to achieve specific goals”
- For the first time in 2023, the American Hospital Association Annual Survey’s Information Technology supplement included multiple questions on “machine learning or predictive model” use
    - Marked the first large-scale data collection on AI use in the United States healthcare industry

AHA Annual Survey IT Supplement

- Rural hospitals in particular benefit from **evaluating** whether predictive models are valid for their specific subset of patients (which may be unique from the sets of patients, typically in larger cities, which models were trained on)

25. Does your hospital use any machine learning or other predictive models that display output or recommendations (e.g., risk scores or clinical decision support) in your EHR or an App embedded in or launched by your EHR?

- **a.** ☐ Machine Learning
- **b.** ☐ Other Non-Machine Learning Predictive Models (e.g., APACHE IV)
- **c.** ☐ Neither (Go to 29)
- **d.** ☐ Don't know (Go to 29)

26. To which of the following uses has your hospital applied machine learning or other predictive models? (Please check all that apply)

- a. ☐ Predicting health trajectories or risks for inpatients (such as early detection of onset of a disease or condition like sepsis; predicting in-hospital fall risk)
- b. ☐ Identify high risk outpatients to inform follow-up care (e.g., readmission risk)
- c. ☐ Monitor health (e.g., through integration with wearables)
- d. ☐ Recommend treatments (e.g., identify similar patients and their outcomes)
- e. ☐ Simplify or automate billing procedures
- f. ☐ Facilitate scheduling (e.g., predicting no-shows or block utilization).
- g. ☐ Other operational process optimization (e.g., supply management) ______________________
- h. ☐ Other clinical use cases ____
- i. ☐ None of the above
- j. ☐ Don't know

27. Who developed the machine learning or other predictive models used at your hospital? (Select all that apply)

a. ☐ Our EHR Developer b. ☐ A third-party developer c. ☐ Self-developed
d. ☐ Public domain e. ☐ Don't know

28. What share of your machine learning or other predictive models have been evaluated using data from your hospital or health system for:

	(1) All models	(2) Most models	(3) Some models	(4) Few models	(5) None	(6) Don't know
a. Model Accuracy (e.g., sensitivity or specificity)	☐	☐	☐	☐	☐	☐
b. Model Bias (e.g., false positive parity across patients from different races, conditions, or other factors)	☐	☐	☐	☐	☐	☐

Ongoing project related to Artificial Intelligence use by hospitals

- Rural – urban differences in specific tasks?
- Determinants of AI adoption in rural hospitals
- Potential impacts of AI use by rural hospitals

Current Literature

- Descriptive statistics (see table) show that some AI uses are more common than others:
    - Predicting inpatient health trajectories (92%)
    - Automate billing (36%)
- Nong et al. also ran 2 weighted multivariate Poisson regressions with a binary outcome to analyze AI use & evaluation

By Paige Nong, Julia Adler-Milstein, Nate C. Apathy, A. Jay Holmgren, and Jordan Everson

Current Use And Evaluation Of Artificial Intelligence And Predictive Models In US Hospitals

Health Affairs

Descriptive statistics of artificial intelligence (AI) and predictive model use in US hospitals, 2023

	Number	Weighted percent
Use of any machine learning or other predictive models that display in the EHR	2,425	100
Machine learning	887	33
Other non–machine learning predictive models	809	32
Neither	482	23
Do not know	247	11
Specific uses of machine learning or other predictive models, among hospitals that integrated models into the EHR	1,688	100
Predict health trajectories or risks for inpatients	1,569	92
Identify high-risk outpatients for follow-up care	1,380	79
Facilitate scheduling	849	51
Recommend treatments	772	44
Simplify or automate billing procedures	633	36
Monitor health	600	34
Other (clinical use cases)	548	34
Other (operational process optimization)	442	25
Developer of predictive models used by the hospital, among hospitals that integrated models into the EHR	1,689	100
EHR developer	1,381	79
Third-party developer	995	59
Self-developed	909	54
Public domain	77	4.4
Local evaluation of most or all models for accuracy or bias[a]	1,660	100
Model accuracy	1,009	61
Model bias	711	44
Model accuracy and bias	709	44

Nong et al. (2025)

- Weighted multivariate Poisson regressions to analyze AI <u>use</u> & <u>evaluation</u>
- Use was associated with many variables, including top quintile operating margins (RR=1.27), **being urban (rural hospital RR=0.90)**, being a system member (RR=2.31), & having 400 beds or more (RR=1.23)
- Though less extreme, these relationships are the same (besides size) for an AI <u>evaluation</u> dependent variable

By Paige Nong, Julia Adler-Milstein, Nate C. Apathy, A. Jay Holmgren, and Jordan Everson

Current Use And Evaluation Of Artificial Intelligence And Predictive Models In US Hospitals

Health Affairs

EXHIBIT 2

Use of artificial intelligence (AI) and predictive models and local evaluation in US hospitals, by hospital

	Used AI or other predictive models integrated into EHR (*n* = 2,425)	
Variables	**RR**	**95% CI**
Top quintile, operating margins	1.27****	1.21, 1.39
Top quintile, uncompensated care	1.06	0.99, 1.13
Top quintile, percent of discharges from Medicaid	1.003	0.94, 1.08
Top quintile, hospital service area SDI	0.92**	0.85, 0.99
Critical access hospital	0.87***	0.79, 0.95
Rural (ref: urban)	0.90***	0.83, 0.97
Count of Alternative Payment Models	1.07****	1.05, 1.09
System member (ref: independent)	2.31***	2.02, 2.65
Size (ref: small [fewer than 100 beds])		
Medium (100–399 beds)	1.08**	1.01, 1.17
Large (400 beds or more)	1.23****	1.12, 1.34
Ownership (ref: nonprofit)		
For-profit	0.75****	0.67, 0.85
Government owned[b]	0.86***	0.77, 0.96
Teaching status (ref: nonteaching)		
Resident program/minor teaching	1.02	0.96, 1.08
Academic medical center/major teaching	0.97	0.87, 1.07
Constant	0.34****	0.29, 0.39

Results

- Comparing descriptive statistics across urban and rural hospitals

Category	Urban Number	Urban Weighted percent	Rural Number	Rural Weighted percent	Different
Use of any machine learning or other predictive models that display in the EHR	1,301	100%	1,018	100%	
Machine learning	538	41%	314	31%	***
Other non–machine learning predictive models	539	41%	246	24%	***
Neither	145	11%	306	30%	***
Do not know	79	6%	152	15%	***
Specific uses of machine learning or other predictive models, among hospitals that integrated models into the EHR	1,076	100%	554	100%	
Predict health trajectories or risks for inpatients	996	93%	517	93%	
Identify high-risk outpatients for follow-up care	849	79%	484	87%	***
Facilitate scheduling	587	55%	243	44%	***
Recommend treatments	526	49%	223	40%	***
Simplify or automate billing procedures	400	37%	218	39%	
Monitor health	402	37%	179	32%	**
Other (clinical use cases)	398	37%	137	25%	***
Other (operational process optimization)	286	27%	144	26%	
Developer of predictive models used by the hospital, among hospitals that integrated models into the EHR	1,076	100%	553	100%	
EHR developer	845	79%	488	88%	***
Third-party developer	698	65%	269	49%	***
Self-developed	616	57%	260	47%	***
Public domain	57	5%	16	3%	**
Local evaluation of most or all models for accuracy or bias	1,052	100%	549	100%	
Model accuracy	650	62%	320	58%	
Model bias	473	45%	215	39%	**
Model accuracy and bias	342	33%	124	23%	***

Rural Higher!

Rural Less Likely to Evaluate for Bias

Results

- For only rural hospitals, comparing descriptive statistics across CAH, MDH, SCH and none of the above categories

Category	Critical Access Hospital Number	Critical Access Hospital Weighted percent	Different	Medicare Dependent Hospital Number	Medicare Dependent Hospital Weighted percent	Different	Sole Community Hospital Number	Sole Community Hospital Weighted percent	Different	None of the Above Number	None of the Above Weighted percent
Use of any machine learning or other predictive models that display in the EHR	611	100%		58	100%		203	100%		147	100%
Machine learning	167	27%	**	18	31%		75	37%		54	37%
Other non–machine learning predictive models	136	22%	***	16	28%		47	23%	**	48	33%
Neither	206	34%	***	17	29%		53	26%		30	20%
Do not know	102	17%	*	7	12%		28	14%		15	10%
Specific uses of machine learning or other predictive models, among hospitals that integrated models into the EHR	301	100%		32	100%		121	100%		101	100%
Predict health trajectories or risks for inpatients	279	93%	*	29	91%	*	111	92%	**	99	98%
Identify high-risk outpatients for follow-up care	276	92%		27	84%		95	79%		87	86%
Facilitate scheduling	121	40%		17	53%		57	47%		49	49%
Recommend treatments	117	39%		13	41%		48	40%		46	46%
Simplify or automate billing procedures	114	38%		15	47%		53	44%		37	37%
Monitor health	90	30%		12	38%		40	33%		38	38%
Other (clinical use cases)	72	24%		11	34%		30	25%		25	25%
Other (operational process optimization)	82	27%		4	13%		33	27%		26	26%
Developer of predictive models used by the hospital, among hospitals that integrated models into the EHR	301	100%		32	100%		120	100%		101	100%
EHR developer	276	92%		28	88%		98	82%		87	86%
Third-party developer	137	46%		19	59%		66	55%		47	47%
Self-developed	137	46%		14	44%		61	51%		49	49%
Public domain	12	4%		1	3%		1	1%		2	2%
Local evaluation of most or all models for accuracy or bias	297	100%		32	100%		120	100%		101	100%
Model accuracy	170	57%		19	59%		71	59%		61	60%
Model bias	125	42%		12	38%		43	36%		36	36%
Model accuracy and bias	63	21%		10	31%		27	23%		25	25%

Regression Results

- Logistic regression (not Poisson as in Nong et al.)
- As such, odds ratios (not relative risks) are provided
- Weights for nonresponse bias derived from a 3rd multivariate logistic regression

Variables	Used AI or other predictive models integrated into EHR (n = 1,018) OR	95% CI	Evaluated models for both accuracy and bias (n = 536) OR	95% CI
Top quintile, operating margins	2.28***	1.36, 3.83	1.29	0.82, 2.01
Top quintile, uncompensated care	2.52	0.36, 17.63	0.96	0.23, 4.04
Top quintile, percent of discharges from Medicaid	0.73	0.48, 1.11	1.04	0.62, 1.75
Top quintile, hospital service area SDI	1.11	0.73, 1.7	0.76	0.44, 1.32
Critical access hospital	0.47**	0.22, 0.99	1.58	0.76, 3.29
System member (ref: independent)	6.72***	4.83, 9.35	1.63*	0.97, 2.73
Resident program/minor teaching	1.23	0.59, 2.59	1.62	0.8, 3.27
Medicare Specialty Designation (ref: not SCH or MDH)				
Sole Community Hospital	0.59*	0.32, 1.08	1.08	0.59, 1.99
Medicare Dependent Hospital	0.60	0.28, 1.29	1.38	0.57, 3.37
Size (ref: small [fewer than 40 beds])				
Medium (40-100 beds)	1.32	0.68, 2.55	0.66	0.32, 1.36
Large (100 beds or more)	1.10	0.5, 2.41	1.27	0.51, 3.16
Ownership (ref: nonprofit)				
For-profit	0.14***	0.08, 0.27	2.43*	1.07, 5.51
Government owned	0.42***	0.29, 0.61	0.71	0.39, 1.29
Constant	0.95	0.43, 2.12	0.34**	0.14, 0.79

So what? Potential Impacts of AI Use

- Coarsened Exact Matching (CEM) procedure allows for comparison among treated (AI users) and control (non-AI users)
  - Bins for: operating margins, Medicare inpatient discharge share, system membership, ownership type, number of beds
- 2022 data was used in previous logit regressions; 2023 data on FTE employees, operating margins, total salaries was added to create 1-year change variables
  - A two-year change variable would be preferred, but 2024 Medicare data is only partially released.
- Univariate regressions run on all observations that were matched using CEM weights (2,077 rural and urban hospitals used, while 239 were unmatched/dropped)

Preliminary Results (all hospitals)

- FTE Employees: *No significant relationship*
- Operating Margins: 0.0080 increase for AI users (0.0195 treated vs 0.0115 control) - *significant at the 10% level*
- Total Salaries: $7.5M (roughly 6%) increase for AI users - *significant at the 1% level*

Thank You!

Questions / Comments?

brian.whitacre@okstate.edu

DEPARTMENT OF
AGRICULTURAL ECONOMICS

As a baby bust hits rural areas, hospital labor and delivery wards are closing down

JULY 15, 2024 · 5:00 AM ET FROM KFF Health News

Rural health clinics are closing after Trump's 'One Big Beautiful Bill,' raising the legislation's political risks

SEP 22, 2025

AI Helps to Improve Speed of Radiology Reviews

New AI tool helps rural hospitals improve financial incomes

October 7, 2025

We're proud to announce that the claims denial navigator is **available now** in the GitHub Models catalog—a free, AI-powered tool developed by Microsoft Partners

Nonresponse Bias Weighting Results

- Derivation of weights shown:

logit response employees_log discharges_log acute_days_log cah ownership_forprofit ownership_nonprofit if rural == 1

Pseudo R2 = 0.0449

response	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
employees_log	0.0064377	0.096682	0.07	0.947	-0.1830555	0.1959309
discharges_log	0.3470055	0.0680321	5.1	0	0.2136651	0.4803459
acute_days_log	-0.1241613	0.0474833	- 2.61	0.009	-0.217227	-0.0310956
cah	0.4902852	0.1280571	3.83	0	0.239298	0.7412725
ownership_forprofit	-0.6143767	0.1931141	- 3.18	0.001	-0.9928734	-0.23588
ownership_nonprofit	0.489873	0.1007625	4.86	0	0.292382	0.687364
_cons	-1.723867	0.4320669	- 3.99	0	-2.570703	-0.8770315