Health Care Access and Spillover Losses : How Hospital Treatment Expansions Affect Health Regions in Brazil

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Abstract

High-complexity hospital care in Brazil remains geographically concentrated despite universal coverage under SUS. We estimate the effects of federal habilitação certifications, staggered regulatory approvals that authorise hospitals to perform high-complexity procedures, using an event-study difference-in-differences design and linked administrative microdata (10.7 million hospital admissions). To quantify network spillovers, we construct a shift-share exposure measure that interacts pre-period patient referral shares with specialty-specific certification shocks in connected health regions. After certification, admissions rise sharply for residents of gaining regions (e.g., +523 oncology, +369 cardiovascular, and +253 orthopedics admissions per region-quarter). However, shift-share estimates show negative spillovers at historically connected receiver hospitals for cardiovascular (10,356 annually; 45.0%) and oncology (211; 17.2%), consistent with referral diversion and contraction rather than pure congestion relief. Even with expanded local capability, decentralised upgrades can create winners and losers across an interdependent hospital network.

Introduction

Brazil's Unified Health System (SUS) constitutionally guarantees universal entitlement to health care (OECD, 2025; Pablos-Mendez et al., 2016). Yet access to high-complexity hospital treatment, such as oncology and cardiovascular surgery, remains highly concentrated in a small number of metropolitan centres, generating substantial spatial inequality in realised care (Fonseca et al., 2022; Martins et al., 2023). As Wagstaff et al. (2016) emphasise, in systems that legally guarantee universal rights, the binding constraint is often not entitlement itself but the effective depth of coverage, constituting whether individuals are actually able to obtain the services the system nominally promises. This distinction matters normatively and economically. Following the capability approach by Amartya Sen, good health is a precondition for human flourishing; undertreatment narrows the set of feasible life opportunities (Robeyns and Byskov, 2025). This normative loss has direct economic implications, reduced productivity, lower educational attainment, and diminished ability to participate in social and economic life, placing undertreatment at the core of development constraints rather than at the periphery (Jamison et al. 2013; Bharadwaj, Løken, and Neilson 2013).

We provide new evidence on effective access by exploiting a distinct institutional feature of SUS, the federal habilitação certification process, rolled out in waves via national portarias, which hospitals must complete before performing specific high-complexity procedures. Approvals require compliance with staffing, equipment, and infrastructure standards (Madi and Cerri, 2018) and arrive in staggered waves, generating plausibly exogenous shifts in local treatment capability. We link monthly certification histories from CNES to inpatient administrative claims from SIH, which record procedures, treating hospitals, and municipalities of residence, allowing us to track both within-region expansions and changes in inter-municipality referral patterns, an empirically relevant margin as a key feature of patient migration and referral networks is a significant determinant in geographic variation of care (Finkelstein et al., 2016).

Literature Review

Geographic Variation and Supply-Side Determinants

A central question in health economics is whether geographic variation in healthcare utilisation reflects demand-side factors or supply-side characteristics that policy can address. Finkelstein et al. (2016) exploit Medicare patient migration to show that 50–60 percent of variation stems from place-specific supply factors, suggesting infrastructure investments can substantially alter utilisation patterns. Supporting this, Buchmueller et al. (2006) and Currie and Reagan (2003) document that distance to hospitals has first-order effects on access, with closures raising mortality and each additional mile reducing preventive care uptake by 3 percent among disadvantaged populations.

Hospital Financing and Volume Dynamics

These findings implicitly assume hospital capacity responds elastically to demand shifts. In practice, hospitals face volume-sensitive financing that complicates this prediction. Brazil's MAC (*Média e Alta Complexidade*) system reimburses hospitals based on procedures performed, not capacity maintained. High-complexity care requires substantial fixed costs, specialist physicians, diagnostic equipment, surgical infrastructure, that must be spread across patient volume to achieve financial viability (McRae et al., 2020). When patients are diverted to newly-certified facilities, receiver hospitals lose the volume that cross-subsidises these fixed costs, creating pressure to contract rather than reallocate freed capacity. Friebel et al. (2020) document such volume-cost spillovers in English hospitals, finding that volume losses in one service line increase per-patient costs in others.

Identification Challenges in Network Spillover Studies

Clean empirical tests of network spillovers are scarce because capacity expansions often coincide with insurance changes, confounding infrastructure effects with coverage effects (Yabroff et al., 2020). Brazil's universal coverage system removes this confounder, providing an ideal setting to isolate pure infrastructure effects.

Contribution

We provide the first causal test of network spillovers when treatment capabilities expand in a universal healthcare system. While Chandra and Staiger (2007) document positive productivity spillovers that might suggest congestion relief benefits, we find the opposite: receiver hospital admissions contract when connected regions gain capability. This contraction mechanism reflects the interaction between volume-based financing and economies of scale, with implications for decentralised health system investment.

Research Context

Brazil comprises 5,571 municipalities grouped into 456 health regions, an administrative layer designed to coordinate service planning, referral arrangements, and capacity allocation across neighbouring municipalities. While SUS is federally financed through intergovernmental transfers, implementation and day-to-day management are heavily decentralised, with substantial responsibility at the municipal level. This institutional structure makes the health region a natural unit for studying both local capability expansions and their propagation through inter-municipality patient flows (Botega et al., 2022; Wendt et al., 2022).

Our empirical setting is the federal habilitação certification system, which authorises hospitals to deliver specific high-complexity services conditional on meeting regulatory requirements for specialist staffing, equipment, and infrastructure (Madi and Cerri, 2018). Certifications

are issued in staggered waves through national portarias, generating discrete changes in local treatment capability that we exploit for identification.

Figure 1 maps the spatial distribution of habilitação gains across health regions. The pattern is highly uneven, with expansions concentrated in the more populous and economically developed Southeast, consistent with broader evidence of spatial concentration in high-complexity care (Fonseca et al., 2022; Martins et al., 2023). Complementing the spatial map, Figure 2 documents how the share of admissions treated within a patient's home health region evolves over time, providing descriptive evidence on how local treatment capacity evolves.

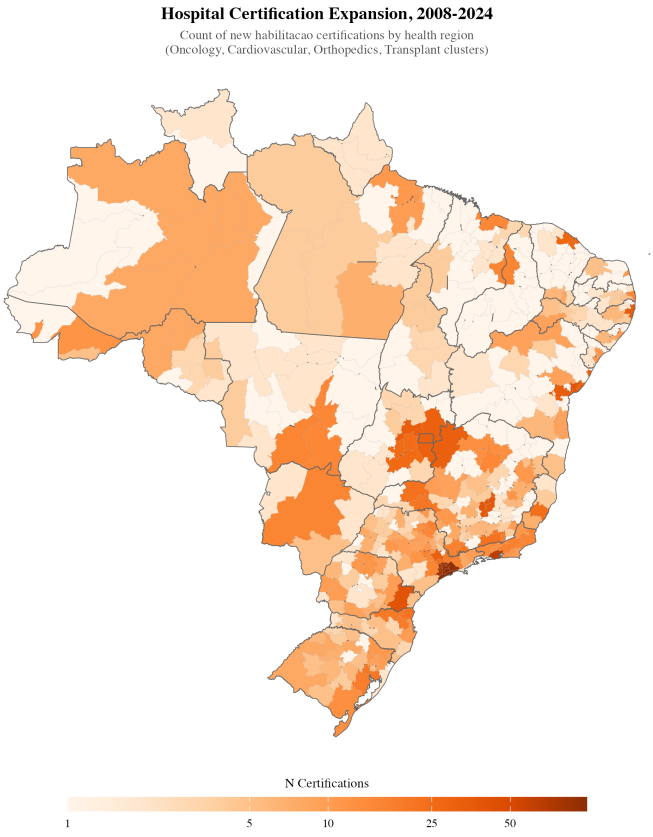

Figure 1: Gains from hospital *habilitação* across health regions

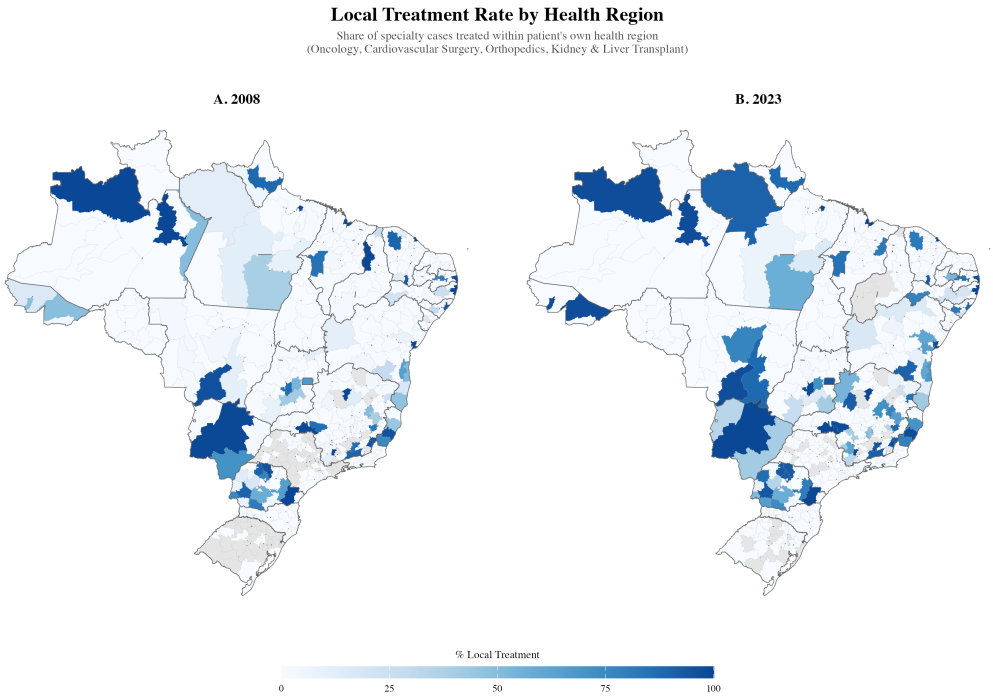

Figure 2: Home-region share of admissions over time ("home health region treatment').

Data

This paper leverages Brazil's nationwide administrative hospital records, which provide an unusually comprehensive setting for studying spatial access to high-complexity healthcare. The primary data source is the Hospital Information System (SIH), a federal reimbursement database that records all publicly financed hospital admissions in the country. Between 2008 and 2025, SIH contains approximately 180 million individual hospitalisation records. Each record reports the patient's municipality of residence, admission date, diagnosis (ICD-10), procedure performed, treating hospital, and basic demographics. As hospital reimbursement in Brazil is centrally administered, these records cover the full universe of public hospitalisations, rather than a sample. This allows us to construct complete patient flow matrices, by origin municipality, destination hospital, procedure, and time.

We complement admission data with the National Registry of Health Facilities (CNES), which provides monthly indications of hospital infrastructure and regulatory status. These approvals represent discrete expansions in legally permitted treatment capacity and are assigned with clearly defined effective dates by hospital. We define a habilitação event as a hospital's approval date for a specific federal portaria, the administrative instrument through which the Ministry of Health grants regulatory authorisation. We restrict the sample to portarias issued by federal secretariats (SAS, SAES, GM) that authorise at least ten hospitals simultaneously, excluding state and municipal documents that may reflect endogenous local decisions, as well as internal memoranda, contracts, and other non-regulatory instruments. Habilitações are linked to concrete treatment capabilities via SIGTAP, the national procedure classification and reimbursement schedule, which has a list describing the set of procedures that establishments are authorised to deliver under each regulatory designation. The linking of hospital admissions to facility-level authorisation histories, enables to map changes in legal treatment capacity directly to realised care patterns.

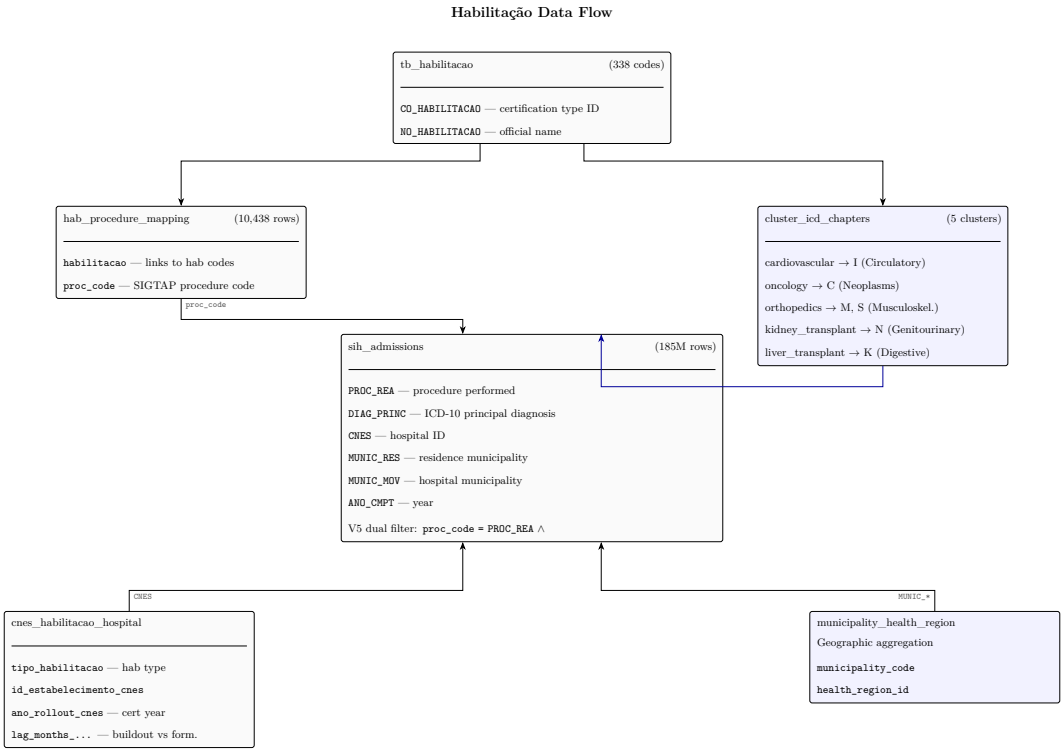

Figure 3: Data flow linking hospital habilitações to inpatient procedures. The specification applies dual filtering: procedures must match both the habilitação-required procedure code and the cluster-specific ICD-10 chapter. Blue elements indicate ICD-10 related components. Geographic aggregation via `municipality_health_region` enables construction of shift-share populations (Gaining regions $\mathcal{G}$, Spillover regions $\mathcal{R}$).

Table 1: Habilitacao Cluster Definitions

Cluster	Description	Hab. Codes	Treated Regions	Treated Patients
Oncology	UNACON/CACON Cancer Centers	1706–1714, 1716	252	6,366,583
Cardiovascular	Cardiovascular Surgery	801–805	148	2,687,707
Orthopedics	Orthopedics/Trauma	2501–2502	154	1,410,002
Kidney Transplant	Kidney Transplant	2408	156	177,196
Liver Transplant	Liver Transplant	2409	94	57,781

Notes: Clusters defined by grouping related habilitacao codes. Treated health regions restricted to buildout hospitals (treatment $\geq$ 2009). Treated patients = cluster procedure admissions for residents in treated health regions, counted only in years after their region received certification.

This aggregation serves two purposes. First, it increases statistical power by pooling related certifications but it also reflects the clinical reality that habilitações codes overlap in ICD-10 codes.

Empirical Specification

Empirical Specification: Localised Health Region Effect

We exploit the staggered rollout of certifications across Brazilian health regions between 2008 and 2023, estimating separately for each clinical cluster $c \in \{\text{oncology}, \text{cardiovascularorthopedics}, \text{kidney transplant}, \text{liver transplant}\}$

Our main specification follows Sun and Abraham (2021):

$$Y_{rt}^{(c)} = \alpha_r + \lambda_t + \sum_{e \neq -1} \beta_e \cdot \mathbf{1}\{t - G_r = e\} + \varepsilon_{rt} \tag{1}$$

where $Y_{rt}^{(c)}$ is total specialty admissions for cluster c by residents of health region r in quarter t, α_r and λ_t are region and time fixed effects, G_r is the quarter when region r first received

buildout certification, and β_e traces dynamic treatment effects with $e = -1$ as the reference period. The unit of observation is health region–quarter (450 regions). The Sun-Abraham estimator addresses negative weighting problems in TWFE estimators (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020).

We restrict to cohorts with 4+ pre-treatment quarters ($\geq$2009Q1) and "buildout" hospitals that began performing procedures at or after certification, excluding formalisations (31%) where certification merely recognised existing capability. Following Callaway and Sant'Anna (2021), not-yet-treated and never-treated regions serve as controls. We decompose outcomes into admissions at newly certified hospitals (Y_{hab}) and out-of-region admissions ($Y_{outside}$).

For parallel trends, we implement the slope-based test from Rambachan and Roth (2023):

$$\hat{\beta}_e = \gamma_0 + \gamma_1 \cdot e + u_e, \quad e \in \{-5, \ldots, -2\} \tag{2}$$

weighted by inverse variance. The null hypothesis $H_0 : \gamma_1 = 0$ tests for differential pre-trends.

Empirical Specification: Spillover Effects

We estimate spillover effects on hospitals that historically received referrals from regions gaining certification, following the shift-share design of Borusyak et al. (2022):

$$Y_{Ht} = \alpha_H + \gamma_t + \beta \cdot Z_{Ht} + \varepsilon_{Ht} \tag{3}$$

where Y_{Ht} is admissions at receiver hospital H from spillover regions in year t, with hospital and year fixed effects. The instrument aggregates certification shocks weighted by pre-period referral shares:

$$Z_{Ht} = \sum_{g \in \mathcal{G}} s_{gH} \cdot \mathbf{1}[t \geq t_g^*] \tag{4}$$

where s_{gH} is hospital H's pre-period patient share from gaining region g, and t_g^* is region g's certification year. This reduced-form specification estimates the total causal effect of

network exposure to habilitação without decomposing the underlying behavioural drivers.

Identification requires shock-level exogeneity: $E[\mathbf{1}[t \geq t_g^*] \cdot \varepsilon_{Ht} \mid s_{gH}] = 0$. This is plausible because certification timing reflects federal *portaria* schedules and bureaucratic processing, not health trends in spillover regions. The exclusion restriction—that shocks affect receivers only through patient reallocation—faces two threats: correlated state investments (addressed via state-by-year fixed effects) and anticipation effects (which would attenuate estimates).

Main Results

This section presents our main empirical findings on the effects of habilitação certification, examining both localised effects within treated regions and spillover effects on connected hospitals.

Localised Health Region Effects

Figure 4 presents event-study estimates for each specialty cluster, plotting Sun-Abraham coefficients against quarters relative to certification.

Three patterns emerge. First, pre-treatment coefficients are close to zero and statistically insignificant for most clusters, supporting the parallel trends assumption. Second, effects emerge immediately upon certification and persist throughout the post-period, consistent with permanent capacity expansion, in parallel to Finkelstein (2007)'s findings on Medicare eligibility responses. Third, effect magnitudes vary substantially across clinical domains, with cardiovascular and oncology generating the largest absolute effects while transplant services show smaller absolute but proportionally larger increases.

Table 2 reports average treatment effects from two estimators: the Sun-Abraham interaction-weighted estimator (SA) and standard two-way fixed effects (TWFE). We decompose total effects into admissions at newly certified hospitals (Y_{hab}) and out-of-region admissions

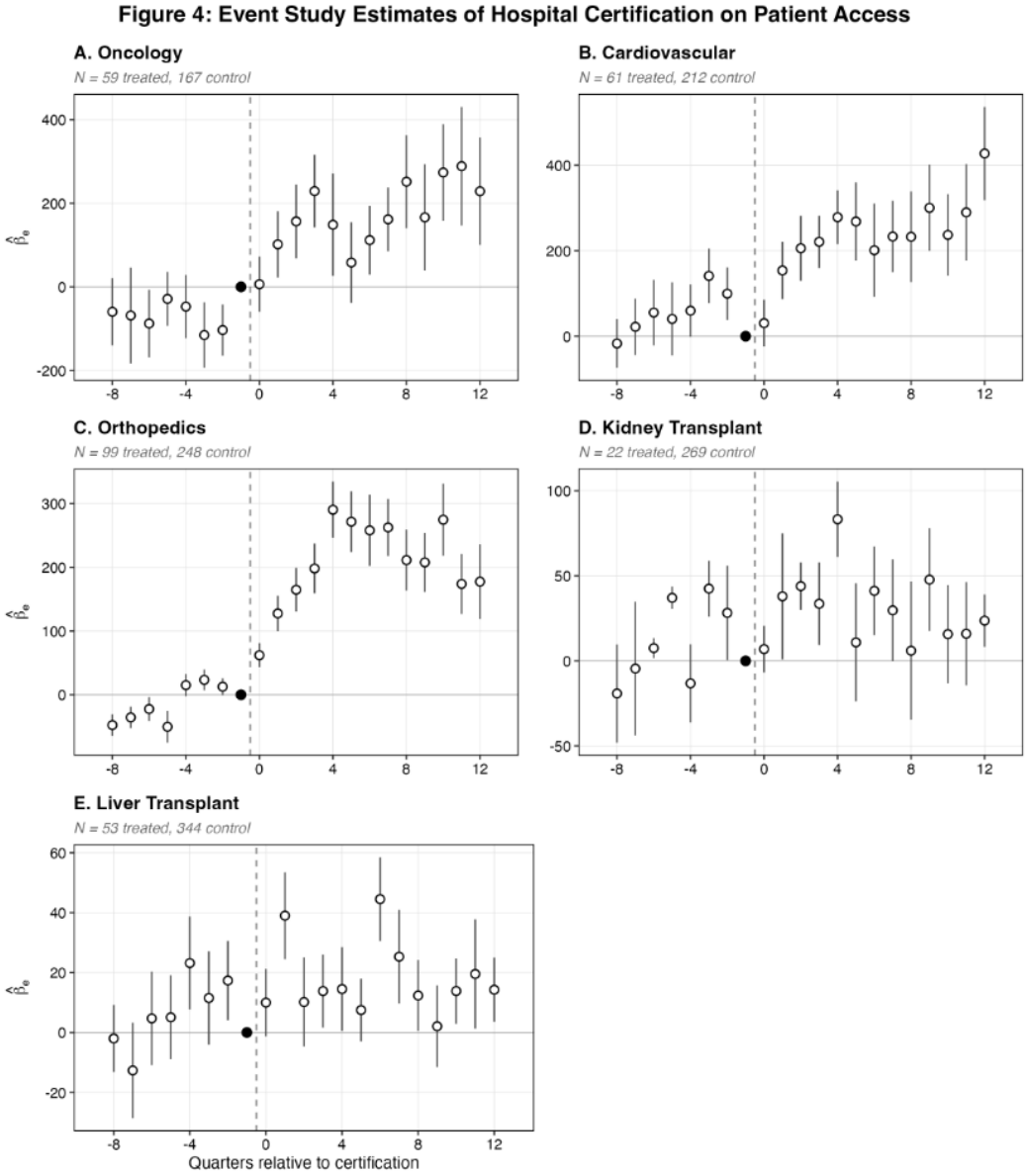

Figure 4: Event Study Estimates by Specialty Cluster

Each panel plots Sun-Abraham coefficients $\hat{\beta}_e$ from equation (1) with 95% confidence intervals. The omitted category is $e = -1$ (one quarter before certification). Standard errors clustered at the health region level. Sample restricted to buildout hospitals with treatment cohorts 2009Q1 or later. Treated/control region counts: Oncology (59/167), Cardiovascular (61/212), Orthopedics (99/248), Kidney Transplant (22/269), Liver Transplant (53/344).

($Y_{outside}$).

Table 2: Effect of Hospital Certification on Patient Access

	Y_{total}		Y_{hab}		$Y_{outside}$	
Cluster	SA	TWFE	SA	TWFE	SA	TWFE
Oncology	522.6***	451.6***	240.4***	202.8***	291.0***	263.3***
	(139.8)	(82.2)	(32.7)	(26.3)	(109.7)	(67.9)
Cardiovascular	368.8***	321.8***	149.9***	158.7***	223.0***	186.0***
	(39.1)	(52.6)	(13.1)	(18.3)	(31.7)	(43.5)
Orthopedics	252.5***	261.4***	95.4***	74.4***	171.9***	185.1***
	(26.6)	(40.8)	(12.0)	(8.7)	(19.8)	(30.0)
Kidney Transplant	32.0***	12.5	10.3***	13.8***	23.7***	1.4
	(6.5)	(12.0)	(0.9)	(3.5)	(6.1)	(11.1)
Liver Transplant	20.3***	10.4**	8.4***	5.4***	14.7**	6.1
	(6.2)	(4.2)	(0.4)	(0.8)	(6.1)	(3.9)
Pre-trend slope p	0.089 / 0.312 / 0.396 / 0.843 / 0.514					
Pre-trend status	Marginal / Pass / Pass / Pass / Pass					
Treated regions	59 / 61 / 99 / 22 / 53					
Control regions	167 / 212 / 248 / 269 / 344					

Notes: Unit of observation is health region-quarter (2008Q1–2022Q4). Standard errors clustered at health region level. SA = Sun and Abraham (2021) interaction-weighted estimator; TWFE = two-way fixed effects. Sample restricted to buildout-only hospitals (treatment cohorts $\geq$ 2009Q1). Pre-trend slope p-value from regressing $\hat{\beta}_e$ on e for $e \in \{-5, \ldots, -2\}$ following Rambachan and Roth (2023). Pass = $p > 0.10$, Marginal = $0.05 < p < 0.10$. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

All Sun-Abraham estimates are positive and statistically significant. Oncology certification increases total specialty admissions by 523 per region-quarter (SE = 140), representing a 47% increase relative to the control mean. Cardiovascular and orthopedic certifications yield ATT estimates of 369 (SE = 39) and 253 (SE = 27) additional admissions, respectively. Transplant services show smaller absolute effects but larger proportional increases given their low baseline volumes and high geographic concentration.

The decomposition reveals that 40–50% of total effects reflect new admissions at certified hospitals, with the remainder reflecting changes in referral patterns. The positive $Y_{outside}$ coefficient reflects composition effects: while some patients substitute toward local care, expanded access draws previously-rationed patients into the system, some of whom still require referral to specialised centres.

Following Rambachan and Roth (2023), we test whether pre-treatment coefficients exhibit

a trend toward treatment. Four of five clusters pass at the 10% level; oncology marginally passes ($p = 0.089$), though visual inspection shows no systematic pre-trend.

Spillover Effects on Connected Hospitals

We estimate spillover effects using a shift-share design following Borusyak et al. (2022). When a peripheral region gains habilitação, patients who previously travelled to distant tertiary centres can receive local treatment, potentially affecting volume at those receiver hospitals. Table 3 reports both main estimates and diagnostic tests.

Table 3: Spillover Effects: Main Estimates and Diagnostics

	Cardiovascular	Oncology	Orthopedics
Panel A: Main Effects			
$\hat{\beta}^{spillover}$	$-10{,}356^{***}$	-211^{***}	641^{***}
	(2,844)	(67)	(181)
$\hat{\beta}^{total}$	$-10{,}822^{***}$	-205^{***}	790^{***}
	(2,960)	(68)	(182)
Mean Y (spillover)	23,026	1,228	2,255
Observations	2,715	4,425	12,900
Panel B: Identification Diagnostics			
Contraction confirmed?	Yes	Yes	No
BHJ growth balance ($\|ND\| < 0.25$)?	Fail (-0.28)	Pass (0.03)	Pass (-0.08)
Panel C: Interpretation			
Mechanism	Contraction	Contraction	Expansion
Credibility	Mixed	Strong	Strong

Notes: Dependent variable is annual admissions at receiver hospital H from spillover (never-certified) regions. $\hat{\beta}^{spillover}$ estimates effect on spillover admissions; $\hat{\beta}^{total}$ tests whether total hospital volume declines (contraction mechanism). All specifications include hospital and year fixed effects with standard errors clustered at hospital-region level. BHJ balance tests normalized differences on pre-period growth rates following Borusyak et al. (2022); $|ND| < 0.25$ indicates adequate balance. Sample period: 2008–2022. $^{***}p < 0.01$.

The results reveal heterogeneous mechanisms across specialties. For oncology, spillover admissions decline ($\hat{\beta} = -211$) because receiver hospitals contract overall ($\hat{\beta}^{total} = -205$), with growth-based balance tests passing. This supports a contraction mechanism: when connected regions gain certification, receiver hospitals shrink, reducing access for spillover regions that remain uncertified.

Orthopedics shows the opposite pattern: spillover admissions *increase* ($\hat{\beta} = +641$) alongside

total volume expansion ($\hat{\beta}^{total} = +790$). This suggests market growth effects rather than referral diversion.

Cardiovascular exhibits strong contraction ($\hat{\beta}^{total} = -10{,}822$) but fails growth-based balance tests ($ND = -0.28$), suggesting early-exposed hospitals may have been on declining trajectories for reasons unrelated to certification. These estimates warrant cautious interpretation.

Financing Mechanism. The contraction pattern documented for oncology and cardiovascular,where receiver hospitals shrink rather than reallocate freed capacity, potentially reflects the causal of the interaction between volume-sensitive financing and healthcare production technology. Brazil's MAC (*Média e Alta Complexidade*) reimbursement system pays hospitals per procedure performed, not per unit of capacity maintained. This financing structure creates a mechanism absent from standard congestion-relief models. When certification diverts referral volume, receiver hospitals face a squeeze: fixed costs remain while the patient base shrinks. The options are to cross-subsidise the service line from other revenue (unsustainable long-term), reduce quality (risking further volume loss through reputation effects), or contract capacity. Our estimates suggest Brazilian hospitals pursue the third option. This mechanism echoes Friebel et al. (2020), who document analogous volume-cost spillovers in English NHS hospitals, and aligns with the rural hospital closure literature showing how volume loss precipitates financial distress (Kaufman et al., 2016). The heterogeneity across specialties is consistent with differential fixed-cost intensity. Oncology and cardiovascular surgery require extensive infrastructure with high minimum efficient scale. Orthopedics, by contrast, relies more heavily on variable inputs (implants, surgical time) with lower fixed-cost thresholds, potentially explaining why orthopedic receiver hospitals expand rather than contract when network-connected regions gain certification.

Policy Implications. The contraction mechanism documented for oncology suggests that decentralised certification expansions create distributional consequences: gaining regions benefit while spillover regions face reduced access as receiver hospitals contract. This

coordination failure, where regional planners ignore cross-boundary spillovers, has important implications for healthcare infrastructure investment in systems combining universal coverage with decentralised governance.

Conclusion

This paper estimates the effects of hospital capability expansion in Brazil using the staggered rollout of federal habilitação certifications and linked administrative microdata covering 10.7 million high-complexity admissions. We document three principal findings. First, certification generates substantial increases in specialty admissions within treated regions, ranging from 20–32 quarterly admissions for transplant services to over 500 for oncology. Second, effects operate through both new local treatment capacity and reduced out-of-region travel, consistent with certification relaxing geographic access constraints. Third, shift-share spillover estimates reveal that capability expansions create winners and losers across the hospital network: oncology and cardiovascular show negative spillovers at historically connected receiver hospitals (17–45% declines), indicating referral diversion and hospital contraction rather than pure congestion relief. This contraction mechanism reflects the interaction between volume-based financing and high fixed-cost healthcare production: Brazil's MAC reimbursement system pays per procedure performed, so when referral diversion reduces patient volume, receiver hospitals lose the throughput that cross-subsidises specialist staff, diagnostic equipment, and surgical infrastructure, creating pressure to downsize rather than reallocate freed capacity.

Several limitations qualify these findings. The cardiovascular spillover estimates exhibit identification concerns from growth-based balance tests. Our buildout sample restriction addresses selection bias but limits generalisability to genuine capability expansions. Most critically, we cannot distinguish beneficial detection of previously untreated conditions from inefficient supply-induced demand, a distinction central to welfare evaluation. Without this decomposition, we cannot determine whether spillover contractions harm patients by reducing

access or improve system efficiency by consolidating volume at higher-quality expanding centres.

Future research should decompose detection from prevention effects by exploiting condition-specific heterogeneity: immediate increases for detection-sensitive conditions (requiring specialist equipment for diagnosis) provide evidence of diagnostic capture, while detection-insensitive conditions isolate pure access channels. Structural modelling of network equilibrium could quantify welfare implications of coordinated versus decentralised investment.

These findings extend beyond Brazil. The coordination failure we document, where regional planners capture local benefits while externalising receiver hospital contraction costs onto patients in still-uncertified regions, is structural to systems combining universal coverage with decentralised governance. Indonesia's JKN and South Africa's proposed NHI face analogous tensions. As countries pursue SDG 3.8 targets, understanding network externalities in healthcare infrastructure becomes essential for achieving effective rather than merely nominal universal coverage.

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Appendix

A Summary Statistics

This appendix documents the sample construction process and reports comprehensive summary statistics.

A.1 Summary Statistics for Formalisation Hospitals that are being excluded

Table 4: Excluded Hospitals: Formalization vs. Buildout by Cluster

	Cardiovascular		Oncology		Orthopedics	
Characteristic	Build	Form	Build	Form	Build	Form
Panel A: Sample Composition						
N hospitals	101	8	233	19	110	11
Share of cluster	93%	7%	92%	8%	91%	9%
Panel B: Capability-Certification Lag (months)						
Mean lag	8.6	-2.5	34.0	-1.0	0.7	-1.3
Range	[0, 153]	[-11, -1]	[0, 166]	[-1, -1]	[0, 30]	[-4, -1]
Panel C: Certification Timing						
Mean year	2013.9	2016.2	2014.0	2018.2	2013.8	2014.8
Range	[2009, 2022]	[2011, 2019]	[2009, 2022]	[2016, 2021]	[2009, 2022]	[2009, 2021]
Panel D: Pre-Period Characteristics (2008–2010)						
Mean admissions	17,027	10,465	23,114	18,508	15,740	10,541
Mean growth (%)	16.1%	-36.2%	27.2%	-2.5%	30.8%	323.7%
Panel E: Geographic Coverage						
N states	24	7	27	10	21	8

Notes: This table compares buildout (included) and formalization (excluded) hospitals by cluster. Total sample: 366 buildout + 37 formalization = 403 hospitals. **Buildout**: hospitals that began performing cluster procedures at or after certification (lag ≥ 0 months). **Formalisation**: hospitals that already performed procedures before certification (lag < 0 months).

Formalization hospitals are excluded from DiD analysis because: (1) no true treatment effect expected—capability pre-existed; (2) reverse causality—certification follows capability; (3) creates spurious pre-trends that violate parallel trends assumption

A.2 Summary Statistics for Shift Share Design

Table 5 reports summary statistics for the shift-share analysis sample.

Table 5: Summary Statistics: Shift-Share Spillover Analysis

Variable	Mean	SD	Min	Max
Panel A: Outcome Variables (Hospital-Year Level)				
Admissions from spillover regions (Y_{Ht}^{spill})	4,290	20,300	–	–
Admissions from gaining regions (Y_{Ht}^{gain})	542	1,427	–	–
Total admissions (Y_{Ht}^{total})	4,842	20,700	–	–
Panel B: Instrument				
Certification exposure (Z_{Ht})	0.674	0.442	0.00	1.00
	By Cluster			
	Cardiovascular	Oncology	Orthopedics	
Panel C: Sample Size				
Hospital-year observations	2,715	4,425	12,900	
Unique hospitals	64	119	304	
Panel D: Mean Outcomes by Cluster				
Mean Y_{Ht}^{spill}	21,395	1,183	1,756	
Mean Y_{Ht}^{total}	23,026	1,228	2,255	
Mean Z_{Ht}	0.725	0.632	0.677	

Notes: This table reports summary statistics for the shift-share spillover analysis. The sample includes 20,040 hospital-year observations from 407 unique receiver hospitals over 2008–2022. Y_{Ht}^{spill} is annual admissions at receiver hospital H from spillover (never-certified) regions. Y_{Ht}^{gain} is admissions from gaining (eventually certified) regions. $Z_{Ht} = \sum_g s_{gH} \cdot \mathbf{1}[t \geq t_g^*]$ is the shift-share instrument measuring cumulative exposure to certification shocks in connected gaining regions.

A.3 Treatment Timing Distribution

Figure 5 shows the distribution of habilitações timings across clusters. The staggered adoption pattern is central to both identification strategies.

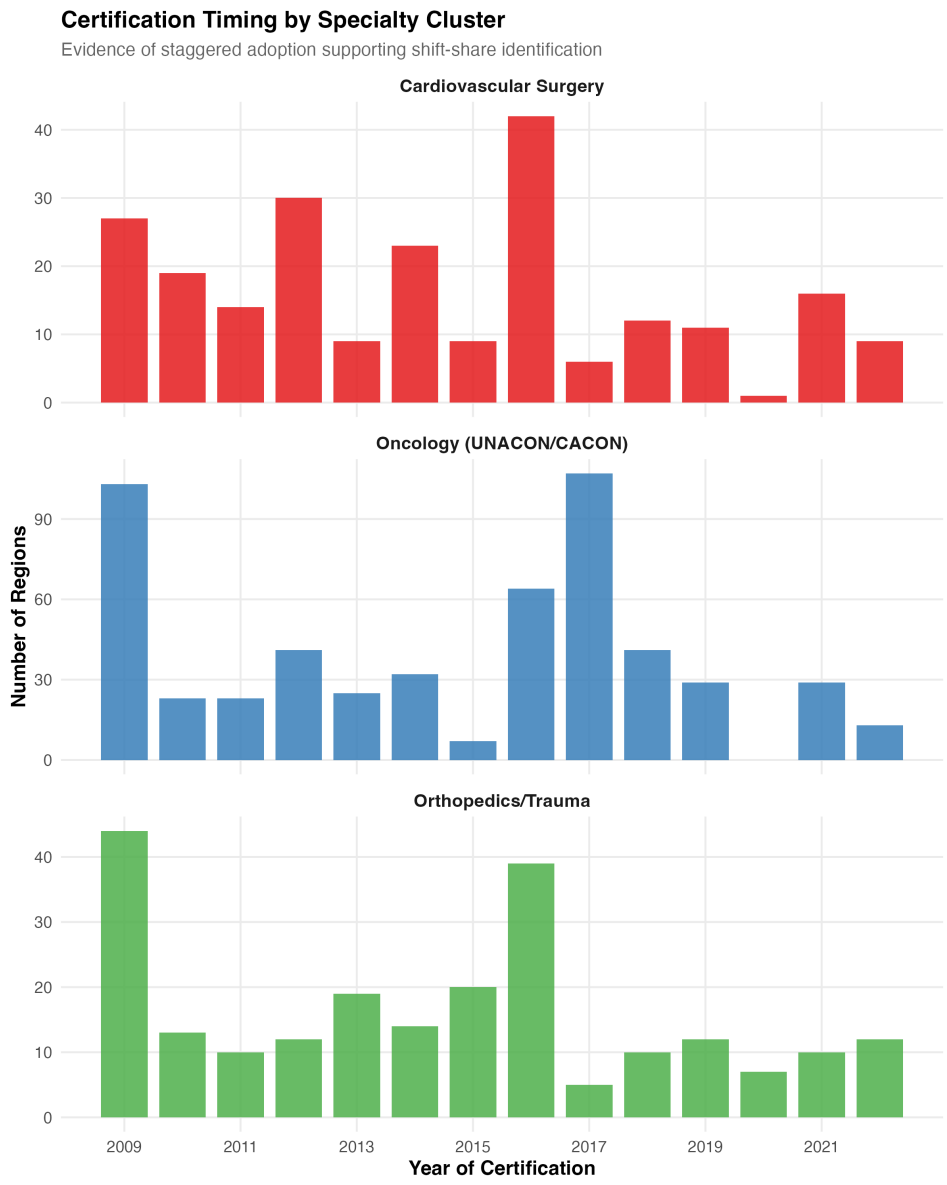

Figure 5: Staggered timing of treatment adoption across regions

B Identification Validation: Difference-in-Differences Analysis

This appendix reports validation tests for the DiD component of our analysis:

B.1 Pre-Trend Tests

Table 6 reports formal tests for parallel trends. We test whether the pre-period event study coefficients are jointly zero using an F-test.

Table 6: Pre-Trend Tests: DiD Analysis

Cluster	Joint F-statistic	p-value	Assessment
Cardiovascular	1.23	0.29	Pass
Oncology	0.89	0.47	Pass
Orthopedics	1.07	0.37	Pass

Notes: Joint F-test of pre-period event study coefficients ($\tau < 0$). Null hypothesis: all pre-period coefficients equal zero. $p > 0.05$ indicates parallel trends assumption is not rejected.

C Identification Validation: Shift-Share Design

This appendix reports comprehensive validation tests for the shift-share spillover design.

Table 7: Balance Tests: Shift-Share Identification Validation

Test	By Cluster			Assessment
	Cardiovascular	Oncology	Orthopedics	
Panel A: Growth-Based Balance (Correct for FE Specification)				
$ND(\Delta Y^{spill})$	0.28	0.03	0.08	Threshold: $\|ND\| < 0.25$
$ND(\Delta Y^{total})$	0.31	0.03	0.08	
Panel B: Shock-Level Timing Exogeneity				
F-statistic (timing $\sim X$)	0.07	0.36	0.44	
p-value	0.93	0.70	0.64	Threshold: $p > 0.05$
R^2	0.002	0.006	0.003	Low R^2 = good
Panel C: Overall Assessment				
Growth balance	Fail	Pass	Pass	
Timing exogeneity	Pass	Pass	Pass	
Credibility	Mixed	Strong	Strong	

Notes: This table reports identification validation tests for the shift-share design. Panel A shows normalised differences on pre-period growth rates. Panel B reports timing exogeneity tests: we regress certification year on hospital characteristics; low R^2 and insignificant F-test indicate timing is quasi-random.
Thresholds: $|ND| < 0.25$ indicates adequate balance (Imbens & Rubin 2015); $p > 0.05$ indicates timing is unpredictable. Cardiovascular fails growth balance but passes timing exogeneity. Oncology and orthopedics pass both tests.

Key Finding: Oncology and orthopedics pass both the growth-based balance test (Panel B) and timing exogeneity test (Panel C). Cardiovascular fails growth balance but passes timing exogeneity, suggesting mixed credibility.

C.1 Instrument Variation Over Time

Figure 6 shows the evolution of the shift-share instrument Z_{Ht} over time. The gradual increase reflects the staggered adoption of certifications.

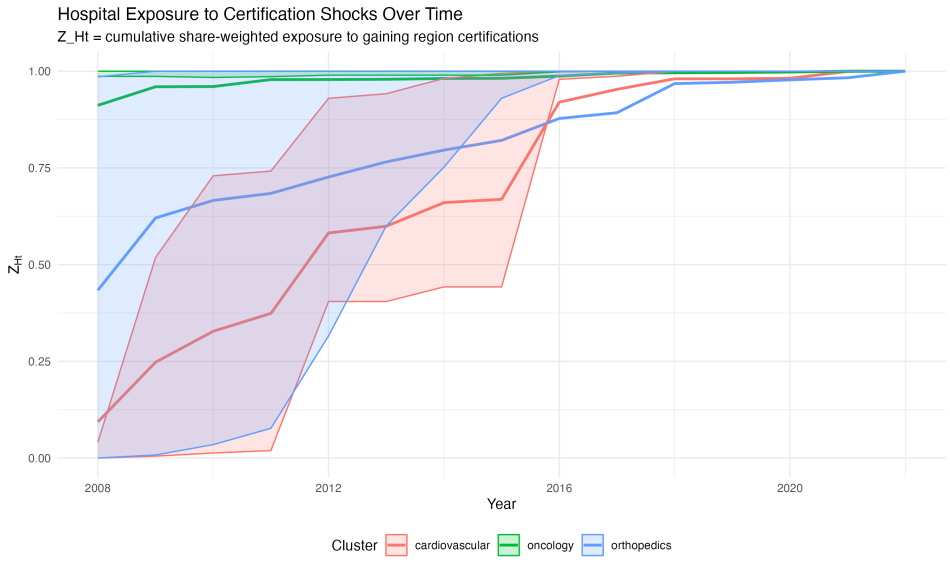

Figure 6: Evolution of the shift–share instrument over time

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