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Do Hospital Beds Fill Themselves? Capacity, Physician Behavior, and Healthcare Spending

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Abstract

We provide causal evidence that increased bed availability induces substitution from outpatient to inpatient care without improving health outcomes—consistent with physicians operating on the "flat of the curve." We find that capacity effects concentrate in regions with abundant physicians and high baseline bed capacity, supporting target income models and Roemer's Law. Conservative estimates suggest these discretionary admissions generate 38-63 million USD potentially avoidable spending annually. Our findings demonstrate that supply-side factors drive geographic variation in healthcare utilization and indicate meaningful scope for cost reduction through capacity optimization without compromising access to medically necessary care in aging societies.

Keywords: Hospital capacity; Physician behavior; Supplier-induced demand; Healthcare expenditure; Aging population
JEL Codes: I11, I18, J14

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Hospital bed capacity represents a central policy lever in healthcare systems worldwide, with substantial cross-national variation in bed supply, occupancy, and hospital infrastructure investment (OECD, 2023). Yet fundamental questions remain about how capacity influences provider behavior and patients' health: Do capacity expansions improve health by facilitating timely treatment, or do they induce discretionary utilization without commensurate health gains? The distinction matters: if the marginal health returns to capacity are low, substantial public resources may be misallocated. Prior research has documented a direct correlation between healthcare expenditure and hospital bed availability (Gaynor & Anderson, 1995), though the causal mechanisms underlying this relationship remain unclear.

Understanding the causal relationship between bed capacity and care delivery and the underlying mechanism is essential for efficient resource allocation. This requires examining the tension between social optimality and individual decision-making under information asymmetry. From a social planner's perspective, expanded bed capacity should improve welfare by reducing waiting time and enabling timely treatment for patients requiring hospitalization. However, standard economic theory predicts more complex behavioral responses when physicians act as imperfect agents in fee-for-service systems. Arrow (1963) identified the informational asymmetry that characterizes medical markets: patients cannot perfectly observe their own healthcare needs or evaluate treatment appropriateness, creating scope for physician discretion. Building on this, Evans (1974) formally articulated how such asymmetries enable physicians to influence patients' utilization decisions for their own economic benefit.

Two complementary theoretical frameworks generate testable predictions about physician responses to capacity changes. The target income hypothesis (McGuire and Pauly, 1991; Gruber and Owings, 1996; McGuire, 2000) suggests that physicians maintain target income levels by adjusting the quantity and types of healthcare services provided when facing negative income shocks. When there are fewer patients and more empty beds available, physicians and hospitals may regard this as a potential income loss and therefore, they have incentives to provide excess care by admitting more patients. This mechanism predicts that increased capacity will shift treatment patterns toward inpatient settings, with stronger effects where physician time constraints are less binding.

In addition, Roemer's Law (Roemer, 1961) posits that available capacity generates its own demand through behavioral adjustments that justify capital investments and spread fixed costs. Fisher et al. (2000) documented that regions with higher hospital bed capacity exhibited higher utilization rates even after controlling for population health characteristics, providing empirical support for this theoretical mechanism. This predicts that capacity effects should be stronger in regions with higher baseline bed capacity, where infrastructure investment creates stronger utilization incentives.

These theoretical frameworks generate five testable predictions that guide our empirical analysis and allow us to distinguish between competing explanations for any observed capacity effects:

- Hypothesis 1 (Treatment Substitution): Increased bed capacity will shift treatment patterns from outpatient to inpatient care.
- Hypothesis 2 (Physician Supply): Capacity effects will be stronger in regions with higher physician density, where time constraints are less binding.
- Hypothesis 3 (Hospital Infrastructure): Capacity effects will be stronger in regions with higher baseline bed capacity per capita.
- Hypothesis 4 (Complementary Inputs): If complementary inputs like nursing staff constitute binding constraints, capacity effects may be attenuated in regions with lower nurse-to-bed ratios.

- Hypothesis 5 (Flat of the Curve): If capacity-induced treatment changes reflect discretionary rather than medically necessary care, we should observe increased utilization and costs without corresponding improvements in health outcomes (mortality).

Our main results test hypotheses 1 and 5, while our heterogeneity analyses directly test hypotheses 2, 3, and 4.

Empirically identifying capacity effects is challenging since bed availability and healthcare utilization are jointly determined. Regions with high hospital capacity may attract sicker populations or physicians with preferences for aggressive treatment, creating selection bias. Simultaneously, treatment patterns affect bed availability through reverse causality: increased admissions and longer stays mechanically reduce empty beds. Early studies documented positive correlations between bed supply and utilization (Roemer, 1961; Fisher et al., 2000) but could not distinguish supply-side effects from demand-side sorting. This identification challenge has limited researchers' ability to provide causal evidence on how physicians respond to capacity constraints and whether these responses reflect efficient resource utilization or discretionary demand inducement.

Recent work has made progress using quasi-experimental designs in specialized medical contexts. Freedman (2016) exploited short-run variation in neonatal intensive care unit (NICU) bed availability, finding that capacity expansions had minimal effects on the sickest infants but increased utilization for the infants with more discretionary admission criteria —evidence consistent with supplier-induced demand at the margin. Goodman et al. (2024) extended this analysis, similarly finding increased NICU utilization for late preterm and non-preterm newborns without detectable reductions in adverse events. In other contexts, Watts et al. (2011) documented correlations between bed capacity and psychiatric admission rates, Walsh et al. (2022) found similar patterns for emergency department patients, and Sharma et al. (2008) provided evidence that constrained capacity leads to earlier discharges while leaving admission decisions relatively unaffected. While these studies consistently suggest that capacity influences utilization, they focus on specialized contexts, especially in neonatal intensive care and emergency settings, where clinical decision-making may differ substantially from typical medical care. Moreover, the exclusive focus on childbirth in the most credibly identified studies (Freedman, 2016; Goodman et al., 2024) leaves open whether capacity effects generalize to the diverse medical conditions affecting older populations who account for the majority of healthcare spending in developed countries.

This paper makes four primary contributions to understanding physician behavior and healthcare resource allocation. First, and most importantly, we provide the first credibly identified estimates of capacity effects on general medical services for a representative elder population with diverse conditions. Prior causal evidence comes almost exclusively from specialized neonatal intensive care settings (Freedman, 2016; Goodman et al., 2024), leaving unclear whether capacity constraints shape treatment patterns for the chronic, age-related conditions that dominate healthcare spending in developed countries. By studying Japan's oldest-old population aged 75 and above (75+)—a demographic of increasing global significance given rapid population aging (WHO, 2024) and accounting for over half of inpatient costs—we examine capacity effects in the economically most significant healthcare context. This population is particularly important to study because elder patients are vulnerable to both physical and mental health challenges, often requiring intensive healthcare services while experiencing substantial information asymmetries that can make them susceptible to induced demand (Hay and Leahy, 1982; Johnson, 2014; Johnson and Rehavi, 2016; Mohammadshahi et al., 2019). Johnson and Rehavi (2016) found that physicians are significantly less likely to receive cesarean sections when giving birth compared to non-physicians with similar risk characteristics, demonstrating that information asymmetry drives treatment variation toward over-utilization for patients who lack medical knowledge. For elder patients with chronic conditions requiring ongoing management, this information gap may be even larger than for acute conditions with clearer clinical protocols. The generalizability question is not merely whether effects exist in different populations, but whether the economic mechanisms (target income behavior, Roemer's Law) operate similarly across the chronic disease management that characterizes elderly care versus acute neonatal interventions. Our evidence demonstrates that capacity effects extend beyond specialized high-technology settings to the routine medical care that drives aggregate healthcare expenditures.

Second, we employ a novel identification strategy exploiting plausibly exogenous variation from pandemic-driven bed allocations, offering methodological advantages over long-run capacity variation. The Japanese government's COVID-19 Hospital Beds Securing Plan required each secondary medical service area (SMA) to designate specific beds exclusively for COVID-19 patients, mechanically reducing capacity available for non-COVID conditions (MHLW, 2024b).[1] Since total bed capacity was predetermined (by six-year medical care plans) and remained fixed during our study period, and assignment decisions responded to pandemic phases rather than pre-existing utilization patterns, this policy provides quasi-random variation in effective capacity. Unlike previous studies exploiting long-run capacity differences potentially confounded by unobserved regional characteristics, our short-run variation isolates the behavioral response to capacity changes while holding constant market structure, physician composition, and treatment culture.

Third, we directly test theoretical predictions about mechanisms through heterogeneity analyses, providing evidence on which resource constraints bind physician decision-making. We find that both physician supply and baseline hospital infrastructure mediate capacity effects: treatment responses

[1] The MHLW's Hospital Beds Securing Plan (April 2021–March 2024) included provisions for temporary medical facilities and designated waiting areas. Details (in Japanese) are available at https://www.mhlw.go.jp/stf/seisakunitsuite/newpage_00062.html (accessed November 18, 2025).

concentrate in regions with abundant physicians and high baseline bed capacity, consistent with Hypotheses 2 and 3. Notably, nurse availability does not moderate responses, suggesting that physical capital rather than complementary nursing inputs constitute the binding constraint—rejecting the mechanism in Hypothesis 4. This pattern of heterogeneity provides the first systematic evidence on which resources enable or constrain capacity-driven utilization changes, with direct implications for optimal resource allocation.

Fourth, we provide comprehensive evidence on the welfare implications through cost and mortality analyses. The observed treatment substitution increases average healthcare costs by approximately 318 JPY (3.2 USD) per percentage point increase in bed capacity, representing a 1.4% increase relative to mean inpatient costs. Crucially, we find no detectable effects on mortality rates across any subgroup or specification, supporting Hypothesis 5. This combination— meaningful cost increase without measurable health improvements—suggests that marginal treatments induced by capacity expansion lie in the 'flat of the curve' region where additional spending yields minimal health benefits (Fuchs, 2004; Chandra and Staiger, 2007; Doyle, 2011). We estimate that capacity-induced discretionary admissions generate approximately 38-63 million USD annually in potentially avoidable spending across Japan's elder population, representing 0.011-0.018% of total healthcare expenditure for this demographic. These findings indicate that capacity-driven utilization changes reflect discretionary practice variation rather than clinically necessary adjustments, with meaningful implications for healthcare efficiency.

Our findings suggest that careful government oversight of hospital bed allocation is crucial for preventing healthcare service over-utilization and managing medical expenses effectively, particularly in healthcare systems with constrained physician resources. More broadly, our results contribute to understanding the behavioral foundations of geographic variation in healthcare spending and the potential for supply-side interventions to improve allocative efficiency in healthcare markets.

While our study focuses on Japan, the findings have broad relevance for aging societies worldwide. By 2050, individuals aged 75+ will comprise over 15% of populations in most OECD countries (United Nations, 2023). Though Japan's institutional configuration—the world's highest hospital bed capacity (27.3 per 1,000 inhabitants) combined with below-average physician supply (2.7 per 1,000)— is extreme (OECD, 2023), the behavioral mechanisms we identify are rooted in general economic principles that operate wherever fee-for-service payment and information asymmetry create scope for discretionary decision-making. Our results therefore provide evidence on how capacity constraints shape physician behavior under conditions—aging populations, fiscal pressures, and resource trade-offs—increasingly common across developed economies.

The remainder of this paper is structured as follows: Section I presents the institutional background of Japan's healthcare system and the COVID-19 bed allocation policy that provides exogenous variation in our identification strategy, and Section II describes the data and measurements with basic statistics. Section III elucidates the identification strategy in detail, including tests of instrument validity and threats to identification. Section IV presents the main results, robustness and heterogeneity analyses. We conduct back-of-the envelope calculations in Section V and discuss the results and their broader implications for healthcare policy and economic theory in Section VI. Section VII offers concluding remarks.

I. Institutional Background

This section describes the institutional context for our empirical analysis. We first outline healthcare utilization patterns among Japan's older population, then explain the regulatory framework governing hospital bed allocation, and finally describe the COVID-19 bed allocation policy that provides identifying variation for our instrumental variable strategy.

A. Healthcare utilization patterns in Japan

Japan's rapid demographic aging has created distinctive healthcare utilization patterns that concentrate medical resources on elderly population. Hospitalization rate reaches 3,568 per 100,000 inhabitants, compared to just 302 per 100,000 for younger populations (MHLW, 2020). Despite gradual reductions in recent decades, Japan maintains exceptionally long hospital stays, with a national average of 12.6 days compared to the OECD average of 4.3 days (Hashimoto et al., 2011; OECD, 2024).[2] For the 75+ age group, average hospitalization duration extends to 45 days (MHLW, 2020), reflecting both the complex healthcare needs of this population and potentially inefficient resource utilization.

These extended stays represent substantial healthcare expenditure. In 2022, inpatient care for the 75+ population reached 8.5 billion USD (calculated at 1USD=100JPY), accounting for approximately 51% of Japan's total inpatient care costs (MHLW, 2024a). This concentration of healthcare spending on elderly inpatient services creates a policy environment where capacity constraints may significantly affect both treatment patterns and fiscal sustainability. Understanding how physicians adjust treatment decisions when inpatient capacity becomes constrained is therefore essential for both healthcare quality and expenditure management in Japan's aging society.

B. Hospital bed regulation in medical service areas

Under the Medical Care Act, the Japanese healthcare provision system is organized into a three-tier hierarchical framework of medical service areas (primary, secondary, and tertiary) designed to ensure

[2] In 2023, hospital beds per 1,000 inhabitants were: Germany 8.9, France 9.1, UK 7.7, South Korea 19.6, US 6.6. Average length of hospital stay (days): Germany 7.7, France 5.5, UK 2.5, South Korea 12.8, US 2.8.

efficient service delivery. Among these tiers, the secondary medical service area (SMA: *Niji-Iryoken* in Japanese) serves as the most critical administrative division in healthcare policymaking (Tanihara et al., 1997; Hosokawa et al. 2020; MHLW, 2022a). As of April 2024, Japan comprises 335 SMAs, defined based on geographic conditions, transportation infrastructure, population density, and other relevant factors (MHLW, 2022b; MHLW, 2024d; Ministry of Internal Affairs and Communication, 2024). National and prefectural governments use these SMAs as the primary unit for medical resource allocation, including the distribution of hospital beds and physicians within their medical care plans.

The number of hospital beds in each SMA is legally regulated by prefectural governments according to a uniform nationwide formula as follows:

$$\text{Number of beds} = \Big((\text{Population by sex and age group}) \times (\text{Discharge ratio by sex and age group}) \times (\text{Average length of hospital stay}) + (\text{Number of inpatients admitted from outside the SMA}) - (\text{Number of inpatients admitted to hospitals outside the SMA})\Big) \div \text{Bed occupancy rate}.$$

Any modification to bed numbers or facility applications requires submission and approval from the prefectural governor, as stipulated by Article 7 of the Medical Care Act. In regions with bed surpluses, prefectural governors may, after consulting the Prefectural Medical Council, deny approval for bed changes or new medical institution establishments. The SMA-based bed standards are revised every six years, coinciding with medical care plan revisions (MHLW, 2022b).

This regulatory framework provides an important institutional foundation for our identification strategy. The standardized nationwide formula for bed allocation, coupled with strict prefectural oversight, creates clear capacity boundaries that are largely independent of local physician preferences or treatment patterns. Moreover, the six-year planning cycle means that total bed capacity within each SMA remains effectively fixed in the short run, making the COVID-19 bed reassignments a true exogenous shock to available capacity for non-COVID conditions.

C. COVID-19 bed allocation: policy implementation and variation

The COVID-19 pandemic prompted the Japanese government to implement the "Hospital Beds Securing Plan" that required each SMA to designate a specific number of hospital beds exclusively for COVID-19 patients.[3] The bed assignment was predetermined by prefectural government directives depending on the local COVID-19 caseloads and the total bed capacity available in each SMA (MHLW,

[3] Japan's COVID-19 response included States of Emergency and business restrictions (Nakamoto et al., 2022; Okamoto, 2022; Sen-Crowe et al., 2021). We focus on the Hospital Beds Securing Plan as it provides exogenous variation in non-COVID capacity.

2024c). Crucially, because total bed capacity available in each SMA is fixed by the six-year medical care plans, these COVID-19 bed assignments mechanically reduced the capacity available for non-COVID-19 medical services. The magnitude of this capacity reduction was determined by prefectural government directives responding to pandemic conditions rather than by pre-existing utilization patterns for non-COVID conditions, thus providing an exogenous variation in effective hospital capacity. This policy's implementation created substantial variation in capacity constraints across both SMAs and time periods. Figure 1 illustrates the variation by showing the average COVID-19 bed assignment rate and the resulting empty bed rates across SMAs from December, 2021 to November, 2022—the core period of our analysis. Panel A displays the proportion of total beds designated for COVID-19 patients in each SMA, revealing considerable cross-sectional heterogeneity in the intensity of bed reassignment. Panel B shows the corresponding variation in empty bed rates, which reflect the net effect of COVID-19 bed assignments on effective capacity available for general medical services.

[Figure 1]

Several patterns emerge from this variation: first, COVID-19 bed assignment rates varied substantially across SMAs, reflecting differences in local pandemic severity and prefectural policy responses. Second, empty bed rates show corresponding variation, with some SMAs experiencing tighter capacity constraints than others during the same time periods. Third, both measures exhibit temporal fluctuation as pandemic waves waxed and waned, creating within-SMA variation over time in addition to cross-sectional differences. This multidimensional variation—across SMAs, over time, and in response to exogenous pandemic shocks rather than endogenous utilization decisions—provides the identifying variation for our instrumental variable strategy. We exploit differences in the timing and magnitude of COVID-19 bed assignments across SMAs to identify how changes in effective capacity affect physicians' treatment decisions for non-COVID patients. Section III describes in detail how we construct our instrumental variable from this policy-induced capacity variation and presents empirical tests of the key identification assumptions, including the exclusion restriction that COVID-19 bed assignments affect non-COVID treatment patterns only through their effect on available capacity.

II. Data and measurements

This study integrates four administrative datasets from Japan's MHLW. Our primary data source is the Medical Claims Data with Income Tax Information for the Oldest-Old for Japan (MCD-Tx), an individual-level panel combining monthly medical claims with income data for individuals aged 75+. As of September 2022, this dataset covers 18.52 million individuals (98.6% of Japan's 75+ population) enrolled in the Latter-Stage Elderly Healthcare System (LSEH).[4] We supplement this with three additional MHLW datasets: the Hospital Report, which provides monthly data on total beds and occupancy by hospital; the Hospital Beds Availability and Utilization Report, which documents COVID-19 bed assignments beginning December 2021; and Vital Statistics, which records individual death information.

Our study period spans from December 2021 to November 2022. We exclude two groups from our analysis. First, we exclude individuals who were ever infected by COVID-19 to ensure that the health status of our sample was not contaminated by COVID-19. This exclusion is essential for our identification to isolate the effect of capacity constraints on non-COVID care. Second, we exclude individuals diagnosed with respiratory system-related diseases during the study period, as these conditions may directly compete for medical resources with COVID patients.[5] We aggregate individual-level data to the SMA-month level, yielding 3,888 observations representing the complete universe of 324 SMAs over the 12-month study period.[6] This panel structure allows us to exploit both cross-sectional and temporal variation in bed availability while controlling for time-invariant SMA characteristics and common temporal trends.

Our primary explanatory variable is the share of empty beds, calculated as the ratio of empty beds to total beds in each SMA-month. This measure captures effective bed availability for non-COVID patients and varies both across SMAs and over time due to differences in COVID-19 bed assignments and baseline capacity. We measure treatment patterns across four dimensions. For inpatient care, we calculate the average hospital admission rate and the average length of hospital stays per patient-month in each SMA. For outpatient care, we calculate the average probability of doctor visits and the average visit frequency per patient-month. To assess economic implications, we also measure the average costs for inpatient and outpatient care per patient-month in each SMA. Finally, we calculate the mortality rate per 1,000 individuals in each SMA-month as our health outcome measure. Table 1 presents summary statistics for our analysis sample. The average empty bed rate is 25.88%, with a COVID-19 bed assignment rate of 2.37% of total bed capacity, indicating substantial remaining capacity for non-COVID care. Treatment patterns reveal a stark contrast: 76% of patients receive outpatient care monthly compared to only 4% receiving inpatient care, reflecting Japan’s emphasis on outpatient management of chronic conditions. The average age is 83 years and the average annual income is 1,792,220 JPY (approximately 17,922 USD). The mortality rate averages 1.2 per 1,000 individuals monthly.

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[4] The Later-Stage Elderly Healthcare (LSEH) system, established in 2008, provides universal coverage for residents aged 75+. Funding comes from government (50%), insurance schemes for those under 75 (40%), and beneficiary premiums (10%) (Ikegami et al., 2011).

[5] We also conducted robustness by including this sample in the Appendix B.

[6] Our sample covers 324 of Japan's 335 SMAs; 11 SMAs were excluded from the MCD-Tx data collection.

[Table 1]

III. Identification strategy

The primary methodological challenge in identifying the causal effect of hospital capacity on treatment patterns lies in the endogeneity problem of reverse causality. Hospital capacity can influence treatment patterns, while simultaneously, physicians' treatment decisions affect bed availability. To address this endogeneity, we employ an instrumental variable (IV) approach to isolate the causal effect of hospital capacity on physicians' treatment patterns.

A. Instrumental variable construction

The Japanese government's "Hospital Beds Securing Plan" provides an exogenous source of variation by requiring each SMA to reserve a specific number of hospital beds exclusively for COVID-19 patients. The total number of beds in each SMA is legally regulated and predetermined by prefectural medical care plans, which remained unchanged during our observation period from December 2021 to November 2022. We calculate the COVID-19 assignment rate as the ratio of beds assigned for COVID-19 patients to the total number of beds in SMA j at month t, which serves as our instrument for the share of empty beds available. The IV is defined as:

$$(1) \qquad COVID\ assignment\ rate_{jt} = \frac{number\ of\ beds\ assigned\ to\ COVID\ patients_{jt}}{total\ number\ of\ beds_{jt}}$$

The magnitude of COVID-19 bed assignments varied substantially across SMAs and over time, driven primarily by local COVID-19 case counts and total SMA bed capacity. Crucially, these assignment decisions were made by prefectural governments based on pandemic conditions rather than pre-existing treatment patterns or physician preferences for non-COVID conditions. As illustrated in Figure 1, assignment rates exhibited considerable cross-sectional and temporal variation, ranging from minimal allocations in lightly affected areas to substantial bed reassignments in regions experiencing larger COVID waves. This variation provides the identifying leverage for our IV approach: differences in assignment rates that are orthogonal to underlying trends in non-COVID healthcare delivery.

B. Identification criteria

We address two critical requirements for IV validity. First, for the instrument to be valid, it must strongly predict the endogenous variable of interest (Angrist and Pischke, 2009)—in our case, the share of empty beds available for non-COVID patients. This relevance condition is intuitive: since the total bed capacity in each SMA remained fixed during our study period (predetermined by six-year medical care plans), COVID-19 bed assignments mechanically reduced the beds available for other conditions. A higher COVID assignment rate necessarily implies fewer empty beds available for non-COVID care, generating a strong negative first-stage relationship. The results section presents empirical evidence confirming this strong correlation, with first-stage F-statistics well above the thresholds for weak instrument concerns.

The second crucial requirement is the exclusion restriction, which stipulates that the IV must affect outcomes only through its impact on the endogenous variable (Angrist and Pischke, 2009). The assignment rates were co-determined by the COVID-19 bed assignment and the total bed capacity, which is unlikely to be correlated with pre-existing healthcare utilization patterns or physician treatment preferences for non-COVID conditions. The total bed capacity was predetermined by a nationwide uniform formula, and the COVID-19 bed assignment operated at the SMA level based on COVID-19 caseloads, which, conditional on our control variables and fixed effects, should be uncorrelated with underlying trends in treatment patterns for non-COVID chronic diseases. The timing and magnitude of assignments varied with pandemic waves rather than healthcare delivery characteristics, providing quasi-random variation in effective capacity.

We address two concerns that potentially threaten our identification. From the physician side, one may be concerned that COVID-19 severity itself might affect non-COVID treatment patterns through channels beyond bed capacity. Our study period (December 2021-November 2022) corresponds to the 6th and 7th Omicron waves, characterized by substantially lower severity and mortality than earlier pandemic phases (Esper et al., 2022; Uemura et al., 2023). and we focus on individuals aged 75 years and above, for whom healthcare provision remains relatively inelastic due to their vulnerable health status (Fu et al., 2025). This institutional context strengthens the plausibility that assignment rates affected treatment patterns primarily through the mechanical reduction in available beds rather than through pandemic-induced changes in clinical protocols. Furthermore, we control directly for the number of confirmed and hospitalized COVID-19 cases in each SMA-month, absorbing any direct effects of pandemic severity on physician or patient behavior independent of capacity constraints. In addition, we restrict our sample to individuals who were never infected by COVID-19, ensuring their health status was not contaminated by the virus. We further exclude individuals with respiratory diseases, as physicians treating respiratory conditions may have been reassigned to COVID units, creating a direct resource allocation channel beyond the mechanical bed capacity effect. While this exclusion is necessary to avoid contamination from direct resource competition with COVID patients, it could bias our estimates if respiratory and non-respiratory patients respond differently to capacity constraints. We address this through robustness checks that include respiratory patients, finding qualitatively similar results (Appendix Table B). For non-respiratory chronic conditions[7], treatment protocols should remain independent of COVID patient loads once we control for pandemic severity and exclude direct resource competition.

Beyond the physician side, one might also worry that individuals avoided medical facilities during high-COVID periods due to infection fears, creating spurious correlations between COVID severity and healthcare utilization. We have confirmed that this is not happening in our study. During the Omicron waves, individual mobility was not restricted and individuals had already developed protective strategies (vaccination, masking), reducing pandemic-related disruptions (Nakamoto et al., 2022; Okamoto, 2022). Figure 2 provides empirical support, demonstrating stable 80% healthcare utilization rates among our study population regardless of COVID-19 case fluctuations—evidence that demand remained relatively constant despite pandemic variation. To formally verify this stability, we directly test whether assignment rates predict healthcare utilization rates, conditional on COVID-19 prevalence. Results show no economically meaningful relationship (Appendix Table A): assignment rates do not significantly affect utilization rates, even controlling for confirmed and hospitalized COVID-19 cases. This stability reflects both the lower severity of Omicron variants (Esper et al., 2022; Uemura et al., 2023) and the relatively inelastic healthcare demand among our elderly population with chronic conditions requiring regular monitoring (Fu et al., 2025). Prior research also suggests hospital avoidance primarily affects younger adults and less-educated populations (Haritha and Praseeda, 2024; Zhang, 2021), consistent with our null finding among elderly patients. The results section provides empirical evidence that utilization rates do not vary with assignment rates conditional on COVID severity, supporting this exclusion restriction argument.

[Figure 2]

Our empirical specification includes SMA fixed effects, absorbing all time-invariant differences across regions (baseline capacity, physician supply, population health, treatment culture), and month fixed effects, controlling for common temporal shocks (national pandemic trends, seasonal patterns, policy changes). The identifying variation comes from within-SMA changes in assignment rates over time, conditional on these fixed effects and time-varying controls including COVID severity measures. For the exclusion restriction to be violated, assignment rate changes would need to be correlated with time-varying, SMA-specific shocks to non-COVID treatment patterns that operate independently of bed

[7] Medical Claims Data with Income Tax Information for the Oldest-Old for Japan (MCD-Tx) encompasses patients diagnosed with cancer, blood and immune system disorders, endocrine diseases, psychiatric conditions, neurological disorders, eye and ear diseases, circulatory diseases, respiratory conditions, digestive and kidney diseases, musculoskeletal conditions, and accident-related injuries.

capacity—a scenario we view as implausible given the institutional context, our rich set of controls, and the pandemic-driven nature of assignment decisions.

C. Interpretation: local average treatment effects

Our IV estimates identify a Local Average Treatment Effect (LATE), capturing the impact of bed capacity changes for the subset of SMAs whose effective capacity was affected by COVID-19 bed assignments (Imbens and Angrist, 1994). The "complier" SMAs in our setting are those that experienced meaningful variation in assignment rates during the study period, driven by temporal fluctuations in pandemic severity. These tend to be medium-to-large SMAs with sufficient bed capacity to absorb COVID patients while still serving non-COVID populations. Our estimates therefore characterize physician behavioral responses in contexts where capacity constraints bind meaningfully but not overwhelmingly—precisely the margin relevant for policy decisions about optimal capacity investment. While our LATE may not generalize to permanently capacity-constrained systems or regions with excess capacity under all conditions, it provides policy-relevant evidence on how physicians adjust treatment patterns when facing binding but variable capacity constraints—the typical scenario in most healthcare systems. Our heterogeneity analyses provide empirical support for this characterization, showing that treatment responses are concentrated in SMAs with higher baseline bed capacity per capita (Table 5), consistent with these regions having sufficient slack capacity to absorb COVID patients while still responding to assignment-induced constraints in non-COVID care.

D. Estimation frameworks

Our estimation proceeds in two stages. First, we estimate the first-stage relationship between our instrument and the endogenous variable:

$$Empty\ Rate_{jt} = \pi_0 + \pi_1 Assignment\ Rate_{jt} + D_{jt}\theta + \gamma_j + \lambda_t + e_{jt} \tag{2}$$

where $\text{Empty Rate}_{\text{jt}}$ represents the share of empty beds available and $\text{Assignment Rate}_{\text{jt}}$ is the proportion of beds assigned to COVID-19 patients in SMA j in month t. We control for time-varying regional characteristics, including the proportion of male patients, average age, average income level, average healthcare utilization rate, and critically, the number of confirmed and hospitalized COVID-19 cases. These COVID severity controls absorb any direct effects of the pandemic on healthcare delivery beyond the capacity channel. We include SMA fixed effects to absorb time-invariant regional characteristics (baseline capacity, physician supply, treatment culture) and month fixed effects to control for common temporal shocks (national pandemic trends, seasonal patterns). Standard errors are clustered at the SMA level to account for serial correlation. The identifying variation comes from within-SMA, over-time changes in assignment rates, conditional on COVID severity and fixed effects.

In the second-stage regression, we estimated:

$$(3) \qquad y_{jt} = \beta_0 + \beta_1 Empty\ Rate_{jt} + D_{jt}\zeta + \eta_j + \phi_t + \varepsilon_{jt}$$

where y_{jt}represents outcome variables in SMA j in month t, encompassing hospital admission rate, length of hospital stays, likelihood of doctor visits, frequency of doctor visits, inpatient and outpatient costs, and mortality rate per 1000 individuals. We incorporate the same fixed effects and controls as the first stage, with standard errors clustered at the SMA level. The coefficient β_1 represents our primary parameter of interest, capturing the causal effect of hospital capacity on physicians' treatment decisions for the complier SMAs whose capacity was affected by the policy-induced assignment variation.

IV. Results

A. First stage results

[Table 2]

Table 2 presents our first-stage estimates from Equation 2, confirming a strong negative relationship between COVID-19 bed assignment rates and empty bed availability for non-COVID care. Column 1 shows the specification with SMA and month fixed effects plus our full set of time-varying controls including COVID case counts. A one percentage point increase in the COVID-19 assignment rate reduces the empty bed rate by 0.611 percentage points, indicating that the policy-induced bed reassignments substantially constrained effective capacity for non-COVID patients.

The strength of the first-stage relationship is verified through multiple diagnostics. The Cragg-Donald Wald F statistic of 160.548 and the Kleibergen-Paap rk Wald F statistic of 74.96 both substantially exceed conventional thresholds for weak instrument concerns (Stock and Yogo, 2005; Keane et al., 2023; Keane et al., 2024), with both statistics well above the 10% critical values for maximal IV bias. Specifically, both statistics exceed Stock-Yogo (2005) critical values at the 10% level (16.38), the 5% level (19.93), and approach the 1% level (29.18), confirming strong instrument relevance. These diagnostics confirm that our instrument strongly predicts the endogenous variable, providing credible identification for the second-stage estimates.

B. Main results

[Table 3]

Table 3 presents our main results using IV and ordinary least squares (OLS) estimates for treatment pattern measures and health outcomes. All specifications include SMA and month fixed effects plus time-varying controls to account for unobserved heterogeneity.

The IV results reveal significant substitution from outpatient to inpatient care when hospital capacity increases. For inpatient services, a one percentage point increase in the share of empty beds raises the probability of hospital admission by 0.041 percentage points with an extension in average length of stay of 0.007 days. On average, this shift toward inpatient care is accompanied by a 318 JPY (approximately 3.2 USD) increase in inpatient care costs, representing a 1.4% increase relative to the mean. The economic magnitude is substantial: the cost increase suggests more resource-intensive treatments are being provided to patients.

For outpatient services, our IV estimates demonstrate corresponding reductions: the probability of doctor visits falls by 0.032 percentage points and average visit frequency declines by 0.004 visits per month. However, outpatient costs show no significant change. Taken together, these patterns indicate clear substitution from lower-cost outpatient settings to higher-cost inpatient settings as capacity expands.

Crucially, we find no detectable effect on mortality. The point estimate for mortality rate per 1000 individuals is 0.066 with a 95% confidence interval between -0.979 and 1.111, economically small and statistically insignificant. Although increased capacity leads to measurably different treatment patterns with substantially higher costs, these changes do not translate into improved (or worsened) survival outcomes. This null effect on health outcomes, combined with the large cost increases, suggests that the marginal treatments induced by capacity expansion lie in the "flat of the curve" region where additional spending yields minimal health benefits (Chandra and Staiger, 2007; Doyle, 2011). The findings indicate that capacity-driven treatment changes reflect discretionary practice variation rather than clinically necessary adjustments affecting patient survival.

The OLS estimates differ markedly from the IV estimates, with some coefficient signs reversed. This discrepancy confirms substantial endogeneity bias in OLS, likely stemming from reverse causality where increased hospital admissions and longer stays mechanically decrease empty bed share.

To validate our findings, we conducted a robustness check by including patients with non-COVID respiratory diseases in Appendix B. While respiratory patients might share resources with COVID patients—our primary reason for excluding them—including them provides a check on whether our sample restriction introduces selection bias. Results remain qualitatively similar, with slightly attenuated magnitudes consistent with respiratory patients experiencing direct resource competition beyond the capacity channel.

C. Mechanisms and heterogeneous effects

To understand the mechanisms driving our main results, we conduct heterogeneity analyses examining how treatment responses vary with local healthcare infrastructure. These analyses directly test the theoretical predictions. We divide SMAs into above-mean and below-mean groups based on three dimensions: physician supply, baseline bed capacity, and nurse availability per bed. The differential effects reported below represent the additional impact in high-resource regions relative to low-resource regions.

Physician availability as a moderating factor

[Table 4]

Table 4 examines heterogeneity by physician density, testing Hypothesis 2 from our theoretical framework. The results provide strong support for the target income hypothesis. SMAs with a larger number of physicians demonstrate substantially stronger treatment responses: a one percentage point increase in empty bed share raises hospital admission by 0.119 percentage points and extends average length of stay by more than 0.023 days. For outpatient services, we observe a 0.065 percentage point reduction in doctor visit probability and 0.012 fewer visits on average. These treatment pattern changes are accompanied by a 776.88 JPY increase in inpatient costs and a 69.44 JPY reduction in outpatient costs.

In contrast, SMAs with fewer physicians show statistically insignificant effects on inpatient care and minimal changes in outpatient patterns. Mortality effects remain insignificant in both groups, reinforcing that these represent discretionary rather than clinically necessary adjustments.

This striking heterogeneity likely stems from physician supply constraints affecting the marginal cost of additional inpatient services. In SMAs with limited physician resources, each additional hospital admission represents a substantial increase in workload for the available physicians, raising the opportunity cost of time and diminishing incentives to shift patients from outpatient to inpatient settings. The fixed time endowment per physician creates a binding constraint: even with available beds, physicians cannot expand inpatient admissions without sacrificing other activities or leisure.

Conversely, in physician-dense areas, the individual burden of additional admissions is distributed across more providers, allowing for more flexible treatment patterns that respond to available bed capacity. This pattern aligns with models of physician behavior that incorporate time allocation decisions and target income hypotheses (McGuire and Pauly, 1991; Gruber and Owings, 1996; McGuire, 2000).

These findings have important policy implications: expanding bed capacity alone has limited effects in physician-scarce regions. Effective capacity expansion requires coordinated investment in both physical infrastructure and physician workforce development.

Hospital infrastructure as moderating factor

[Table 5]

Table 5 analyzes heterogeneity by total bed capacity in each SMA, testing Hypothesis 3 regarding Roemer's Law. The findings closely mirror the physician density results, providing complementary evidence on infrastructure-based mechanisms. SMAs with higher baseline bed allocations demonstrate more pronounced substitution from outpatient to inpatient care: a one percentage point increase in empty bed share leads to a 0.115 percentage point increase in hospital admission probability accompanied by an average increase of approximately 0.024 days in length of stay, and a reduction of 0.073 percentage points in doctor visit probability with 0.014 fewer visits on average. Inpatient costs increase by 747.77 JPY while outpatient costs decrease by 85.43 JPY. In contrast, SMAs with fewer baseline beds per capita show only marginal reductions in outpatient care and negligible effects on inpatient care metrics.

This pattern suggests that healthcare providers in resource-rich SMAs face stronger incentives to optimize bed utilization, consistent with Roemer's Law (Roemer, 1961), which posits that healthcare capacity tends to generate its own demand. The substantial infrastructure investment in high-capacity regions creates economic pressure to maximize resource utilization—both to justify the capital expenditure and to spread fixed costs across more patients. Hospital administrators and physicians may view empty beds as "wasted" capacity, creating implicit or explicit organizational pressure to maintain high occupancy rates. Moreover, high-capacity regions typically possess complementary infrastructure (diagnostic equipment, specialized facilities) that facilitates inpatient care delivery, reducing the barriers to admission. Physicians practicing in these well-resourced environments face lower transaction costs for hospitalization decisions, enabling capacity-driven treatment adjustments.

The complementarity between physician supply (Table 4) and bed capacity (Table 5) is noteworthy. Both human capital and physical infrastructure must be simultaneously available for capacity to influence treatment patterns—consistent with healthcare production functions requiring multiple complementary inputs. Neither beds alone nor physicians alone suffice; both resources must be present for discretionary treatment adjustments to occur.

Mortality effects remain null in both capacity groups, suggesting that neither scarce- nor abundant-capacity regions achieve better health outcomes from marginal changes in bed availability. Consistent with the physician analysis, we find no significant effects of empty bed availability on health outcomes in either high-capacity or low-capacity areas. The estimates remain statistically insignificant and economically small across both strata.

Nurse availability as a moderating factor: A negative result

[Table 6]

Table 6 explores heterogeneity by the number of nurses per bed, testing Hypothesis 4. Unlike physician supply and bed capacity, nurse availability shows no significant heterogeneity: both high-nurse and low-nurse SMAs exhibit similar substitution patterns. In low-nurse areas, a one percentage point increase in empty bed share raises admissions by 0.044 percentage points and extends stays by 0.009 days, with outpatient reductions of 0.039 percentage points and 0.004 fewer visits. High-nurse areas show comparable admission effects (0.039 percentage points) and outpatient reductions (0.028 percentage points), though with no significant length-of-stay effects. Inpatient costs increase significantly in high-nurse areas (323.81 JPY) but not in low-nurse areas, possibly reflecting more intensive treatments when nursing support is available.

This null result for heterogeneity carries important theoretical and empirical implications. First, the absence of nurse-based heterogeneity contrasts sharply with physician and bed capacity results, suggesting that bed capacity rather than complementary nursing inputs constitutes the primary constraint binding physician admission decisions. Even if some nurses were reassigned to COVID-19 units during the pandemic, physicians adjusted treatment patterns based on bed availability, not nursing availability. This indicates that nurses are more substitutable than physicians in production functions for inpatient care, or that nurse staffing ratios adjust flexibly in response to patient loads.

Second, this finding addresses a potential identification threat to our instrumental variable strategy. If nurse reallocation to COVID-19 care were the operative mechanism rather than bed capacity per se, we would expect strong heterogeneity by baseline nurse levels—specifically, larger treatment effects in high-nurse regions where absolute numbers of reassigned nurses would be greater. The similarity of effects across nurse availability levels supports our exclusion restriction argument that the

COVID-19 bed assignment instrument affects non-COVID treatment patterns primarily through the mechanical bed capacity channel rather than through correlated changes in other healthcare inputs.

Third, from a policy perspective, this result suggests that investments in bed capacity do not require proportional increases in nursing staff to generate treatment responses. However, this should not be interpreted as endorsing capacity expansion without adequate nursing support—our mortality results indicate that capacity-driven treatment changes do not improve health outcomes, suggesting that these marginal admissions may not meet quality standards if nurse-to-patient ratios deteriorate.

Mortality effects remain null across nurse availability groups, consistent with all previous heterogeneity analyses. Taken together, the heterogeneity analyses reveal a clear mechanism: capacity effects operate through interactions between physician time constraints and hospital infrastructure capacity, with bed availability serving as the binding constraint rather than complementary inputs like nursing staff. The concentration of effects in high-physician, high-capacity regions indicates that discretionary treatment adjustments require slack in both human and physical resources simultaneously.

V. Back-of-the-envelope calculations of welfare costs

Having established the causal effects of bed capacity on treatment patterns and costs, we now translate these estimates into aggregate welfare implications. These back-of-the-envelope calculations, while approximate, provide important context for evaluating the economic magnitude and policy relevance of our findings.

[Figure 3]

We begin by examining the distribution of empty bed rates across SMAs. Figure 3 presents this distribution for our sample of 324 SMAs over the study period (3,888 SMA-month observations). The distribution is approximately normal with a slight right skew, with a mean of 25.9% and standard deviation of 7.0 percentage points (Table 1). The full distribution ranges from 8.1% to 69.5% empty beds, with the median at 24.5%. Notably, approximately 71.3% of observations fall in the middle range of 20-35% empty beds, while only 2.9% operate near full capacity (below 15% empty beds) and 5.3% have substantial excess capacity (above 40% empty beds). This distribution reveals considerable variation in available bed capacity across regions and over time, which we exploit in our welfare analysis below.

Our IV estimate indicates that a one percentage point increase in empty bed share raises inpatient costs by 318 JPY (3.2 USD) per patient-month. To translate this into aggregate annual costs, we consider two approaches.

First, we examine variation across the capacity distribution. The distribution in Figure 3 shows that the 19th and 81st percentiles correspond to approximately 19% and 33% empty beds, respectively, representing regions approximately one standard deviation below and above the mean of 25.9%. Moving a patient from a low-availability region at the 19th percentile to a high-availability region at the 81st percentile implies a 14 percentage point capacity difference, yielding annual excess spending of 53,424 JPY (534 USD) per patient.[8] Aggregating across the 18.52 million patients aged 75 and above yields total excess spending of 989 billion JPY (9.9 billion USD), representing approximately 0.28% of total healthcare expenditure on the 75+ population.

Second, we consider a policy-relevant one percentage point reduction in empty bed rates applied uniformly across the full elderly population. This calculation yields annual savings of 70.7 billion JPY (approximately 707 million USD).[9] However, this linear extrapolation likely overstates potential savings for several reasons. At very low capacity levels (below 15% empty beds), where only 2.9% of observations fall, medical necessity increasingly binds decisions, and further reductions would likely affect medically appropriate admissions. Conversely, at very high capacity levels (above 40% empty beds), where 5.3% of observations fall, discretionary effects might plateau as hospitals have already filled beds through discretionary admissions to the extent possible.

A more conservative estimate focuses on the middle range of the capacity distribution (20-35% empty beds), where approximately 71% of observations fall. However, even within this range, implementation constraints and heterogeneous treatment effects suggest that achievable capacity reductions would be modest. We assume that a 0.10 percentage point reduction in empty bed rates is feasible on average across the 71% of the elderly population receiving care in SMAs operating in this middle range.[10] Allowing for uncertainty in both the achievable reduction (0.08-0.12 percentage points) and the effective population share (68-74%), we estimate annual savings of approximately 38-63 million USD. This conservative estimate represents approximately 0.011-0.018% of total healthcare expenditure for this demographic and accounts for both the concentration of observations in the middle capacity range and the likely non-linear effects at distribution extremes.

For comparison, this 38-63 million USD in potentially avoidable spending, while modest relative to total healthcare expenditure, nonetheless represents an identifiable source of inefficiency that could be addressed through improved capacity management. The savings would be sufficient to fund approximately 1,500-1,800 additional home care workers annually or to expand community-based preventive care programs in underserved regions.

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[8] Annual excess spending per patient=318 JPY×14 ×12 months=53,424 JPY (534 USD). Aggregate annual excess spending=53,424 JPY×18.52 million patients=989 billion JPY (9.9 billion USD).

[9] Annual savings=318 JPY×1.0×18.52 million×12 months=70.7 billion JPY (approximately 707 billion USD).

[10] Annual savings=318 JPY×0.10×12 months×(0.71×18.52 million patients)=318×0.10×12×13.15 million=5.02 billion JPY≈5.0 million USD.

These welfare calculations carry important caveats. First, they assume null health effects based on our mortality findings, but we cannot rule out effects on other health dimensions (complications, functional status, quality of life) that might provide some value. Second, capacity-induced admissions may generate patient satisfaction value even without health improvements, as some patients may prefer inpatient care for convenience, perceived safety, or relief for caregivers. Third, our estimates represent short-run effects; long-run behavioral responses and patient outcomes may differ as physicians and patients adjust to new capacity constraints. Fourth, general equilibrium effects could alter the magnitudes if capacity reductions are implemented nationally, as physician practice patterns might shift in ways not captured by our cross-sectional variation. Despite these caveats, the identification of capacity-driven discretionary admissions provides evidence of allocative inefficiency that, while modest in magnitude than initially calculated, nonetheless indicates scope for improved resource allocation in Japan's healthcare system.

VI. Discussion

Our findings provide causal evidence that hospital bed capacity influences physician treatment patterns through supply-side mechanisms rather than pure medical necessity. The observed substitution from outpatient to inpatient care, combined with increased costs but null mortality effects, provides empirical support for theoretical predictions of supplier-induced demand (McGuire, 2000) and Roemer's Law (Roemer, 1961). This section discusses the broader implications of our results for economic theory, healthcare policy, and research methodology.

A. Connection to existing literature

Our findings complement and extend prior research on capacity effects in several ways. The null mortality effects align closely with evidence from Chandra and Staiger (2007) and Doyle (2011) on the "flat of the curve" phenomenon in U.S. healthcare. Chandra and Staiger documented that geographic variation in heart attack treatment intensity bore no relationship to survival outcomes, suggesting that high-spending regions operated on the flat portion of the health production function. Doyle similarly found that Medicare patients treated far from home—and thus exposed to different practice styles—experienced large spending variations without corresponding mortality differences.

Our contribution differs in two key dimensions. First, we identify causal effects of a specific resource constraint (bed capacity) rather than general practice style variation. This allows us to isolate the supply-side determinant and quantify the behavioral response. Second, we focus on elderly patients with chronic conditions requiring ongoing management, whereas prior flat-of-the curve evidence concentrated on acute care episodes (heart attacks, emergency admissions). Our results suggest that capacity-driven treatment changes occur on the flat of the curve even for chronic disease management—a setting where one might expect medical necessity to more tightly bind decisions.

Regarding specialized care settings, our findings both confirm and qualify results from neonatal intensive care. Freedman (2016) and Goodman et al. (2024) found that NICU capacity expansions increased utilization for marginal (less sick) infants without detectable health improvements. Our results demonstrate that similar mechanisms operate in general medical services for elderly populations, suggesting that capacity effects are not unique to high-technology specialty care. However, the mechanism differs: in neonatal care, physician discretion centers on the admission decision threshold (which infants are "sick enough" for NICU admission), whereas in elderly care, discretion involves treatment setting choice (inpatient versus outpatient management of chronic conditions). This distinction is important because it implies different policy levers: neonatal care may benefit from clearer admission protocols, while elderly care may require payment reforms that equalize incentives across treatment settings.

The heterogeneity patterns we document add nuance to prior findings. Our evidence that capacity effects concentrate in high-physician, high-capacity regions echoes findings on defensive medicine and treatment intensity variation (Finkelstein et al., 2016), where physician practice norms and local infrastructure jointly determine care patterns. The target income mechanism we identify has precedent in Gruber and Owings's (1996) cesarean delivery study, though we extend it to capacity-driven rather than payment-driven adjustments. Unlike Gruber and Owings, who found that physicians increased procedure intensity when fee reductions threatened income, we show that physicians substitute toward time-efficient services when capacity permits—maintaining income while reducing workload.

Our null finding for nurse availability heterogeneity is somewhat surprising given that nursing care constitutes an essential input for inpatient treatment. This may reflect two factors: first, elderly chronic disease management may be less nursing-intensive than acute care; second, our focus on treatment location choice (inpatient vs. outpatient) rather than inpatient mortality may miss nursing effects that matter for quality conditional on admission. Future research could examine whether nurse availability affects outcomes within the inpatient setting even if it does not affect admission decisions.

B. Policy implications

The welfare costs documented in Section V—approximately 38-63 million USD annually in potentially avoidable spending without detectable health benefits—indicate that capacity optimization represents a meaningful frontier for healthcare cost containment. Importantly, the distribution of empty bed rates (Figure 3) reveals that this inefficiency is widespread rather than concentrated in a few outlier regions. With 71% of observations falling in the 20-35% empty bed range and only 2.9% operating near full capacity (below 15% empty beds), the scope for policy intervention is substantial. Moreover, our conservative estimate assumes only a 0.10 percentage point reduction in empty bed rates within the middle capacity range, suggesting that even modest interventions could yield meaningful savings. Several specific policy interventions merit consideration.

First, policymakers should recognize that coordinated planning of physical infrastructure and physician workforce development is essential. Increasing bed capacity alone has limited effects in physician-scarce regions, as our heterogeneity results (Table 4) demonstrate. The finding that only 2.9% of observations reflect near-capacity operation (below 15% empty beds) indicates that capacity shortages are not the primary constraint facing Japan's healthcare system. Rather, the challenge is optimizing utilization of existing capacity. Countries experiencing physician shortages should prioritize workforce expansion over bed capacity increases. For Japan specifically, the current policy emphasis on reducing bed capacity (from approximately 12.7 to 9.2-9.5 per 1,000 inhabitants under the Regional Medical Care Vision targeting 1.15-1.19 million total beds by 2025) may be appropriate, but only if accompanied by physician workforce investment to ensure remaining capacity is appropriately utilized.

Second, payment policies may need mechanisms to counterbalance supply-side incentives. Our evidence that physicians substitute toward inpatient care when capacity permits suggests that fee-for-service reimbursement combined with excess capacity creates incentives for discretionary utilization. Given that the vast majority of SMAs operate with substantial available capacity (71% in the 20-35% range, with an additional 5.3% above 40%), the current payment system provides persistent incentives for discretionary admissions across most of the country. Bundled payment approaches—where providers receive fixed payments for episodes of care regardless of treatment setting—would eliminate the differential revenue from inpatient versus outpatient management. Japan's recent experimentation with diagnosis-related group (DRG) payments represents a step in this direction, though our findings suggest that more aggressive reforms may be warranted.

Third, long-term care investment may offer better value than acute care capacity expansion. Many elderly admissions reflect social needs rather than strict medical necessity. Redirecting resources toward home health services, adult day care, and respite care for caregivers could address underlying social determinants while reducing costly hospitalizations. International evidence suggests that comprehensive home-based care reduces hospitalizations and long-term institutional care without worsening mortality outcomes (Elkan et al., 2001; Ulmanen and Szebehely, 2015; Shepperd et al., 2016), with Scandinavian countries demonstrating successful large-scale implementation of such models (Szebehely and Ulmanen, 2022). Given the widespread nature of the capacity-utilization problem (affecting 71% of regions in the middle capacity range), alternative care models could potentially be deployed at scale rather than targeted to specific high-capacity outliers.

Fourth, financial incentives for hospitals to develop high-quality outpatient alternatives could redirect care toward more appropriate, lower-cost settings. For conditions where our results suggest discretionary admission decisions, enhanced outpatient monitoring programs, telemedicine consultations, or short-stay observation units might provide clinically equivalent care at lower cost. The feasibility of such alternatives is supported by our finding that even a modest 0.10 percentage point reduction in empty bed rates across the 71% of regions operating in the middle capacity range would generate approximately 50 million USD in annual savings, suggesting that small shifts toward outpatient care could have meaningful fiscal impact.

C. Broader implications and limitations

Our results contribute to understanding the behavioral foundations of geographic variation in healthcare spending. Finkelstein et al. (2016) decomposed spending variation into demand-side and supply-side components, finding supply factors dominant. Our findings provide a specific mechanism for supply-side variation: physical capacity constraints shape physician decision-making even controlling for patient characteristics, creating geographic spending differences that reflect resource availability rather than medical necessity. This has implications for evaluating healthcare system efficiency. Standard measures of capacity utilization (occupancy rates) may be misleading indicators of optimal resource allocation. High occupancy could reflect either appropriate matching of capacity to demand or aggressive utilization to fill available beds. Our evidence suggests that occupancy rates should be interpreted in conjunction with health outcomes and patient appropriateness measures. A region with 85% occupancy and good outcomes may be more efficient than a region with 95% occupancy achieved through discretionary admissions.

The findings also inform debates about healthcare infrastructure investment in aging societies. Our results suggest that capacity expansion without attention to appropriate utilization may exacerbate fiscal pressures without improving population health. Alternative approaches—enhancing outpatient care quality, investing in preventive services, developing community-based long-term care—might achieve better outcomes per dollar spent. Cost-effectiveness analyses should account for induced utilization when evaluating infrastructure investments.

Several limitations warrant acknowledgement. First, we cannot observe precise physician allocation within hospitals or SMAs. If physicians were reassigned to COVID-19 care, this could affect treatment patterns through labor supply channels beyond the bed capacity mechanism we identify. We address this by controlling for COVID-19 cases and hospitalization—factors likely correlated with physician reallocation—and by excluding respiratory patients to minimize shared resources with COVID treatment. Second, our study period coincides with the pandemic, potentially limiting generalizability to non-pandemic contexts. Although we selected a timeframe with stable healthcare-seeking behavior and excluded COVID-19 patients, replication in non-pandemic settings would strengthen external validity. The mechanism we identify should operate similarly in normal times, possibly with larger effects. Third, our focus on Japan's oldest-old population may limit generalizability to younger patients or different healthcare systems, though the behavioral mechanisms are rooted in general economic principles that operate across contexts.

Regarding external validity, the economic mechanisms we identify should operate similarly for younger elderly populations with chronic conditions, though effects might be smaller for working-age adults with acute conditions. Japan represents an extreme case with high bed capacity and below-average physician supply among OECD countries, suggesting that our estimates may represent an upper bound. Countries with similar capacity-workforce imbalances should exhibit similar patterns, while countries with balanced ratios might show smaller effects. Our findings most directly apply to fee-for-service or mixed payment systems where providers face volume incentives, though organizational pressure to utilize available capacity may create analogous effects even in capitated systems. The Local Average Treatment Effect interpretation means that our estimates characterize physician responses for medium-to-large SMAs with moderate capacity variation—precisely the settings relevant for capacity planning policies.

VII. Conclusion

This study demonstrates that hospital bed availability causally influences physician treatment decisions for elderly populations, with our back-of-the-envelope calculations (Section V) indicating that capacity-driven utilization generates approximately 38-63 million USD annually in potentially avoidable spending in Japan without detectable health benefits—a conservative estimate focusing on the 71% of regions operating in the middle capacity range where modest reductions are feasible. These findings reveal that both physical infrastructure and human capital jointly determine treatment patterns, with capacity effects concentrated in regions where physician supply is adequate. Importantly, with only 2.9% of observations reflecting near-capacity operation, the scope for optimization is substantial without compromising access to medically necessary care. The identifiable inefficiency we document suggests that capacity optimization—through coordinated workforce and infrastructure planning, payment reform, and alternative care models—represents a meaningful frontier for healthcare cost containment in aging societies.

As populations age globally and healthcare costs strain public budgets, evidence on optimal resource allocation becomes increasingly critical. Our results demonstrate that resource availability shapes treatment patterns independent of population health needs, creating geographic spending variation amenable to policy intervention. Unlike many sources of healthcare waste that requiring complex clinical interventions, capacity-driven utilization can be addressed through supply-side regulation and payment reform. Given the scale of resources involved and aging demographic trends across developed economies, capacity optimization merits priority attention from policymakers seeking to improve healthcare efficiency without compromising quality. Future research should examine whether these mechanisms operate similarly in other institutional contexts, explore patient-centered outcomes beyond mortality, and evaluate specific policy interventions designed to optimize capacity utilization while preserving appropriate access.

Appendix A

Table A1: Effect of assignment rates on healthcare utilization

	Healthcare Utilization Rate	
	(1)	(2)
Assignment rate	-0.159 (0.072)	-0.151 (0.071)
Number of COVID-19 confirmed cases	0.000 (0.000)	0.000 (0.000)
Number of COVID-19 patients in hospital		-0.000 (0.00001)
Region FE	X	X
Observations	3,888	3,888

Source: Authors' calculations based on the Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx) and Hospital Beds Availability and Utilization Report, both provided by the MHLW.

Note: Column (1) reports the coefficients of the $Assignment\ Rate_{jt}$ without controlling for regional characteristics, while column (2) includes regional characteristics. All regressions control for regional and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix B

Table B1: Robustness with respiratory diseases

	Hospital admission	Length of hospital stay	Doctor visits	Frequency of doctor visits	Inpatient care cost	Outpatient care cost	Moratlity rate
Regression methods							
IV	0.027*	0.003	-0.022**	-0.005	154.60	-9.28	0.082
	(0.015)	(0.003)	(0.008)	(0.003)	(119.50)	(25.23)	(0.528)
OLS	-0.021**	-0.004***	0.007***	-0.001*	-120.68	-4.42	-0.045
	(0.003)	(0.001)	(0.002)	(0.001)	(19.47)	(4.51)	(0.109)
Covariates							
Cragg-Donald Walf F Stat	160.235	160.235	160.235	160.235	160.235	160.235	160.235
KP rk Wald F Stat	73.198	73.198	73.198	73.198	73.198	73.198	73.198
10% Stock-Yogo critical value	16.38	16.38	16.38	16.38	16.38	16.38	16.38
Observations	3,888	3,888	3,888	3,888	3,888	3,888	3,888

Source: For the outcomes, we use the "Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx)," provided by the MHLW. For SMA characteristics, we use the "Hospital Report" and "Hospital Beds Availability and Utilization Report", also provided by the MHLW.

Note: The parameters for both IV and OLS show coefficients of $Empty\ Rate_{jt}$. All regressions are adjusted for regional characteristics, fixed effects for SMA, and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed COVID-19 cases and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

This appendix presents results from our robustness analysis that includes patients with respiratory diseases, who were excluded from our main analysis due to potential resource-sharing concerns with COVID-19 treatment. Table B1 summarizes the instrumental variable (IV) estimates for our key outcome measures when these patients are included in the analytical sample.

The robustness check confirms our main findings while revealing some nuanced differences. When respiratory disease patients are included, a one percentage point increase in the share of empty beds increases the probability of hospital admission by 0.027 percentage points, compared to 0.022 percentage points in our baseline specification. The pattern of substitution remains consistent, and there is no effect on mortality rate observed.

These results provide additional support for our core finding: increased hospital capacity leads to a systematic shift from outpatient to inpatient service provision. However, the magnitude of the substitution effect is attenuated when respiratory patients are included. This difference is consistent with our theoretical framework regarding resource allocation during the pandemic. Respiratory specialists and related medical resources were more likely to be shared between COVID-19 and non-COVID respiratory patients, potentially constraining physicians' ability to alter treatment patterns in response to bed availability.

The smaller effect sizes in this expanded sample suggest that the degree of supply-side response to capacity changes is sensitive to the availability of complementary medical resources, particularly specialized physician labor. This provides further evidence for our hypothesis that capacity-induced changes in treatment patterns are moderated by the overall resource environment, not just bed availability alone.

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Figures and Tables

Table 1: Summary statistics

	Mean	SD	N	Min	Max
Independent variable					
Empty bed rate (%)	25.88	7.44	3,888	8.07	69.53
IV					
COVID-19 bed assignment rate (%)	2.37	1.49	3,888	0	13.54
Outcomes					
Hospital admission rate (%)	3.77	1.49	3,888	0.01	9.71
Length of hospital stay	0.81	0.34	3,888	0.19	2.3
Probability of doctor visits (%)	76.14	12.44	3,888	0.31	85.35
Frequency of doctor visits	1.78	0.31	3,888	0.98	2.79
Inpatient care costs	22512.19	8318.45	3,888	1733.21	55973.2
Outpatient care costs	17651.41	3947.53	3,888	2225.5	24872.4
Moratlity rate per 1000 individuals	0.92	0.26	3,888	0.32	2.26
SMA characteristics					
Proportion of male in the SMA (%)	37.24	2.05	3,888	32.50	43.08
Average age of patients in the SMA	82.92	0.62	3,888	81.28	84.52
Average income level (JPY)	1,792,220	449,311	3,888	213589.7	3713310
Healthcare utilization rate (%)	78.19	12.77	3,888	0.34	89.90
Total number of beds	4,281.94	4627,49	3,888	175	41527
Total number of empty beds	1,117.26	1,248.99	3,888	58	12977
COVID-19 beds	96.84	126.90	3,888	0	1448
COVID-19 patients in hospital	37.40	65.42	3,888	0	1132
Number of confirmed cases	52079.06	85577.39	3,888	0	757621
Total number of physicians	912.50	1,334.46	3,888	27	170553

Source: Authors' calculations based on the Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx), provided by the MHLW. SMA characteristics are drawn from the Hospital Report and Hospital Beds Availability and Utilization Report, also provided by the MHLW.

Note: The study period covers December 2021 to November 2022, encompassing Japan's 6th and 7th waves of the COVID-19 pandemic. All statistics are averages over the entire observation period.

Table 2: First stage

	Empty bed rate	
	(1)	(2)
Assignment rate	-0.600*** (0.072)	-0.611*** (0.071)
Region FE	X	X
Regional Characteristics		X
Cragg-Donald Walf F Stat	154.869	160.548
KP rk Wald F Stat	69.24	74.96
10% Stock-Yogo critical value	16.38	16.38
Observations	3,888	3,888

Source: Authors' calculations based on the Hospital Report and Hospital Beds Availability and Utilization Report, both provided by the MHLW.

Note: Column (1) reports the coefficients of the $Assignment\ Rate_{jt}$ without controlling for regional characteristics, while column (2) includes regional characteristics. All regressions control for regional and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Effects of share of empty beds on healthcare utilization (IV and OLS)

	Hospital admission	Length of hospital stay	Doctor visits	Frequency of doctor visits	Inpatient care cost	Outpatient care cost	Moratlity rate
Regression methods							
IV	0.041** (0.015)	0.007* (0.004)	-0.032** (0.009)	-0.004* (0.003)	317.59** (137.70)	-0.158 (23.08)	0.066 (0.531)
OLS	-0.020*** (0.003)	-0.004*** (0.0007)	0.007*** (0.002)	-0.001* (0.053)	-111.28*** (19.78)	-0.991 (4.448)	-0.050 (0.109)
Covariates							
Cragg-Donald Walf F Stat	160.548	160.548	160.548	160.548	160.548	160.548	160.548
KP rk Wald F Stat	74.96	74.96	74.96	74.96	74.96	74.96	74.959
10% Stock-Yogo critical value	16.38	16.38	16.38	16.38	16.38	16.38	16.38
Observations	3,888	3,888	3,888	3,888	3,888	3,888	3,888

Source: Authors' calculations based on the Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx), provided by the MHLW. SMA characteristics are obtained from the Hospital Report and Hospital Beds Availability and Utilization Report, also provided by the MHLW.

Note: Both IV and OLS parameters report the coefficients of $Empty\ Rate_{jt}$. All regressions control for regional characteristics, SMA fixed effects, and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Heterogeneity by number of physicians

	Hosptial admission	Length of hospital stay	Doctor visits	Frequency of doctor visits	Inpatient costs	Outpatient costs	Mortality rate
Panel A: Below mean							
Empty bed rate	0.021	0.003	-0.021**	-0.004	226.75*	16.00	0.200
	(0.0124)	(0.004)	(0.009)	(0.002)	(134.73)	(22.70)	(0.531)
Cragg-Donald Wald F Stat	163.605	163.605	163.605	163.605	163.605	163.605	163.605
KP rk Wald F Stat	92.335	92.335	92.335	92.335	92.335	92.335	92.335
Observations	2,772	2,676	2,676	2,676	2,676	2,676	2,772
Panel B: Above mean							
Empty bed rate	0.119**	0.023**	-0.065**	-0.012*	776.88**	-69.44**	-0.871
	(0.036)	(0.008)	(0.021)	(0.006)	(273.64)	(34.79)	(0.621)
Cragg-Donald Wald F Stat	44.645	44.645	44.645	44.645	44.645	44.645	44.645
KP rk Wald F Stat	28.167	28.167	28.167	28.167	28.167	28.167	28.167
Observations	1,116	1,116	1,116	1,116	1,116	1,116	1,116

Source: Authors' calculations based on the Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx), provided by the MHLW. SMA characteristics are obtained from the Hospital Report and Hospital Beds Availability and Utilization Report, also provided by the MHLW.

Note: Both IV and OLS parameters report the coefficients of $Empty\ Ratejt$. All regressions control for regional characteristics, SMA fixed effects, and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Heterogeneity by number of beds

	Hosptial admission	Length of hospital stay	Doctor visits	Frequency of doctor visits	Inpatient costs	Outpatient costs	Mortality rate
Panel A: Below mean							
Empty bed rate	0.022	0.003	-0.021**	-0.003	245.00*	19.20	0.200
	(0.014)	(0.004)	(0.009)	(0.002)	(136.67)	(23.28)	(0.579)
Cragg-Donald Wald F Stat	151.039	151.039	151.039	151.039	151.039	151.039	151.039
KP rk Wald F Stat	90.325	90.325	90.325	90.325	90.325	90.325	90.325
Observations	2,594	2,594	2,594	2,594	2,594	2,594	2,594
Panel B: Above mean							
Empty bed rate	0.115**	0.024**	-0.073**	-0.014**	747.77**	-85.43***	-0.601
	(0.034)	(0.008)	(0.021)	(0.006)	(253.84)	(33.93)	(0.523)
Cragg-Donald Wald F Stat	45.835	45.835	45.835	45.835	45.835	45.835	45.835
KP rk Wald F Stat	32.519	32.519	32.519	32.519	32.519	32.519	32.519
Observations	1,293	1,293	1,293	1,293	1,293	1,293	1,293

Source: Authors' calculations based on the Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx), provided by the MHLW. SMA characteristics are obtained from the Hospital Report and Hospital Beds Availability and Utilization Report, also provided by the MHLW.

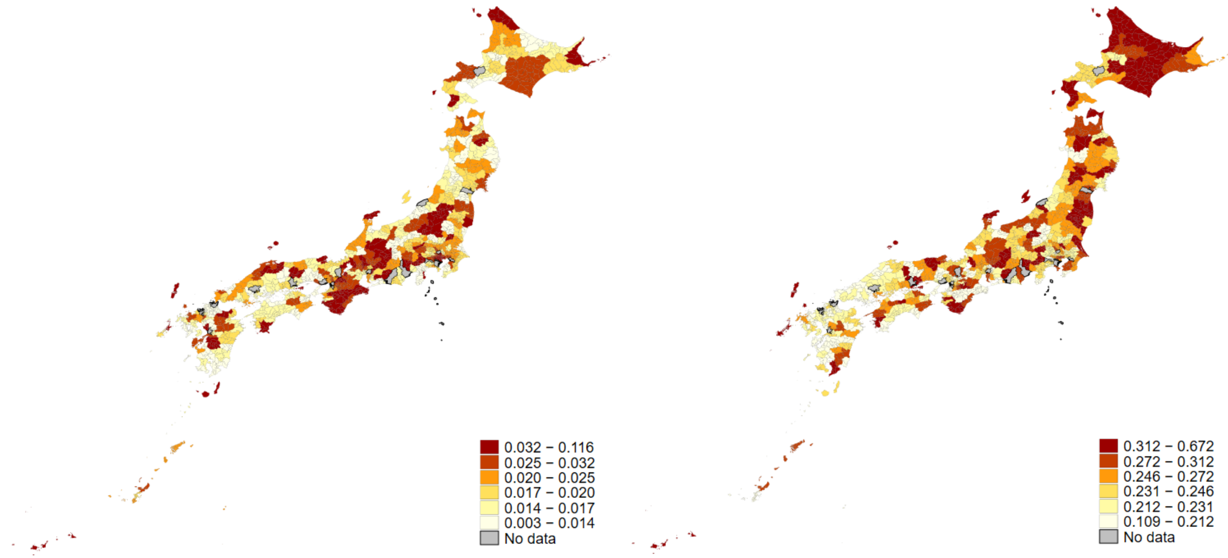
Note: Both IV and OLS parameters report the coefficients of $Empty\ Ratejt$. All regressions control for regional characteristics, SMA fixed effects, and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Heterogeneity by nurse availability

	Hosptial admission	Length of hospital stay	Doctor visits	Frequency of doctor visits	Inpatient costs	Outpatient costs	Mortality rate
Panel A: Below mean							
Empty bed rate	0.044*	0.009*	-0.039**	-0.004*	313.10	-31.44	0.707
	(0.023)	(0.005)	(0.014)	(0.002)	(190.20)	(39.86)	(0.732)
Cragg-Donald Wald F Stat	78.116	78.116	78.116	78.116	78.116	78.116	78.116
KP rk Wald F Stat	28.902	28.902	28.902	28.902	28.902	28.902	28.902
Observations	2,043	2,043	2,043	2,043	2,043	2,043	2,043
Panel B:Above mean							
Empty bed rate	0.039**	0.006	-0.028**	-0.003	323.82*	26.12	-0.384
	(0.029)	(0.005)	(0.012)	(0.003)	(186.00)	(26.97)	(0.776)
Cragg-Donald Wald F Stat	83.467	83.467	83.467	83.467	83.467	83.467	83.467
KP rk Wald F Stat	45.524	45.524	45.524	45.524	45.524	45.524	45.524
Observations	1,838	1,838	1,838	1,838	1,838	1,838	1,838

Source: Authors' calculations based on the Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx), provided by the MHLW. SMA characteristics are obtained from the Hospital Report and Hospital Beds Availability and Utilization Report, also provided by the MHLW.

Note: Both IV and OLS parameters report the coefficients of $Empty\ Ratejt$. All regressions control for regional characteristics, SMA fixed effects, and time fixed effects. Regional characteristics include the proportion of male patients, average age of patients, average income level, healthcare utilization rate, and the number of confirmed and hospitalized COVID-19 patients in each SMA. Standard errors are clustered at the SMA level. "***" "**" and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.



(a) Assignment rate (b) Empty bed rate

Figure 1: Variation of assignment rate and empty bed rate across prefectures

Source: The Hospital Report and Hospital Beds Availability and Utilization Report provided by the MHLW.

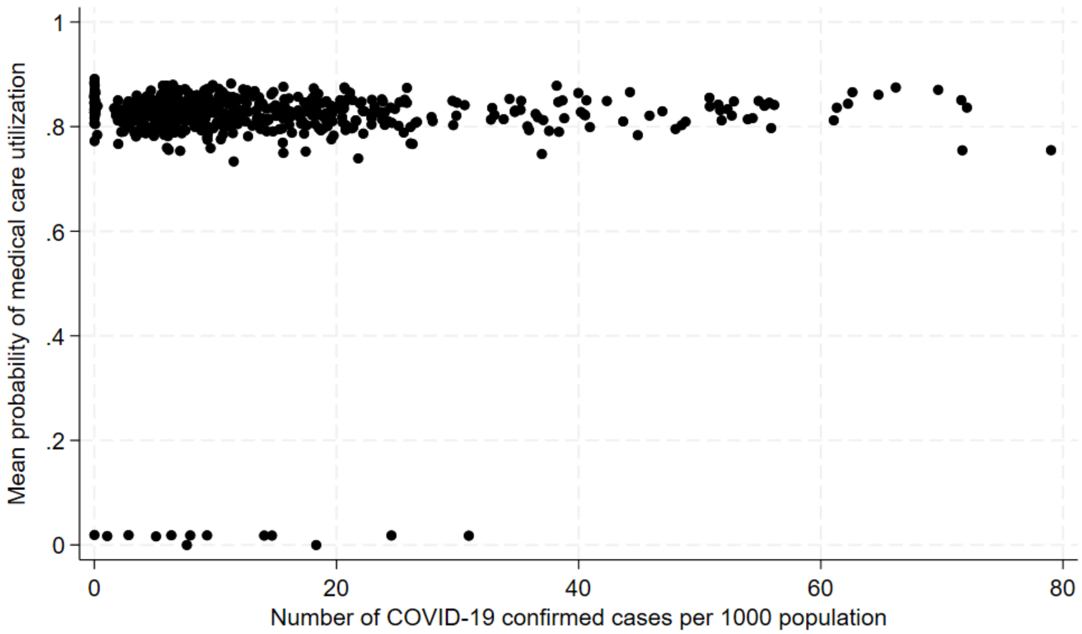


Figure 2: Correlation between number of COVID-19 confirmed per 1,000 population and probability of medical care utilization

Source: The Medical Claims Data with Income Tax Information for the Oldest-Old in Japan (MCD-Tx) obtained from the MHLW.

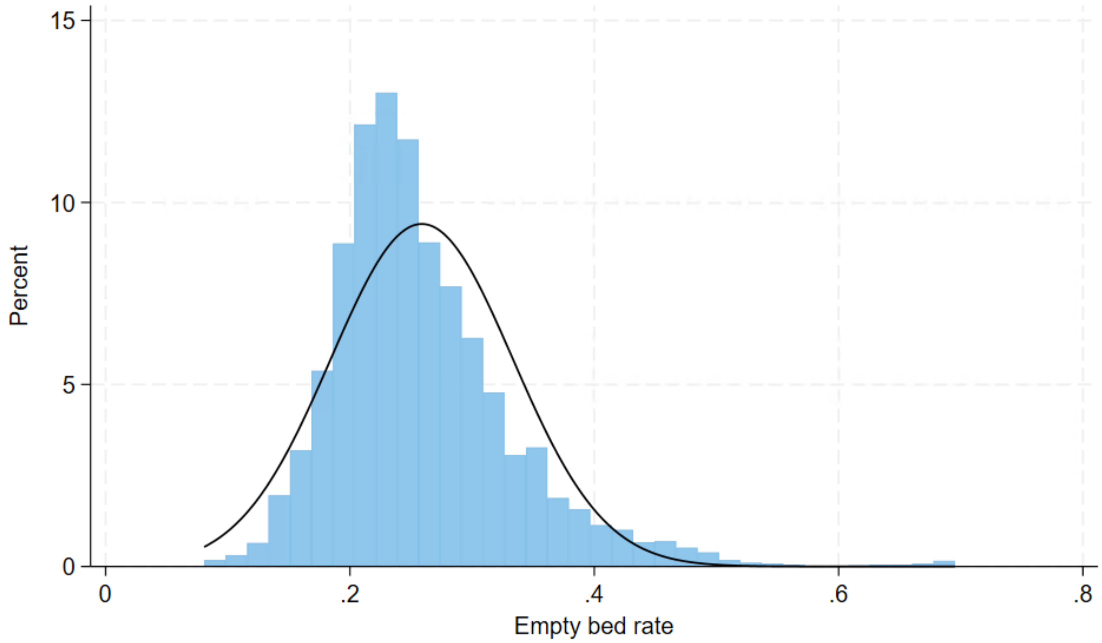


Figure 3: Distribution of empty bed rates across SMAs

Source: Source: The Hospital report and Hospital Beds Availability and Utilization Report provided by the MHLW.

Notes: The figure shows the distribution of empty bed share across 3,888 SMA-month observations (341 SMAs over 12 months). The histogram bins are 2.5 percentage points wide, with a kernel density overlay. Mean = 25.9%, SD = 7.0%, Median = 24.5%, Min = 8.1%, Max = 69.5%. Approximately 2.9% of observations fall below 15% empty beds (near full capacity) and 5.3% fall above 40% empty beds (substantial excess capacity).